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Air Pollution Control and Sustainable Development

Pollution Control and Economic Growth

Edited by

Weixin Yang, Guanghui Yuan and Yunpeng Yang

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Preface to ”Air Pollution Control and Sustainable Development: Pollution Control and Economic Growth”

Our world is facing the growing threat of air pollution. On the one hand, particulate matter with a diameter of less than 10 (so-called respirable particulate matter PM_{10}) can enter the bronchi of the lower respiratory tract of the human body. The different types of PM_{10} includes particulate matter with a diameter of less than 2.5 ($PM_{2.5}$), which can enter the alveoli of human lungs. When $PM_{2.5}$ particles reach human lungs, they attach themselves to the alveoli and stay within the human body for years. They can even travel to other organs of the human body through blood circulation and therefore can cause major damage to people's health.

On the other hand, air pollution also poses a huge threat to the economic growth of the world. The dust and fumes contained in waste gases seriously impact agricultural and industrial production as well as transportation. Hazardous substances such as SO_2 and NO_x become acid deposition and cause damage and erosion to soil, vegetables, and industrial plants and other buildings. Moreover, the particles in waste gas cause direct and indirect climatic effects and result in an imbalance in solar irradiance between the Earth and the Sun so that drought regions will suffer more drought while flood-prone regions will suffer more floods.

In the face of the serious consequences of air pollution, governments have adopted various policies and measures to control and mitigate the adverse effects of air pollution, including China's "Blue Sky Defense War" action plan, India's "National Clean Air Program", Brazil's new "Air Quality standards (PI_{-1}, PI_{-2}, PI_{-3}, PF)", etc. These policies have played positive roles in improving the air quality and promoting economic growth.

Therefore, we have edited and published this book to discuss air pollution control and sustainable development in the world, especially in terms of the relationship between pollution control and economic growth. Scholars from different countries have delved into the issues of pollution control and economic growth in the 10 academic papers, which provide excellent materials for students at the level of BSc, MSc, and PhD level, as well as researchers to understand the situation of air pollution control and its impacts on economic growth in different countries all over the world.

Weixin Yang, Guanghui Yuan, and Yunpeng Yang
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Article

Research on Air Pollution Control in China: From the Perspective of Quadrilateral Evolutionary Games

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Abstract: By constructing a quadrilateral evolutionary game model involving the central government, local governments, polluting enterprises, and the public, this paper attempts to comprehensively analyze the development and implementation of China's air pollution control policies. Through the quadrilateral evolutionary game model, this paper systematically studies the evolutionary stable strategies of the four parties involved and obtains 27 equilibrium points, strategy sets, and their corresponding policy performance with the help of the four-dimensional dynamic system. The research results show that there are five equilibrium points that represent the least ideal scenarios, 14 equilibrium points that represent the less than ideal scenarios, four equilibrium points that represent the ideal scenarios, three equilibrium points that represent the more than ideal scenarios, and one equilibrium point that represents the most ideal scenarios. By analyzing the eight equilibrium points that represent the ideal, more than ideal and most ideal scenarios, especially the four stable points, this paper has obtained the conditions as well as policy implications of the four stable points in China's air pollution control campaign.

Keywords: evolutionary game; quadrilateral game; air pollution; pollution control policy

1. Introduction

Severe air pollution will not only lead to a high incidence of diseases and low level of social welfare but also impose immeasurable negative impacts on sustainable development in the long run [1–3]. As a large developing country that is at a critical stage of economic transformation, China has realized the significance of air pollution problems. The top leadership has clearly stated that we must "speed up structural reform on ecological civilization and build a beautiful China" [4].

In order to fight against severe air pollution, the Chinese government has issued a large number of air pollution control policies, such as the "Air Pollution Prevention and Control Action Plan" implemented in 2013 [5]; the "Temporary Provisions on the Management of Pollutant Discharge Permits" issued in December 2016 that has accelerated the implementation of a permit system for pollutant emission control [6]; the revised "Air Pollution Prevention and Control Law" effective 26 October 2018 that requires clean production inspection in key industries including the steel, cement, and chemical industries, the adoption of advanced technologies, processes, and equipment, as well as clean production technology transformation for key areas and weak links in energy conservation and emission reduction campaigns [7]; and the "Key Points on 2019 Nation-wide Air Pollution Prevention and Control" published in March 2019 that requires various local governments to make efforts on air pollution prevention and control and continuously improve air quality [8]. Assessing the results of these policies is of paramount importance, to check if these are delivering results. This can be done using air quality models [9], satellite data [10], or measurements [11].

At the same time, the Chinese government also attaches great importance to the public participation in air pollution control. In 2016, China established the "12369 Environmental Protection Whistleblowing Inter-Connected Management Platform," which has integrated multiple information channels including hotlines, WeChat, and the Internet, realized the sharing of whistleblowing information among the four levels of "national-provincial-city-district," and encouraged the public to play an active role in air pollution control by blowing the whistle [12]. In November 2019, the platform received a total of 34,942 environment-related reports, including 14,277 reports through hotlines, 16,475 reports through WeChat, and 4190 reports through the Internet. In terms of pollution types, air pollution is most frequently reported, accounting for 51.5% of total reports (see Figure 1) [13].

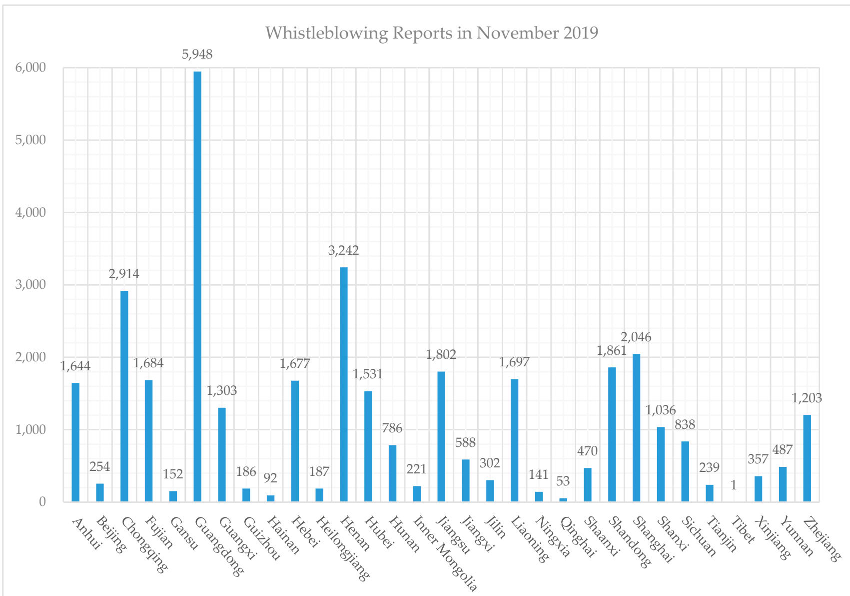

Figure 1. Whistleblowing Reports on China's "12369 Environmental Protection Whistleblowing Inter-Connected Management Platform" in November 2019.

Therefore, throughout the development and implementation of existing air pollution control policies, there are four participants: the central government, the local government, polluting enterprises, and the public (whistleblowers). During the overall process of policy development and implementation, the relationship between these four parties is quite complicated.

1. There is to information asymmetry with the central government [14–16], competition between local governments for official promotion and in the area of environmental regulation, and local governments not only take orders from the central government but also have countermeasures and non-cooperation relationships with the central government [17–19].
2. From the perspective of polluting enterprises, which are one of the main sources of air pollution in China [20,21] and the main source of pollution explored in this paper, because a large number of polluting enterprises are the major tax-payers that the local government relies heavily on, and some are even state-owned enterprises directly under the State-Owned Assets Supervision and Administration Commission (SASAC), the local governments have a certain collusion relationship with the polluting enterprises [22–24].

3. From the perspective of public participation, on the one hand, air pollution should cause the public (the direct victims of pollution) to blow the whistle; on the other hand, the personal information leakage during whistleblowing and harassment and retaliation by polluters after whistleblowing would weaken the public's initiative to participate. Therefore, it might be the case that some victims of pollution did not blow the whistle [25–28].

So far, in the academia, there have been quite a few studies on the multi-party relationship in air pollution control based on Game Theory. For example, Shi et al. constructed a transboundary air pollution model based on game theory to analyze the cooperative SO_2 reduction in three cities of Hunan province, China. Their results proved that those cities would fully cooperate to reduce emissions when the welfare from full cooperation was reasonably allocated. Therefore, the welfare allocation may affect the sustainability of cooperation significantly in environment protection [29]. Chang et al. established a transboundary pollution game model, including emission permits trading and pollution abatement costs. Based on the model, they studied the optimal emission paths and pollution abatement strategies under cooperative and noncooperative games [30]. Wang et al. have presented a generalized Nash equilibrium game model to study the SO_2 reduction in Yangtze River Delta region in China. This new model resulted in an optimal SO_2 removal solution with savings of $\$4.8 \times 10^7$ USD. They also simulated the effects of changes in the SO_2 reduction targets to help policy makers develop more effective pollutant reduction strategies [31]. Hong et al. studied the links between air pollution, interpersonal trust, and preferences to buy stock in companies emitting air pollutants. By recruiting volunteers in 31 provinces of mainland China and testing their behavior using game models, they have found the robust main effect of pollution and an interaction effect between participants' subjective socioeconomic status and real-time $PM_{2.5}$ levels in China. They argued that the environment pollution could establish a bad norm, which would undermine interpersonal trust and environmental protection behavior [32]. Shi et al. have used the agent-based model in a complex network to simulate the behavior of enterprises to policies spurring low-carbon technology diffusion. Playing evolutionary games with their neighbors, those enterprises demonstrated adaptiveness and equilibrium. Their results showed that all these policies turn out to be inefficient or even harmful to enterprises because of the adaptiveness of the whole system. Nonetheless, policymakers could choose measures to enlarge the size of green markets to solve the problem [33].

Unfortunately, existing studies usually construct the game model for the government and enterprises based on exogenous mechanisms, and therefore have the following shortcomings:

1. Most studies focused on dual party games and did not consider the participation and influence of the public [34–36]. Although this simplifies theoretical derivation, it cannot reflect the actual situation in China's air pollution control.
2. Although many studies have further expanded dual-party games to tri-party games covering the central government, local governments, and polluting enterprises, these studies still failed to fully reflect the complex process of air pollution control in China [37]. In our tri-party game study in 2019, although we innovatively included the public into the pollution control game, regretfully, we did not include polluting enterprises as a game participant in the research framework [38].

In view of this, based on above studies, this paper has made further innovations by constructing a Quadrilateral Evolutionary Game Model covering the central government, local governments, polluting enterprises, and the public in order to comprehensively analyze the development and implementation process of China's air pollution control policies. By adopting the Quadrilateral Evolutionary Game Model, this paper has systematically studied the evolutionary stable strategy of the four parties involved, and proposed solutions to air pollution control in China, making theoretical and practical contributions to the construction of air pollution control systems in developing countries.

The structure of this paper is as follows: Section 2 constructs the Quadrilateral Evolutionary Game Model, Section 3 obtains the evolutionary stable strategies and stability conditions of various parties, Section 4 reveals the condition and process of formation of evolutionary stable strategies by constructing and solving the four-dimensional dynamic system of dynamic game evolution, and Section 5 concludes the paper and provided relevant policy recommendations based on the results of game analysis.

2. Materials and Methods

2.1. The Parties in the Game and Their Strategy Choices

2.1.1. The Central Government

The central government determines the performance of local governments in environmental supervision by checking whether the local government's supervision report is consistent with on-site inspection results and determines whether the enterprises comply with the regulations on emissions by monitoring various emission indicators of the polluting enterprises [39]. Given the strategies of the local government and polluting enterprises, the central government can choose to monitor (let the probability be x) or not to monitor (let the probability be $(1-x)$) the air pollution control work in different places. Let the long-term social welfare brought by the long-term monitoring of the central government on environmental protection be S_1, the monitoring cost be C_1, and the cost of not monitoring be 0; let the reputation loss due to lack of monitoring by the central government be L_1.

2.1.2. The Local Government

When the central government requires local governments to supervise whether enterprises comply with regulations on emissions, the local governments may implement regulations for the improvement of local environment. However, the local government may also choose not to regulate due to the high regulatory cost or concerns that strict regulations might result in lower fiscal revenues [40,41]. Therefore, the local governments' behavior strategies include regulating (let the probability be y) and not regulating (let the probability be $(1-y)$). When the local governments choose to regulate, this will pressure the enterprises to comply with regulations on emissions, so that improve the long-term reputation and political achievement of the local government (let it be S_2), but this will incur regulatory cost at the same time (let it be C_2). When the local government chooses not to regulate, public health will be adversely impacted, and the local government will face reputation loss and other losses due to population migration and labor force decrease in the long term (let it be L_2). If the fact that the local government chooses not to regulate takes place during the central government's environmental inspection, the local government will be subject to political penalties (let it be P_2).

2.1.3. Enterprises

When the local government requires enterprises to strictly follow the stated emission allowance, the enterprises may, out of a sense of responsibility to the environment or fear of supervision by the central and local governments, choose to comply with the regulations (let the probability be z); the enterprises may also choose not to comply due to technology investment cost and potential negative impacts on their operation income (let the probability be $(1-z)$) [42,43]. If the illegal polluting activity of enterprises is discovered by the central or local governments, the enterprises will be subject to economic penalties (let it be P_3) collected by the central government [44] and suffer from a reputation loss (let it be L_3).

2.1.4. The Public

When the public interest is violated due to the excessive emissions of polluting enterprises within the jurisdiction of the local government, the public could not blow the whistle, i.e., tolerate the enterprises' non-compliant emissions and hope the local government would enforce the regulations. In this case, the public will suffer a health loss of L_4. The public could also choose to blow the whistle in order to protect their legitimate rights and interests. If the non-compliant emissions or illegal polluting activities of the enterprise are confirmed, the whistleblower will receive a reward of B_4 [45]. Therefore, the public's behavior strategies include blowing the whistle (let the probability be θ) and not blowing the whistle (let the probability be $(1-\theta)$). As for the local government, regarding the excessive emissions of polluting enterprises within its jurisdiction, it may choose to regulate for the benefit of public interests; it may also choose not to regulate due to concerns that the local economy might suffer from strict environmental regulations [46,47]. When the public chooses to blow the whistle and the local government chooses to regulate, the whistleblower will receive an extra compensation from the polluting enterprise for negative externalities (let it be R_4). However, when the public choose to blow the whistle, they face a cost of C_4.

2.2. The Game Tree and Parameters

Based on the above-mentioned game participants and strategy choices, this paper has obtained the Quadrilateral Game Tree related to air pollution whistleblowing and air pollution control and supervision, as shown in Figure 2.

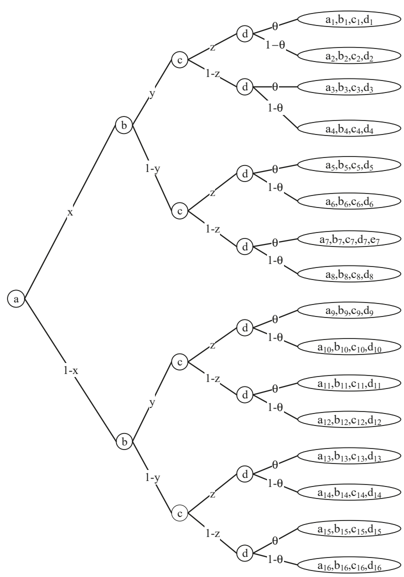

Figure 2. Quadrilateral Game Tree for air pollution whistleblowing, air pollution control, and supervision.

Further, Table 1 has listed the parameter description, definition, and value range of different game participants in Section 2.1, in which the parameters x, y, z, θ are dimensionless ones, while the other parameters $S_1, C_1, \ldots, P_3, L_4$, etc. are economic variables of the same order of magnitude. This paper has not set specific units for them, which will not affect model calculations and results analysis.

Table 1. Definition of parameters related to different game strategies.

Parameter	Definition	Range
x	The probability that the central government chooses to monitor	$x \in [0, 1]$
$1 - x$	The probability that the central government chooses not to monitor	$(1 - x) \in [0, 1]$
y	The probability that the local government chooses to regulate	$y \in [0, 1]$
$1 - y$	The probability that the local government chooses not to regulate	$(1 - y) \in [0, 1]$
z	The probability that enterprises comply with the regulations	$z \in [0, 1]$
$1 - z$	The probability that enterprises violate the regulations	$(1 - z) \in [0, 1]$
θ	The probability that the public choose to blow the whistle	$\theta \in [0, 1]$
$1 - \theta$	The probability that the public choose not to blow the whistle	$(1 - \theta) \in [0, 1]$
S_1	The long-term social welfare due to air quality improvement when the central government monitors, the local government regulates polluting activities, and enterprises comply with the regulations	$S_1 \gg max\{C_1, L_1, P_2, P_3, B_4\} > 0$
C_1	The monitoring cost of the central government	$C_1 > 0$
L_1	The reputation loss if the central government chooses not to monitor	$L_1 > 0$
S_2	The long-term reputation gain and political achievement of the local government if it chooses to regulate polluting activities and encourage emission reduction	$S_2 > 0$
C_2	The cost of the local government if it chooses to regulate polluting activities and the economic loss brought by strict regulation	$C_2 > 0$
L_2	The reputation loss if the local government chooses not to regulate	$L_2 \geq 0$
P_2	The punishment on the local government if the local government chooses not to regulate and enterprises' polluting activity is caught by the central government	$P_2 \geq 0$
C_3	The technology investment cost required by enterprises to comply with the regulations and related impacts on their main operation income	$C_3 > 0$
L_3	The reputation loss of the enterprise if it chooses to violate the regulations	$L_3 > 0$
P_3	The penalty on enterprises if their illegal polluting activity is caught by the local government or central government, which belongs to the central government	$P_3 > 0$
C_4	The cost of the public to blow the whistle	$C_4 > 0$
B_4	The reward granted to the whistleblower by the central government	$B_4 > 0$
R_4	The compensation to the whistleblower from polluting enterprises if the local government chooses to regulate	$R_4 > 0$
L_4	The adverse health impact on the public if the local government chooses not to regulate	$L_4 > 0$

2.3. The Game Model

2.3.1. The Payoff Matrix of Quadrilateral Game Participants

Based on the parameters introduced in Section 2.2, the payoff matrix of the Quadrilateral Evolutionary Game for air pollution control is shown in Table 2.

Table 2. The payoff matrix of the quadrilateral evolutionary game for air pollution control.

				The Central Government (a)			
				Monitor (x)		Not Monitor $(1-x)$	
				The Local Government (b)			
				Regulate (y)	Not Regulate $(1-y)$	Regulate (y)	Not Regulate $(1-y)$
Enterprises (c)	Comply with Regulations (z)	The Public (d)	Blow the Whistle (θ)	(a_1,b_1,c_1,d_1)	(a_5,b_5,c_5,d_5)	(a_9,b_9,c_9,d_9)	$(a_{13},b_{13},c_{13},d_{13})$
			Not Blow the Whistle $(1-\theta)$	(a_2,b_2,c_2,d_2)	(a_6,b_6,c_6,d_6)	$(a_{10},b_{10},c_{10},d_{10})$	$(a_{14},b_{14},c_{14},d_{14})$
	Violate Regulations $(1-z)$		Blow the Whistle (θ)	(a_3,b_3,c_3,d_3)	(a_7,b_7,c_7,d_7)	$(a_{11},b_{11},c_{11},d_{11})$	$(a_{15},b_{15},c_{15},d_{15})$
			Not Blow the Whistle $(1-\theta)$	(a_4,b_4,c_4,d_4)	(a_8,b_8,c_8,d_8)	$(a_{12},b_{12},c_{12},d_{12})$	$(a_{16},b_{16},c_{16},d_{16})$

The elements of the Payoff Matrix are shown in Equation (1).

$$\begin{bmatrix} S_1-C_1-B_4 & S_2-C_2 & -C_3 & -C_4+B_4 \\ S_1-C_1 & S_2-C_2 & -C_3 & 0 \\ -C_1-B_4+P_3 & -C_2 & -P_3-R_4-L_3 & -C_4+B_4+R_4-L_4 \\ -C_1-P_3 & -C_2 & -P_3-L_3 & -L_4 \\ S_1-C_1-B_4 & 0 & -C_3 & -C_4+B_4 \\ S_1-C_1 & 0 & -C_3 & 0 \\ -C_1-B_4+P_2+P_3 & -P_2 & -P_3-R_4-L_3 & -C_4+B_4+R_4-L_4 \\ -C_1+P_3+P_2 & -L_2-P_2 & -P_3-L_3 & -L_4 \\ -L_1 & S_2-C_2 & -C_3 & -C_4 \\ -L_1 & S_2-C_2 & -C_3 & 0 \\ -L_1+P_3 & -C_2 & -P_3-R_4-L_3 & -C_4+R_4-L_4 \\ -L_1+P_3 & -C_2 & -P_3-L_3 & -L_4 \\ -L_1 & -L_2 & -C_3 & -C_4 \\ -L_1 & -L_2 & -C_3 & 0 \\ -L_1 & -L_2 & -L_3 & -C_4-L_4 \\ -L_1 & -L_2 & -L_3 & -L_4 \end{bmatrix} \tag{1}$$

In the above payoff matrix, the four parties will continuously adjust their strategies in order to maximize their expected return. According to the Evolutionary Game Theory, when the return of a certain strategy is higher than the average return of the game system, this strategy will gradually evolve and develop in the system [48–50], i.e., the proportion of individuals adopting such strategy will grow at a rate greater than zero. This process is called the replicator dynamics equation, which is a dynamic differential equation of the frequency with which a particular strategy is adopted in a system [51–53].

$$\frac{dx}{dt} = x\left(U_{X1} - \overline{U}_X\right) \tag{2}$$

Based on the different strategies of the four parties and their corresponding payoff, this paper has established the replicator dynamics equation of each party as follows:

2.3.2. The Replicator Dynamics Equation of the Central Government

The expected return of the central government *a* when it chooses to monitor can be expressed as

$$\begin{aligned} U_{\mathrm{A1}} = {} & y*z*\theta*a_1 + y*z*(1-\theta)*a_2 + y*(1-z)*\theta*a_3 + y*(1-z)*(1-\theta)*a_4 \\ & +(1-y)*z*\theta*a_5 + (1-y)*z*(1-\theta)*a_6 + (1-y)*(1-z)*\theta*a_7 \\ & +(1-y)*(1-z)*(1-\theta)*a_8 \end{aligned} \tag{3}$$

The expected return of the central government *a* when it chooses not to monitor can be expressed as

$$\begin{aligned} U_{\mathrm{A2}} = {} & y*z*\theta*a_9 + y*z*(1-\theta)*a_{10} + y*(1-z)*\theta*a_{11} + y*(1-z)*(1-\theta)*a_{12} \\ & +(1-y)*z*\theta*a_{13} + (1-y)*z*(1-\theta)*a_{14} + (1-y)*(1-z)*\theta*a_{15} \\ & +(1-y)*(1-z)*(1-\theta)*a_{16} \end{aligned} \tag{4}$$

Let the probability of the central government *a* choosing to monitor and not to monitor be x and $(1-x)$ respectively, then the expected return of the central government can be expressed as

$$U_A = x*U_{\mathrm{A1}} + (1-x)*U_{\mathrm{A2}} \tag{5}$$

The growth rate of the monitoring strategy by the central government $\frac{dx}{dt}$ is positively correlated to the payoff of this strategy and difference in payoff with other strategies. Therefore, the replicator dynamics equation of the central government can be calculated as follows:

$$\begin{cases} \frac{dx}{dt} = F(x) = x(U_{A1} - U_A) = (1-x)xA(y,z,\theta) \\ A(y,z,\theta) = -(\theta B_4 + C_1 - L_1 - P_2 + yP_2 + zP_2 - yzP_2 - P_3 + yP_3 + zP_3 - yzP_3 - zS_1) \end{cases} \tag{6}$$

2.3.3. The Replicator Dynamics Equation of the Local Government

The expected return of the local government *b* when it chooses to regulate emissions can be expressed as

$$\begin{aligned} U_{\mathrm{B1}} = {} & x*z*\theta*b_1 + x*z*(1-\theta)*b_2 + x*(1-z)*\theta*b_3 + x*(1-z)*(1-\theta)*b_4 \\ & +(1-x)*z*\theta*b_9 + (1-x)*z*(1-\theta)*b_{10} + (1-x)*(1-z)*\theta*b_{11} \\ & +(1-x)*(1-z)*(1-\theta)*b_{12} \end{aligned} \tag{7}$$

The expected return of the local government *b* when it chooses not to regulate emissions can be expressed as

$$\begin{aligned} U_{\mathrm{B2}} = {} & x*z*\theta*b_5 + x*z*(1-\theta)*b_6 + x*(1-z)*\theta*b_7 + x*(1-z)*(1-\theta)*b_8 \\ & +(1-x)*z*\theta*b_{13} + (1-x)*z*(1-\theta)*b_{14} + (1-x)*(1-z)*\theta*b_{15} \\ & +(1-x)*(1-z)*(1-\theta)*b_{16} \end{aligned} \tag{8}$$

Let the probability of the local government *b* choosing to regulate and not to regulate emissions be y and $(1-y)$ respectively, then the expected return of the local government can be expressed as

$$U_B = y*U_{\mathrm{B1}} + (1-y)*U_{\mathrm{B2}} \tag{9}$$

The growth rate of the regulating strategy by the local government $\frac{dy}{dt}$ is positively correlated to the payoff of this strategy and difference in payoff with other strategies. Therefore, the replicator dynamics equation of the local government can be calculated as follows:

$$\begin{cases} \frac{dy}{dt} = F(y) = y(U_{B1} - U_B) = (1-y)yB(x,z,\theta) \\ B(x,z,\theta) = -(C_2 + (-1 + x(z + \theta - z\theta))L_2 - xP_2 + xzP_2 - zS_2) \end{cases} \tag{10}$$

2.3.4. The Replicator Dynamics Equation of Enterprises

The expected return of the enterprise c when it chooses to comply with regulations on emissions can be expressed as

$$\begin{array}{c} U_{C1} = x*y*\theta*c_1 + x*y*(1-\theta)*c_2 + x*(1-y)*\theta*c_5 + x*(1-y)*(1-\theta)*c_6 \\ +(1-x)*y*\theta*c_9 + (1-x)*y*(1-\theta)*c_{10} + (1-x)*(1-y)*\theta*c_{13} \\ +(1-x)*(1-y)*(1-\theta)*c_{14} \end{array} \tag{11}$$

The expected return of the enterprise c when it chooses to violate the regulations on emissions can be expressed as

$$\begin{array}{c} U_{C2} = x*y*\theta*c_3 + x*y*(1-\theta)*c_4 + x*(1-y)*\theta*c_7 + x*(1-y)*(1-\theta)*c_8 \\ +(1-x)*y*\theta*c_{11} + (1-x)*y*(1-\theta)*c_{12} + (1-x)*(1-y)*\theta*c_{15} \\ +(1-x)*(1-y)*(1-\theta)*c_{16} \end{array} \tag{12}$$

Let the probability of the enterprise c choosing to comply with and violate the regulations on emissions be z and $(1-z)$ respectively, then the expected return of the enterprise can be expressed as:

$$U_C = z*U_{C1} + (1-z)*U_{C2} \tag{13}$$

The growth rate of the compliance strategy by the enterprise $\frac{dz}{dt}$ is positively correlated to the payoff of this strategy and difference in payoff with other strategies. Therefore, the replicator dynamics equation of the enterprise can be calculated as follows:

$$\begin{cases} \frac{dz}{dt} = F(z) = z(U_{C1} - U_C) = (1-z)zC(x,y,\theta) \\ C(x,y,\theta) = -(C_3 - L_3 + (x(-1+y)-y)(P_3 + \theta R_4)) \end{cases} \tag{14}$$

2.3.5. The Replicator Dynamics Equation of The Public

The expected return of the public d when they choose to blow the whistle can be expressed as

$$\begin{array}{c} U_{D1} = x*y*z*d_1 + x*y*(1-z)*d_3 + x*(1-y)*z*d_5 + x*(1-y)*(1-z)*d_7 \\ +(1-x)*y*z*d_9 + (1-x)*y*(1-z)*d_{11} + (1-x)*(1-y)*z*d_{13} \\ +(1-x)*(1-y)*(1-z)*d_{15} \end{array} \tag{15}$$

The expected return of the public d when they choose not to blow the whistle can be expressed as

$$\begin{array}{c} U_{D2} = x*y*z*d_2 + x*y*(1-z)*d_4 + x*(1-y)*z*d_6 + x*(1-y)*(1-z)*d_8 \\ +(1-x)*y*z*d_{10} + (1-x)*y*(1-z)*d_{12} + (1-x)*(1-y)*z*d_{14} \\ +(1-x)*(1-y)*(1-z)*d_{16} \end{array} \tag{16}$$

Let the probability of the public d choosing to blow the whistle and not blow the whistle be θ and $(1-\theta)$ respectively, then the expected return of the public can be expressed as

$$U_D = \theta*U_{D1} + (1-\theta)*U_{D2} \tag{17}$$

The growth rate of the whistleblowing strategy by the public $\frac{d\theta}{dt}$ is positively correlated to the payoff of this strategy and difference in payoff with other strategies. Therefore, the replicator dynamics equation of the public can be calculated as follows:

$$\begin{cases} \frac{d\theta}{dt} = F(\theta) = \theta(U_{D1} - U_D) = (1-\theta)\theta D(x,y,z) \\ D(x,y,z) = (xB_4 - C_4 + (x(-1+y)-y)(-1+z)R_4) \end{cases} \tag{18}$$

3. Results

Based on the game model constructed in Section 2, this paper will discuss the stable strategies and stability conditions from the perspective of all parties.

3.1. The Dynamic Trend and Evolutionary Stable Points of the Central Government

It can be seen from Equation (6) that the main factors that determine the central government's tendency to choose the monitoring strategy include the following:

1. The probability of the other parties' strategy decisions, such as the probability of the local government choosing to regulate y, the probability of the enterprise choosing to comply with regulations on emissions z, and the probability of the public choosing to blow the whistle θ;
2. The costs and benefits of the central government's strategies, including the monitoring cost C_1, the long-term social welfare due to long-term monitoring S_1, the reputation loss due to lack of monitoring L_1, the economic or political penalties on local governments P_2, the penalties on non-compliant enterprises P_3, and the reward to whistleblowers B_4.

According to Equation (6), let $A(y,z,\theta) = 0$, and when any of the three conditions listed in Equation (19) is met:

$$\begin{cases} y = y_1 = \frac{\theta B_4 + C_1 - L_1 - P_2 + zP_2 - P_3 + zP_3 - zS_1}{(-1+z)(P_2+P_3)}, \ or \\ z = z_1 = \frac{\theta B_4 + C_1 - L_1 - P_2 + yP_2 - P_3 + yP_3}{-P_2 + yP_2 - P_3 + yP_3 + S_1}, \ or \\ \theta = \theta_1 = \frac{-C_1 + L_1 + P_2 - yP_2 - zP_2 + yzP_2 + P_3 - yP_3 - zP_3 + yzP_3 + zS_1}{B_4} \end{cases} \tag{19}$$

It can be obtained that $F(x) \equiv 0$, which means that when any of the probabilities listed above meets the specified conditions, the central government will choose not to monitor, and the game system will be in a stable state, as shown in Figure 3a, below.

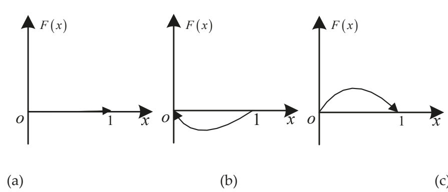

Figure 3. The evolutionary phase diagram of the central government's strategy choices: (**a**) $0 < y = z_1 < 1$, $0 < z = z_1 < 1$, $0 < \theta = \theta_1 < 1$; (**b**) $0 < y_1 < y < 1$, $0 < z_1 < z < 1$, $0 < \theta_1 < \theta < 1$; (**c**) $0 < y < y_1 < 1$, $0 < z < z_1 < 1$, $0 < \theta < \theta_1 < 1$.

In the case of $A(y,z,\theta) \neq 0$, let $F(x) = 0$, two stable points of x can be obtained: 0 and 1. It can be inferred from Equation (6) that

$$\begin{cases} \frac{dF(x)}{dx} = (1-2x)A(y,z,\theta) \\ A(y,z,\theta) = -(\theta B_4 + C_1 - L_1 - P_2 + yP_2 + zP_2 - yzP_2 - P_3 + yP_3 + zP_3 - yzP_3 - zS_1) \end{cases} \tag{20}$$

In Equation (20), if $A(y,z,\theta) < 0$, i.e., $y > y_1, z > z_1, \theta > \theta_1$, then $\frac{dF(x)}{dx}|x-0 < 0$ and $\frac{dF(x)}{dx}|x-1 > 0$. In this case, $x = 0$ is the evolutionary stable point, which represents the only global evolutionary stable strategy, that is, the central government will tend to choose the stable strategy of not monitoring, as shown in Figure 3b. This means that when the probability of the local government choosing to regulate is higher than the critical value y_1, when the probability of the enterprise choosing to comply with regulations on emissions is higher than the critical value z_1, or when the probability of the public choosing to blow the whistle is higher than the critical value θ_1, the enterprises will have a higher probability of compliant emissions, the air pollution will be effectively controlled, and the central government will reduce its monitoring efforts. In this case, the optimal strategy choice of the central government is "not monitoring".

Conversely, if $A(y,z,\theta) > 0$, i.e., $y < y_1, z < z_1, \theta < \theta_1$, then $\frac{dF(x)}{dx}|x-0 < 0$ and $\frac{dF(x)}{dx}|x-0 > 0$. In this case, $x = 1$ is the evolutionary stable point, which represents the only global evolutionary stable strategy—that is, the central government will tend to choose the stable strategy of monitoring, as shown in Figure 3c. This means that when the probability of the local government choosing to regulate is lower than the critical value y_1, when the probability of the enterprise choosing to comply with regulations on emissions is lower than the critical value z_1, or when the probability of the public choosing to blow the whistle is lower than the critical value θ_1, the local government will spend less efforts on regulatory activities, the public will have less incentive to blow the whistle, resulting in a lower probability of compliant emissions by polluting enterprises, the air pollution will not be effectively controlled. In this case, the optimal strategy choice of the central government is "monitoring".

3.2. The Dynamic Trend and Evolutionary Stable Points of the Local Government

It can be seen from Equation (10) that the main factors that determine the local government's tendency to choose the regulating strategy include:

1. The probability of the other parties' strategy decisions, such as the probability of the central government choosing to monitor x, the probability of the enterprise choosing to comply with regulations on emissions z, and the probability of the public choosing to blow the whistle θ;
2. The costs and benefits of the local government's strategies, including the regulatory cost of the local government C_2, the reputation and political achievement due to long-term regulatory efforts S_2, the reputation loss due to insufficient regulatory efforts L_2, and the economic or political penalties on local governments P_2.

According to Equation (10), let $B(x,z,\theta) = 0$, and when any of the three conditions listed in Equation (21) below is met:

$$\begin{cases} x = x_2 = \frac{C_2-L_2-zS_2}{-zL_2-\theta L_2+z\theta L_2+P_2-zP_2},\ or \\ z = z_2 = \frac{C_2-L_2+x\theta L_2-xP_2}{-xL_2+x\theta L_2-xP_2+S_2},or \\ \theta = \theta_2 = \frac{C_2-L_2+xzL_2-xP_2+xzP_2-zS_2}{x(-1+z)L_2} \end{cases} \tag{21}$$

It can be obtained that $F(y) \equiv 0$, which means that when any of the probabilities listed above meets the specified conditions, the local government will choose not to regulate, and the game system will be in a stable state, as shown in Figure 4a.

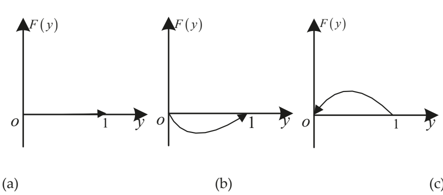

Figure 4. The evolutionary phase diagram of the local government's strategy choices: (**a**) $0 < x = x_2 < 1, 0 < z = z_2 < 1, 0 < \theta = \theta_2 < 1$; (**b**) $0 < x < x_2 < 1, 0 < z < z_2 < 1, 0 < \theta_2 < \theta < 1$; (**c**) $0 < x_2 < x < 1, 0 < z_2 < z < 1, 0 < \theta < \theta_2 < 1$.

In the case of $B \neq 0$, let $F(y) = 0$, two stable points of y can be obtained: 0 and 1. It can be inferred from Equation (10) that

$$\begin{cases} \frac{dF(y)}{dy} = (1-2y)B(x,z,\theta) \\ B(x,z,\theta) = -(C_2 + (-1 + x(z+\theta - z\theta))L_2 - xP_2 + xzP_2 - zS_2) \end{cases} \tag{22}$$

In Equation (22), if $B(x,z,\theta) < 0$, i.e., $x < x_2, z< z_2, \theta > \theta_2$, then $\frac{dF(y)}{dy}\Big| y = 0 > 0$ and $\frac{dF(y)}{dy}\Big| y = 1 < 0$. In this case, $y = 1$ is the evolutionary stable point, which represents the only global evolutionary stable strategy, that is, the local government will tend to choose the stable strategy of regulating emissions, as shown in Figure 4b. This means that, when the probability of the central government choosing to monitor is lower than the critical value x_2, when the probability of the enterprise choosing to comply with regulations on emissions is lower than the critical value z_2, or when the probability of the public choosing to blow the whistle is higher than the critical value θ_2, with less monitoring of the central government, the enterprises will have a lower probability of compliant emissions, the public will have a stronger tendency to blow the whistle, the air pollution will not be effectively controlled. In this case, the optimal strategy choice of the local government is "regulating emissions".

Conversely, if $B(x,z,\theta) > 0$, i.e., $x > x_2, z > z_2, \theta < \theta_2$, then $\frac{dF(y)}{dy}\Big| y = 0 < 0$ and $\frac{dF(y)}{dy}\Big| y = 1 > 0$. In this case, $y = 0$ is the evolutionary stable point, which represents the only global evolutionary stable strategy, that is, the local government will tend to choose the stable strategy of not regulating emissions, as shown in Figure 4c. This means that when the probability of the central government choosing to monitor is higher than the critical value x_2, when the probability of the enterprise choosing to comply with regulations on emissions is higher than the critical value z_2, or when the probability of the public choosing to blow the whistle is lower than the critical value θ_2, the air pollution will be effectively controlled. In this case, from the cost perspective, the optimal strategy choice of the local government is "not regulating emissions".

3.3. The Dynamic Trend and Evolutionary Stable Points of the Enterprises

It can be seen from Equation (14) that the main factors that determine the enterprises' tendency to choose the compliance strategy include the following:

1. The probability of the other parties' strategy decisions, such as the probability of the central government choosing to monitor x, the probability of the local government choosing to regulate y, and the probability of the public choosing to blow the whistle θ;
2. The costs and benefits of the enterprises' strategies, including the cost of complying with regulations on emissions C_3, penalty cost due to non-compliant emissions P_3, and compensation to whistleblowers by polluting enterprises for negative externalities caused R_4.

According to Equation (14), let $C(x,y,\theta) = 0$, and when any of the three conditions listed in Equation (23) below is met:

$$\begin{cases} x = x_3 = \frac{-C_3+L_3+yP_3+y\theta R_4}{(-1+y)(P_3+\theta R_4)}, or \\ y = y_3 = \frac{-C_3+L_3+xP_3+x\theta R_4}{(-1+x)(P_3+\theta R_4)}, or \\ \theta = \theta_3 = \frac{-C_3+L_3+xP_3+yP_3-xyP_3}{(-x-y+xy)R_4} \end{cases} \tag{23}$$

It can be obtained that $F(z) \equiv 0$, which means that when any of the probabilities listed above meets the specified conditions, the enterprises will choose to violate the regulations on emissions, and the game system will be in a stable state, as shown in Figure 5a.

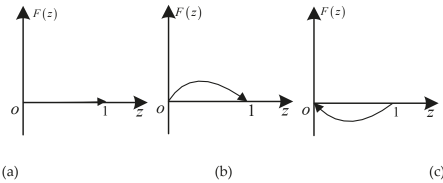

Figure 5. The evolutionary phase diagram of the enterprises' strategy choices: (**a**) $0 < x < x_3 < 1, 0 < y = y_3 < 1, 0 < \theta = \theta_3 < 1$; (**b**) $0 < x_3 < x < 1, 0 < y_3 < y < 1, 0 < \theta_3 < \theta < 1$; (**c**) $0 < x < x_3 < 1, 0 < y < y_3 < 1, 0 < \theta < \theta_3 < 1$.

In the case of $C(x, y, \theta) \neq 0$, let $F(z) = 0$, two stable points of z can be obtained: 0 and 1. It can be inferred from Equation (14) that

$$\begin{cases} \frac{dF(z)}{dz} = (1 - 2z)C(x, y, \theta) \\ C(x, y, \theta) = -(C_3 - L_3 + (x(-1 + y) - y)(P_3 + \theta R_4)) \end{cases} \quad (24)$$

Because $(-1 + y)(P_3 + \theta R_4) < 0$, $(-1 + x)(P_3 + \theta R_4) < 0, (-x - y + xy)R_4 < 0$, if $C(x, y, \theta) > 0$, i.e., $x > x_3, y > y_3, \theta > \theta_3$, then $\frac{dF(z)}{dz}|z - 1 < 0$ and $\frac{dF(z)}{dz}|z - 0 > 0$. In this case, $z = 1$ is the evolutionary stable point, which represents the only global evolutionary stable strategy, that is, the enterprises will tend to choose the stable strategy of complying with regulations on emissions, as shown in Figure 5b. This means that when the probability of the central government choosing to monitor is higher than the critical value x_3, when the probability of the local government choosing to regulate is higher than the critical value y_3, or when the probability of the public choosing to blow the whistle is higher than the critical value θ_3, the supervision and regulation on air pollution is tightening, with closer monitoring by the central government, stricter regulations on pollution emissions issued by the local government, and stronger willingness of the public to blow the whistle. In this case, in order to avoid penalties charged by the central government and compensation paid to the whistleblowers, the enterprises will choose the optimal strategy of "complying with regulations on emissions".

Conversely, if $C(x, y, \theta) < 0$, i.e., $x < x_3, y < y_3, \theta < \theta_3$, then $\frac{dF(z)}{dz}|z - 0 < 0$ and $\frac{dF(z)}{dz}|z - 1 > 0$. In this case, $z = 0$ is the evolutionary stable point, which represents the only global evolutionary stable strategy, that is, the enterprises will tend to choose the stable strategy of not complying with regulations on emissions, as shown in Figure 5c. This means that when the probability of the central government choosing to monitor is lower than the critical value x_3, when the probability of the local government choosing to regulate is lower than the critical value y_3, or when the probability of the public choosing to blow the whistle is lower than the critical value θ_3, the supervision and regulation on air pollution is loosening, with less monitoring by the central government, less regulations on pollution emissions issued by the local government, and less initiative of the public to blow the whistle. In this case, from the cost perspective, the optimal strategy choice of the enterprises is "violating the regulations on emissions".

3.4. The Dynamic Trend and Evolutionary Stable Points of the Public

It can be seen from Equation (18) that the main factors that determine the public's tendency to choose the whistleblowing strategy include:

1. The probability of the other parties' strategy decisions, such as the probability of the central government choosing to monitor x, the probability of the local government choosing to regulate y, and the probability of the enterprises choosing to comply with regulations on emissions z;
2. The costs and benefits of the public's strategies, including the reward from the central government B_4, the cost of whistleblowing C_4, and the compensation from polluting enterprises for negative externalities caused R_4.

According to Equation (18), let $D(x,y,z) = 0$, and when any of the three conditions listed in Equation (25) below is met:

$$\begin{cases} x = x_4 = \frac{C_4 - yR_4 + yzR_4}{B_4 + R_4 - yR_4 - zR_4 + yzR_4}, or \\ y = y_4 = \frac{-xB_4 + C_4 - xR_4 + xzR_4}{(-1+x)(-1+z)R_4}, or \\ z = z_4 = \frac{-xB_4 + C_4 - xR_4 - yR_4 + xyR_4}{(-x-y+xy)R_4} \end{cases} \tag{25}$$

It can be obtained that $F(\theta) \equiv 0$, which means that when any of the probabilities listed above meets the specified conditions, the public will choose not to blow the whistle, and the game system will be in a stable state, as shown in Figure 6a below.

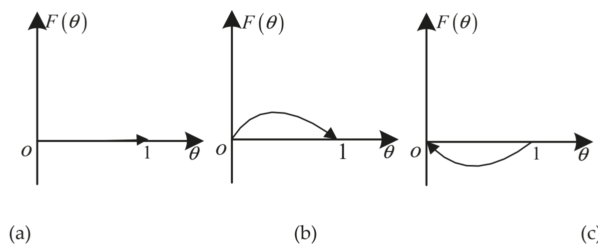

Figure 6. The evolutionary phase diagram of the public's strategy choices: (**a**) $0 < x = x_4 < 1, 0 < y = y_4 < 1, 0 < z = z_4 < 1$; (**b**) $0 < x_4 < x < 1, 0 < y_4 < y < 1, 0 < z < z_4 < 1$; (**c**)$0 < x < x_4 < 1, 0 < y < y_4 < 1, 0 < z_4 < z < 1$.

In the case of $D(x,y,z) \neq 0$, let $F(\theta) = 0$, two stable points of θ can be obtained: 0 and 1. It can be inferred from Equation (18) that

$$\begin{cases} \frac{dF(z)}{dz} = (1-2\theta)D(x,y,z) \\ D(x,y,z) = (xB_4 - C_4 + (x(-1+y) - y)(-1+z)R_4) \end{cases} \tag{26}$$

Because $(-x-y+xy)R_4 < 0$, if $D(x,y,z) > 0$, i.e., $x > x_4, y > y_4, z < z_4$, then $\frac{dF(\theta)}{d\theta}|\theta - 1 < 0$ and $\frac{dF(\theta)}{d\theta}|\theta - 0 > 0$. In this case, $\theta = 1$ is the evolutionary stable point, which represents the only global evolutionary stable strategy, that is, the public will tend to choose the stable strategy of blowing the whistle, as shown in Figure 6b. This means that when the probability of the central government choosing to monitor is higher than the critical value x_4, when the probability of the local government choosing to regulate is higher than the critical value y_4, or when the probability of the enterprises choosing to comply with regulations on emissions is lower than the critical value z_4, most enterprises would choose to violate the regulations on pollution emissions, so air pollution will not be effectively controlled. In this case, with stronger monitoring by the central government and growing regulatory efforts by the local government, from the perspective of health and financial compensation, the optimal strategy choice of the public is "blowing the whistle".

Conversely, if $D(x,y,z) < 0$, i.e., $x < x_4,\ y < y_4, z > z_4$, then $\frac{dF(\theta)}{d\theta}|\theta - 1 > 0$ and $\frac{dF(\theta)}{d\theta}|\theta - 0 < 0$. In this case, $\theta = 0$ is the evolutionary stable point, which represents the only global evolutionary stable strategy, that is, the public will tend to choose the stable strategy of not blowing the whistle, as shown in Figure 6c. This means that when the probability of the central government choosing to monitor is lower than the critical value x_4, when the probability of the local government choosing to regulate is lower than the critical value y_4, or when the probability of the enterprises choosing to comply with regulations on emissions is higher than the critical value z_4, most enterprises would choose to comply with the regulations on pollution emissions, so air pollution will be effectively controlled and the public's health will be protected. In this case, from a cost perspective, the optimal strategy choice of the public is "not blowing the whistle".

4. Discussion

4.1. The Four-Dimensional Dynamic System and Its Equilibrium Points

In order to reveal the condition and process of the formation of above evolutionary stable strategies, this section will expand the analysis by constructing and solving a four-dimensional dynamic system of dynamic game evolution. According to Friedman, the stability of the equilibrium point of a group dynamic system represented by a differential equation can be determined by the stability analysis of the Jacobian matrix [54]. Therefore, this paper has adopted the Jacobian matrix stability analysis method to study the stability of the equilibrium points in the evolutionary game. A four-dimensional dynamic system is obtained based on the replicator dynamics equations of the four parties, as shown in Equation (27), which is the combination of Equation (6), (10), (14), and (18).

$$\begin{cases} \frac{dx}{dt} = F(x) = (1-x)xA(y,z,\theta) \\ \frac{dy}{dt} = F(y) = (1-y)yB(x,z,\theta) \\ \frac{dz}{dt} = F(z) = (1-z)zC(x,y,\theta) \\ \frac{d\theta}{dt} = F(\theta) = (1-\theta)\theta D(x,y,z) \end{cases} \tag{27}$$

This paper solves this four-dimensional dynamic system made up of the game strategies of the central government, the local government, enterprises, and the public. When $F(x) = 0,\ F(y) = 0,\ F(z) = 0,\ F(\theta) = 0$, this paper has obtained multiple feasible solutions:

1. There are 16 equilibrium points for four-party pure strategy solutions, which are:

$$\begin{cases} E_0(x=0,y=0,z=0,\theta=0) \\ E_1(x=0,y=0,z=0,\theta=1) \\ E_2(x=0,y=0,z=1,\theta=0) \\ E_3(x=0,y=1,z=0,\theta=0) \\ E_4(x=1,y=0,z=0,\theta=0) \\ E_5(x=0,y=0,z=1,\theta=1) \\ E_6(x=0,y=1,z=1,\theta=0) \\ E_7(x=1,y=1,z=0,\theta=0) \\ E_8(x=1,y=0,z=0,\theta=1) \\ E_9(x=1,y=0,z=1,\theta=0) \\ E_{10}(x=0,y=1,z=0,\theta=1) \\ E_{11}(x=1,y=1,z=1,\theta=0) \\ E_{12}(x=1,y=1,z=0,\theta=1) \\ E_{13}(x=1,y=0,z=1,\theta=1) \\ E_{14}(x=0,y=1,z=1,\theta=1) \\ E_{15}(x=1,y=1,z=1,\theta=1) \end{cases} \tag{28}$$

Equation (28) indicates the four-party pure strategy solutions, which mean that the probability of the strategy selection of quadrilateral game participants is a certain value of 0 or 1. According to Equation (28), it can be seen that the probability of the quadrilateral game participants is all 0 or 1, and there are 16 strategy sets.

2. There are at least eight equilibrium points for dual-party pure strategy solutions, which are

$$\begin{cases} E_{16}\left(x=0, y=1, z=\frac{-C_4+R_4}{R_4}, \theta=\frac{C_3-L_3-P_3}{R_4}\right) \\ E_{17}\left(x=0, y=\frac{C_3-L_3}{P_3}, z=\frac{-C_2+L_2+xP_2}{xP_2-S_2}, \theta=0\right) \\ E_{18}\left(x=0, y=\frac{C_3-L_3}{P_3+R_4}, z=\frac{-C_2+L_2+xP_2}{xP_2-S_2}, \theta=1\right) \\ E_{19}\left(x=1, y=0, z=\frac{B_4-C_4+R_4}{R_4}, \theta=\frac{C_3-L_3-P_3}{R_4}\right) \\ E_{20}\left(x=\frac{C_4}{B_4+R_4}, y=0, z=0, \theta=\frac{-C_1+L_1+P_2+P_3}{B_4}\right) \\ E_{21}\left(x=\frac{C_4}{B_4}, y=0, z=1, \theta=\frac{-C_1+L_1+S_1}{B_4}\right) \\ E_{22}\left(x=\frac{C_3-L_3}{P_3}, y=0, z=\frac{-C_1+L_1+P_2+P_3}{P_2+P_3-S_1}, \theta=0\right) \\ E_{23}\left(x=\frac{C_3-L_3}{P_3+R_4}, y=0, z=\frac{-B_4-C_1+L_1+P_2+P_3}{P_2+P_3-S_1}, \theta=1\right) \end{cases} \tag{29}$$

Equation (29) indicates the dual-party pure strategy solutions, which mean that only two parties in the quadrilateral game participants have a strategy selection probability of 0 or 1, and the remaining two parties have a policy selection probability of uncertain values. According to Equation (29), there are at least eight strategy sets.

3. There are at least two equilibrium points for single-party pure strategy solutions, which are

$$\begin{cases} E_{24}\left(x=0, y=-\frac{C_4(xP_2-S_2)}{R_4(-C_2+L_2+S_2)}, z=\frac{-C_2+L_2+xP_2}{xP_2-S_2}, \theta=\frac{-xC_4P_2P_3+C_2C_3R_4-C_3L_2R_4-C_2L_3R_4+L_2L_3R_4+C_4P_3S_2-C_3R_4S_2+L_3R_4S_2}{C_4R_4(xP_2-S_2)}\right) \\ E_{25}\begin{pmatrix} x=\frac{-B_4C_3+B_4L_3+C_4P_2+C_4P_3-C_4S_1}{B_4P_2+C_1R_4-L_1R_4-B_4S_1-R_4S_1}, \\ y=0, \\ z=\frac{B_4^2C_3-B_4^2L_3-B_4C_4P_3+B_4C_3R_4+C_1C_4R_4-C_4L_1R_4-B_4L_3R_4-C_4P_2R_4-C_4P_3R_4}{R_4(B_4C_3-B_4L_3-C_4P_2-C_4P_3+C_4S_1)}, \\ \theta=\frac{-B_4C_3P_2+B_4L_3P_2-B_4C_3P_3+B_4L_3P_3+C_4P_2P_3+C_4P_3^2-C_1C_3R_4+C_3L_1R_4+C_1L_3R_4-L_1L_3R_4+B_4C_3S_1-B_4L_3S_1-C_4P_3S_1+C_3R_4S_1-L_3R_4S_1}{R_4(B_4C_3-B_4L_3-C_4P_2-C_4P_3+C_4S_1)} \end{pmatrix} \end{cases} \tag{30}$$

Equation (30) indicates the single-party pure strategy solutions, which mean that only three parties in the quadrilateral game participants have a strategy selection probability of 0 or 1. According to Equation (30), there are at least two strategy sets.

4. There may be a mixed strategy solution $E_{26}(x^*, y^*, z^*)$, whose existence requires the following conditions to be satisfied:

$$\begin{cases} A(y,z,\theta)=0 \\ B(x,z,\theta)=0 \\ C(x,y,\theta)=0 \\ D(x,y,z)=0 \end{cases} \quad and\ x^*, y^*, z^*, \theta^* \epsilon (0,1) \tag{31}$$

To summarize, when solving Equation (27), we can get a large number of feasible solutions. However, many solutions have only mathematical meaning rather than practical significance. Therefore, this paper choses feasible solutions that can represent real situations and can be represented by mathematical expressions, which include 16 feasible solutions for four-party pure strategy solutions (E_0 to E_{15}), eight feasible solutions for dual-party pure strategy (E_{16} to E_{23}) and two feasible for single-party pure strategy (E_{24} and E_{25}).

4.2. The Stability of the Four-Dimensional Dynamic System

In a multiple-party evolutionary game, the necessary and sufficient condition for an evolutionary stable equilibrium E is that E represents a strict Nash equilibrium [55]. If the evolutionary stable equilibrium E is asymptotically stable, then E must satisfy a strict Nash equilibrium, and the strict Nash equilibrium must be a pure strategy equilibrium [56]. According to Lyapunov's stability theory [57,58], the eigenvalues of the Jacobian matrix can determine the asymptotic stability of the equilibrium points of the system, that is, the necessary and sufficient condition for an equilibrium point in a replicator dynamics system to represent an evolutionary stable strategy is that all the eigenvalues of its Jacobian matrix are negative real numbers [59]. The Jacobian matrix of the four-dimensional dynamic system is shown in Equation (32):

$$J = \begin{bmatrix} (1-2x)A & \frac{(1-x)xdA}{dy} & \frac{(1-x)xdA}{dz} & \frac{(1-x)xdA}{d\theta} \\ \frac{(1-y)ydB}{dx} & (1-2y)B & \frac{(1-y)ydB}{dz} & \frac{(1-y)ydB}{d\theta} \\ \frac{(1-z)ydC}{dx} & \frac{(1-z)ydC}{dy} & (1-2z)C & \frac{(1-z)ydC}{d\theta} \\ \frac{(1-\theta)\theta dD}{dx} & \frac{(1-\theta)\theta dD}{dy} & \frac{(1-\theta)\theta dD}{dz} & (1-2\theta)D \end{bmatrix} \tag{32}$$

When the equilibrium point is $E_0(x=0, y=0, z=0, \theta=0)$, the Jacobian matrix is written as Equation (33).

$$J = \begin{bmatrix} -C_1+L_1+P_2+P_3 & 0 & 0 & 0 \\ 0 & -C_2+L_2 & 0 & 0 \\ 0 & 0 & -C_3+L_3 & 0 \\ 0 & 0 & 0 & -C_4 \end{bmatrix} \tag{33}$$

Similarly, the Jacobian matrix and its eigenvalues can be obtained for the 27 equilibrium points of the system, as shown in Table 3. According to Lyapunov's stability conditions, when all the eigenvalues of the Jacobian matrix λ is negative ($\lambda < 0$), that is, when all the eigenvalues of the Jacobian matrix are negative real numbers, the corresponding equilibrium point is a stable point; when all the eigenvalues of the Jacobian matrix are positive real numbers, the corresponding equilibrium point is an unstable point [60,61]; and when the eigenvalues of the Jacobian matrix contain both negative and positive real numbers, the corresponding equilibrium point is a saddle point [62,63].

Table 3. The stability of equilibrium points in the quadrilateral evolutionary game.

Equilibrium Point	Eigenvalues				Asymptotic Stability Condition
	λ_1	λ_2	λ_3	λ_4	
E_0	$-C_1+L_1+P_2+P_3$	$-C_2+L_2$	$-C_3+L_3$	$-C_4$	$\lambda_1<0$ & $\lambda_2<0$ & $\lambda_3<0$ & $\lambda_4<0$
…	…	…	…	…	…
E_2	$-C_1+L_1+S_1$	$-C_2+L_2+S_2$	C_3-L_3	$-C_4$	…
…	…	…	…	…	…
E_9	$C_1-L_1-S_1$	$-C_2+S_2$	$C_3-L_3-P_3$	B_4-C_4	…
…	…	…	…	…	…
E_{11}	$C_1-L_1-S_1$	C_2-S_2	$C_3-L_3-P_3$	B_4-C_4	…
…	…	…	…	…	…
E_{13}	$B_4+C_1-L_1-S_1$	$-C_2+S_2$	$C_3-L_3-P_3-R_4$	$-B_4+C_4$	…
…	…	…	…	…	…
E_{15}	$B_4+C_1-L_1-S_1$	C_2-S_2	$C_3-L_3-P_3-R_4$	$-B_4+C_4$	…
…	…	…	…	…	…

In Table 3, it is difficult to determine the evolutionary stability of the quadrilateral evolutionary game system based on the available information. Considering that this paper mainly focuses on the compliant emission behavior of the enterprises under the supervision and regulation of governments and monitoring of the public, this paper has neglected the equilibrium points in which the enterprises violate or partially comply with the regulations on emissions and only keep the eight equilibrium points that represent the most ideal, more-than-ideal, and ideal scenarios. Then, this paper studies stability conditions of these 8 equilibrium points. Taking E_2 as an example, the asymptotic stability condition for E_2 is: $C_1 > L_1 + S_1$ and $C_2 > L_2 + S_2, C_3 < L_3, C_4 > 0$. According to the parameter settings in Section 2.2 based on real world situations, $S_1 \gg max\{C_1, L_1, P_2, P_3, B_4\} > 0$. Therefore, the condition of ($C_1 > L_1 + S_1$) cannot be satisfied, and thus the equilibrium point E_2 is not an asymptotically stable point.

Similarly, the condition for E_5 to be asymptotically stable ($-B_4 - C_1 + L_1 + S_1 < 0$) also cannot be satisfied. After analyzing the rest 6 equilibrium points using the same method, this paper has obtained 4 possible asymptotically stable points: $E_9(x = 1, y = 0, z = 1, \theta = 0)$, $E_{11}(x = 1, y = 1, z = 1, \theta = 0)$, $E_{13}(x = 1, y = 0, z = 1, \theta = 1)$, and $E_{15}(x = 1, y = 1, z = 1, \theta = 1)$. However, from the perspective of the local government and the public, they must require positive payoff. Therefore, only $E_{15}(x = 1, y = 1, z = 1, \theta = 1)$ has the best chance of meeting the asymptotic stability condition: $B_4 + C_1 - L_1 - S_1 < 0$ and $C_2 - S_2 < 0, C_3 - L_3 - P_3 - R_4 < 0, -B_4 + C_4 < 0$.

It can be inferred from the stability conditions of these four equilibrium points that the value of the environmental political achievement (S_2) is critical to the local government. If the value of the environmental political achievement is lower than the environmental regulatory cost, the stable equilibrium point of the system will move towards E_9 and E_{13}, which will increase the pressure on the central government to enhance monitoring. The public's battle against pollution by enterprises puts restrictions on the enterprises' environmental behaviors and plays the role of third-party supervision. The reputation loss of enterprises if the whistle is blown (P_3) and the design of mechanisms of compensation for negative externalities (R_4) and reward (B_4) are particularly critical. If the whistleblowing cost is too high, the stable equilibrium point of the system will move towards E_{11}, greatly reducing the incentive of the public to play an active role in whistleblowing.

Therefore, in China's air pollution control campaign, in order to achieve the most ideal evolutionary stable strategy in which the central government monitors, the local governments regulate, and the enterprises follow the regulations, the key points include emphasizing the environmental political achievement of the local governments, the environmental reputation of enterprises, and the whistleblowing incentive mechanism innovation. The environmental management of China should utilize the third-party supervisory role of the public apart from administrative intervention and market mechanisms.

4.3. The Ideality of the Solutions for the Four-Dimensional Dynamic System

This paper has classified the outcomes of 16 equilibrium points for four-party pure strategy solutions, eight equilibrium points for dual-party pure strategy solutions, two equilibrium points for single-party pure strategy solutions, and the mixed strategy solution into five categories, which in the order from the best to the worst scenarios are Most Ideal, More than Ideal, Ideal, Less than Ideal, and Least Ideal (see Table 4).

Among the outcomes, the least ideal scenario is that the enterprises choose to violate the regulations on emissions regardless of the monitoring, regulations or whistleblowing activities by the governments and the public, which is represented by five equilibrium points. The less-than-ideal scenario is that the enterprises choose to violate the regulations on emissions or partially comply with the regulations with the monitoring, regulations or whistleblowing activities by the governments and the public, which includes 14 equilibrium points. The ideal scenario is that the enterprises choose to comply with the regulations on emissions with the monitoring, regulations and whistleblowing activities by the governments and the public, which is represented by four equilibrium points. The more-than-ideal scenario is that the enterprises choose to comply with the regulations on emissions with either the monitoring, regulations or whistleblowing activities by the governments and the public, which covers three equilibrium points. The most ideal scenario is that the enterprises choose to comply with the regulations on emissions without the monitoring, regulations or whistleblowing activities by the governments and the public, which is represented by one equilibrium point.

Table 4. The equilibrium points, strategy set, and policy performance of the quadrilateral evolutionary game.

Equilibrium Point	Strategy Set of Game Participants	Policy Performance
$E_0(x=0, y=0, z=0, \theta=0)$	(Not Monitor, Not Regulate, Violate Regulations, Not Blow the Whistle)	Least Ideal
$E_1(x=0, y=0, z=0, \theta=1)$	(Not Monitor, Not Regulate, Violate Regulations, Blow the Whistle)	Less than Ideal
$E_2(x=0, y=0, z=1, \theta=0)$	(Not Monitor, Not Regulate, Comply with Regulations, Not Blow the Whistle)	Most Ideal
$E_3(x=0, y=1, z=0, \theta=0)$	(Not Monitor, Regulate, Violate Regulations, Not Blow the Whistle)	Less than Ideal
$E_4(x=1, y=0, z=0, \theta=0)$	(Strictly Monitor, Not Regulate, Violate Regulations, Not Blow the Whistle)	Less than Ideal
$E_5(x=0, y=0, z=1, \theta=1)$	(Not Monitor, Not Regulate, Comply with Regulations, Blow the Whistle)	More than Ideal
$E_6(x=0, y=1, z=1, \theta=0)$	(Not Monitor, Regulate, Comply with Regulations, Not Blow the Whistle)	More than Ideal
$E_7(x=1, y=1, z=0, \theta=0)$	(Monitor, Regulate, Violate Regulations, Not Blow the Whistle)	Least Ideal
$E_8(x=1, y=0, z=0, \theta=1)$	(Monitor, Not Regulate, Violate Regulations, Blow the Whistle)	Least Ideal
$E_9(x=1, y=0, z=1, \theta=0)$	(Monitor, Not Regulate, Comply with Regulations, Not Blow the Whistle)	More than Ideal
$E_{10}(x=0, y=1, z=0, \theta=1)$	(Not Monitor, Regulate, Violate Regulations, Blow the Whistle)	Less than Ideal
$E_{11}(x=1, y=1, z=1, \theta=0)$	(Monitor, Regulate, Comply with Regulations, Not Blow the Whistle)	Ideal
$E_{12}(x=1, y=1, z=0, \theta=1)$	(Monitor, Regulate, Violate Regulations, Blow the Whistle)	Least Ideal
$E_{13}(x=1, y=0, z=1, \theta=1)$	(Monitor, Not Regulate, Comply with Regulations, Blow the Whistle)	Ideal
$E_{14}(x=0, y=1, z=1, \theta=1)$	(Not Monitor, Regulate, Comply with Regulations, Blow the Whistle)	Ideal
$E_{15}(x=1, y=1, z=1, \theta=1)$	(Monitor, Regulate, Comply with Regulations, Blow the Whistle)	Ideal
E_{16}	(Not Monitor, Regulate, Partially Comply with Regulations, Partially Blow the Whistle)	Less than Ideal
E_{17}	(Not Monitor, Partially Regulate, Partially Comply with Regulations, Not Blow the Whistle)	Less than Ideal
E_{18}	(Not Monitor, Partially Regulate, Partially Comply with Regulations, Blow the Whistle)	Less than Ideal
E_{19}	(Monitor, Not Regulate, Partially Comply with Regulations, Partially Blow the Whistle)	Less than Ideal
E_{20}	(Partially Monitor, Not Regulate, Violate Regulations, Partially Blow the Whistle)	Least Ideal
E_{21}	(Partially Monitor, Not Regulate, Comply with Regulations, Partially Blow the Whistle)	Less than Ideal
E_{22}	(Partially Monitor, Not Regulate, Partially Comply with Regulations, Not Blow the Whistle)	Less than Ideal
E_{23}	(Partially Monitor, Not Regulate, Partially Comply with Regulations, Blow the Whistle)	Less than Ideal
E_{24}	(Partially Monitor, Not Regulate, Partially Comply with Regulations, Partially Blow the Whistle)	Less than Ideal
E_{25}	(Partially Monitor, Not Regulate, Partially Comply with Regulations, Partially Blow the Whistle)	Less than Ideal
E_{26}	(Partially Monitor, Partially Regulate, Partially Comply with Regulations, Partially Blow the Whistle)	Less than Ideal

5. Conclusions

This paper has innovatively constructed a quadrilateral evolutionary game model involving the central government, local governments, polluting enterprises, and the public in order to comprehensively analyze the development and implementation of China's air pollution control policies. By using the quadrilateral evolutionary game model, this paper has systematically studied the evolutionary stable strategies of the four parties involved and obtains 27 equilibrium points, strategy sets, and their corresponding policy performance with the help of the four-dimensional dynamic system. The research results show that the least ideal scenario is that the enterprises choose to violate the regulations on emissions regardless of the monitoring, regulations or whistleblowing activities by the governments and the public, which includes five equilibrium points; the less-than-ideal scenario is that the enterprises choose to violate the regulations on emissions or partially comply with the regulations with the monitoring, regulations or whistleblowing activities by the governments and the public, which includes 14 equilibrium points; the ideal scenario is that the enterprises choose to comply with the regulations on emissions with the monitoring, regulations and whistleblowing activities by the governments and the public, which is represented by four equilibrium points; the more-than-ideal scenario is that the enterprises choose to comply with the regulations on emissions with either the monitoring, regulations or whistleblowing activities by the governments and the public, which covers three equilibrium points; and the most ideal scenario is that the enterprises choose to comply with the regulations on emissions without the monitoring, regulations or whistleblowing activities by the governments and the public, which is represented by one equilibrium point. By analyzing the eight equilibrium points that represent the ideal, more-than-ideal, and most ideal scenarios, especially the four asymptotically stable points among them, this paper has obtained the conditions for these four stable points as well as related policy implications.

In order to achieve the ideal or most ideal outcome of air pollution control policies when there are multiple parties involved, on the one hand, costs need to be reduced, including the monitoring cost, the regulatory cost, the compliance cost, and the whistleblowing cost; on the other hand, the supervisory responsibility of the central government on air pollution control should be shared with the local governments and the public, which requires further enhancement in the understanding and motivation of the local governments on environmental regulation, further reduction in the regulatory cost of local governments and the compliance cost of enterprises, and further encouraging the public to actively report air pollution incidents and sources. For the enhancement of local governments' understanding and motivation of environmental regulation, performance evaluation (to enhance understanding and motivation) and air pollution special funds (to reduce regulatory and compliance costs) could be used as well as setting up performance evaluation indicators in addition to economic indicators such as GDP growth. In order to encourage the public to actively report air pollution incidents and participate in the battle against air pollution, first of all, it is necessary to strengthen the public's awareness of environmental protection. Apart from that, a better reward and compensation system for whistleblowing activities should be designed, including honors and cash rewards. Finally, better whistleblowing channels should be provided to the public, such as developing the smartphone mobile application and WeChat Applet for the "12369 Environmental Protection Whistleblowing Inter-Connected Management Platform".

The research in this paper is mainly a theoretical analysis of air pollution control and the quadrilateral regulatory system. Based on this research, we will evaluate the process of air pollution control in the future, which may help improve air pollution governance in China.

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References

1. Yuan, G.; Yang, W. Evaluating China's Air Pollution Control Policy with Extended AQI Indicator System: Example of the Beijing-Tianjin-Hebei Region. *Sustainability* **2019**, *11*, 939. [CrossRef]
2. Gao, H.; Yang, W.; Yang, Y.; Yuan, G. Analysis of the Air Quality and the Effect of Governance Policies in China's Pearl River Delta, 2015–2018. *Atmosphere* **2019**, *10*, 412. [CrossRef]
3. Yang, W.; Yuan, G.; Han, J. Is China's air pollution control policy effective? Evidence from Yangtze River Delta cities. *J. Clean. Prod.* **2019**, *220*, 110–133. [CrossRef]

4. Xi, J. Report at the 19th National Congress of the Communist Party of China. Available online: http://www.gov.cn/zhuanti/2017-10/27/content_5234876.htm (accessed on 29 December 2019).
5. State Council of the People's Republic of China. Notice of the State Council on Printing and Distributing the "Air Pollution Prevention and Control Action Plan". Available online: http://www.gov.cn/zhengce/content/2013-09/13/content_4561.htm (accessed on 29 December 2019).
6. Ministry of Environmental Protection. Temporary Provisions on the Management of Pollutant Discharge Permits. Available online: http://www.gov.cn/gongbao/content/2017/content_5217757.htm (accessed on 29 December 2019).
7. Air Pollution Prevention and Control Law of the People's Republic of China. In Proceedings of the Sixth Meeting of the Standing Committee of the Thirteenth National People's Congress, Beijing, China, 22–26 October 2018; China Legal Publishing House: Beijing, China, 2018.
8. Ministry of Ecology and Environment of the People's Republic of China. Key Points on 2019 Nation-wide Air Pollution Prevention and Control. Available online: http://www.mee.gov.cn/xxgk2018/xxgk/xxgk05/201903/t20190306_694550.html (accessed on 29 December 2019).
9. Thunis, P.; Clappier, A.; Pisoni, E.; Degraeuwe, B. Quantification of non-linearities as a function of time averaging in regional air quality modeling applications. *Atmos. Environ.* **2015**, *103*, 263–275. [CrossRef]
10. Di Nicolantonio, W.; Cacciari, A.; Bolzacchini, F.; Ferrero, L.; Volta, M.; Pisoni, E. MODIS aerosol optical properties over North Italy for estimating surface-level PM2.5. In *Proceedings of Envisat Symposium*; ESA Publications Division: Montreux, Switzerland, 2007; Volume 636.
11. Querol, X.; Tobías, A.; Pérez, N.; Karanasiou, A.; Amato, F.; Stafoggia, M.; García-Pando, C.P.; Ginoux, P.; Forastiere, F.; Gumy, S.; et al. Monitoring the impact of desert dust outbreaks for air quality for health studies. *Environ. Int.* **2019**, *130*, 104867. [CrossRef] [PubMed]
12. Ministry of Ecology and Environment of the People's Republic of China. Report on the National "12369" Environmental Protection Whistleblowing Management Platform in 2016. Available online: http://www.mee.gov.cn/gkml/hbb/bgth/201705/t20170512_414013.htm (accessed on 29 December 2019).
13. Ministry of Ecology and Environment of the People's Republic of China. Report of the Ministry of Ecology and Environment on the National "12369" Environmental Protection Whistleblowing in November 2019. Available online: http://www.mee.gov.cn/xxgk2018/xxgk/xxgk15/201912/t20191212_748408.html (accessed on 29 December 2019).
14. Yang, W.; Li, L. Efficiency Evaluation and Policy Analysis of Industrial Wastewater Control in China. *Energies* **2017**, *10*, 1201. [CrossRef]
15. Liu, Y.; Yao, X.; Wei, T. Energy efficiency gap and target setting: A study of information asymmetry between governments and industries in China. *China Econ. Rev.* **2019**, *57*, 101341. [CrossRef]
16. Liu, G.; Wei, L.; Gu, J.; Zhou, T.; Liu, Y. Benefit distribution in urban renewal from the perspectives of efficiency and fairness: A game theoretical model and the government's role in China. *Cities* **2020**, *96*, 102422. [CrossRef]
17. Wang, J.; Wu, Q.; Yan, S.; Guo, G.; Peng, S. China's local governments breaking the land use planning quota: A strategic interaction perspective. *Land Use Policy* **2020**, *92*, 104434. [CrossRef]
18. Yuan, G.; Yang, W. Study on optimization of economic dispatching of electric power system based on Hybrid Intelligent Algorithms (PSO and AFSA). *Energy* **2019**, *183*, 926–935. [CrossRef]
19. Yang, W.X.; Li, L.G. Analysis of total factor efficiency of water resource and energy in China: A study based on DEA-SBM model. *Sustainability* **2017**, *9*, 1316. [CrossRef]
20. Du, Y.; Li, Z.; Du, J.; Li, N.; Yan, B. Public environmental appeal and innovation of heavy-polluting enterprises. *J. Clean. Prod.* **2019**, *222*, 1009–1022. [CrossRef]
21. Wang, X.; Zhang, C.; Zhang, Z. Pollution haven or porter? The impact of environmental regulation on location choices of pollution-intensive firms in China. *J. Environ. Manag.* **2019**, *248*, 109248. [CrossRef] [PubMed]
22. Zhao, X.; Li, H.; Wu, L.; Qi, Y. Implementation of energy-saving policies in China: How local governments assisted industrial enterprises in achieving energy-saving targets. *Energy Policy* **2014**, *66*, 170–184. [CrossRef]
23. Yang, W.; Li, L. Energy Efficiency, Ownership Structure, and Sustainable Development: Evidence from China. *Sustainability* **2017**, *9*, 912. [CrossRef]
24. Yao, X.; Zhang, X.; Guo, Z. The tug of war between local government and enterprises in reducing China's carbon dioxide emissions intensity. *Sci. Total Environ.* **2020**, *710*, 136140. [CrossRef] [PubMed]

25. Moy, G.G. The role of whistleblowers in protecting the safety and integrity of the food supply. *NPJ Sci. Food* **2018**, *2*, 8. [CrossRef]
26. Yang, W.; Li, L. Efficiency evaluation of industrial waste gas control in China: A study based on data envelopment analysis (DEA) model. *J. Clean. Prod.* **2018**, *179*, 1–11. [CrossRef]
27. Chen, L. A Review of Research on Whistle-Blowing. *Am. J. Ind. Bus. Manag.* **2019**, *9*, 295–305. [CrossRef]
28. Chordiya, R.; Sabharwal, M.; Relly, J.E.; Berman, E.M. Organizational protection for whistleblowers: A cross-national study. *Public Manag. Rev.* **2019**, 1–26. [CrossRef]
29. Shi, G.; Wang, J.; Fu, F.; Xue, W. A study on transboundary air pollution based on a game theory model: Cases of SO2 emission reductions in the cities of Changsha, Zhuzhou and Xiangtan in China. *Atmos. Pollut. Res.* **2017**, *8*, 244–252. [CrossRef]
30. Chang, S.; Qin, W.; Wang, X. Dynamic optimal strategies in transboundary pollution game under learning by doing. *Phys. A Stat. Mech. Appl.* **2018**, *490*, 139–147. [CrossRef]
31. Wang, Q.; Zhao, L.; Guo, L.; Jiang, R.; Zeng, L.; Xie, Y.; Bo, X. A generalized Nash equilibrium game model for removing regional air pollutant. *J. Clean. Prod.* **2019**, *227*, 522–531. [CrossRef]
32. Hong, Y.; Li, K.; Huang, B.; Tam, T. Real-time PM2.5 air pollution and social preferences: A large-scale behavioural game study using mobile apps in mainland China. *Lancet Planet. Health* **2019**, *3*, S15. [CrossRef]
33. Shi, Y.; Han, B.; Zeng, Y. Simulating policy interventions in the interfirm diffusion of low-carbon technologies: An agent-based evolutionary game model. *J. Clean. Prod.* **2020**, *250*, 119449. [CrossRef]
34. Huang, X.; He, P.; Zhang, W. A cooperative differential game of transboundary industrial pollution between two regions. *J. Clean. Prod.* **2016**, *120*, 43–52. [CrossRef]
35. Lai, J.; Wan, J.W.L.; Zhang, S. Numerical methods for two person games arising from transboundary pollution with emission permit trading. *Appl. Math. Comput.* **2019**, *350*, 11–31. [CrossRef]
36. da Silva Rocha, A.B.; Salomão, G.M. Environmental policy regulation and corporate compliance in evolutionary game models with well-mixed and structured populations. *Eur. J. Oper. Res.* **2019**, *279*, 486–501. [CrossRef]
37. Zhou, Z.; Tan, Z.; Yu, X.; Zhang, R.; Wei, Y.; Zhang, M.; Sun, H.; Meng, J.; Mi, Z. The health benefits and economic effects of cooperative PM2.5 control: A cost-effectiveness game model. *J. Clean. Prod.* **2019**, *228*, 1572–1585. [CrossRef]
38. Yang, Y.; Yang, W. Does Whistleblowing Work for Air Pollution Control in China? A Study Based on Three-party Evolutionary Game Model under Incomplete Information. *Sustainability* **2019**, *11*, 324. [CrossRef]
39. Ministry of Ecology and Environment of the People's Republic of China. Institutional Duties of the Central Ecological Environmental Protection Supervision Office. Available online: http://www.mee.gov.cn/zjhb/bjg/dcb/ (accessed on 29 December 2019).
40. Li, Y.; Huang, S.; Yin, C.; Sun, G.; Ge, C. Construction and countermeasure discussion on government performance evaluation model of air pollution control: A case study from Beijing-Tianjin-Hebei region. *J. Clean. Prod.* **2020**, *254*, 120072. [CrossRef]
41. Shen, X.; Yang, W.; Sun, S. Analysis of the Impact of China's Hierarchical Medical System and Online Appointment Diagnosis System on the Sustainable Development of Public Health: A Case Study of Shanghai. *Sustainability* **2019**, *11*, 6564. [CrossRef]
42. Shen, L.; Wang, Y. Supervision mechanism for pollution behavior of Chinese enterprises based on haze governance. *J. Clean. Prod.* **2018**, *197*, 571–582. [CrossRef]
43. Ma, J.; Hou, A.; Tian, Y. Research on the complexity of green innovative enterprise in dynamic game model and governmental policy making. *Chaos Solitons Fractals X* **2019**, *2*, 100008. [CrossRef]
44. Xinhua News Agency. The First Round of Central Ecological and Environmental Supervision and "Look Back": More than 150,000 Environmental Problems, 2.46 Billion RMB in Fines, 2,264 People Detained. Available online: http://www.gov.cn/hudong/2019-05/15/content_5391977.htm (accessed on 29 December 2019).
45. Wang, L. Research on Environmental Right of Reporting and its Protection in China. Master's Thesis, Wangjian Law School, Soochow University, Suzhou, China, 2017.
46. Feng, Y.; Ning, M.; Lei, Y.; Sun, Y.; Liu, W.; Wang, J. Defending blue sky in China: Effectiveness of the "Air Pollution Prevention and Control Action Plan" on air quality improvements from 2013 to 2017. *J. Environ. Manag.* **2019**, *252*, 109603. [CrossRef]

47. Li, Y.; Yang, W.; Shen, X.; Yuan, G.; Wang, J. Water Environment Management and Performance Evaluation in Central China: A Research Based on Comprehensive Evaluation System. *Water* **2019**, *11*, 2472. [CrossRef]
48. Adami, C.; Schossau, J.; Hintze, A. Evolutionary game theory using agent-based methods. *Phys. Life Rev.* **2016**, *19*, 1–26. [CrossRef]
49. Babu, S.; Mohan, U. An integrated approach to evaluating sustainability in supply chains using evolutionary game theory. *Comput. Oper. Res.* **2018**, *89*, 269–283. [CrossRef]
50. Park, O.; Shin, H.; Thourdos, A. Evolutionary Game Theory based Multi-Objective Optimization for Control Allocation of Over-Actuated System. *IFAC PapersOnLine* **2019**, *52*, 310–315. [CrossRef]
51. Shi, Y.; Pan, M.; Peng, D. Replicator dynamics and evolutionary game of social tolerance: The role of neutral agents. *Econ. Lett.* **2017**, *159*, 10–14. [CrossRef]
52. Křivan, V.; Galanthay, T.E.; Cressman, R. Beyond replicator dynamics: From frequency to density dependent models of evolutionary games. *J. Theor. Biol.* **2018**, *455*, 232–248. [CrossRef]
53. Wang, Q.; He, N.; Chen, X. Replicator dynamics for public goods game with resource allocation in large populations. *Appl. Math. Comput.* **2018**, *328*, 162–170. [CrossRef]
54. Friedman, D. On economic applications of evolutionary game theory. *J. Evol. Econ.* **1998**, *8*, 15–43. [CrossRef]
55. Brady, M.; Mamanduru, V.K.; Tiwari, M.K. An evolutionary algorithmic approach to determine the Nash equilibrium in a duopoly with nonlinearities and constraints. *Expert Syst. Appl.* **2017**, *74*, 29–40. [CrossRef]
56. Selten, R. A note on evolutionarily stable strategies in asymmetric animal conflicts. *J. Theor. Biol.* **1980**, *84*, 93–101. [CrossRef]
57. Mengüç, E.C.; Acir, N. Real-time implementation of Lyapunov stability theory-based adaptive filter on FPGA. *IEICE Trans. Electron.* **2016**, *99*, 129–137. [CrossRef]
58. Huang, Z.; Xiong, X.; Chen, W.; Zhang, Q.; Liu, Y.; Chen, Y. Three bounded proofs for nonlinear multi-input multi-output approximate dynamic programming based on the Lyapunov stability theory. *Optim. Control Appl. Methods* **2018**, *39*, 35–50. [CrossRef]
59. Xu, L.; Du, J.; Wang, W. Evolutionary Game Analysis on Rural Water Environmental Governance. *China Popul. Environ.* **2017**, *27*, 17–26. (In Chinese)
60. Mondié, S.; Egorov, A.V.; Gomez, M.A. Stability conditions for time delay systems in terms of the Lyapunov matrix Partially supported by Project Conacyt 180725. *IFAC PapersOnLine* **2018**, *51*, 136–141. [CrossRef]
61. Braun, P.; Kellett, C.M.; Zaccarian, L. Complete control Lyapunov functions: Stability under state constraints P. Braun and C. M. Kellett are supported by the Australian Research Council (Grant number: ARC-DP160102138). L. Zaccarian is supported in part by ANR via project HANDY, number ANR-18. *IFAC PapersOnLine* **2019**, *52*, 358–363. [CrossRef]
62. Goebel, R. Stability and robustness for saddle-point dynamics through monotone mappings. *Syst. Control Lett.* **2017**, *108*, 16–22. [CrossRef]
63. Liu, F.; Zhang, B.; Yang, Z. Lyapunov stability and numerical analysis of excursive instability for forced two-phase boiling flow in a horizontal channel. *Appl. Therm. Eng.* **2019**, *159*, 113664. [CrossRef]

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Association between Atrial Fibrillation Incidence and Temperatures, Wind Scale and Air Quality: An Exploratory Study for Shanghai and Kunming

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Abstract: As a common cardiovascular disease, atrial fibrillation has the characteristics of high morbidity, high disability, and high fatality rates, seriously endangering human health and sustainability. Some research has confirmed that environmental factors are related to the risk of illness and death from cardiovascular diseases (including atrial fibrillation), while there is still little comparison on the situation of the two cities in China. This research uses medical data in Shanghai and Kunming establishing, through two-step research, logistic models to compare the impacts on atrial fibrillation incidence to figure out the association between environmental factors (including air pollution, weather, temperature, and wind scales) and atrial fibrillation. Finally, this research shows that environmental impacts on atrial fibrillation prevalence have generality, regionality, and lagging characteristics. The result is significant for atrial fibrillation patients and provides a reliable medical theory basis for nursing measures. Besides, this research provides a prospective method of offering early warning for potential atrial fibrillation patients, helping to maintain human beings' sustainable development.

Keywords: atrial fibrillation; environmental factors; binary logistic model; sustainable development; early warning

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1. Introduction

Atrial fibrillation (AF) is a disease that seriously endangers human health, recognized as a common complication of cardiovascular diseases. AF refers to the loss of routine and regular diastolic and contraction activities of the heart muscle, replaced by fast and uncoordinated weak peristalsis, causing the atrium to lose normal and effective contraction. Hence, blood tends to stagnate in the atrium and form a thrombus. The prevalence of AF in adults is about 3.0%, increasing with age and cardiovascular complications. In 2010, there were 33.5 million patients with AF worldwide. In the European Union and the United States, about one quarter of middle-aged people may suffer from AF [1]. In contrast, studies declare that AF's prevalence in China has increased by 20 times in the past ten years [2]. The total AF prevalence rate of people over 35 years old is 0.7%, and that of people over 80 is 7.5%, with the overall patient population reaching 4.87 million; however, 34.0% of them do not realize their AF history [3,4].

What is more, AF has seriously affected the sustainable development of human life. All-cause mortality caused by AF has increased by 1.5 times in men and 2 times in women [1]. Thromboembolic complications are the leading cause of death and disability in AF, and stroke is the most common manifestation, where strokes caused by AF account for 20.0% of all strokes [5–7]. Compared with non-AF-related strokes, AF-related strokes have severe symptoms, high disability, high mortality, and high recurrence. Its fatality rate is twice that of non-AF-related stroke [8].

As an essential part of the natural environment, climate profoundly impacts the global natural ecosystem and socio-economic system and even restricts all humankind's sustainable development. At present, many studies have confirmed that the lag-pattern impact of air pollutants may lead to the number of outpatients increasing, especially those who come to the hospital due to cardiovascular diseases, and an increase in the death rate of patients [9,10]. Besides, many governments have highlighted the importance of protecting the environment through sustainable development, wherein the air pollution index is vital [11,12]. With the increasing consciousness of air pollution's impact on human health [13,14], many scholars have focused on researching the association between air pollutant concentration and cardiovascular disease (CVD) prevalence. Nevertheless, as a sub-category of CVD, the association between environmental factors and AF are less concentrated. Therefore, this paper concentrates on the impact of environmental factors, researching the association between environmental factors and AF incidence to protect human health and provide early warnings.

2. Literature Review and Research Gap

Deeply researching and comprehending the impact of air pollution on the prevalence of AF is of significance. As AF is a sub-category of CVD, many scholars concentrate on researching the relationship between air pollution and CVD. Epidemiological studies have confirmed that air pollution impacts the cardiovascular system, and changes in air pollution concentrations are significantly related to the mortality and morbidity of CVD [15–18]. The previous research points out that every 10 $\mu g/m^3$ increase in the concentration of PM_{10} in the air would increase the death rate from cardiovascular diseases by 2.4% [19], where PM_{10} denotes particulate matter (PM) with aerodynamic diameters $\leq$ 10 μm, with the unit of concentration being $\mu g/m^3$. Similarly, a study evaluated the effects of long-term exposure to air pollution on Seoul residents' cardiovascular system, which carried out a 7-year follow-up of 136,094 participants in Seoul, asserting that the risk of cardiovascular events increased linearly with the increase in the average concentration of $PM_{2.5}$ [20], where $FPM_{2.5}$ denotes PM with aerodynamic diameters $\leq$ 2.5 μm, recognized as a significant part of the total suspended particulate (TSP) as PM_{10} above, with the unit of concentration being $\mu g/m^3$. Besides, a prospective cohort study of 189,793 men over the age of 40 in 45 regions of China figured out that for every 10 $\mu g/m^3$ increase in $PM_{2.5}$, cardiovascular disease mortality increased by 9% [21]. Similarly, in 2010, the American Heart Association (AHA) published the scientific statement Air Pollution and Cardiovascular Diseases, stating that fine particulate matter exposure can lead to an increase in the incidence and mortality of CVD; therefore, fine particulate matter exposure is considered to be a form of controllable risk factor for the disease [21]. To sum up, it is of significance to develop the impact of air pollution on the prevalence of AF.

As a common complication of CVD, the prevalence of AF is considerably affected by air pollution, proven by many scholars. Studies have shown that in the general population of Asia, long-term exposure to $PM_{2.5}$ is associated with an increased incidence of new-onset AF, and the situation for obese male subjects over 60 years of age with a history of hypertension or myocardial infarction is more serious [22]. It could be explained as ambient air pollution being positively correlated with elevated blood pressure and hypertension [23]. Furthermore, the Chinese Cardiovascular Health and Disease Report of 2019 points out, a series of studies based on daily data of air pollution and causes of death from 2013 to 2015 in 272 cities in China found that $PM_{2.5}$, O_3, SO_2, and NO_2 increased by 10 $\mu g/m^3$, and for every 1 mg/m^3 increase in CO, the risk of cardiovascular death increased by 0.3%, 0.3%, 0.7%, 0.9%, and 1.1%, respectively [24–28].

Different research figured out a similar result: air pollution's impact has a lag-effect pattern. For example, Kim et al. point out that the number of lag days for $PM_{2.5}$'s effect on CVD depends on its chemical composition, and different lag times may vary with the patient's health status and disease [29]. Moreover, the correlation between $PM_{2.5}$ and CVD mortality mainly occurred in the first 6 days, and the relationship between them lag from 0.5 to 3 days, and mortality was the largest [30].

Adding weather and wind scales into consideration, previous researchers have more specific conclusions. Y Ma et al. focused on the relationship between different air pollutants and the incidence of CVD on sandy and dusty days, and announced that PM_{10} and SO_2 lag 1 day, and NO_2 lags 2 days [31]. Research by Su Chang et al. asserts that the association between air pollutants and CVD incidence is more substantial in spring and winter, and the wind indirectly affects the incidence of CVD; meanwhile, the study also observed that the reduction in air pollution levels led to a reduction in the incidence of CVD [32]. Similarly, Ghanizadeh G et al. collected 1021 articles and pointed out that climate change parameters such as temperature, humidity, and air pollution significantly affect cardiorespiratory health [33]. What is more, it has been proven that meteorological fluctuations are most related to heart failure in the first 3 days of hospitalization, and that temperature and heart failure have a two-way relationship [34].

To sum up, although many studies have linked the increase of single or multiple air pollutants with adverse cardiovascular outcomes, the correlation between aggravated air pollution and AF has not been well investigated in China.

Therefore, this study explores the correlation between the concentrations and changes of different air pollutants (PM, O_3, NO_2, SO_2, CO, et cetera) and AF by performing Holter monitoring on patients to provide a reliable medical theoretical basis to reduce the prevalence of AF, which is helpful for the assessment of the cause of AF in patients and the nursing measures for some high-risk groups. Those air pollutants are selected based on the WHO Air Quality Guidelines, which figured out that the four most common air pollutants are particulate matter (PM), ozone (O_3), nitrogen dioxide (NO_2), and sulfur dioxide (SO_2).

3. Materials and Methods

3.1. Data Collection and Resources

Shanghai MicroPort Medical (Group) Co., Ltd. (Shanghai, China) provided the research data containing the participants' test location, test time (date), and their health statuses (whether at a high risk of AF). All the data were collected through the investigation, and there was no private data of the participants. What is more, the duration of the investigations in Shanghai and Kunming were 1 year and 6 months, respectively. In addition, the related environmental factors were provided, including the current day and the previous 14 days' weather, temperature (with the unit of degrees Celsius), wind force scales, air quality indexes (AQI), and air pollution concentrations ($PM_{2.5}$, PM_{10}, NO_2, SO_2, O_3, CO), where the first five kinds of pollutants used the unit of $\mu g/m^3$, except for CO, with the unit of mg/m^3. Therefore, there are 11 independent variables for each day, 15 days involved, and the AF status is the dependent variable.

In this research, two databases of Kunming and Shanghai were used to analyze the impact of the air pollution issue and the effect of other environmental factors. There were 3518 records collected, and after removing the incomplete records, 3160 records were kept (732 for Shanghai and 2428 for Kunming, respectively). Meanwhile, the high-risk AF (ICD-10 code I48) rate for Shanghai and Kunming participants were 9.3% and 2.8%, respectively. This research divided the data into two parts based on the AF status, as modeling parts (80%) and checking parts (20%), according to the locations.

3.2. Research Logic and Data Curation

This paper establishes a two-step analysis process, and the variables are categorized into five types. The first step is to convert the parameters into binary variables and analyze whether they are significantly related to AF or not. The second step is to use the primary data to establish a logistic regression model to interrupt the effect quantitatively.

In the first step, every related factors' differences were calculated to demonstrate the changes between the following days, shown in Equation 1 below.

$$\Delta(X)^{i,B}_{j,t} = \begin{cases} 1 & \text{when } (X)^{i}_{j,t} - (X)^{i}_{j,t+1} > 0 \\ 0 & \text{when } (X)^{i}_{j,t} - (X)^{i}_{j,t+1} \leq 0 \end{cases} \tag{1}$$

where $\Delta(X)^{i,B}_{j,t}$ is a binary variable recording the increase or decrease of the variable X between the day t and a day before for participant i, for which 1 means an increase and 0 means a decrease or equal. $(X)^{i}_{j,t}$ denotes the value of the factor X on the day t for the tester i in city j. For instance, $(AQI)^{i}_{5}$ represents the AQI index for the participant i on the day (5 days before the test day). Hence, if the $\Delta(X)^{i,B}_{j,t}$ is positive, it means that the environment is getting worse from day t + 1 to day t.

In this research, all $\Delta(X)^{i,B}_{j,t}$ are classified into the first-order difference category. What is more, to denote AF's situation, this paper use 1 to represent the patient being at a high risk of AF (over 50% chance of AF), and 0 for low risk (less than 50%). Furthermore, this research calculates the second-order differences, categorized into the second-order-difference type, to illustrate the fluctuating rate, shown in Equation (2) below.

$$\Delta'(X)^{i,B}_{j,t} = \begin{cases} 1 & \text{when } \Delta(X)^{i}_{j,t-1} - \Delta(X)^{i}_{j,t} > 0 \\ 0 & \text{when } \Delta(X)^{i}_{j,t-1} - \Delta(X)^{i}_{j,t} \leq 0 \end{cases} \tag{2}$$

where $\Delta'(X)^{i,B}_{j,t}$ denotes whether the fluctuating speed of the difference of variable X between the day $t - 1$ and t and the difference between the day t and t + 1 for the participant i in city j. Based on the definition of the second-order-difference variables, if the value is zero, it means that the change is stable, keeping an unchanging tendency. However, if it is positive, it could represent one of the following three situations: (1) the value's decreasing rate is getting lower. (2) The value's increasing speed is getting faster. (3) $(X)^{i}_{j,t}$ is the smallest compared with $(X)^{i}_{j,t-1}$ and $(X)^{i}_{j,t+1}$. To sum up, if the second-order-difference variable is positive, it describes a more complicated environmental degradation.

Therefore, there are 384 variables in this two-step research, divided into five categories (AF, primary pollution indexes, temperature, weather, and wind scale, first-order difference, and second-order difference, respectively). This research uses SPSS software (International Business Machines Corporation. Armonk, NY, USA. Version 25) to analyze the association between environmental factors and the incidence of AF and establish binary logistic models to elaborate on the relationship.

In the first step, all differences of variables (first-order difference and second-order difference) were converted into binary variables for modeling, 1 denoting the increase and 0 for the decrease.

3.3. Binary Logistic Regression

This research established two models through binary logistic regression, one for Shanghai and one for Kunming (called model 1 and model 2). Many scholars have used this method to determine the association between the risk factors and CVD [31–33], while this research concentrates on the changing of environmental factors. With the binary logistic regression, this research established the models as:

$$p^{i}_{j} = \frac{e^{(c+D^{i}_{j}+U^{i}_{j,0}+U^{i}_{j,1}+U^{i}_{j,2})}}{1+e^{(c+D^{i}_{j,0}+U^{i}_{j,0}+U^{i}_{j,1}+U^{i}_{j,2})}} \tag{3}$$

$$U^{i}_{j,0} = \sum_{t} \beta^{j,0}_{X,t} \times (X)^{i}_{j,t} \tag{4}$$

$$U^{i}_{j,1} = \sum_{t} \beta^{j,1}_{X,t} \times \Delta(X)^{i}_{j,t} \tag{5}$$

$$U^{i}_{j,2} = \sum_{t} \beta^{j,2}_{X,t} \times \Delta\prime(X)^{i}_{j,t} \tag{6}$$

$$D^{i}_{j} = \begin{cases} 0 & \text{if } (X)^{i}_{j,t} = 0 \\ \sum\limits_{d,l} \beta^{l}_{d,t} & \text{if } (X)^{i}_{j,t} = 1 \end{cases} \tag{7}$$

where p^{i}_{j} denotes the probability that participant i has a high risk of AF, and $U^{i}_{j,0}$, $U^{i}_{j,1}$, and $U^{i}_{j,2}$ represents the utility of the sum of the primary factors (except for weather and wind scale), and the utilities of the sum of the first-order category factors and the second-order category factors, respectively. D^{i}_{j} is the sum of the dummy variables, representing the different situations of the weather and wind scales. $\beta^{j,2}_{X,t}$ is the coefficients of the factor X in location j (Shanghai or Kunming, or the composition of the two cities) of the difference calculating order n (0 or 1 or 2) of the time t. Using the binary variables and the primary value of the factors, the p^{i}_{j} value could be calculated.

With 95% confidence interval (95% CI), this research first selected the statistically significant variables by checking their Wald statistic. What is more, this research reconsidered the correlations between every two variables to optimize the models.

With the binary logistic model results, the effect of the factors could be estimated by the coefficients' value. Besides, the odds ratio (OR) values were calculated to demonstrate the factors' impact, which equaled the exponential of $\beta^{j,n}_{X,t}$. If the OR value was larger than 1, it represented the specific factor's increase, positively related to the increase of the AF risk.

3.4. Model Tests

In this part, the models were tested by three methods, including chi-square tests, receiver operating characteristic curve (ROC curve) plotting, and applying to the new data sample to check the accuracy.

This research firstly analyzed the models' goodness of fit via omnibus tests and the Hosmer and Lemeshow test. They both use the chi-square value to check whether the model is further optimized to reject the null hypothesis. By comparing the chi-square values and the related *p*-values, it is persuasive to reject the null hypothesis evidently. Moreover, as many scholars have used the ROC-AUC approach in this field [34–37], this research used this method to examine this model's accuracy.

In conclusion, this research firstly checked the significance of all the variables and then used four methods to determine the models' statistical significance to determine the association between environmental factors and AF.

4. Results

This research establishes two models through the analysis methods above, and they could show three vital results about the environmental factors to AF, from the epidemical, geographical, and lag-affect pattern aspects.

4.1. Qualitative Models' Results

Analyzing the data using SPSS, this research figured out the factors that significantly affect the AF status qualitatively as the first step to establishing the models. The result is shown in Figures 1 and 2 (the qualitative model is in the Appendix A in Table A1).

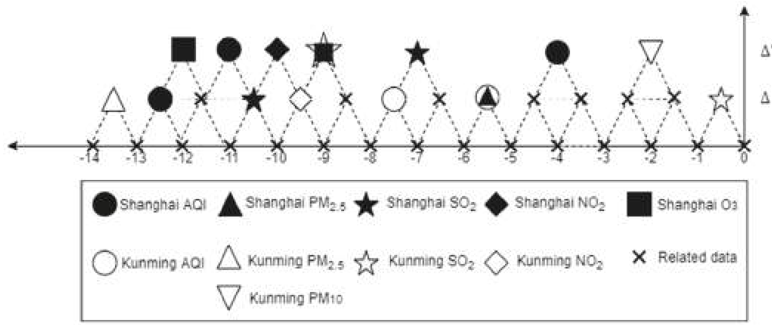

Figure 1. The impact of the air pollutants.

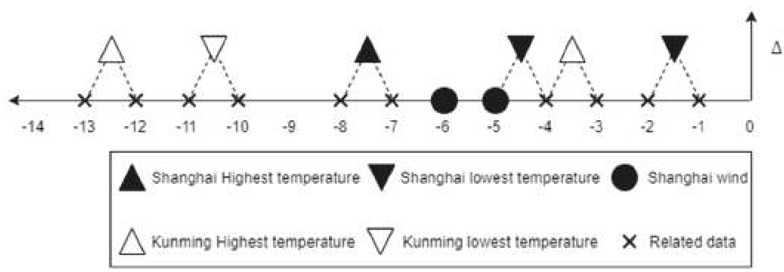

Figure 2. The impact of the weather, wind, and temperature difference.

As mentioned above, the Δ and Δ′ in the two figures above denote the first and second-time differences. This step is used to figure out the significant factors and the related variables.

4.2. Quantitative Models Results

Using SPSS 25, the following two models in Table 1 below exhibit the quantitative relationship between the specific environmental factors and AF.

In the tables above, the OR value is the impact of per 1 unit increase of the particular variable on AF's incidence when other conditions are all kept unchanged, which equals to the exp(β). The following Figures 3 and 4 plot the OR values with their lower and upper bounds, where the Y-axis shows the variables and the X-axis shows the corresponding OR values range with 95% CI and the expected OR value.

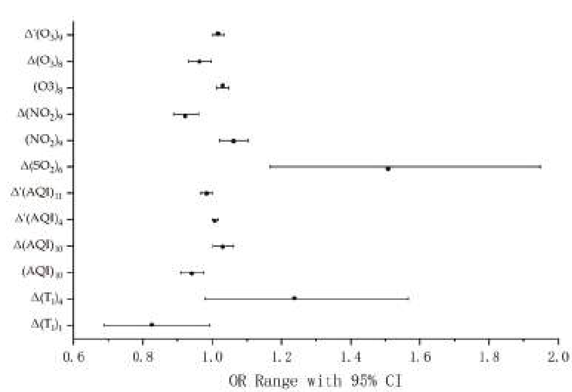

Figure 3. The odds ratio value in model 1.

Table 1. The results of the quantitative models.

Description	Variables	Shanghai						Kunming					
						OR [4] 95% CI						OR [4] 95% CI	
		B [1]	Std. [2]	Sig. [3]	OR	Lower Bound	Upper Bound	β	Std.	Sig.	OR	Lower Bound	Upper Bound
wind	$W_5(1)$	−1.645	0.649	0.011	0.193	0.054	0.689						
	$W_6(1)$	1.121	0.426	0.009	3.067	1.330	7.076						
Temperature	$(T_h)_3$							−0.207	0.072	0.004	0.813	0.706	0.936
	$(T_h)_4$							0.200	0.080	0.012	1.221	1.044	1.427
	$(T_l)_{10}$							0.347	0.153	0.023	1.416	1.048	1.911
	$(T_l)_{11}$							−0.553	0.170	0.001	0.575	0.412	0.802
	$(T_h)_{13}$							0.151	0.062	0.015	1.163	1.030	1.313
	$\Delta(T_l)_1$	−0.190	0.093	0.041	0.827	0.689	0.992						
	$\Delta(T_l)_4$	0.214	0.120	0.075	1.238	0.978	1.567						
AQI	$(AQI)_{10}$	−0.060	0.018	0.001	0.942	0.909	0.975						
	$\Delta(AQI)_5$							0.041	0.011	0.000	1.042	1.019	1.066
	$\Delta(AQI)_7$							0.029	0.013	0.030	1.029	1.003	1.056
	$\Delta'(AQI)_4$	0.008	0.005	0.089	1.008	0.999	1.018						
	$\Delta'(AQI)_{11}$	−0.016	0.008	0.047	0.984	0.968	1.000						
TSP	$\Delta(PM_{2.5})_{13}$							0.125	0.033	0.000	1.133	1.062	1.208
	$\Delta(PM_{10})_1$							0.009	0.017	0.602	1.009	0.976	1.043
SO_2	$\Delta(SO_2)_0$							−0.157	0.058	0.007	0.855	0.763	0.958
	$\Delta(SO_2)_6$	0.411	0.130	0.002	1.508	1.168	1.947						
	$\Delta'(SO_2)_9$							0.109	0.041	0.008	1.116	1.029	1.209
NO_2	$(NO_2)_2$	0.060	0.020	0.002	1.062	1.021	1.104	−0.014	0.023	0.531	0.986	0.943	1.031
	$\Delta(NO_2)_9$	−0.080	0.020	0.000	0.923	0.887	0.960						
O_3	$(O_3)_8$	0.031	0.009	0.000	1.031	1.014	1.049						
	$\Delta(O_3)_8$	−0.037	0.016	0.024	0.964	0.933	0.995						
	$\Delta'(O_3)_9$	0.017	0.009	0.044	1.017	1.000	1.034						
Constant	c	−4.008	0.874	0.000	0.018			−3.098	1.478	0.036	0.045		

[1] The β in this table represents the coefficients of the variables. [2] The Std. in this table represents the coefficients' standard deviation value. [3] The sig. in this table denotes the *p*-value of the variables. [4] The OR in this table denotes the odds ratio value.

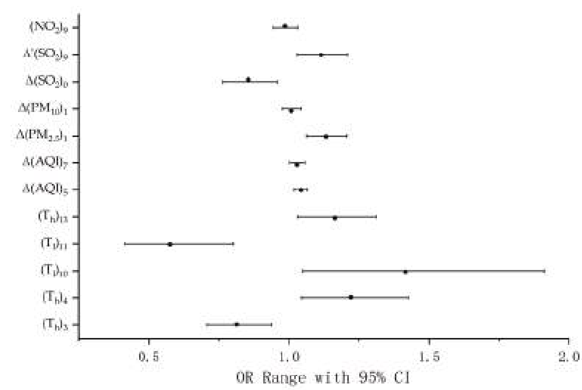

Figure 4. The odds ratio value in model 2.

For example, the $\Delta(SO_2)_6$ in Table 1 model 1 is 1.508 (95% CI: 1.168, 1.947), larger than 1, showing that, with all other variables kept the same, for every 1 unit increase of the SO_2 index from the seventh day before the test date to the sixth day, the risk would increase by 1.508 times. In contrast, for the $(T_h)_3$ (OR value as 0.813) in model 2, if the highest temperature occurred on the third day before the record increasing 1 degree, the patients in Kunming would have a lower probability of getting AF on the testing day, and the probability would decrease by about 20%. Therefore, the models' results could illustrate the relationship between environmental conditions changing and AF risk changing. What is more, with the descriptive statistics, the absolute value of the variables and related variables could be illustrated, showing the results more detailed and evidently.

As air pollution could last for days, and the air quality tendency is ordinarily stable in a particular city, the correlation between variables in this research is appropriately released. Hence, some variables may still be kept for the accuracy of the models. Moreover, by analyzing the data of air quality, wind scale, and temperature to assist in analyzing the association, this research used Figures 5 and 6 to illustrate the value of those selected variables. In the two figures, the boxes to the left of the vertical lines are for model 1, and others for model 2, and they describe the upper and lower bound of the value of the factors with their 25% to 75% range. The spots and the horizontal lines inside the boxes denote the mean and median values, respectively.

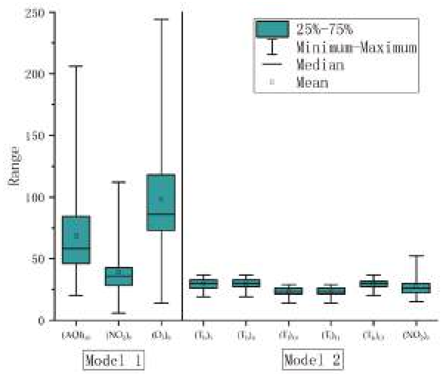

Figure 5. The description of the primary air quality and temperature data.

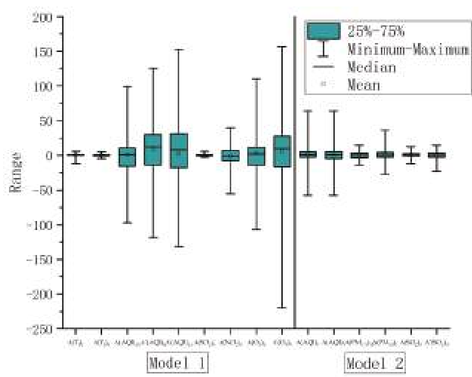

Figure 6. The description of the differential variables.

As most coefficients in the two models were from −1 to 1, with a larger value of the variable, this specific factor would cause a more significant impact. For instance, the $(O_3)_8$ in model 1 is statistically significant, and the mean and median value of this variable were close to 100, larger than other factors'; therefore, the impact of the concentration of O_3 (lag of 8 days) could be evidently shown. Besides, judging by this graph, some insignificant variables could be explained, for example, $\Delta(PM_{10})_1$ in model 2 (p-value is 0.602). In Figure 6, it is clear that the variable's value was close to 0, and half of them distributed close to 0. Therefore, the impact given by PM_{10}'s concentration changing was limited. Hence, compared with other factors, it could be statistically insignificant. In conclusion, these two figures above can explain the models' results by analyzing the distribution and value of the variables.

What is more, many variables were insignificant in the models because they could explain the first step's results. For example, the second-difference AQI value of four days before the test day in Shanghai (denoted as Δ' $(AQI)_4$) was insignificant, with 95% CI (*p*-value as 0.089), which is kept to show the impact of the AQI changing from the fifth day to the third day before the test day, which was found significant in the first step. Other insignificant variables played the same role. Besides, all insignificant variables' OR interval skipped 1, so it is hard to identify them to judge their impact confidently. Nevertheless, those variables are vital to support the conclusion achieved in the first step.

According to the tests of the models, the results of the goodness of fit test results are shown in Table 2. With the omnibus test's chi-square values and the significance values of all passing the test, it is evident that we can judge that the models are eloquent. As the *p*-values for the omnibus tests are all less than 0.5, this represents that the null hypothesis test could be rejected. Besides, the Hosmer and Lemeshow test results show that the information of the data has been fully extracted (all *p*-values are larger than 0.05), which means the models have good fitness. Therefore, from the results of these two tests of the models, all models have been proven to be relatively accurate.

Table 2. The results of models' goodness of fit tests.

Location	Omnibus Tests of Model Coefficients			Hosmer and Lemeshow Test		
	Chi-Square	**df**	**Sig.**	**Chi-Square**	**df**	**Sig.**
Shanghai	63.89	14	0	15.394	8	0.052
Kunming	44.41	12	0	10.039	8	0.262

The ROC-AUC test results are shown in Table 3 below. As the AUC represents the degree or measure of separability of the model, it was chosen to be an approach to analyze the models' accuracy. Therefore, taking the AUC value for Shanghai's model as an example, which is 0.824 (95% CI: 0.771, 0.877), it represents excellent discrimination. Besides, the AUC value for model 2 is 0.756, denoting that the model is acceptable and has excellent abilities to separate AF's risk level.

Table 3. The description of the ROC curves and AUC.

Location	Area	Std. Error	Asymptotic Sig.	Asymptotic 95% Confidence Interval	
				Lower Bound	**Upper Bound**
Shanghai	0.824	0.027	0	0.771	0.877
Kunming	0.756	0.034	0	0.689	0.822

Furthermore, by calculating the accuracy by checking the sample data, the accuracy was 88.8% and 97.3% for the two models mentioned above. As this research focused on the association between environmental factors and AF prevalence, the accuracy could prove the models' validity.

In conclusion, all models have shown great accuracy, separability, and information extraction through these three tests' results. Hence, these models were selected to analyze the association between AF and environmental factors.

4.3. Epidemicical Results

The epidemical result is that three of the most common air pollutants mentioned by the WHO were positively correlated with the prevalence of AF, as PM, NO_2, and SO_2. Moreover, as the AQI is a synthetic factor in measuring the pollution level, the OR values of the AQI could demonstrate the impact of air pollution comprehensively.

Judging by the models, it is clear that with PM and SO_2 concentration increasing, it poses a higher risk for people getting AF, proven by the OR value of the concentration increase of $PM_{2.5}$ 13 days prior to the test day in Kunming (95% CI: 1.062, 1.208) and SO_2 6 days prior in Shanghai (95% CI: 1.168, 1.947), respectively. Moreover, model 1 highlights that the concentration of O_3 had a negative impact, which was proven by the OR value for the O_3 concentration per 1 unit increase in fluctuation around the ninth day before the record date (95% CI: 1.000, 1.034). What is more, the AQI's increase 5 days (95% CI: 1.019, 1.066) and 7 days (95% CI: 1.003, 1.056) previously in model 2 prove that the comprehensive air pollution increase will cause the patients to get into a more dangerous environment.

Concentrating on the fluctuation of air pollutant concentrations (defined by the second-order difference category), all coefficients were positive, except for one, the AQI fluctuation 11 days before the test day in model 1. However, by analyzing the primary data, it shows that the AQI index from the 12 days prior to the 10 days before the test day followed the increasing trend, while the increasing speed slowed down. Therefore, this research concludes that if the air pollution situation shows the tendency of going down initially and then immediately going up, there will be a higher risk of AF.

This paper uses the following Figures 7 and 8 to illustrate the impact of the pollutants and temperature changes.

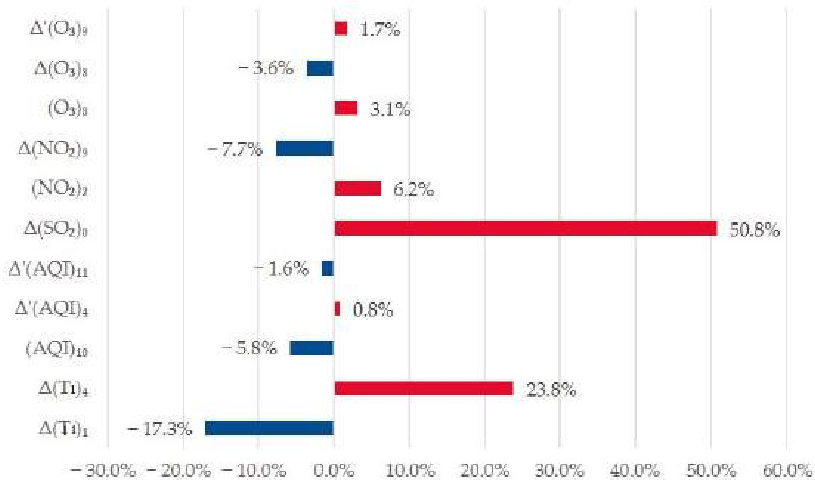

Figure 7. The odds change in Shanghai.

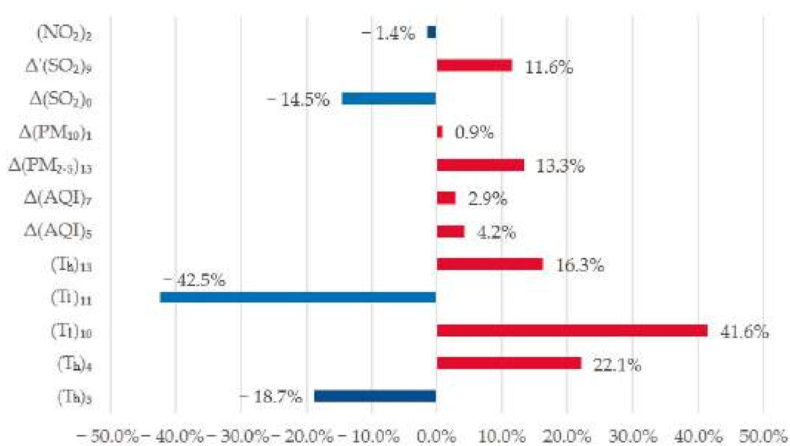

Figure 8. The odds change in Kunming.

The X-axis value is the odds change value, representing the changing of AF's incidence when the specific variable increases by 1 unit. From the two figures shown above, it is clear that different cities are sensitive to different parameters. What is more, SO_2 is more significant than the other variables, not only because the odds change is larger than for the others (close to 0.5), but also because both models contain this pollutant. Besides, as shown in Figures 7 and 8, it is clear that with the pollution getting severe, regardless of the absolute index or the polluting speeding up, people will have a higher risk of AF. For instance, the probability of AF for patients in Kunming will have 4% increase if there is 1 unit increase of the AQI, since from the sixth day to the fifth before the test day. The SO_2 increase 1 day previously played a protective role, because, in Kunming, the SO_2 concentration was relatively stable (mean and standard error for the increase is 0.21 and 0.057); if the concentration increases significantly, the impact could be significant.

Finally, both models' constant coefficients were negative, as a protecting factor from AF. There are few high-risk patients in the database (67 in Kunming and 68 in Shanghai) compared to low-risk people through the statistical analysis. Therefore, the constants here demonstrate that only a few people are at high risk in the initial stage.

To sum up, from the results related to the pollutants' concentrations, it is clear that air pollution may cause the prevalence of AF growth. Similarly, the second-order difference demonstrates that the fluctuating rate of the air pollutants' concentrations changing can significantly affect AF prevalence.

4.4. Geographical Results

The geographical effect is clear from the models, mainly represented by the model variables involved. According to model 1 and model 2, it is clear that they contain different variables. The following Figure 9 illustrates the comparisons of the odds change of the temperature and wind on AF.

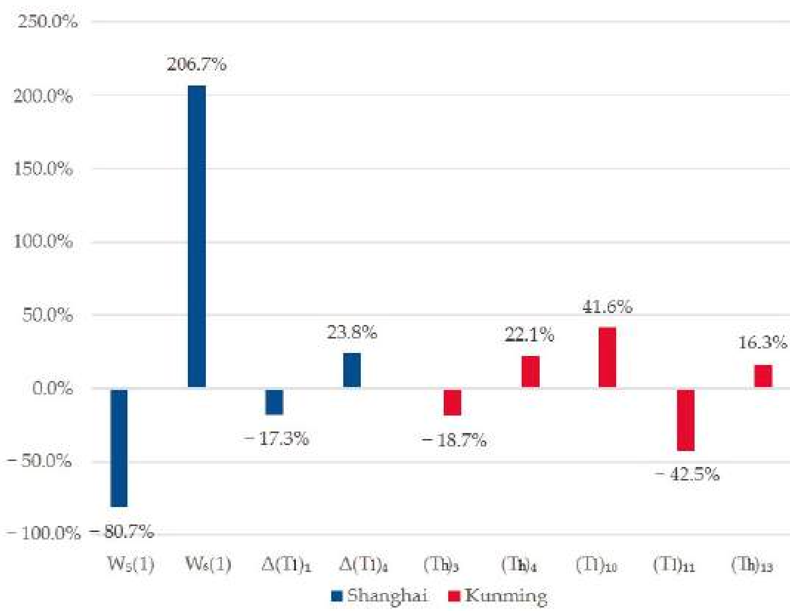

Figure 9. The odds change by the wind scale and temperature.

Nevertheless, different cities are sensitive to different days. From Figure 9, the AF incidence in Shanghai was not sensitive to the temperature, while it was closely related to the weather. In contrast, the situation in Kunming was the opposite. The OR values of the lowest temperature that occurred in Kunming (10 and 11 days lag for Kunming) were 1.416 (95% CI: 1.048, 1.911) and 0.575 (95% CI: 0.412, 0.802), showing that the different days' temperature had a different impact. Although the temperature was usually kept at a relatively stable level, the impacts may have offset each other, and may have caused a considerable effect when the temperatures were changing a lot during those days.

Concentrating on the wind scales' impacts, it had a relatively complex influence. If the wind scale was above level 4 on the sixth day before the test, people had a higher probability of getting AF (95% CI: 1.330, 7.076) in Shanghai, while the wind on the five days lag decreased the chance (95% CI: 0.054, 0.689).

In conclusion, the models describe the difference caused by the location of the patients. The impact of geography is entire, while the negative impact of air pollution is the same.

4.5. Pollution's Lag-Pattern Impact

In this research, most of the variables were not directly related to the test date, with a lag of 3 to 12 days. Therefore, it is reasonable to conclude that the risk of AF is associated with the environment and air pollutions. Comparing the models, nearly all the significant variables had at least three days lag, representing that the impact of the pollution could not immediately cause AF.

5. Discussion

5.1. The Influence of Air Pollution Factors on AF

There has been some research concentrating on the medical mechanism of the impact given by environmental factors on CVD. For example, Bhatnagar [38] in 2004 asserted that, as important components of $PM_{2.5}$, metals in the environment deposit in the heart and blood vessels, and their toxicity increases the risk of CVD. Besides, some gaseous pollutants can mediate or modify PM, which may cause ischemic heart diseases. Similarly, it has been proven that O_3 is highly related to pulmonary inflammation and edema, but it is still unclear whether it is associated with CVD [39]. Besides, other research figured out that environmental factors (especially air pollution) can cause CVD, such as endothelial dysfunction and the role of oxidative stress [40], which proves this paper's results. What is more, PM can cause atherosclerosis via promoting vascular dysfunction and alternating the vasoactive mediators' responsiveness [41]. These results explain the medical mechanism of CVD related to environmental factors, and they highlight the significant impact of environmental factors, which shows the importance of this paper's research.

After adjusting for other gaseous pollutants, the significance of $PM_{2.5}$, PM_{10}, SO_2, NO_2, and O_3 in research results is highlighted, suggesting that they are currently the main pollutants in Shanghai and Kunming. There is a positive correlation between the risk of AF for people in Shanghai and Kunming and the increase in PM concentration [42]. Other studies have evaluated the impact of six major environmental pollutants on the risk of AF in patients with cardiac implantable electronic devices (CIED). With a 10 $\mu g/m^3$ increase in $PM_{2.5}$ and PM_{10} concentrations, the risk of AF increased by 3.8% and 2.7%, respectively; however, the correlation with other gaseous pollutants (SO_2, NO_2, CO, O_3) was not statistically significant [43,44], which is similar to this research's results. Furthermore, this research emphasizes the impact of air pollution fluctuations in Shanghai and Kunming, filling the blanks of previous research.

On the other hand, statistics show that the increase in the number of visits for arrhythmia in the emergency room was significantly related to $PM_{2.5}$ on warm days (>23 °C) and cold days (<23 °C), and high levels of $PM_{2.5}$ would increase the risk of emergency visits due to arrhythmia [45]. In this research, the average highest temperature in Shanghai on the seventh and eighth day before was 23.3 °C, and 22.8 °C (standard error as 0.334 °C and 0.312 °C), respectively, and the lowest temperature in Kunming was close to 23 °C as well, which meets the conclusion. A large number of studies have explained this impact from the perspective of pathology, as certain substances can cause oxidative stress, cardiovascular inflammation, endothelial dysfunction, high C-reactive protein level, myocardial ischemia, and right atrial pressure [46–50], all of which are related to atrial remodeling and AF pathophysiology [51–54].

Therefore, it is persuasive to confirm that air pollution has the risk of increasing the probability of arrhythmia or other acute cardiac events. Hence, patients at high risk of AF should be educated to monitor the local air quality index and follow the recommendations to reduce exposure and reduce outdoor activities. What is more, this research helps prevent AF's high-risk situation and can give an early warning to the number of outpatients increasing through the lag-affect analysis of air pollution and wind. Therefore, this research can further strengthen the theoretical basis of urban air pollution control, establish air pollution control measures, and optimize community and hospital diagnoses and treatment configuration.

5.2. AF Risk Factors Are Variable in Different Cities

According to this research, for the results of model 1 and model 2, air pollution particles' impact on AF incidence was similar, while the impact of temperature factors showed opposite laws. Besides, the risk of AF in Shanghai was more sensitive to the effects wind scale, while that in Kunming was not.

Many studies have shown that the effects of seasons and temperature on the incidence and mortality of cardiovascular diseases are different in different cities [55,56]. The results of an epidemiological study containing 16 cities in China showed that PM_{10} was significantly associated with deaths from cardiopulmonary system diseases, and the association is still statistically significant after adjusting for other gaseous pollutants; additionally, the relationship between PM_{10} and death risk in different cities differed due to the different levels of pollutants in each city [57]. It explains the reason why the impact of PM_{10}'s concentration increase has different lag periods.

The seasons' effect on the risk of AF is another consideration. K Spengos et al. analyzed the symptom onset pattern of more than 300 patients with acute cardiogenic stroke in Greece for the first time due to AF, figuring out that the patients' symptoms were cyclically distributed, with the peak season in winter and the incidence in summer declining [58]. Similarly, J Ahn et al.'s study of the seasonal changes in AF incidence in Seoul also showed that the frequency of AF in summer was significantly lower than in other seasons [59]. Moreover, a national statistical study in Germany showed that when the outdoor temperature was between 0 and 10 °C, the hospital admission rate for arrhythmia, including AF, reached its peak [60]; however, some studies have shown that in some temperate countries, cardiovascular diseases in winter are lower than in summer [61]. Although most participants took the test in autumn in this research, it is hard to show the seasonal impact, and the different impacts of changing temperature, weather, and wind scale on AF risk have been pointed out.

In summary, different cities have different effects on the incidence of AF due to the intensity, mode of action, duration of the effect of cold and heat, and maybe the local residents' physical fitness. Therefore, different locations may have their own specific models to estimate the risk of AF, which might be another way to describe whether a city is livable or not.

5.3. The Impact's Lag-Affect Pattern

The lag-effect of environmental factors' impact on AF is shown by the variables' OR values, most of which show a three to twelve days lag. For example, the increase of the previous six day's SO_2's concentration is statistically significant in Shanghai. Although the four kinds of air pollutants ($PM_{2.5}$, PM_{10}, SO_2, and O_3) could significantly affect AF incidence, they all show lag-affect influence.

Many studies have also confirmed that the lag of air pollutants may affect the occurrence of CVD and the mortality rate. The correlation between $PM_{2.5}$ and CVD mortality mainly occurred in the first 6 days, with the fourth day being the most significant [62]. Additionally, LC Martins and other scholars have asserted that air pollutants' delayed effects (CO, PM_{10}, O_3, NO_2, and SO_2) have different effects on different genders. Besides heart failure inducing diseases, the delayed effects have more noticeable effects on women for other cardiovascular diseases [63]. Similarly, M Dastoorpoor et al. announced that for people over age 60 and under 18, after a delay of 3 days and 13 days, there was also a significant relationship between the increase in the interquartile range (IQR) of particles below 10 µm and cardiovascular death. For those under 18 years old (lag 11) and over 60 years old (lag 9), there was a significant relationship between the increase in IQR of NO_2 and CO and cardiovascular death, respectively [64]. Kim et al. pointed out that the number of lag days for the impact of $PM_{2.5}$ on CVD depended on its chemical composition, and the different lag times may vary with the patient's health status and disease [65].

This research selected the medical records in Shanghai and Kunming for statistical research, and the conclusion showed the similarity with the previous study. Notably, the pollutants' delayed impact on AF in the two cities was different, which may be due to the study cities' different characteristics, such as indoor air quality, local climate type, residents' sensitivity to pollutants (such as economic level, population age, and smoking rate), pollutant concentration levels, and differences in pollutant composition.

5.4. Research Significance, Limitations and Prospects

This research attempted to figure out the association between environmental factors and AF, which is of significance to the government, medical research, and patients. As it emphasizes the hysteresis of air pollutions and weather changes' impact, the government and hospitals can use these conclusions to improve and optimize weather reports and forecasting. Meanwhile, this research uses the data of two cities in China, comparing and demonstrating the different impacts caused by the different locations. Therefore, other researchers can follow this direction to determine the overall regularity, boosting AF and CVD comprehension. Furthermore, patients with a history of AF could be alerted by this research to pay more attention to air pollution and take self-protection more seriously. On the other hand, medical workers may also remind the patients to remember the air pollution conditions in order to protect them in the following days.

However, there were still some limitations to this research. This research used the average value of each monitoring site in each city as the population exposure level of pollutants. However, each monitoring site's pollutant measurement methods may differ, so the environmental monitoring results and the individual level of pollutant exposure might not be accurate enough. Hence, this study cannot calculate the precise individual exposure in each city, affecting the analysis results. Meanwhile, as the participants' gender and age level were often misrecorded in the records, this research does not contain those two vital factors to optimize the model. What is more, as most of the data were collected in the summer and autumn, some contingents might exist in this paper's results. Therefore, more data are being collected by a more extended duration investigation and tracking surveys, which can help to improve the results. In the subsequent research, more detailed data will be used to optimize the models and provide more conclusions.

6. Conclusions

Increasing environmental pollution will increase the incidence of atrial fibrillation, and the concentration of the increase of the two major air pollutants (PM_{10} and SO_2) will raise the risk significantly. Meanwhile, the environmental impact of each region is regional and lagging. Besides, the acceleration of air pollution will also increase the probability of atrial fibrillation. Therefore, continuously monitoring the environmental indexes are of importance for warning and protecting potential patients. What is more, different cities may have their unique model to evaluate and estimate the significant factors to improve the local environmental departments' working process, as integrating the previous environmental indexes into the daily weather reports has a strong impact on the sustainability of AF.

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Appendix A

Table A1. The qualitative model results.

Description	Variables	Shanghai						Kunming					
		β [1]	Std. [2]	Sig. [3]	OR	OR [4] 95% CI Lower Bound	OR [4] 95% CI Upper Bound	β	Std.	Sig.	OR	OR [4] 95% CI Lower Bound	OR [4] 95% CI Upper Bound
Wind	$W_5(1)$	−2.900	0.760	0.000	0.055	0.012	0.244						
	$W_6(1)$	2.498	0.552	0.000	12.162	4.119	35.917						
Temperature	$\Delta(T_l)_1$	−1.213	0.439	0.006	0.297	0.126	0.703						
	$\Delta(T_l)_4$	1.999	0.455	0.000	7.378	3.022	18.013						
	$(T_h)_7$	1.662	0.454	0.000	5.267	2.162	12.833						
	$\Delta(T_h)_3$							−0.906	0.370	0.014	0.404	0.196	0.835
	$\Delta(T_l)_{10}$							1.095	0.336	0.001	2.988	1.545	5.777
	$\Delta(T_h)_{12}$							−1.983	0.541	0.000	0.138	0.048	0.397
AQI	$\Delta(AQI)_5$							0.763	0.309	0.014	2.144	1.170	3.928
	$\Delta(AQI)_7$							−1.105	0.346	0.001	0.331	0.168	0.652
	$\Delta(AQI)_{12}$	−1.857	0.453	0.000	0.156	0.064	0.379						
	$\Delta'(AQI)_4$	1.935	0.445	0.000	6.925	2.893	16.578						
	$\Delta'(AQI)_{11}$	−1.834	0.477	0.000	0.160	0.063	0.407						
TSP	$\Delta(PM_{2.5})_5$	0.926	0.422	0.028	2.525	1.105	5.770						
	$\Delta(PM_{2.5})_{13}$							0.827	0.316	0.009	2.285	1.230	4.246
	$\Delta'(PM_{10})_2$							0.770	0.345	0.026	2.160	1.098	4.248
SO_2	$\Delta(SO_2)_0$							−1.156	0.372	0.002	0.315	0.152	0.652
	$\Delta(SO_2)_{10}$	1.305	0.424	0.002	3.686	1.606	8.457						
	$\Delta'(SO_2)_7$	1.960	0.416	0.000	7.102	3.142	16.056						
	$\Delta'(SO_2)_9$							0.763	0.345	0.027	2.145	1.091	4.218
NO_2	$\Delta(NO_2)_9$							−1.264	0.349	0.000	0.283	0.143	0.560
	$\Delta'(NO_2)_{10}$	−1.419	0.430	0.001	0.242	0.104	0.562						
O_3	$\Delta'(O_3)_9$	0.913	0.425	0.032	2.491	1.083	5.726						
	$\Delta'(O_3)_{12}$	−1.363	0.437	0.002	0.256	0.109	0.603						
Constant	c	−4.222	0.854	0.000	0.015			−3.773	0.579	0.000	0.023		

[1] The β in this table represents the coefficients of the variables. [2] The Std. in this table represents the coefficients' standard deviation value. [3] The sig. in this table denotes the *p*-value of the variables. [4] The OR in this table denotes the odds ratio value.

References

1. Camm, A.J.; Kirchhof, P.; Lip, G.Y.H.; Schotten, U.; Savelieva, I.; Ernst, S.; Van Gelder, I.C.; Al Attar, N.; Hindricks, G.; Prendergast, B.; et al. Guidelines for the management of atrial fibrillation: The Task Force for the Management of Atrial Fibrillation of the European Society of Cardiology (ESC). *Eur. Heart J.* **2010**, *31*, 2369–2429.
2. Guo, Y.; Tian, Y.; Wang, H.; Si, Q.; Wang, Y.; Lip, G.Y.H. Prevalence, incidence, and lifetime risk of atrial fibrillation in China: New insights into the global burden of atrial fibrillation. *Chest* **2015**, *147*, 109–119. [CrossRef]

3. Wang, Z.; Chen, Z.; Wang, X.; Zhang, L.; Li, S.; Tian, Y.; Shao, L.; Hu, H.; Gao, R. The Disease Burden of Atrial Fibrillation in China from a National Cross-sectional Survey. *Am. J. Cardiol.* **2018**, *122*, 793–798. [CrossRef] [PubMed]
4. Zhou, Z.; Hu, D. An epidemiological study on the prevalence of atrial fibrillation in the Chinese population of mainland China. *J. Epidemiol.* **2008**, *18*, 209–216. [CrossRef] [PubMed]
5. Friberg, L.; Rosenqvist, M.; Lip, G.Y.H. Evaluation of risk stratification schemes for ischaemic stroke and bleeding in 182 678 patients with atrial fibrillation: The Swedish Atrial Fibrillation cohort study. *Eur. Heart J.* **2012**, *33*, 1500–1510. [CrossRef]
6. Gao, H.; Yang, W.; Wang, J.; Zheng, X. Analysis of the Effectiveness of Air Pollution Control Policies based on Historical Evaluation and Deep Learning Forecast: A Case Study of Chengdu-Chongqing Region in China. *Sustainability* **2021**, *13*, 206. [CrossRef]
7. Liu, H.; Liu, J.; Yang, W.; Chen, J.; Zhu, M. Analysis and Prediction of Land Use in Beijing-Tianjin-Hebei Region: A Study Based on the Improved Convolutional Neural Network Model. *Sustainability* **2020**, *12*, 3002. [CrossRef]
8. Andrew, N.E.; Thrift, A.G.; Cadilhac, D.A. The prevalence, impact and economic implications of atrial fibrillation in stroke: What progress has been made? *Neuroepidemiology* **2013**, *40*, 227–239. [CrossRef]
9. Kim, H.; Kim, Y.; Hong, Y.-C. The lag-effect pattern in the relationship of particulate air pollution to daily mortality in Seoul, Korea. *Int. J. Biometeorol.* **2003**, *48*, 25–30. [CrossRef] [PubMed]
10. Khajavi, A.; Khalili, D.; Azizi, F.; Hadaegh, F. Impact of temperature and air pollution on cardiovascular disease and death in Iran: A 15-year follow-up of Tehran Lipid and Glucose Study. *Sci. Total Environ.* **2019**, *661*, 243–250. [CrossRef]
11. Shen, X.; Yang, W.; Sun, S. Analysis of the Impact of China's Hierarchical Medical System and Online Appointment Diagnosis System on the Sustainable Development of Public Health: A Case Study of Shanghai. *Sustainability* **2019**, *11*, 6564. [CrossRef]
12. Li, Y.; Yang, W.; Shen, X.; Yuan, G.; Wang, J. Water environment management and performance evaluation in central China: A research based on comprehensive evaluation system. *Water* **2019**, *11*, 2472. [CrossRef]
13. Yang, W.; Yuan, G.; Han, J. Is China's air pollution control policy effective? Evidence from Yangtze River Delta cities. *J. Clean. Prod.* **2019**, *220*, 110–133. [CrossRef]
14. Jiang, B.; Li, Y.; Yang, W. Evaluation and Treatment Analysis of Air Quality Including Particulate Pollutants: A Case Study of Shandong Province, China. *Int. J. Environ. Res. Public Health* **2020**, *17*, 9476. [CrossRef] [PubMed]
15. Wordley, J.; Walters, S.; Ayres, J.G. Short term variations in hospital admissions and mortality and particulate air pollution. *Occup. Environ. Med.* **1997**, *54*, 108–116. [CrossRef] [PubMed]
16. Sun, Q.; Hong, X.; Wold, L.E. Cardiovascular Effects of Ambient Particulate Air Pollution Exposure. *Circulation* **2010**, *121*, 2755–2765. [CrossRef] [PubMed]
17. Balakrishnan, K.; Dey, S.; Gupta, T.; Dhaliwal, R.S.; Brauer, M.; Cohen, A.J.; Stanaway, J.D.; Beig, G.; Joshi, T.K.; Aggarwal, A.N.; et al. The impact of air pollution on deaths, disease burden, and life expectancy across the states of India: The Global Burden of Disease Study 2017. *Lancet Planet. Health* **2019**, *3*, e26–e39. [CrossRef]
18. Newell, K.; Kartsonaki, C.; Lam, K.B.H.; Kurmi, O.P. Cardiorespiratory health effects of particulate ambient air pollution exposure in low-income and middle-income countries: A systematic review and meta-analysis. *Lancet Planet. Health* **2017**, *1*, e360–e367. [CrossRef]
19. Neophytou, A.M.; Yiallouros, P.; Coull, B.A.; Kleanthous, S.; Pavlou, P.; Pashiardis, S.; Dockery, D.W.; Koutrakis, P.; Laden, F. Particulate matter concentrations during desert dust outbreaks and daily mortality in Nicosia, Cyprus. *J. Expo. Sci. Environ. Epidemiol.* **2013**, *23*, 275–280. [CrossRef]
20. Kim, H.; Kim, J.; Kim, S.; Kang, S.; Kim, H.; Kim, H.; Heo, J.; Yi, S.; Kim, K.; Youn, T.; et al. Cardiovascular Effects of Long-Term Exposure to Air Pollution: A Population-Based Study With 900 845 Person-Years of Follow-up. *J. Am. Heart Assoc.* **2017**, *6*, e007170. [CrossRef] [PubMed]
21. Brook, R.D.; Rajagopalan, S.; Pope, C.A., 3rd; Brook, J.R.; Bhatnagar, A.; Diez-Roux, A.V.; Holguin, F.; Hong, Y.; Luepker, R.V.; Mittleman, M.A.; et al. Particulate matter air pollution and cardiovascular disease: An update to the scientific statement from the American Heart Association. *Circulation* **2010**, *121*, 2331–2378. [CrossRef] [PubMed]
22. Kim, I.; Yang, P.; Lee, J.; Yu, H.T.; Kim, T.; Uhm, J.; Pak, H.; Lee, M.; Joung, B. Long-term exposure of fine particulate matter air pollution and incident atrial fibrillation in the general population: A nationwide cohort study. *Int. J. Cardiol.* **2019**, *283*, 178–183. [CrossRef] [PubMed]
23. Yang, B.; Qian, Z.; Howard, S.W.; Vaughn, M.G.; Fan, S.; Liu, K.; Dong, G. Global association between ambient air pollution and blood pressure: A systematic review and meta-analysis. *Environ. Pollut.* **2018**, *235*, 576–588. [CrossRef]
24. Chen, R.; Yin, P.; Meng, X.; Liu, C.; Wang, L.; Xu, X.; Ross, J.A.; Tse, L.A.; Zhao, Z.; Kan, H.; et al. Fine Particulate Air Pollution and Daily Mortality. A Nationwide Analysis in 272 Chinese Cities. *Am. J. Respir. Crit. Care Med.* **2017**, *196*, 73–81. [CrossRef] [PubMed]
25. Wang, L.; Liu, C.; Meng, X.; Niu, Y.; Lin, Z.; Liu, Y.; Liu, J.; Qi, J.; You, J.; Tse, L.A.; et al. Associations between short-term exposure to ambient sulfur dioxide and increased cause-specific mortality in 272 Chinese cities. *Environ. Int.* **2018**, *117*, 33–39. [CrossRef] [PubMed]
26. Liu, C.; Yin, P.; Chen, R.; Meng, X.; Wang, L.; Niu, Y.; Lin, Z.; Liu, Y.; Liu, J.; Qi, J.; et al. Ambient carbon monoxide and cardiovascular mortality: A nationwide time-series analysis in 272 cities in China. *Lancet Planet. Health* **2018**, *2*, e12–e18. [CrossRef]

27. Chen, R.; Yin, P.; Meng, X.; Wang, L.; Liu, C.; Niu, Y.; Lin, Z.; Liu, Y.; Liu, J.; Qi, J.; et al. Associations Between Ambient Nitrogen Dioxide and Daily Cause-specific Mortality: Evidence from 272 Chinese Cities. *Epidemiology* **2018**, *29*, 482–489. [CrossRef] [PubMed]
28. Yin, P.; Chen, R.; Wang, L.; Meng, X.; Liu, C.; Niu, Y.; Lin, Z.; Liu, Y.; Liu, J.; Qi, J.; et al. Ambient Ozone Pollution and Daily Mortality: A Nationwide Study in 272 Chinese Cities. *Environ. Health Perspect.* **2017**, *125*, 117006. [CrossRef] [PubMed]
29. Kim, S.Y.; Peel, J.L.; Hannigan, M.P.; Dutton, S.J.; Sheppard, L.; Clark, M.L.; Vedal, S. The temporal lag structure of short-term associations of fine particulate matter chemical constituents and cardiovascular and respiratory hospitalisations. *Environ. Health Perspect.* **2012**, *120*, 1094–1099. [CrossRef]
30. Staniswalis, J.G.; Yang, H.; Li, W.; Kelly, K.E. Using a continuous time lag to determine the associations between ambient PM2.5 hourly levels and daily mortality. *J. Air Waste Manag. Assoc.* **2009**, *59*, 1173–1185. [CrossRef]
31. Ma, Y.; Zhang, H.; Zhao, Y.; Zhou, J.; Yang, S.; Zheng, X.; Wang, S. Short-term effects of air pollution on daily hospital admissions for cardiovascular diseases in western China. *Environ. Sci. Pollut. Res.* **2017**, *24*, 14071–14079. [CrossRef]
32. Su, C.; Breitner, S.; Schneider, A.; Liu, L.; Franck, U.; Peters, A.; Pan, X. Short-term effects of fine particulate air pollution on cardiovascular hospital emergency room visits: A time-series study in Beijing, China. *Int. Arch. Occup. Environ. Health* **2016**, *89*, 641–657. [CrossRef] [PubMed]
33. Ghanizadeh, G.; Heidari, M.; Seifi, B.; Jafari, H.; Pakjouei, S. The effect of climate change on cardiopulmonary disease—A systematic review. *J. Clin. Diagn. Res* **2017**, *11*, IE01–IE04. [CrossRef]
34. Das, D.; Bakal, J.A.; Westerhout, C.M.; Hernandez, A.F.; O'Connor, C.M.; Atar, D.; McMurray, J.J.V.; Armstrong, P.W.; Ezekowitz, J.A. The association between meteorological events and acute heart failure: New insights from ASCEND-HF. *Int. J. Cardiol.* **2014**, *177*, 819–824. [CrossRef]
35. Guzder, R.N.; Gatling, W.; Mullee, M.A.; Byrne, C.D. Impact of metabolic syndrome criteria on cardiovascular disease risk in people with newly diagnosed type 2 diabetes. *Diabetologia* **2006**, *49*, 49–55. [CrossRef] [PubMed]
36. Amiri, M.; Majid, H.A.; Hairi, F.; Thangiah, N.; Bulgiba, A.; Su, T.T. Prevalence and determinants of cardiovascular disease risk factors among the residents of urban community housing projects in Malaysia. *BMC Public Health* **2014**, *14* (Suppl. 3), S3. [CrossRef] [PubMed]
37. Yang, Y.; Yang, W.; Chen, H.; Li, Y. China's energy whistleblowing and energy supervision policy: An evolutionary game perspective. *Energy* **2020**, *213*, 118774. [CrossRef]
38. Bhatnagar, A. Cardiovascular pathophysiology of environmental pollutants. *Am J Physiol. Heart Circ. Physiol.* **2004**, *286*, H479. [CrossRef] [PubMed]
39. Tertre, A.L.; Medina, S.; Samoli, E.; Forsberg, B.; Katsouyanni, K. Short-term effects of particulate air pollution on cardiovascular diseases in eight european cities. *J. Epidemiol. Community Health* **2002**, *56*, 773–779. [CrossRef]
40. Münzel, T.; Steven, S.; Frenis, K.; Hahad, O.; Daiber, A. Environmental factors such as noise and air pollution and vascular disease. *Antioxid. Redox Signal.* **2020**, *33*, 581–601. [CrossRef]
41. Chin, M.T. Basic mechanisms for adverse cardiovascular events associated with air pollution. *Heart* **2015**, *101*, 253–256. [CrossRef] [PubMed]
42. Yang, W.; Yang, Y. Research on Air Pollution Control in China: From the Perspective of Quadrilateral Evolutionary Games. *Sustainability* **2020**, *12*, 1756. [CrossRef]
43. Khorasani, Z.M.; Bagheri, R.K.; Yaghoubi, M.A.; Chobkar, S.; Aghaee, M.A.; Abbaszadegan, M.R.; Sahebkar, A. The association between serum irisin levels and cardiovascular disease in diabetic patients. *Diabetes Metab. Syndr.* **2019**, *13*, 786–790. [CrossRef] [PubMed]
44. Yang, W.X.; Li, L.G. Efficiency evaluation of industrial waste gas control in China: A study based on data envelopment analysis (DEA) model. *J. Clean. Prod.* **2018**, *179*, 1–11. [CrossRef]
45. Ware, L.J.; Rennie, K.L.; Kruger, H.S.; Kruger, I.M.; Greeff, M.; Fourie, C.M.T.; Huisman, H.W.; Scheepers, J.D.W.; Uys, A.S.; Kruger, R.; et al. Evaluation of waist-to-height ratio to predict 5 year cardiometabolic risk in sub-Saharan African adults. *Nutr. Metab. Cardiovasc. Dis.* **2014**, *24*, 900–907. [CrossRef]
46. Shi, Z.; Tuomilehto, J.; Kronfeld Schor, N.; Alberti, G.K.; Stern, N.; El Osta, A.; Bilu, C.; Einat, H.; Zimmet, P. The circadian syndrome predicts cardiovascular disease better than metabolic syndrome in Chinese adults. *J. Intern. Med.* **2020**, *12*, 13204. [CrossRef]
47. Barton, T.J.; Low, D.A.; Bakker, E.A.; Janssen, T.; de Groot, S.; van der Woude, L.; Thijssen, D.H.J. Traditional Cardiovascular Risk Factors Strongly Underestimate the 5-Year Occurrence of Cardiovascular Morbidity and Mortality in Spinal Cord Injured Individuals. *Arch. Phys. Med. Rehabil.* **2021**, *102*, 27–34. [CrossRef]
48. Liu, X.; Kong, D.; Liu, Y.; Fu, J.; Gao, P.; Chen, T.; Fang, Q.; Cheng, K.; Fan, Z. Effects of the short-term exposure to ambient air pollution on atrial fibrillation. *Pacing Clin. Electrophysiol.* **2018**, *41*, 1441–1446. [CrossRef]
49. Chiu, H.; Tsai, S.; Weng, H.; Yang, C. Short-term effects of fine particulate air pollution on emergency room visits for cardiac arrhythmias: A case-crossover study in Taipei. *J. Toxicol. Environ. Health A* **2013**, *76*, 614–623. [CrossRef]
50. Rich, D.Q.; Mittleman, M.A.; Link, M.S.; Schwartz, J.; Luttmann-Gibson, H.; Catalano, P.J.; Speizer, F.E.; Gold, D.R.; Dockery, D.W. Increased Risk of Paroxysmal Atrial Fibrillation Episodes Associated with Acute Increases in Ambient Air Pollution. *Environ. Health Perspect.* **2006**, *114*, 120–123. [CrossRef]

51. Delfino, R.J.; Gillen, D.L.; Tjoa, T.; Staimer, N.; Polidori, A.; Arhami, M.; Sioutas, C.; Longhurst, J. Electrocardiographic ST-segment depression and exposure to traffic-related aerosols in elderly subjects with coronary artery disease. *Environ. Health Perspect.* **2011**, *119*, 196–202. [CrossRef]
52. Korantzopoulos, P.; Kolettis, T.M.; Galaris, D.; Goudevenos, J.A. The role of oxidative stress in the pathogenesis and perpetuation of atrial fibrillation. *Int. J. Cardiol.* **2007**, *115*, 135–143. [CrossRef]
53. Pekkanen, J.; Peters, A.; Hoek, G.; Tiittanen, P.; Brunekreef, B.; de Hartog, J.; Heinrich, J.; Ibald-Mulli, A.; Kreyling, W.G.; Lanki, T.; et al. Particulate air pollution and risk of ST-segment depression during repeated submaximal exercise tests among subjects with coronary heart disease: The Exposure and Risk Assessment for Fine and Ultrafine Particles in Ambient Air (ULTRA) study. *Circulation* **2002**, *106*, 933–938. [CrossRef] [PubMed]
54. Peters, A.; Fröhlich, M.; Döring, A.; Immervoll, T.; Wichmann, H.E.; Hutchinson, W.L.; Pepys, M.B.; Koenig, W. Particulate air pollution is associated with an acute phase response in men; results from the MONICA-Augsburg Study. *Eur. Heart J.* **2001**, *22*, 1198–1204. [CrossRef] [PubMed]
55. Fabritz, L.; Guasch, E.; Antoniades, C.; Bardinet, I.; Benninger, G.; Betts, T.R.; Brand, E.; Breithardt, G.; Bucklar-Suchankova, G.; Camm, A.J.; et al. Expert consensus document: Defining the major health modifiers causing atrial fibrillation: A roadmap to underpin spersonalised prevention and treatment. *Nat. Rev. Cardiol.* **2016**, *13*, 230–237. [CrossRef] [PubMed]
56. Hu, Y.; Chen, Y.; Lin, Y.; Chen, S. Inflammation and the pathogenesis of atrial fibrillation. *Nat. Rev. Cardiol.* **2015**, *12*, 230–243. [CrossRef] [PubMed]
57. Gutierrez, A.; Van Wagoner, D.R. Oxidant and Inflammatory Mechanisms and Targeted Therapy in Atrial Fibrillation: An Update. *J. Cardiovasc. Pharmacol.* **2015**, *66*, 523–529. [CrossRef] [PubMed]
58. Chung, M.K.; Martin, D.O.; Sprecher, D.; Wazni, O.; Kanderian, A.; Carnes, C.A.; Bauer, J.A.; Tchou, P.J.; Niebauer, M.J.; Natale, A.; et al. C-reactive protein elevation in patients with atrial arrhythmias: Inflammatory mechanisms and persistence of atrial fibrillation. *Circulation* **2001**, *104*, 2886–2891. [CrossRef]
59. Huang, C.; Barnett, A.G.; Wang, X.; Tong, S. The impact of temperature on years of life lost in Brisbane, Australia. *Nat. Clim. Chang.* **2012**, *2*, 265–270. [CrossRef]
60. Watanabe, E.; Kuno, Y.; Takasuga, H.; Tong, M.; Sobue, Y.; Uchiyama, T.; Kodama, I.; Hishida, H. Seasonal variation in paroxysmal atrial fibrillation documented by 24-h Holter electrocardiogram. *Heart Rhythm* **2007**, *4*, 27–31. [CrossRef]
61. Chen, R.; Kan, H.; Chen, B.; Huang, W.; Bai, Z.; Song, G.; Pan, G. Association of particulate air pollution with daily mortality: The China Air Pollution and Health Effects Study. *Am. J. Epidemiol.* **2012**, *175*, 1173–1181. [CrossRef] [PubMed]
62. Spengos, K.; Vemmos, K.; Tsivgoulis, G.; Manios, E.; Zakopoulos, N.; Mavrikakis, M.; Vassilopoulos, D. Diurnal and seasonal variation of stroke incidence in patients with cardioembolic stroke due to atrial fibrillation. *Neuroepidemiology* **2003**, *22*, 204–210. [CrossRef] [PubMed]
63. Ahn, J.; Uhm, T.; Han, J.; Won, K.-M.; Choe, J.C.; Shin, J.Y.; Park, J.S.; Lee, H.W.; Oh, J.-H.; Choi, J.H.; et al. Meteorological Factors and Air Pollutants Contributing to Seasonal Variation of Acute Exacerbation of Atrial Fibrillation: A Population-Based Study. *J. Occup. Environ. Med.* **2018**, *60*, 1082–1086. [CrossRef] [PubMed]
64. Shiue, I.; Perkins, D.R.; Bearman, N. Relationships of physiologically equivalent temperature and hospital admissions due to I30-I51 other forms of heart disease in Germany in 2009–2011. *Environ. Sci. Pollut. Res. Int.* **2016**, *23*, 6343–6352. [CrossRef] [PubMed]
65. Martens, W.J.M. Climate change, thermal stress and mortality changes. *Soc. Sci. Med.* **1998**, *46*, 331–344. [CrossRef]

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Review

Challenges of a Healthy Built Environment: Air Pollution in Construction Industry

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Abstract: Air pollution is a global concern, especially in cities and urban areas, and has many implications for human health and for the environment. In common with other industrial sectors, the construction industry emits air pollutants. In scientific literature, the contribution the construction industry makes to air pollution is underexposed. This systematic literature review (SLR) paper gives an overview of the current literature regarding air pollution within the construction industry. Air pollution is discussed focusing mainly on three levels: (i) buildings and their building life cycle stages, (ii) construction processes and components, and (iii) building material and interior. The final sample of the SLR comprises 161 scientific articles addressing different aspects of the construction industry. The results show that most articles address the use stage of a building. Particulate matter in different sizes is the most frequently examined air pollutant within the SLR. Moreover, about a third of the articles refer to indoor air pollution, which shows the relevance of the topic. The construction industry can help to develop a healthier built environment and support the achievement of cleaner air within various life cycle stages, e.g., with optimized construction processes and healthier materials. International agreements and policies such as the Sustainable Development Goals (SDGs) can support the sustainable development of the construction industry.

Keywords: air pollution; construction industry; sustainable development goals; sustainable construction; healthy living environment

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1. Introduction

Urbanization is a global megatrend. According to the United Nations (UN), around 68% of the world's population will live in cities and urban areas by 2050 [1]. Urban areas also need sustainable development, as reflected in the Sustainable Development Goals (SDGs), especially in SDG11—Sustainable Cities and Communities. All UN member states have committed themselves to implement the global development agenda of the SDGs [2]. One of the issues reflected in the SDGs is air pollution. The importance of this is highlighted by its mention in the following SDG targets:

1. SDG target 3.9.: Reduce illnesses and deaths from hazardous chemicals and pollution;
2. SDG target 7.1.: Universal access to modern energy sources;
3. SDG target 11.6.: Reduce the environmental impacts of cities.

In target 11.6, emission-related environmental pollution is addressed via the indicator particulate matter with the indicator 11.6.2 Annual mean levels of fine particulate matter (e.g., PM2.5 and PM10) in cities (population weighted) [1].

Particulate matter (PM) is one of the most common air pollutants globally together with nitrogen oxides (NOx), photochemical oxidants incl. ozone (O3), carbon monoxide (CO), lead (Pb), and sulfur dioxides (SO2) [2]. Numerous people suffer from diseases such as acute respiratory diseases, chronic obstructive pulmonary disease, lung cancer, heart disease, and strokes due to air pollution. Others even die due to household and ambient air pollution and its consequences; the number of these fatalities was around 7 million in 2016 [3]. All regions worldwide are affected by air pollution, and the air pollution limits set by the World Health Organization (WHO) are met for only 9% of the world's people [4]. Most at risk are people living in low- and middle-income countries, where 94% of all pollution-related deaths occur [5]. According to the European Environmental Bureau, air pollution is also the reason for over 400,000 premature deaths in the European Union (EU) [6]. In addition, the health-related economic cost of air pollution is estimated between 330 and 940 billion euros just for Europe [7].

Air pollutants occur e.g., not only in the transport, industry, or coal combustion sectors [6,8] but also in the construction sector [9–13]. Thereby pollutants have different sources of origin within the construction sector or the built environment. Outdoor sources include, e.g., construction activities, which can lead to dust production [14,15], or the use of construction machinery at sites [16,17], production of building materials [18,19], or pollutant emergence at other different life cycle stages of buildings such as the end-of-life stage [20,21]. Pollutants from indoor sources such as the emissions from glues and paints used for interiors [22], the emissions during cooking [23], heating [24,25], or the emissions caused by ventilation systems [26], however, are also of great significance in terms of air pollution.

Due to the authors' knowledge, there is no research article addressing explicitly construction industry and air pollution in a comprehensive way in just one literature review paper. Therefore, this article analyzes the air pollution caused by the construction industry and gives an outline of trends based on a systematic literature review (SLR). The aim is to determine the current state of research and thus to present an up-to-date status of current work in the field. The results of the article facilitate the work of researchers in this field in a new, comprehensive way and help to identify research gaps or further topics for discussion in this area. Four research questions (RQs) are addressed to achieve the defined goals:

- RQ1: How has the number of publications changed in recent years and in which regions are the most research results published? What are the scientific journals that cover the area of air pollution in the construction industry?
- RQ2: What have been the most widely used research designs in recent years that have been applied in current research practice in the field of air pollution in the construction industry?
- RQ3: What are the most addressed building types in current research on air pollution in the construction industry? Is a classification in detailed construction processes possible and how can the research articles be divided according to life cycle stages?
- RQ4: Is the current research focus on indoor or outdoor pollution? Which pollutants within the construction industry are the most addressed in the published scientific articles?

2. Materials and Methods

2.1. Literature Selection

By using the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) guideline, in this section, the literature selection with the method of systematic literature review (SLR) and its steps are presented.

2.1.1. Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) and Systematic Literature Review (SLR)

Following the reporting guideline PRISMA, an SLR about air pollution in the construction industry was conducted. The SLR is a systematic process for identifying relevant published sources in a special field to provide syntheses of the state of knowledge with the aim to identify future research priorities, to identify problems in primary research that should be addressed in future studies, or even for identifying relevant published sources to obtain a broad and comprehensive review of the literature that has been published for a given RQ [27–29]. While conducting the SLR and data analysis, the 27 items checklist of the PRISMA reporting guideline was followed to conduct a transparent, complete, and accurate review [27] shows the entire review process using the PRISMA flowchart.

2.1.2. Search Strings and Constraints

Referring to the formulated RQs, relevant search strings are identified and conducted in a scientific database. This article aims at answering the RQs mentioned in Section 1. In addition to the defined RQs, the starting point for the SLR is the definition of the keywords within the search strings. Based on the objectives of the research, the search strings consist of two term areas.

The database selected for the SLR was ScienceDirect. The search results were restricted to the English language only and excluded grey literature such as reports, books/chapters, conference papers, master's and/or doctoral theses. In addition, a constraint was set for the year of publication, which only includes articles in the period from January 2000 to April 2020. To avoid biases, all steps of the SLR were double-checked by the authors. The search strings used with the associated Boolean operators as well as the constraints are shown in Figure 1.

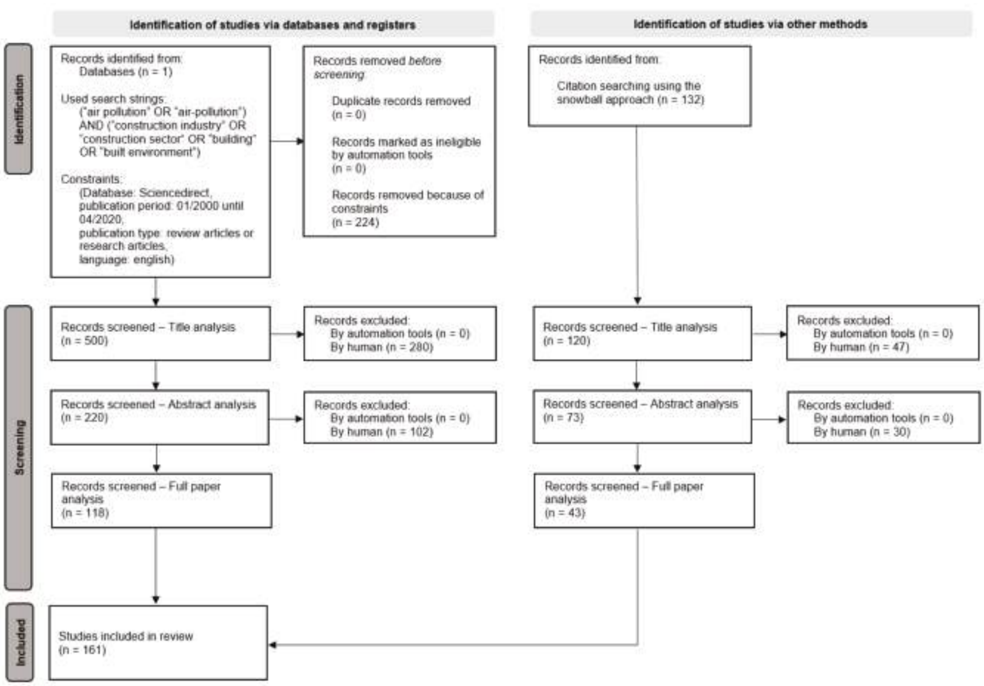

Figure 1. PRISMA 2020 flow diagram for new systematic reviews which included searches of databases, registers, and other sources supplemented by detailed information about the SLR and the snowball approach [27].

2.1.3. Data Analysis and Research Approach

As shown in Figure 1, the SLR results obtained after the first step were filtered in three further phases: (1) relevance by title, (2) relevance by abstract, and (3) relevance by full paper. In the first SLR phase, 724 papers were identified as relevant research articles. By filtering by title in phase two, the scope was limited to 500 papers. After reviewing the abstracts in phase three, 220 papers were left, and after reviewing the full papers in the last phase, 118 articles for in-depth analysis of papers were gathered. In addition, we collected further relevant literature using the "snowball" approach, proposed by Wohlin et al., by reviewing the references of the collected articles [29]. The identified research articles after applying the "snowball" approach were also sorted according to the three phases (title, abstract, full paper). After completion of the SLR and after applying the "snowball" approach, the final sample for the in-depth analysis included 161 records.

2.2. Literature Background

Air pollution is recognized as serious health and environmental problem for the world and as a strong risk factor for health [30]. Inhaling particulate matter (PM) of varying sizes, e.g., can lead to a range of health problems and early death [31]. It was estimated in 2017 that the cause of death for 8.7% of the world population was air pollution, meaning in total around 4.9 million deaths globally [32]. The global community thus has clear ambitions to improve the global situation with regard to cleaner air.

2.2.1. Policies for Clean Air and Air Pollution Reduction

Many different international institutions, organizations, and nation-states have issued policies and roadmaps to address this serious issue.

The United Nations Economic Commissions for Europe is addressing air pollution through the Geneva Convention on Long-range Transboundary Air Pollution; with this convention from 1979 health and environmental impact of air pollution should be reduced [33]. Another important resolution is the Stockholm Convention on Persistent Organic Pollutants, which was adopted in May 2001. Its goal is to restrict the use of persistent organic pollutants (POPs) [34].

On the EU level, an important regulation policy has been issued to reduce air pollution in the Clean Air Policy Package adopted in 2013, which was the result of the evaluation of the European air policy [35]. Amongst others, the Clean Air Policy Package included a proposal for the National Emission reduction Commitments directive [34,35]. Moreover, the Ambient Air Quality Directive and source-specific legislation also play an important role in European air-related policies and regulations [36,37].

The Agenda 2030 of the United Nations (UN), also known as the Sustainable Development Goals (SDGs), was adopted by the UN in 2015 [38]. SDG 3—Good health and well-being, SDG 7—Affordable and clean energy, SDG 11—Sustainable Cities and Communities, and SDG 13—Climate action are explicitly addressing the importance of reducing air pollution within their targets [33].

Moreover, the World Health Organization (WHO) has put in place the initiative The Global Platform on Air Quality and Health to build up capabilities for monitoring and assessing air pollution, enhance research and policies addressing and reducing air pollution and its health consequences [39]. Additionally, the WHO adopted the resolution Health and the environment: addressing the health impact of air pollution, and a draft road map for an enhanced global response to the adverse health effects of air pollution by its assembly in 2016 [33,39].

In December 2017, the UN Environmental Assembly of the United Nations Environment Programme (UNEP) adopted the resolution for preventing and reducing air pollution to improve air quality globally [40,41]. The European Commission issued the *Action Plan*: "*Towards* a *Zero Pollution* for *Air*, *Water* and *Soil*" as part of the European Green Deal called Pathway to a Healthy Planet on 12 May 2021 [42,43]. The action plan is explicitly referred to air pollution in the context of buildings as well as indoor air quality.

Two further important global initiatives are the Climate and Clean Air Coalition to Reduce Short-Lived Climate Pollutants (CCAC) and the BreathLife campaign, issued by the WHO, CCAC, UNEP, and the World Bank [44,45].

2.2.2. Air Pollutants

The definition of limits for air pollution differs in various countries [46]. The present article has taken the six defined air pollutants of the U.S. Environmental Protection Agency (EPA) as the basis for air pollution categories applied for researching and categorizing literature within the SLR. According to the National Ambient Air Quality Standards of the

EPA six pollutants are defined as air pollutants: carbon monoxide (CO), lead (Pb), nitrogen oxides (NOx, mainly nitrogen dioxide-NO2), photochemical oxidants (mainly ground-level ozone, O3), particulate pollution (often referred to as particulate matter), and sulfur oxides (SOx, mainly sulfur dioxide (SO2) [2]. Furthermore, volatile organic compounds (VOC), ultrafine particulate matter (UFP), and ammonia were included in the article as significant pollutants because they often occur within a building, when addressing indoor air pollution.

Air pollution and climate change influence each other by complex correlations in the atmosphere. For example, increasing greenhouse gas (GHG) emissions (i.e., CO_2-eq.) can lead to significantly higher ozone (O3) pollution in the future [47]. Moreover, Steinemann 2017 explicitly addressed climate change in combination with GHG emissions and their implications for indoor air quality in the context of green buildings [48]. The findings show that the link between air pollution and GHG emissions is complex and that there are various GHG emission effects on indoor air quality, whether on indoor pollutants themselves, building factors such as reduced ventilation rate, or behavior of occupants. In this context, many articles qualitatively describe the influence of air pollution on GHG emissions and often state that a reduction of air pollutants also reduces GHG emissions.

Detailed descriptions regarding the most common origin in general as well as about the effects of air pollutants can be found in [10,16,49–53].

2.2.3. Outdoor (Ambient) Air Pollution

Outdoor air pollution occurs in many different sectors, in cities, and in rural areas. Air pollution has various health implications for the global population and around 91% of people on the globe are affected by air pollution according to WHO standards. The WHO thus suggests reducing air pollution by means of improvement measures in transport, energy-efficiency, power generation, industry, and municipal waste management in order to contribute to clean air and better air quality globally [54]. The EU Air quality in Europe—2020 report shows that the main emission sectors for air pollutions in Europe are (i) transport (road and non-road), (ii) the residential, commercial, institutional sector, (iii) energy supply, (iv) manufacturing and extractive industries (including heavy and light industry), (v) agriculture, and (vi) the waste sector (including wastewater management) [6].

2.2.4. Indoor (Household) Air Pollution

Indoor pollution plays an important role as people are spending most of their lifetime, according to studies up to 90%, indoors [55,56]. In this context, the sick building syndrome describes health effects on occupants due to indoor air pollution and poor air quality during their time spent in buildings, respectively [12,57–60]. Indicators can be e.g., "complain of symptoms associated with acute discomfort, i.e., headache, eye, nose, or throat irritation; dry cough; dry or itchy skin; dizziness and nausea; difficulty in concentrating; fatigue; and sensitivity to odors". Causes can be inadequate ventilation, chemical contaminants from indoor or outdoor sources, or biological contaminants. Possible solutions and measures for better air quality within buildings can include the removal or modification of pollutants, higher ventilation rates, air cleaning, and education as well as better communication [61]. Further anthropogenic causes for indoor air pollution can include such important and essential everyday activities as cooking or heating with solid fuels (e.g., wood, charcoal, animal dung, etc.) [61,62].

2.3. Air Pollution within the Construction Industry

The construction industry emits air pollutants in various life cycle stages of buildings. In general, it can be stated that the construction industry causes both outdoor air pollution and indoor air pollution [17,57,63–65]. The construction sector is a major contributor to air pollution in different countries [10,66,67], and a contributor to particulate matter pollution [10,68–70]. Air pollution emerges within the construction industry and occurs within all stages of the building life cycle according to EN 15804 and EN 15978 [71,72].

From the authors' point of view, the challenges should be differentiated according to production, construction, the end-of-life stage, and the use stage in the construction sector. Production, construction, and the end-of-life phase involve direct air pollution caused by, e.g., construction site works, construction site transports (fuel combustion and tire wear), or other dust generation. The construction sector is responsible for nearly 40% of global GHG emissions. Current studies have shown a significant air-pollutant potential (O3) induced by increasing GHG (i.e., CO_2-eq.) emissions. In order to significantly reduce GHG emissions in the construction sector, for example, a growing number of countries have put in place policies to improve buildings' energy performance in recent years. However, a rapidly growing building sector, especially in developing countries, has offset those improvements. In other words, efficiency gains are not sufficient to compensate for the increase of total energy consumption caused by parameters as e.g., increasing population, increasing floor area, and/or other activities. To overcome these burdens a systemic view and consistency approach (instead of an efficiency approach) will urgently need to be considered in future policy strategies.

The European Parliament's EU policy on air quality presents policy measures for European cities to improve air quality. In the context of the construction industry and its contribution to air pollution, the energy efficiency of construction projects is outlined. Continuous improvement of the energy efficiency of buildings not only reduces the operating energy in the use phase but also tries to take into account the embodied energy from the manufacturing, construction, and deconstruction phases.

In the individual best practice recommendations of the European cities, measures for the construction site and for reducing air pollution during the construction and demolition of buildings are particularly relevant [73].

European guidelines do not specify mandatory construction requirements for individual air pollutants. However, a connection can be made through the mandatory energy standards [74]. In this context, according to the European Directive on the Energy Performance of Buildings (EPBD) new buildings in Europe may only be built to the lowest energy standard [75].

In addition to the building regulations in the individual countries, numerous building certification systems have been established in the last two decades, which, for instance, check criteria such as indoor air pollution or various environmental impacts as part of a life cycle assessment (LCA) on a voluntary basis.

2.3.1. Product Stage (A1–A3)

Within the product stage, air pollution can occur within the raw material supply, transport, or manufacturing. Additionally, the production of building, materials such as cement adds to air pollution and the emission of hazardous gases [19]. Within this stage transportation from the mining of raw materials to the production plant of building materials and their pollutants can also have an important role. In this context, construction machinery and the construction methods used in the extraction of raw materials, as well as the choice of transport vehicles (air pollution from fuel or tire abrasion), influence the effect on air pollution.

2.3.2. Construction Process Stage (A4–A5)

During the construction process stage, construction sites and construction-related traffic play a major role in air pollution. Construction activities and operations emit huge amounts of particles to the environment, putting both construction workers and people living in the surrounding construction sites at risk. Moreover, construction machinery and equipment can also add to air pollution at construction sites [17]. Part of the operation and supply of construction sites are traffic-related emissions [3].

2.3.3. Use Stage (B1–B7)

Buildings consume a lot of energy in their use stage and emit pollutants throughout this period. Heating, ventilation, and air-conditioning (HVAC) systems thus also play an important role within the use stage and can affect especially indoor air pollution.

Factors that additionally influence indoor air pollution concentrations are building physics and indoor airflows, ventilation rate, outdoor pollution concentration, and indoor emission sources [76]. Ruan and Rim state that the ventilation rate affects indoor air quality especially in polluted urban areas [17]. Furthermore, HVAC systems and their setup influence indoor air quality [77,78].

Another source for indoor air pollution can be the material used and its specific functions or interior design, e.g., furniture or decoration [79]. Common indoor air pollution sources are household products, building materials, or plasticizers [57]. Depending on the different variables such as the choice of materials, material properties, and the material-specific function or material treatment (e.g., chemical treatments, coatings) the built substance itself can also release emissions and can considerably contribute to (indoor) air pollution [77]. Moreover, the right materials can also favor or reduce pollutants or even compensate and degrade them [80–82].

For a healthy living environment of tenants in terms of hygienic-sanitary conditions in the use stage, buildings and rooms need to be properly designed and executed as well as operated. Energy performance certificates could be a possible instrument to improve the regulations and energy management to better, comfortable, and healthy well-being of inhabitants as well as a better building performance. Another solution towards a healthier interior can be the application of evaluation and monitoring [83].

2.3.4. End-of-Life Stage (C1–C4)

After the use stage of the buildings, building materials, e.g., after demolition, can be recycled and used in a second (building) life cycle [84]. In practice, however, challenges regarding circularity and recycling still need to be solved [85]. Moreover, transport is also a source of pollution in the end-of-life stage of buildings. Additionally, air pollutants can be emitted during de-construction or the demolition of buildings and infrastructure, respectively [69,86]. Proper demolition management can decrease air pollution [10,87].

3. Results

3.1. Development of Publications over Time (RQ1)

To give an introductory (metadata) overview of the chronological development of the research area as well as the geographical distribution of the universities investigating the addressed research area, the articles were analyzed by their year of publication and by the affiliation of the first author. In Figure 2, the number of published research articles in the field of air pollution in the construction industry according to the publication year is presented. There is a rising trend of relevant research articles published on the topic of air pollution in the construction industry. The number of research articles published rose from two in 2001 to a total of 161 by the end of April 2020. In the years 2001 to 2011, the number of published research articles identified as relevant within the SLR in the field was less than six research articles per year. In the years 2012 to 2020 publications continued to increase regularly. This trend clearly shows the increase in relevance of the topic of air pollution within the construction sector.

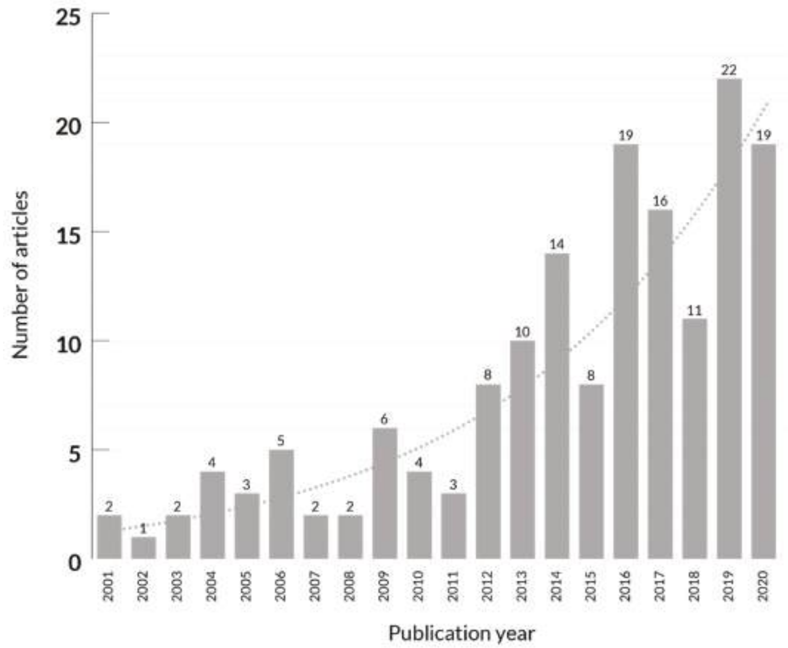

Figure 2. Development of published research articles in the field of air pollution and construction within the last years (until April 2020).

3.2. Geographic Distribution of Publications (RQ1)

Figure 3 presents the geographic distribution of the first author's affiliation on a world map. Most articles of the conducted SLR are published by authors from universities in China (36), in the United States (19), the United Kingdom (10), in Germany (9), Italy (9), and Hong Kong (6). It can be deduced that countries facing the challenge of air pollution, such as China, the United States, and the United Kingdom, are also publishing more scientific articles about air pollution in the construction industry.

Figure 3. Geographic distribution of published articles by first author's affiliation.

3.3. Distribution by Publication Journal (RQ1)

For the identification of scientific journals that frequently address and support the mentioned field of research, the research articles are classified by journals. This representation supports prospective scientists in their search for suitable journals in context with the addressed research area. In Table 1, the distribution of articles on air pollution in the construction industry according to the publication journals is shown.

Table 1. Overview of research articles and their distribution by publication journals.

No.	Journal Title	Amount	(%)
1	Building and Environment	29	18.0
2	Atmospheric Environment	18	11.2
3	Science of the Total Environment	16	9.3
4	Journal of Cleaner Production	9	5.6
5	Energy and Buildings	6	3.7
6	Environmental Pollution	5	3.1
7	Sustainable Cities and Society	5	3.1
8	Environment International	4	2.5
9	Indoor Air	4	2.5
10	Procedia Engineering	4	2.5
11	Sustainability	4	2.5
12	Applied Energy	3	1.9
13	Energy	3	1.9
14	Energy Procedia	3	1.9
15	Journal of Environmental Management	3	1.9
16	Journal of the Air & Waste Management Association	3	1.9
17	Renewable and Sustainable Energy Reviews	3	1.9
18	Urban Forestry & Urban Greening	3	1.9
19	American Society of Civil Engineers	2	1.2
20	Atmospheric Pollution Research	2	1.2
21	Construction and Building Materials	2	1.2
22	Ecotoxicology and Environmental Safety	2	1.2
23	Environmental Research	2	1.2
24	Journal of Building Engineering	2	1.2
25	Journal of Hazardous Materials	2	1.2
26	Acta Polytechnica Hungarica	1	0.6
27	APCBEE Procedia	1	0.6
28	Applied Geography	1	0.6
29	Atmospheric Environment	1	0.6
30	Atmospheric Research	1	0.6
31	Chemosphere	1	0.6
32	Ecological Indicators	1	0.6
33	Energy Conversion and Management	1	0.6
34	Energy Policy	1	0.6
35	Environmental Chemistry Letters	1	0.6
36	Environmental Monitoring and Assessment	1	0.6
37	Environmental Modelling & Software	1	0.6
38	Environmental Science & Policy	1	0.6
39	Environmental Science & Technology	1	0.6
40	Frontiers of Environmental Science & Engineering	1	0.6
41	IFAC PapersOnLine	1	0.6
42	Indoor Built Environ	1	0.6
43	International Journal of Hygiene and Environmental Health	1	0.6
44	Journal of Environmental Engineering	1	0.6
45	Journal of Cultural Heritage	1	0.6
46	Journal of Transport & Health	1	0.6
47	Safety Science	1	0.6
48	Urban Climate	1	0.6
Total		161	100.0

Most of the reviewed research articles were published in the scientific journals Building and Environment (29), Atmospheric Environment (18), and Science of the Total Environment (16). Nine articles were published in the Journal of Cleaner Production, six in Energy and Buildings, and five in the Journal Environmental Pollution and Sustainable Cities and Society. Environment International, Indoor Air, Procedia Engineering, Sustainability followed by four published research articles each.

3.4. Research Designs for Air Pollution Research in Construction Industry (RQ2)

In this RQ, the articles of the final sample are classified according to research designs and an overview of applied methods is presented. Therefore, the articles were assigned to the defined research designs in Table 2.

Table 2. Overview of research designs.

Research Design	Description
Literature reviews	With the application of a literature overview in the study, a summary of the most relevant scientific literature to the research topic of the study is provided. Moreover, an introductory chapter with literature references is also considered as a literature review.
Measurement/Method development	Measurements of the air pollutants that occur are conducted in various experimental and study setups. Moreover, the theoretical development of existing methods, methodological approaches, or measurement instruments can be advanced to improve existing (evaluation) methods, methodologies, or measurement instruments.
Model development	The development of modeling approaches for air pollution are advanced in the course of the study to improve existing models.
Case study (field experiment)	The subject of the study is demonstrated resp. tested with specific case studies, using (field) experiments on-site to test the hypothesis resp. to answer the research question(s) posed.
Case studies based on virtual simulation	The topic of the study is demonstrated resp. tested, with specific case studies based on virtual simulations (such as air flow simulations) to test the hypothesis resp. answer the research question(s).
Surveys	The study method comprises the conducting of a survey, meaning the relevant topic is examined through a series of questions (=questionnaire) and sent out to the appropriate target group to receive answers and, therefore, results.
Interviews	The study method is conducting interviews (e.g., with experts, semi-structured or guideline-based interviews).
Other methods	All other methods and methodologies which are not mentioned above are subsumed within this category.

Figure 4 presents a pie-chart with the number of published research articles assigned to different research designs.

Some of the research articles are based on several research designs. Since multiple answers were possible, the sum of the research articles in the pie chart (n = 345) exceeded the number of identified articles (n = 161). On this basis, 35% of reviewed research articles can be classified in the category *Case study (field experiment)*, and 28% used *Measurement/Method development* to reach their results and findings. In about 10% of the articles *Model development* was used and in 9% *Case studies based on virtual simulation* were the preferred research design. *Literature reviews* were conducted in 7% of the overall sample of the SLR and 4% used *surveys* as their research design. 1% of the research articles chose *interviews* as their preferred research design and 1% used *other methods,* which cannot be assigned to any of the defined research designs.

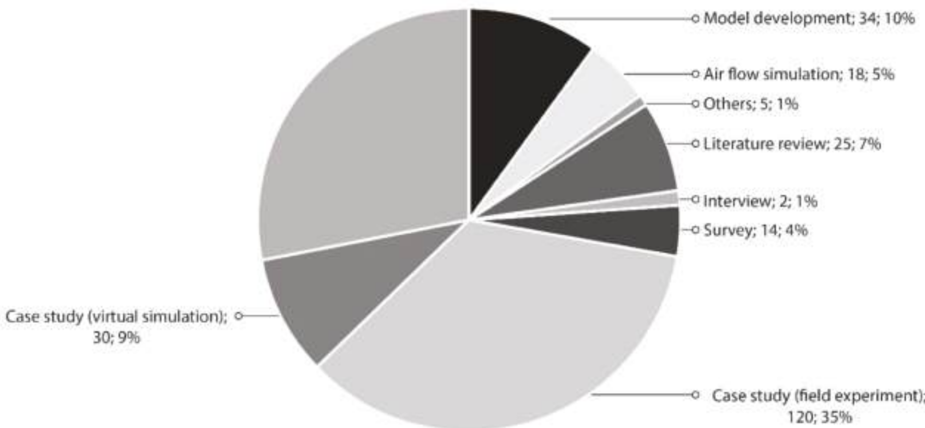

Figure 4. Overview of articles and applied research designs.

Many papers used field experiments in case studies to illustrate air pollution in cities or rural areas. In some studies, using case studies (field experiments), construction sites and construction activities, as well as their polluting influence on air, are the focus. Amongst others, De Moraes et al. have researched construction sites with a focus on air pollution in the context of concrete and masonry works [69]. Font et al. studied local air pollution at road construction works, which occurred as a result of road widening projects [88]. Giunta et al. also examined construction activities in a motorway construction project, and they identified the most significant air-polluting emissions during this process [89]. They also identified measures to reduce emissions and projected them for the future [89,90]. Moreover, air pollution (particulate matter) at bicycle lanes was researched by Thai et al., whereas it was shown that cycle roads were especially polluted next to construction sites with air pollutants (PM2.5 + PM10) [91]. Furthermore, Yan et al. also investigated the field of construction activities and dust pollution in China, showing that this topic has importance also in China [92]. In addition, indoor air quality was measured using case studies with field tests [9,93].

Tang et al. evaluate building materials and their potential to reduce urban air pollution, specifically the NOx abatement capacity of TiO2-coated granules used in roofing products and there the method of use measurements [94]. Furthermore, measurements are applied as well, e.g., in the study Bossa et al. about Titanium dioxide nanomaterial within photocatalytic cement and its potential to reduce air pollution [95].

Air flow simulations are used e.g., by Bai et al., where ammonia in concrete walls is evaluated [96]. Moreover, Schripp et al. studied air flow simulations interaction of ozone (O3) and wooden building products as well as their emissions (e.g., volatile organic compounds or terpenes) [97].

The study of George et al. used a laboratory, field studies, and a smog chamber to test the potential of depollution of photocatalysis within construction materials and can be classified within the category different methods [98].

Surveys were applied, e.g., within a study that examined health problems of office clerks after relocation to a new office building [99]. The study found that the floor coating was the source of the air pollutant, with the consequence that it was removed afterward. Moreover, a survey was also conducted to investigate households in China and to compare regional differences in heating and air pollution in the different regions [100]. Also, Lindgren examined indoor air quality, specifically ammonia pollution in a new office building in Beijing [12]. Zhao et al. examined indoor air quality in residential buildings [79], and Sun et al. focused on the perception of public buildings by the occupants and users in the context of air quality using questionnaires [101].

Next to the building level and indoor air pollution, dust pollution control and mitigation measures were also researched with a survey [14], and also the indoor-outdoor association of NO2 was examined [102]. Moreover, Chiesa et al. examined PM and NOx reduction measures and policies in Italy using questionnaires [50]. Summing up, it can be said that in many papers indoor air quality and its consequences were studied using surveys. Furthermore, some scientific articles also addressed mitigation measures and policy with surveys or questionnaires, respectively. Literature reviews were also used in some of the articles. Cheriyan and Choi give a detailed overview of the construction industry and its particulate matter pollution using a literature review [10]. Tham reviewed the past 30 years of indoor air quality research and its and impacts on people [59]. Steinemann presented a literature review in the format of 10 questions and addressed green buildings and indoor air quality [56]. Mukherjee gives an overviewed of global PM sources and their occurrence and impacts on health in his literature review [53]. Furthermore, Fan gives a short literature review on silica exposure, its limits, and the most important guidelines as well as dust control measures connected to concrete drilling, the main topic of his article [103].

3.5. Addressed Sub-Sectors and Building Types within the Construction Industry (RQ3)

The results based on this RQ present a distribution of the investigated research articles to sub-sectors in construction sectors. In addition, the research articles are assigned to different building types and to the life cycle stages according to EN 15978 and EN 15084 [71,72]. In the process of the result analysis, the construction sector was divided into the sub-sectors buildings and infrastructure.

As shown in Figure 5, 6% of the examined research articles are addressing the sector *infrastructure*, most articles (94%) are referring to the sector *building*. In the sector building, *residential buildings* are addressed the most (27%), followed by the category *office buildings* (13%), *educational buildings* (11%), and *healthcare buildings* (1%). In 34% of the research articles referring to buildings, no specific building type was mentioned. 14% of the research articles examined were assigned to the category *Others*. This category includes buildings such as shopping centers, factories, or cultural buildings such as museums or theatres.

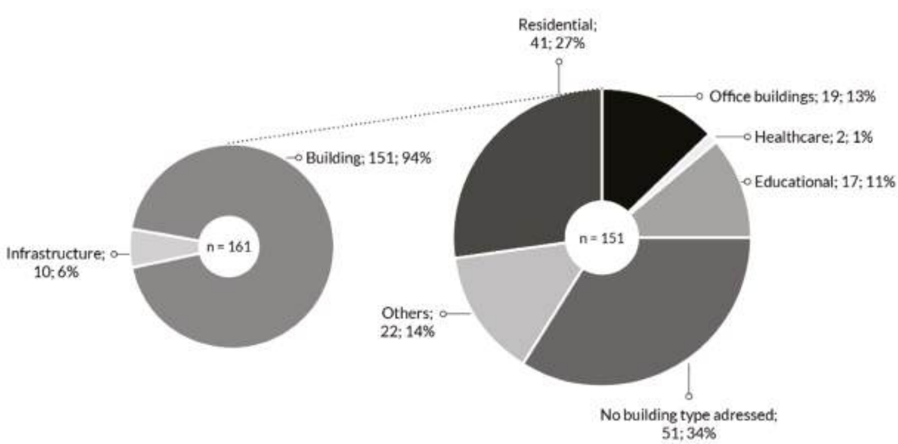

Figure 5. Addressed sub-sector and building types within the identified research articles.

Articles in the SLR which refer to infrastructure focused mainly on road construction works. For example, Faber et al. found that construction sites in Germany produce PM10 emissions and represent a high share (17%) of the overall PM10 emissions of the country [104]. Font et al. examine air pollution from a road widening scheme during and after construction [82]. Fuller and Green examined road and construction works and addressed PM10 emissions, and Giunta and Giunta et al. refer to gas and dust emissions of road construction and road works or pavement materials and technologies for urban roads [89,90,105].

Pollutants within residential and office buildings were examined in detail, as offices and residential buildings represent the two most important building types according to the SLR [17,26,50,55,106,107]. Within residential buildings, the most addressed pollutants are particulate matter (UFP, PM2.5, and PM10), followed by NO2 and NO2 as well as CO. For office buildings, PM2.5 is mentioned most often, followed by OC and O3 as well as NO2 and CO (see Figure 6).

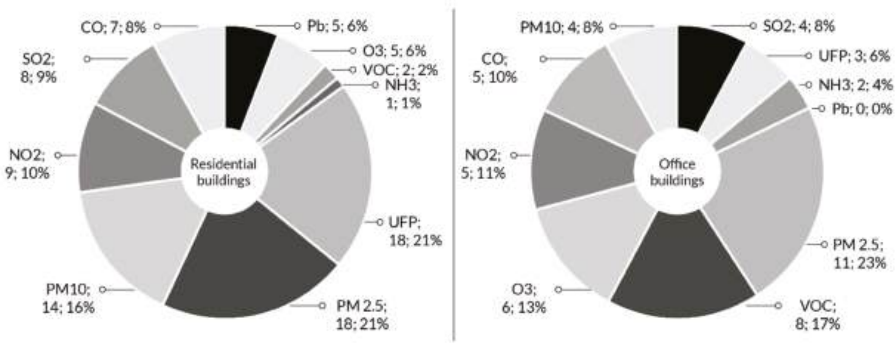

Figure 6. The most common pollutants in residential buildings and office buildings.

Healthcare buildings are addressed by Jing and Aung [108,109]. The study of Aung, a medical university, referred to as a healthcare building, is one of the sampling sites of Yangon, where air pollution measurements are conducted to close data gaps of indoor and outdoor air pollution [109]. In the study of Jing, the category hospital is among one of the five research building categories within the Chinese study, which offers supervision and an approach for evaluation of solid oxide fuel cell-based, combined cooling heating, and power demonstrations [108].

Educational buildings, which are largely schools, were the context for several different studies [57,64,65,110,111]. Moreover, Zanoletti's study was conducted at a university laboratory and proposes a new hybrid material for the sequestration of PM [82]. Additionally, Kozlovtseva's study refers to indoor air pollution with PM2.5 and PM10 in academic buildings at the Volgograd State University of Architecture and Civil Engineering in the Russian Federation [112].

Industrial construction was not addressed in detail, although one article by Bozkurt referring to air pollution in an industrial city in Turkey and Ekinci examined cement production and its implications for urban air pollution measures connected to growing urban air pollution with growing demand in the construction sector [19,113].

3.6. Construction Processes and Components

A further detailed breakdown was made for construction sites and construction activities, construction equipment (including machinery), and building components.

Figure 7 shows how many research articles address *construction sites and construction activities* (49), *construction machinery* (7), and *building components* (157). Articles addressing *building components* are again divided into the four sub-categories (i) *building envelope*, (ii) *building materials*, (iii) *interior*, and (iv) *heating, ventilation, and air conditioning (HVAC) systems*.

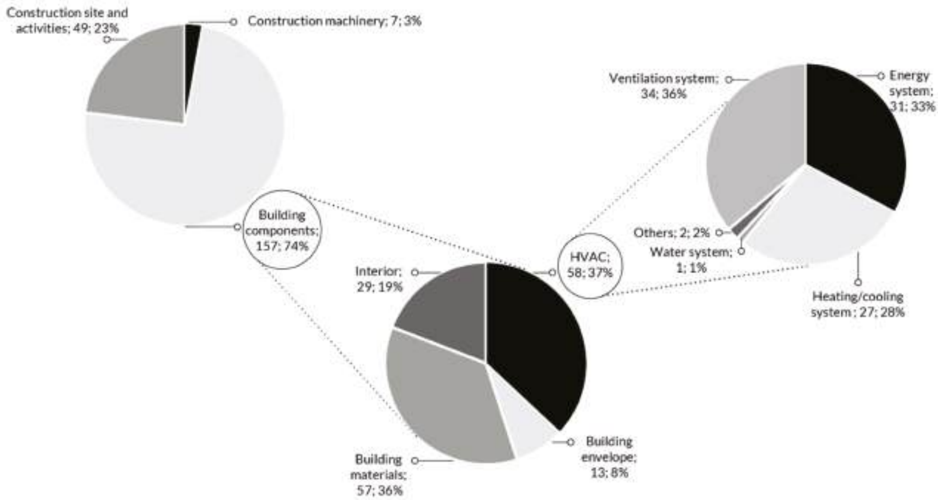

Figure 7. Overview of construction processes and (technical) components.

The results indicate that the *building envelope* is addressed 13 times, the *building materials* 57 times, the *interior* 29 times, and the *HVAC systems* 58 times in the research articles. The sub-category *HVAC systems* is again divided up into five more sub-fields, which are (i) *ventilation system* (34), (ii) *energy system* (31), (iii) *heating/cooling system* (27), (iv) *water system* (1), and (v) *others* (2).

Many studies of the final SLR sample are looking into construction sites and activities [14,114–116]. Alvanchi et al. are addressing construction management in their study and how improved construction schedules within infrastructure projects can improve the situation of urban air pollution [117]. Hassan et al. evaluated fugitive particulate matter emissions from construction sites in the Middle East, and Kinsey et al. examined fugitive dust and its relationship to mud or dirt discharge from a particular construction site in Kansas City [11,70]. Construction dust emission in a motorway project is the focus of Giunta et al. [89]. Faber et al. examined among other issues road construction in Germany and its emission effects on local air quality; one of the conclusions drawn from this study is that there are significant effects on air pollution [104]. Cheriyan and Choi reviewed PM in the construction industry and provided a summary of this issue in a literature overview [10]. Moreover, Liu et al. addressed construction activities in terms of construction as an economic sector. Their sector analysis shows that construction is the major source for CO2, SO2, NOx, PM2.5, and BC emissions from a consumption perspective [118].

The following articles were referring to construction machinery [10,21,92]. The study of Faber et al. is looking into local air quality and aerosol emissions from construction sites, whereby the role of construction machinery is explicitly mentioned and researched in the study [104]. It shows that construction machinery is adding to air pollution, especially through organic particles and trace gases. The article of Giunta et al. studied emissions from construction activities for motorways. In this study, construction machinery was also a part of the overall emissive balance sheet. The study shows that trucks transit on unpaved or paved roads has the highest share of particulate emissions in the construction process [90]. Moreover, machinery and plant are responsible for CO pollution in construction activities. Heidari et al. conducted a cross-exanimation of the measured and the predicted emissions in their study. They found that significant discrepancies appeared between real-life data and the forecast emissions from different models [115].

In Figure 8, air pollutants in the context of the building envelope were examined. The results show that particulate matter (PM2.5—6 times, PM10—5 times) in various sizes is mainly addressed in the relevant articles focusing on the building envelope. Furthermore, also NO2 and SO2 emissions, as well as the category others, are each mentioned 4 times. Ozone (O3) is addressed 3 times, and the air pollutants UFP, CO, and VOC 2 times each.

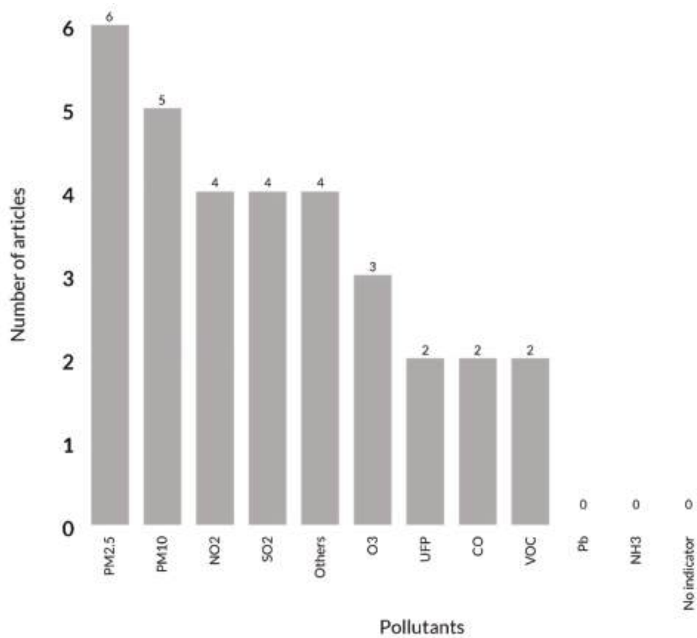

Figure 8. Overview of the pollutants mentioned in the building envelope context.

Building materials are addressed in 57 articles of the final sample. The pollutants most found in these articles were PM2.5 (84 times), PM10 (64 times), and VOC (57 times). Other pollutants such as CO (34 times), SO2 (32 times), and NO2 (31 times) also play a significant role. As shown in Figure 9, UFP and O3 are mentioned 26 times. Lead (Pb) and ammonia (NH3) are of less relevance and are each mentioned only 7 times.

Building interiors are referred to in 29 scientific articles. Figure 10 indicates that the most significant pollutant in these articles is VOC. VOC was mentioned in 26 out of 29 articles, suggesting a strong correlation between interiors and VOCs. The category *Others* is addressed 11 times, ozone 4 times, and PM2.5 3 times. UPF, PM10, and CO are addressed 2 times each. NO2 and Pb play an even less significant role, while SO2 and NH3 are not mentioned at all.

HVAC, as part of the studies reviewed, is mentioned, e.g., in the study of Che et al., who focused on a retrofitted HVAC system and its effects, and where in an office building, energy consumption and indoor air quality respectively environment are examined together [77]. Azuma et al. examined building-related symptoms and indoor air quality, which could affect human health in office buildings equipped with air conditioning in Japan. One result of the study was the finding that greater quantities of suspended particulate matter could enter the building via air conditioning systems in winter and that it is spread throughout the building with the indoor air. They suggest implementing filters for an improved air conditioning system and point out that correct maintenance is part of the solution for air pollution reduction [119].

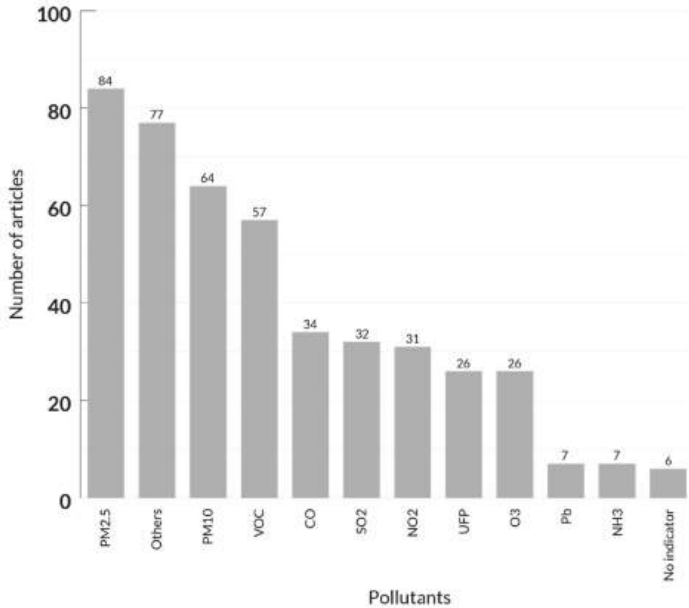

Figure 9. Overview of pollutants mentioned in the context of building materials.

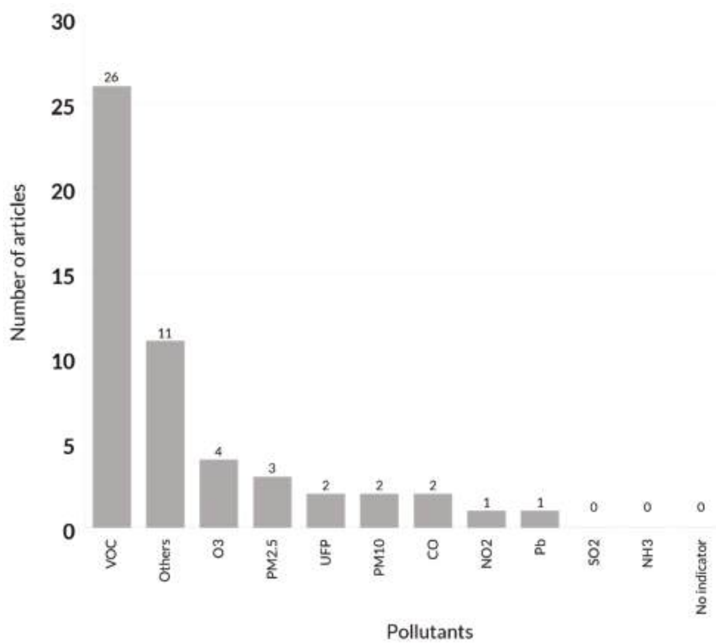

Figure 10. Overview of air emissions mentioned in the context of interiors.

Moreover, HVAC systems are targeted in the studies of Gabbe et al. and Asere et al. [106,120]. Moreover, Asere et al. are assessing indoor air quality in buildings in Latvia with an improved energy efficiency of the buildings. One of the results of the study is that ventilation systems and air exchange rates could be improved, which then on the other hand need more energy and contradict the original intention of energy efficiency measures [120]. Indoor air pollution is also caused by the interior and building materials with high emission potential [121]. For example, particle boards that are often used for furniture or floors are sources of formaldehyde and VOC emissions [122]. Additionally, decoration or interior elements such as floors or coatings can cause indoor air pollution [79,99,123].

3.7. Life Cycle Stages of Constructions

A further result of this RQ presents the assignment of the investigated research articles to the life cycle stages according to EN 15978 and EN 15084 [71,72].

The standard EN 15978 and EN 15084 classify the life cycle of construction works in the production stage (A1–A3), the construction stage (A4–A5), the use stage (B1–B7), the end-of-life stage (C1–C4) and benefits (D).

Figure 11 shows that by far the main life cycle stage addressed within the reviewed literature can be assigned to stage *Use* (module B1) with 73 mentions, followed by *Operational energy use* (module B6) with 31 mentions, and *Construction-installation process* (module A5) with 30 mentions. Life cycle modules *Transport* (module A4) and *Manufacturing* (module A3) are mentioned 23 times. Further important stages are *Maintenance* (module B2) and *Refurbishment* (module B5), as well as *Raw material supply* (module A1). All other life cycle modules are addressed 5 times or less.

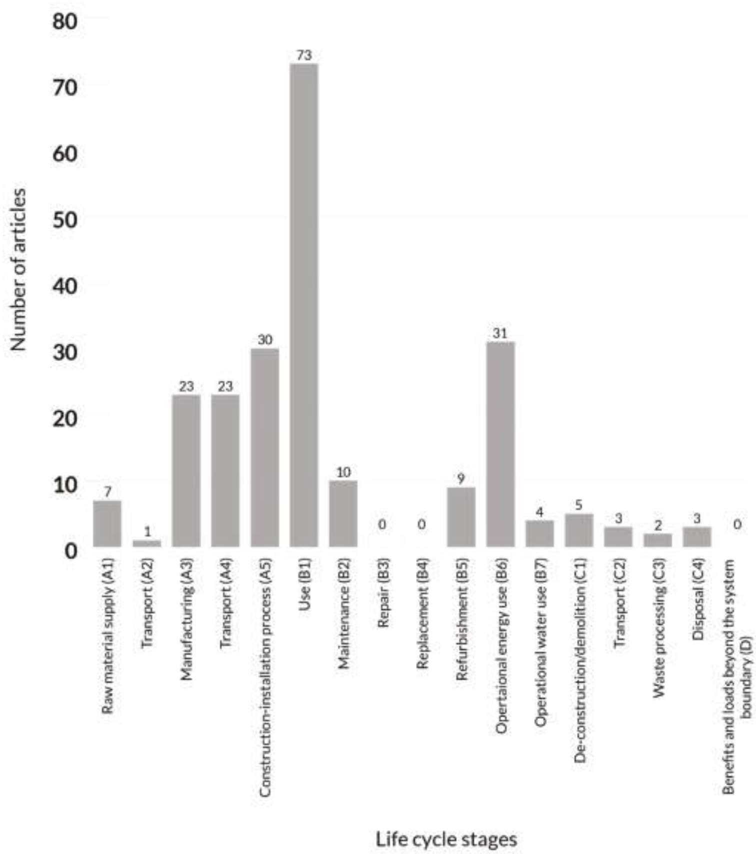

Figure 11. Addressed life cycle stages within the final sample.

Transport is the most important air emission sector in Europe [6]. Transport occurs in different phases and modules during the lifecycle of a building [13,104,124]. It is part of the production stage (module A2) as transport of raw material to the manufacturing company, as well as part of the construction stage itself, e.g., for the transport to the construction-installation process/construction site (module A4). Moreover, it can also be part of the end-of-life stage of a building, i.e., as the transport needed for delivering the demolition or de-construction material to waste processing (module C2).

The production stage (module A1–A3) is part of the study of Asim et al., where catalyst geopolymers as a depolluting alternative to the concrete are studied and discussed [125]. Furthermore, Bossa et al. researched building materials, more specifically photocatalytic cement, as a possible pollution reduction option in the context of TiO2-nanomaterial release [95]. The study of Guttikunda et al. addressed air pollution and potential air pollution control measures for brick kilns with cleaner technology for brick production [126], among others. Böhm et al. are analyzing formaldehyde emissions from wooden products, i.e., solid wood, plywood, flooring, and block board [49]; the emissions were different for various products but highest in the first week after production for all.

The construction stage (module A4–A5) mainly refers to construction sites and construction work as well as the associated air pollution, especially particulate matter. In the course of the one-year study by Juda-Rezler et al., construction work is identified as one of the six main origins of everyday PM2.5 pollution in Poland [127]. Further to this, Ahmed and Arocho compare PM pollution (PM1.0, PM2.5, PM4.0, PM10) on two construction sites, one using steel and the other cross-laminated timber [128]. In addition, Guttikunda et al. are mentioning construction activities as important dust and particulate matter source (PM10 and PM2.5) within the city of Bengaluru [129].

The most widely addressed modules in the use stage (B1–B7) for the final SLR sample are B1 as the general use stage and B6 as the operational energy use stage.

Järnström et al. researched indoor air pollution concentrations, and measure VOC, ammonia, and formaldehyde concentrations during the first year of recently erected residential buildings [130]. Asere et al. have studied the effects of energy efficiency on air quality during the use stage of a building [120]. Du and Sun analyzed the correlation of regional characteristics of building heating systems and local air quality in China with different methods [100]. Among others, Guariso and Sangiorgio examine how the residential building stock should be renovated in terms of energy, looking to environmental and economic benefits and targets [131]. Additionally, local (air) pollution in the Italian region of Lombardia is addressed, as well as energy consumption and heating systems [125]. Dominikovic et al. are integrating and applying the aspect of air pollution in their optimization model for the planning of energy systems in tropical regions [126]. The study shows with its case study Singapore, that integration of energy systems helps to reduce air pollution and socio-economic costs of energy supply on the city level. Next to that, energy efficiency is identified as a part of the measures on the building level [48]. Additionally, Tunno et al. are looking into the topic of wood smoke during days and nights in Christchurch, New Zealand, which is, amongst others, a source for PM2.5 concentrations [132].

Besides that, Tong et al. are examining a tool, which helps to quantify impacts of retrofitting measures for buildings, which help to reduce the problem of air pollution in Ulaanbaatar in Mongolia [133]. Moreover, Shafique et al. investigate potential benefits of green roofing on air pollution reduction (in terms of CO_2) and CO_2-sequestration, and Karteris et al. are researching benefits for Greek large-scale green roof tops [134,135]. Next to air pollution by CO_2, green roofs, respectively their plants, can absorb also other air pollutants such as ozone, PM10, or NO2.

Fuller et al. referred to the end-of-life phase (module C1–C4) in the context of air pollution (PM10 and PM2.5) by examining the demolition works for a chemical factory building and also a road case study in London [108]. Wu et al. also examined in their study about dust prevention and control, one construction site out of three in the stage of demolition [14].

3.8. Distribution by Indoor and Outdoor Pollution (RQ4)

Air pollution can be divided into indoor and outdoor pollution. In a pie chart, the proportions are shown and then analyzed in more detail.

Figure 12 presents which kind of air pollution is addressed in the analyzed research articles. Around half (51%) of the articles are addressing outdoor pollution, almost a third (31%) of the articles are addressing indoor pollution and a further 14% are addressing indoor and outdoor pollution.

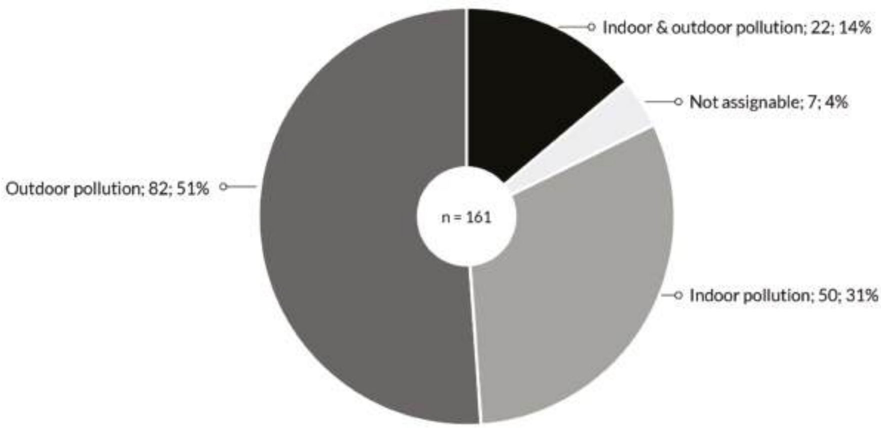

Figure 12. Classification of articles by indoor, outdoor, and indoor/outdoor pollution.

In several cases, indoor air quality (IAQ) measurements were conducted for different materials or building elements such as walls or different laboratory tests to better understand the functions and developments of indoor air pollutants [94–97,136].

Indoor or outdoor air pollutants were also researched in schools or cities such as the Yangon City in Myanmar [20,57,63,109,111]. As an example, PM2.5. concentrations in schools were researched in the studies of Amato et al. and Cancha et al. The use of materials and their effect on air pollution was measured within the study of Rella et al. [65,66,113]. Furthermore, the studies of Vervoort et al. focussed on a decrease of particulate matter in a school [27,111]. Wargocki and Wyon show in their study that the indoor (air) environment in schools matters because it can have a significant effect on the performance of school children [62]. Additionally, Yang et al. investigated the concentration of various air pollutants (CO, CO_2, PM10, total microbial count, total volatile organic compound, formaldehyde) in Korean school buildings. It was shown that furnishings, building materials, and insufficient ventilation were all sources of bad indoor air quality. Moreover, indoor/outdoor ratios of air pollution were measured [20]. The study of Kim et al. focussed on indoor air pollution in the pre-occupancy stage of flats [93]. As a reduction measure for VOCs, the authors suggested better ventilation within the apartments, and the alternative could be decomposing agents.

Furthermore, office buildings and their indoor air quality were investigated in several studies. For example, Ruan and Rim examined two office building case studies in the US and in China [17]. They measured indoor O3 and PM2.5 concentrations in offices in Los Angeles and in Beijing and the effect of ventilation flow rates from the outside as well as the efficiency of filters. Hutter et al. investigated the health implication of office workers in a new office building. One of the findings was that tris-(2-butoxyethyl)-phosphate (TBEP) pollution developed mainly from floor coatings (90%), which as a result were removed in order to reduce health issues connected with this material [65,99].

3.9. Pollutants Analyzed in the Investigated Research Articles (RQ4)

Air pollutants addressed in the research articles are shown in a pie chart in Figure 13 below. The population of investigated research articles (n = 451) exceeds the number of identified research articles (n = 161) due to multiple answers.

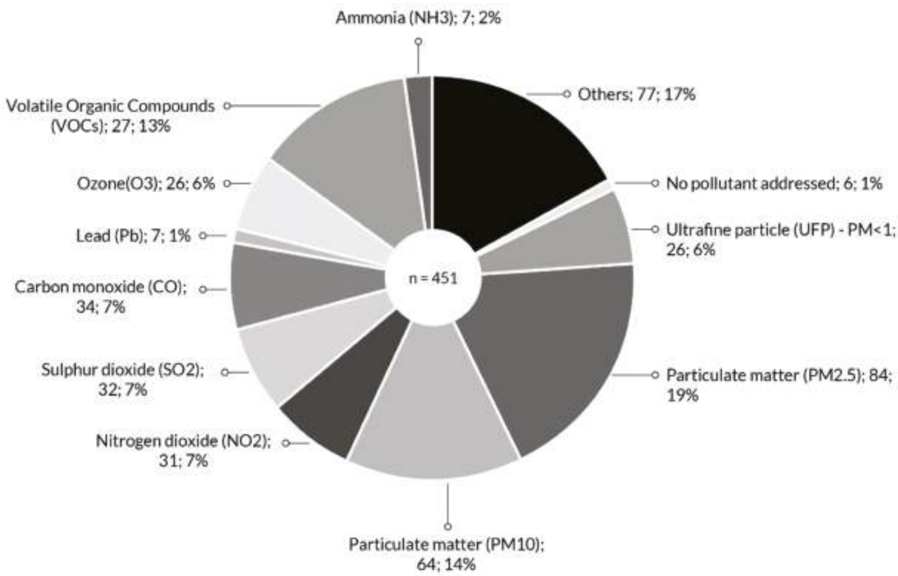

Figure 13. Overview of addressed air pollutants within the final SLR sample.

Particulate matter (PM) in different sizes can be identified in most of the air pollutants in the examined research articles. *Particulate matter (PM2.5)* represents a share of 19%, *Particulate matter (PM10)* 14%, and *Ultrafine particle (UFP)*, which is PM < 1, constitute 6% of the population. With 17%, the category of *Others* is the second biggest category after PM2.5, which comprises of, e.g., black carbon, NOx, and SOx. The third-largest group is represented by *Volatile Organic Compounds (VOCs)*. With 7%, *Sulphur dioxide (SO2)*, *Nitrogen dioxide (NO2)*, and *Carbon monoxide (CO)* are addressed with equal frequency. *Ozone (O3)* with 6% is mentioned as often as UFP. *Ammonia (NH3)* is only examined in 7 research articles, which represents a 2% share of the analyzed research articles. *Lead (Pb)* represents 2% of the overall research articles and is covered in 7 research articles. In 1% (6 research articles), *No pollutant* is addressed explicitly

PM of different sizes in construction sites was addressed in the article of Ahmed and Arocho, which provides clear confirmation that construction sites emit PM in different sizes (PM1.0, PM2.5, PM4, PM10) [128]. Saliba et al. investigated PM and its composition at urban sites in Beirut [137]. The study found that construction debris is also a source of pollution with fine PM. In the study of Azuma et al., air quality and effects on the health (building-related symptoms) of office workers in offices were examined, whereby UFP, in particular, had an effect on building-related symptoms, and VOCs or toluene were linked with health effects on upper respiratory symptoms [119].

In the study of Liu et al., a structural path analysis was conducted, the authors looked at the embodied emission of supply chains such as NOx or SO2, where on the consumption side, construction contributed a larger share to this emission (20–38%) [118]. The construction sector and building materials were among the leading areas regarding important emissions [90,118].

4. Discussion

The aim of the study was to gain a comprehensive overview of how the construction industry contributes to air pollution, where air pollution occurs, and what topic-related research has been conducted in the various fields of the construction industry—in all its aspects.

Three main areas were analyzed with the final sample of the SLR. Firstly, the building level and its life cycle stages, secondly, the construction processes and elements (e.g., construction sites and building components), and thirdly, construction materials and the interiors of buildings. Only one review article of the SLR provides a review of PM air pollution in the explicit context of the construction industry. PM is a prime focus of this article with particular emphasis on the health impacts due to PM exposure for construction workers. The second focus of this study was put on construction dust and especially the monitoring of construction dust from construction activities [10].

Therefore, the first step was to identify important journals and research fields (RQ1). Their variety shows the multi- and interdisciplinarity of the research topic (air pollution in the construction industry), which is rooted in building science, air pollution research, and environmental research. It is in the nature of that topic that no one single research method or methodology can be used to cover this diverse field. Therefore, the articles conveyed a variety of methods and research designs (RQ2) from different disciplines and journals. Another trend observed was that the number of publications in the field of construction is rising (RQ1). In geographical terms, most of these papers are published by Chinese universities. The intense research on air pollution is most probably a reflection of the attempt that is being made to tackle the huge air pollution problem in China. Chinese publications are followed by publications originating from the United States.

One research interest of the SLR study was to identify types, activities, and stages of the built environment or buildings in the current literature (RQ3). The research articles were assigned to different building types and life cycle modules according to EN 15978 and EN15804. The analysis showed that most of the reviewed articles addressed buildings (94% of articles) and that only a small percentage addressed infrastructure (6%). Residential buildings, office buildings, and educational buildings are the most intensively represented of the building types addressed. Additionally, construction processes and construction components were addressed. A classification was thus made in the analysis according to construction component types. Many of the research articles addressed building components (157), construction sites and activities (49), or construction machinery (7). In detail the components were divided into four sub-categories: (i) building envelope, (ii) building materials, (iii) interior, and (iv) heating, ventilation, and air conditioning (HVAC) systems.

Particulate matter (PM) in various sizes is among the most frequently addressed air pollutant in the final sample with 17%, the category Other (this category includes, e.g., black carbon or NOx and Sox) being the second largest category after PM2.5. As the third-largest group, Volatile Organic Compounds (VOCs) can be identified. Air pollutants can be found indoors, outdoors, and in both. Moreover, indoor pollution articles comprised almost a third of the final sample and in this light, could be regarded as an independent (sub) research field. Building materials and interiors both play important roles in this area.

Moreover, one of the implicit set questions is how to improve the situation of air pollution reduction in the construction industry and furthermore to include air pollution reduction measures for fulfilling international agreements and policies such as the Agenda 2030, in order to contribute to sustainable development and transformation of the construction industry.

In the SLR, the scientific articles were also screened for their connection with different sustainable development goals (SDGs). Measures for cleaner and better air in the construction industry can be set either on a technical and operational level or on a policy level. The Agenda 2030 can provide a framework for policy instruments and measures for transforming the construction industry in the interest of a more sustainable and healthier built environment. As the SDGs are interrelated and there are systemic interactions among the SDGs in the construction industry [138,139], some SDGs and their targets refer to air pollution. The topic of health is addressed in SDG target 3.9. and is also reflected in the articles, e.g., through the sick building syndrome or the topic of well-being in buildings, in schools and offices among others, and in the research field of indoor air pollution and indoor air quality. Sustainable urbanization and air pollution are addressed in SDG target 11.6 with UN indicator 11.6.2., which for example, includes only PM (e.g., PM2.5 and PM10) in cities but does not address other relevant air pollutants such as NOx, O3, Pb, or SO2, although they are relevant air pollutants, as outlined in the Section 3. This emphasizes the need for tackling the challenge of air pollution in the construction industry especially in cities and urban areas.

As with other sustainability aspects that need to be taken into account at an early stage in the construction industry, a holistic and systemic view of the influencing criteria is also required in connection with the reduction of air pollution, as well as awareness-raising among the stakeholders involved [140,141]. On a technical and operational level, various measures within the entire life cycle of a building or even an infrastructure contribute to ensuring cleaner air and to both healthier people and a healthier planet. Measures for achieving these goals could be e.g., a reduction of transport activities together with a better management of construction sites or construction schedules in a city in order to optimize distances and avoid traffic jams, which can contribute to higher emissions. Further measures include shortening the distances for the transport of building material by using local enterprises and services and using regional building materials. Technical measures and improvements such as the humidification of tires on construction sites to prevent dust emissions or the optimization of construction site equipment to protect residents and neighbors from dust and noise can be helpful. One possible measure at the legal and administrative levels is the increased integration of dust and air pollution control measures into official tendering and awarding procedures, e.g., the use of hybrid or electrical construction machinery. Measures can be implemented by different actors such as construction companies or owners of buildings on the level of cities and communities or even on policy level on a national or international scale. The international and national guidelines should be implemented at the regional level by local government or at the individual level, e.g., by building owners and construction companies.

In addition, the cooperation of stakeholders from science to industry can also be helpful for the creation of knowledge and the implementation of cleaner air measures. In this context, the Austrian UniNEtZ project can be pointed out, in which a total of 17 universities co-operate in order to implement the SDGs in Austria [142]. One goal of the project is to propose an options paper to the Austrian government as a recommendation for the implementation of various measures to achieve the Agenda 2030 goals.

In this context, all of the 161 screened articles contribute directly or indirectly to sustainable development. However, none of the articles explicitly mentioned the SDGs. The results of the SLR show that air pollution is receiving increasing attention in the scientific community. This is probably due to its environmental, economic, and social implications. Nevertheless, the number of comprehensive reviews on air pollution in the construction industry could be increased, for example by examining certain specific aspects or subtopics such as specific pollutants in different life cycle stages or the linkage of air pollution reduction measures in general or in combination with greenhouse gas (GHG) emission reduction measures and emphasizing synergies between these two topics. Several SLR articles mentioned GHG emissions in the construction industry context [56,63,141]. The relationship between air pollutants and GHG emissions, however, is not quantified in the SLR papers reviewed. It is striking, however, that the connection between GHG emission (i.e., CO_2-eq.) and air pollution is not addressed.

Finally, it can be shown that in both the SLR articles and in policy, e.g., the Agenda 2030 and its SDG targets, a special emphasis on PM can be identified. Other problematic emissions and air pollutants, which are also heavily burdening the environment, are underexposed in scientific literature.

In this context, the question is whether this is because PM is the most harmful air pollutant in construction, or because it is one of the easiest to measure and research. An allocation of air pollution to the construction industry is difficult due to the overlapping system boundaries. Air pollution itself does not consider the construction industry as a separate sector but is interwoven in different sectors such as transport, industry, or energy. It is apparent from the SLR that the formulated RQs are not yet being addressed with great frequency in specific academic fields and universities, or in specific geographical areas such as African or South American countries.

Limitations

A thematic limitation of the study and the conducted SLR is that it focuses mainly on buildings and infrastructure. Literature focusing on other topics such as urban forms, urban planning, the urban built environment in general, and urban greenery such as green walls, green roofs or trees, was excluded. Moreover, the effect air pollution has on buildings, building materials, and the built environment is not yet being addressed. Further articles focusing on cooking, which also contributes to air pollution, were not part of this literature review. Additional constraints are shown in Figure 1.

5. Conclusions and Future Perspectives

This article is the first comprehensive overview of the literature specifically on air pollution in the construction industry and its various aspects. It can be concluded that air pollution is a relevant environmental issue in the construction industry and in the whole construction process.

The research field of air pollution related to the construction industry still has a lot of potentials, because, mostly, only single topics or aspects of "air pollution" and "construction industry" are treated and investigated in individual articles. According to the SLR, the number of articles on air pollution in the construction industry has been rising in the last few years. That the combination of both research issues is a broad field can also be seen in the variety of the journals addressed. There is not just one overall method or methodology set to explore this interdisciplinary research area, even if case studies with field experiments and measurements/method development are most often used in the studies of the final SLR sample. Residential, office, and educational buildings stand out the most in the category of building types and particulate matter in different sizes represents the most common pollutant within the SLR. In addition, one of the results is that both outdoor and indoor air pollution can be considered important for air pollution, the construction industry, and a healthy living environment.

The implementation of a systemic view (i.e., the consideration of a set of sustainable development performance indicators in assessing the appropriateness of air pollutant reduction measures) involves a crucial increase in complexity. The current (scientific) lack of reliable data, the choice of meaningful system boundaries, and the current prevailing reductive thinking approaches of air pollution reduction strategies in the construction sector are the chief limiting factors from the authors' point of view.

According to the Austrian Federal Environment Agency, the sectors of industry (34%), small-scale consumption (21%), agriculture (20%), and transport (18%) are responsible for the generation of particulate matter. In the small-scale consumption sector, combustion processes (stoves, heaters) and in the transport sector, the operation of engines (mainly diesel engines), through brake and tire abrasion as well as dust whirling up on the road are responsible for the emissions. From the point of view of the construction industry, emissions from domestic heating (due to old solid fuel heating systems) and construction sites are particularly relevant.

However, the distinction between the sectors industry and transport, which should be partially within the system boundary of the construction industry, is unclear. Another obstacle is the insufficient understanding regarding the relocation of "dirty" technologies to countries that already are struggling with their bad air quality conditions.

There are different areas, where measures and activities can be taken to reduce air pollution within the various stages of a life cycle of a building. Building materials also influence clean air, especially inside a building. In this way, taking measures against air pollution and for cleanliness, a decrease of premature mortality and different diseases can be achieved. With the right measures and policies, (co-) benefits and synergies between health, climate, air quality, and the environment can be used, and, in this way, the building occupants can also profit. Appropriate actions can achieve and contribute to various policy agendas such as the SDGs and their targets. This will require better planning and management of construction projects and buildings by taking their life cycles and the built environment into consideration. In addition to this, improved materials that are both reusable and recyclable, together with thoroughly adequate technologies and approaches will help us to generate a reduced environmental impact.

Possible ways to give an overview about environmental impacts or to reduce the impact on the environment are methods such as life cycle assessment (LCA), which can be integrated as a decision tool in the construction planning process at an early stage. Green and sustainable public procurements policies, which consider social and environmental criteria and make every effort to avoid negative social and environmental impacts should be considered and implemented from the beginning of the life cycle.

Furthermore, it is important to integrate findings from different disciplines to provide a holistic view of sustainable construction practices and construction materials for clean air and to avoid air pollution in the future. To these terms, the construction industry can contribute cleaner building practices and help to achieve cleaner air.

In this context, the key remaining question will be how to create a systemic understanding of air pollution effects (induced by the construction sector) across all 17 SDGs. Therefore, and as a basis, the consideration of transdisciplinary effects within the policy-making process is of particular importance in order to raise awareness between various sectors and stakeholders.

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References

1. WHO. Air quality and Health. In *Fact Sheets on Sustainable Development Goals: Health Targets*; World Health Organization Region Office for Europe: Copenhagen, Denmark, 2018.
2. EPA. Criteria Air Pollutants. Available online: https://www.epa.gov/criteria-air-pollutants#sel (accessed on 9 June 2021).
3. WHO. *World Health Statistics 2020: Monitoring Health for the SDGs, Sustainable Development Goals*; WHO: Geneva, Switzerland, 2020.
4. WHO. Ambient Air Pollution. Available online: https://www.who.int/data/gho/data/themes/topics/topic-details/GHO/ambient-air-pollution (accessed on 9 June 2021).

5. WHO. *Public Health Social and Environmental Determinants of Health Department Burden of Disease from the Joint Effects of Household and Ambient Air Pollution for 2016*; WHO: Geneva, Switzerland, 2018.
6. European Environment Agency (EEA). *Air Quality in Europe—2020 Report*; European Environment Agency (EEA): Copenhagen, Denmark, 2020; ISBN 978-92-9480-292-7.
7. European Commission. *Impact Assessment on Air Pollution in Europe: An Executive Summary*; European Commission Working Document; European Commission: Brussels, Belgium, 2013.
8. Xu, P.; Chen, Y.; Ye, X. Haze, air pollution, and health in China. *Lancet* **2013**, *382*, 2067. [CrossRef]
9. Bourdin, D.; Mocho, P.; Desauziers, V.; Plaisance, H. Formaldehyde emission behavior of building materials: On-site measurements and modeling approach to predict indoor air pollution. *J. Hazard. Mater.* **2014**, *280*, 164–173. [CrossRef]
10. Cheriyan, D.; Choi, J. A review of research on particulate matter pollution in the construction industry. *J. Clean. Prod.* **2020**, *254*, 120077. [CrossRef]
11. Kinsey, J.; Linna, K.; Squier, W.; Muleski, G.; Cowherd, C. Characterization of the Fugitive Particulate Emissions from Construction Mud/Dirt Carryout. *J. Air Waste Manag. Assoc.* **2004**, *54*, 1394–1404. [CrossRef] [PubMed]
12. Lindgren, T. A case of indoor air pollution of ammonia emitted from concrete in a newly built office in Beijing. *Build. Environ.* **2010**, *45*, 596–600. [CrossRef]
13. Muleski, G.; Cowherd, C.; Kinsey, J. Particulate Emissions from Construction Activities. *J. Air Waste Manag. Assoc.* **2005**, *55*, 772–783. [CrossRef]
14. Wu, Z.; Zhang, X.; Wu, M. Mitigating construction dust pollution: State of the art and the way forward. *J. Clean. Prod.* **2016**, *112*, 1658–1666. [CrossRef]
15. Yang, S.; Liu, J.; Bi, X.; Ning, Y.; Qiao, S.; Yu, Q.; Zhang, J. Risks related to heavy metal pollution in urban construction dust fall of fast-developing Chinese cities. *Ecotoxicol. Environ. Saf.* **2020**, *197*, 110628. [CrossRef] [PubMed]
16. Challoner, A.; Gill, L. Indoor/outdoor air pollution relationships in ten commercial buildings: $PM_{2.5}$ and NO_2. *Build. Environ.* **2014**, *80*, 159–173. [CrossRef]
17. Ruan, T.; Rim, D. Indoor air pollution in office buildings in mega-cities: Effects of filtration efficiency and outdoor air ventilation rates. *Sustain. Cities Soc.* **2019**, *49*, 101609. [CrossRef]
18. Bogush, A.A.; Stegemann, J.A.; Zhou, Q.; Wang, Z.; Zhang, B.; Zhang, T.; Zhang, W.; Wei, J. Co-processing of raw and washed air pollution control residues from energy-from-waste facilities in the cement kiln. *J. Clean. Prod.* **2020**, *254*, 119924. [CrossRef]
19. Ekinci, E.; Kazancoglu, Y.; Mangla, S.K. Using system dynamics to assess the environmental management of cement industry in streaming data context. *Sci. Total Environ.* **2020**, *715*, 136948. [CrossRef]
20. Yang, W.; Sohn, J.; Kim, J.; Son, B.; Park, J. Indoor air quality investigation according to age of the school buildings in Korea. *J. Environ. Manag.* **2009**, *90*, 348–354. [CrossRef]
21. Zhang, X.; Shen, L.; Zhang, L. Life cycle assessment of the air emissions during building construction process: A case study in Hong Kong. *Renew. Sustain. Energy Rev.* **2013**, *17*, 160–169. [CrossRef]
22. Berghmans, P.; Bleux, N.; Panis, L.I.; Mishra, V.K.; Torfs, R.; Van Poppel, M. Exposure assessment of a cyclist to PM_{10} and ultrafine particles. *Sci. Total Environ.* **2009**, *407*, 1286–1298. [CrossRef] [PubMed]
23. Shao, Z.; Bi, J.; Ma, Z.; Wang, J. Seasonal trends of indoor fine particulate matter and its determinants in urban residences in Nanjing, China. *Build. Environ.* **2017**, *125*, 319–325. [CrossRef]
24. Bencs, L.; Spolnik, Z.; Worobiec, A.; Samek, L.; Jütte, B.A.H.G.; Van Grieken, R. Effects of IR heating on distribution and transport of gaseous air pollutants in urban and mountain churches in Poland. *J. Cult. Herit.* **2019**, *36*, 200–209. [CrossRef]
25. Jaber, J.O. Prospects of energy savings in residential space heating. *Energy Build.* **2002**, *34*, 311–319. [CrossRef]
26. Quang, T.N.; He, C.; Morawska, L.; Knibbs, L.D. Influence of ventilation and filtration on indoor particle concentrations in urban office buildings. *Atmos. Environ.* **2013**, *79*, 41–52. [CrossRef]
27. Page, M.J.; McKenzie, J.E.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *J. Clin. Epidemiol.* **2021**, *134*, 178–189. [CrossRef]
28. Higgins, J.; Green, S. *Cochrane Handbook for Systematic Reviews of Interventions*; Cochrane Book Series; The Cochrane Collaboration: London, UK, 2008; ISBN 978-0-470-69951-5.
29. Wholin, C. Guidelines for Snowballing in Systematic Literature Studies and a Replication in Software Engineering. In Proceedings of the 18th International Conference on Evaluation and Assessment in Software Engineering, London, UK, 13–14 May 2014.
30. Richie, H.; Roser, M. Air Pollution. Available online: https://ourworldindata.org/air-pollution (accessed on 9 June 2021).
31. Apte, J.S.; Brauer, M.; Cohen, A.J.; Ezzati, M.; Pope, C.A. Ambient $PM_{2.5}$ Reduces Global and Regional Life Expectancy. *Environ. Sci. Technol. Lett.* **2018**, *5*, 546–551. [CrossRef]
32. Health Effects Institute. *State of Global Air 2019. Special Report*; Health Effects Institute: Boston, MA, USA, 2019. Available online: https://www.stateofglobalair.org/sites/default/files/soga_2019_report.pdf (accessed on 9 June 2021).
33. WHO. Policy and Progress—Ambient Air Pollution. Available online: https://www.who.int/teams/environment-climate-change-and-health/air-quality-and-health/ambient-air-pollution/policy-and-progress (accessed on 9 June 2021).
34. UNEP. *Stockholm Convention on Persiten Organic Pollutants (POPS)—Text and Annexes—Revised in 2019*; UNEP: Geneva, Switzerland, 2020; p. 79.

35. European Commission Clean Air Programme. Available online: https://ec.europa.eu/environment/air/clean_air/index.htm (accessed on 21 June 2011).
36. European Parliament and Council. *Directive 2008/50/EC of the European Parliament and of the Council of 21 May 2008 on Ambient Air Quality and Cleaner Air for Europe*; European Parliament and Council: Strasbourg, France, 2008.
37. European Commission Air Quality—Existing Legislation. Available online: https://ec.europa.eu/environment/air/quality/existing_leg.htm (accessed on 11 June 2021).
38. United Nations. *Resolution A/RES/70/1—Transforming Our World: The 2030 Agenda for Sustainable Development*; United Nations: New York, NY, USA, 2015; Volume 16301, pp. 1–35.
39. WHO. *First WHO Global Conference on Air Pollution and Health—Ambient Air Quality Monitoring, Modelling and Forecasting*; WHO: Geneva, Switzerland, 2018.
40. UNEP. Preventing and Reducing Air Pollution to Improve Air Quality Globally (Resolution Adopted at the 2017 UN Environment Assembly). Available online: https://www.ccacoalition.org/en/resources/preventing-and-reducing-air-pollution-improve-air-quality-globally-resolution-adopted-2017 (accessed on 9 June 2021).
41. The United Nations Environmental Assembly of the United Nations Environment Programme. *Preventing and Reducing Air Pollution to Improve Air Quality Globally*; UNEP: Geneva, Switzerland, 2017; Volume 6736, pp. 1–4.
42. European Commission. *The European Green Deal*; European Commission: Brussels, Belgium, 2019; Volume 53, p. 24.
43. European Commission. *COM(2021) 400 Final: Pathway to a Healthy Planet for All—EU Action Plan: 'Towards Zero Pollution for Air, Water and Soil*; European Commission: Brussels, Belgium, 2021.
44. Climate and Clean Air Coalition the Coalition. Available online: https://www.ccacoalition.org/en/content/coalition (accessed on 11 June 2021).
45. WHO; CCAC; UNEP; WB. Breathlife Campaign. Available online: https://breathelife2030.org/about/ (accessed on 9 June 2021).
46. Liang, C.-S.; Duan, F.-K.; He, K.-B.; Ma, Y.-L. Review on recent progress in observations, source identifications and countermeasures of $PM_{2.5}$. *Environ. Int.* **2016**, *86*, 150–170. [CrossRef]
47. European Environment Agency (EEA). *Assessment of Ground-Level Ozone in Eea Member Countries, with A Focus on Long-Term Trends*; European Environment Agency (EEA): Copenhagen, Denmark, 2009.
48. Dominković, D.F.; Dobravec, V.; Jiang, Y.; Nielsen, P.S.; Krajačić, G. Modelling smart energy systems in tropical regions. *Energy* **2018**, *155*, 592–609. [CrossRef]
49. Böhm, M.; Salem, M.Z.M.; Srba, J. Formaldehyde emission monitoring from a variety of solid wood, plywood, blockboard and flooring products manufactured for building and furnishing materials. *J. Hazard. Mater.* **2012**, *221–222*, 68–79. [CrossRef]
50. Chiesa, M.; Perrone, M.G.; Cusumano, N.; Ferrero, L.; Sangiorgi, G.; Bolzacchini, E.; Lorenzoni, A.; Ballarin Denti, A. An environmental, economical and socio-political analysis of a variety of urban air-pollution reduction policies for primary PM_{10} and NO_x: The case study of the Province of Milan (Northern Italy). *Environ. Sci. Policy* **2014**, *44*, 39–50. [CrossRef]
51. Kunkel, D.A.; Gall, E.T.; Siegel, J.A.; Novoselac, A.; Morrison, G.C.; Corsi, R.L. Passive reduction of human exposure to indoor ozone. *Build. Environ.* **2010**, *45*, 445–452. [CrossRef]
52. He, Z.; Zhang, Y.; Wei, W. Formaldehyde and VOC emissions at different manufacturing stages of wood-based panels. *Build. Environ.* **2012**, *47*, 197–204. [CrossRef]
53. Mukherjee, A.; Agrawal, M. World air particulate matter: Sources, distribution and health effects. *Environ. Chem. Lett.* **2017**, *15*, 283–309. [CrossRef]
54. WHO. Ambient (Outdoor) Air Pollution. Available online: https://www.who.int/en/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health (accessed on 11 June 2021).
55. Fazli, T.; Stephens, B. Development of a nationally representative set of combined building energy and indoor air quality models for U.S. residences. *Build. Environ.* **2018**, *136*, 198–212. [CrossRef]
56. Steinemann, A.; Wargocki, P.; Rismanchi, B. Ten questions concerning green buildings and indoor air quality. *Build. Environ.* **2017**, *112*, 351–358. [CrossRef]
57. Cecchi, T. Identification of representative pollutants in multiple locations of an Italian school using solid phase micro extraction technique. *Build. Environ.* **2014**, *82*, 655–665. [CrossRef]
58. Kumar, P.; Skouloudis, A.N.; Bell, M.; Viana, M.; Carotta, M.C.; Biskos, G.; Morawska, L. Real-time sensors for indoor air monitoring and challenges ahead in deploying them to urban buildings. *Sci. Total Environ.* **2016**, *560–561*, 150–159. [CrossRef] [PubMed]
59. Tham, K.W. Indoor air quality and its effects on humans—A review of challenges and developments in the last 30 years. *Energy Build.* **2016**, *130*, 637–650. [CrossRef]
60. Yu, C.; Kim, J. Building Pathology, Investigation of Sick Buildings—VOC Emissions. *Indoor Built Environ.* **2010**, *19*, 30–39. [CrossRef]
61. U.S. Environmental Protection Agency, Environments Division. *Indoor Air Facts No. 4 Sick Building Syndrome*; EPA—Air Radiation (6609J); Research and Development (MD-56); Environmental Protection Agency: Washington, DC, USA, 1991; pp. 1–4.
62. WHO. Household Air Pollution and Health. Available online: https://www.who.int/news-room/fact-sheets/detail/household-air-pollution-and-health (accessed on 12 June 2021).
63. Amato, F.; Rivas, I.; Viana, M.; Moreno, T.; Bouso, L.; Reche, C.; Àlvarez-Pedrerol, M.; Alastuey, A.; Sunyer, J.; Querol, X. Sources of indoor and outdoor $PM_{2.5}$ concentrations in primary schools. *Sci. Total Environ.* **2014**, *490*, 757–765. [CrossRef] [PubMed]

64. Canha, N.; Almeida, S.M.; do Carmo Freitas, M.; Wolterbeek, H.T.; Cardoso, J.; Pio, C.; Caseiro, A. Impact of wood burning on indoor $PM_{2.5}$ in a primary school in rural Portugal. *Atmos. Environ.* **2014**, *94*, 663–670. [CrossRef]
65. Wargocki, P.; Wyon, D.P. Providing better thermal and air quality conditions in school classrooms would be cost-effective. *Build. Environ.* **2013**, *59*, 581–589. [CrossRef]
66. Li, C.Z.; Zhao, Y.; Xu, X. Investigation of dust exposure and control practices in the construction industry: Implications for cleaner production. *J. Clean. Prod.* **2019**, *227*, 810–824. [CrossRef]
67. Li, N.; Long, X.; Tie, X.; Cao, J.; Huang, R.; Zhang, R.; Feng, T.; Liu, S.; Li, G. Urban dust in the Guanzhong basin of China, part II: A case study of urban dust pollution using the WRF-Dust model. *Sci. Total Environ.* **2016**, *541*, 1614–1624. [CrossRef]
68. Chang, Y.-M.; Hu, W.-H.; Su, K.-T.; Chou, C.-M.; Kao, C.M.; Lin, K.-L. PM_{10} Emissions Reduction from Exposed Areas Using Grass-Planted Covering: Field Study of a Construction Site. *J. Environ. Eng.* **2014**, *140*, 6014006. [CrossRef]
69. De Moraes, R.J.B.; Costa, D.B.; Priscylla, I.; Araújo, S. *Particulate Matter Concentration from Construction Sites: Concrete and Masonry Works*; ASCE: Reston, VA, USA, 2011; pp. 1–11. [CrossRef]
70. Hassan, H.A.; Kumar, P.; Kakosimos, K.E. Flux estimation of fugitive particulate matter emissions from loose Calcisols at construction sites. *Atmos. Environ.* **2016**, *141*, 96–105. [CrossRef]
71. *CEN EN 15804:2012+A2:2019 Sustainability of Construction Works—Environmental Product Declarations—Core Rules for the Product Category of Construction Products*; National Standards Authority of Ireland: Dublin, Ireland, 2019; p. 72.
72. *CEN EN 15978:2011 Sustainability of Construction Works—Assessment of Environmental Performance of Buildings—Calculation Method*; National Standards Authority of Ireland: Dublin, Ireland, 2011; p. 60.
73. European Parliament. *EU Policy on Air Quality: Implementation of Selected EU Legislation*; European Parliament: Brussels, Belgium, 2021; ISBN 978-92-846-7683-5.
74. Prada, M.; Prada, I.F.; Cristea, M.; Popescu, D.E.; Bungău, C.; Aleya, L.; Bungău, C.C. New solutions to reduce greenhouse gas emissions through energy efficiency of buildings of special importance—Hospitals. *Sci. Total Environ.* **2020**, *718*, 137446. [CrossRef]
75. European Parliament. *Directive 2010/31/EU of the European Parliament and of the Council of 19 May 2010 on the Energy Performance of Buildings*; European Parliament and Council: Strasbourg, France, 2010.
76. Milner, J.; Vardoulakis, S.; Chalabi, Z.; Wilkinson, P. Modelling inhalation exposure to combustion-related air pollutants in residential buildings: Application to health impact assessment. *Environ. Int.* **2011**, *37*, 268–279. [CrossRef]
77. Che, W.W.; Tso, C.Y.; Sun, L.; Ip, D.Y.K.; Lee, H.; Chao, C.Y.H.; Lau, A.K.H. Energy consumption, indoor thermal comfort and air quality in a commercial office with retrofitted heat, ventilation and air conditioning (HVAC) system. *Energy Build.* **2019**, *201*, 202–215. [CrossRef]
78. Cheng, S.; Chen, D.; Li, J.; Wang, H.; Guo, X. The assessment of emission-source contributions to air quality by using a coupled MM5-ARPS-CMAQ modeling system: A case study in the Beijing metropolitan region, China. *Environ. Model. Softw.* **2007**, *22*, 1601–1616. [CrossRef]
79. Zhao, Y.; Chen, B.; Guo, Y.; Peng, F.; Zhao, J. Indoor air environment of residential buildings in Dalian, China. *Energy Build.* **2004**, *36*, 1235–1239. [CrossRef]
80. Parhizkar, H.; Khoraskani, R.A.; Tahbaz, M. Double skin façade with Azolla; ventilation, Indoor Air Quality and Thermal Performance Assessment. *J. Clean. Prod.* **2020**, *249*, 119313. [CrossRef]
81. Thevenet, F.; Debono, O.; Rizk, M.; Caron, F.; Verriele, M.; Locoge, N. VOC uptakes on gypsum boards: Sorption performances and impact on indoor air quality. *Build. Environ.* **2018**, *137*, 138–146. [CrossRef]
82. Zanoletti, A.; Bilo, F.; Federici, S.; Borgese, L.; Depero, L.E.; Ponti, J.; Valsesia, A.; La Spina, R.; Segata, M.; Montini, T.; et al. The first material made for air pollution control able to sequestrate fine and ultrafine air particulate matter. *Sustain. Cities Soc.* **2020**, *53*, 101961. [CrossRef]
83. Bungău, C.C.; Prada, I.F.; Prada, M.; Bungău, C. Design and Operation of Constructions: A Healthy Living Environment-Parametric Studies and New Solutions. *Sustainability* **2019**, *11*, 6824. [CrossRef]
84. Ng, W.Y.; Chau, C.K. New Life of the Building Materials-Recycle, Reuse and Recovery. *Energy Procedia* **2015**, *75*, 2884–2891. [CrossRef]
85. Sigrid Nordby, A. Barriers and opportunities to reuse of building materials in the Norwegian construction sector. *IOP Conf. Ser. Earth Environ. Sci.* **2019**, *225*, 12061. [CrossRef]
86. Dassonville, C.; Demattei, C.; Laurent, A.-M.; Moullec, Y.; Seta, N.; Momas, I. Assessment and predictor determination of indoor aldehyde levels in Paris newborn babies' homes. *Indoor Air* **2009**, *19*, 314–323. [CrossRef]
87. Derbez, M.; Berthineau, B.; Cochet, V.; Pignon, C.; Ribéron, J.; Wyart, G.; Mandin, C.; Kirchner, S. A 3-year follow-up of indoor air quality and comfort in two energy-efficient houses. *Build. Environ.* **2014**, *82*, 288–299. [CrossRef]
88. Font, A.; Baker, T.; Mudway, I.S.; Purdie, E.; Dunster, C.; Fuller, G.W. Degradation in urban air quality from construction activity and increased traffic arising from a road widening scheme. *Sci. Total Environ.* **2014**, *497–498*, 123–132. [CrossRef]
89. Giunta, M. Assessment of the environmental impact of road construction: Modelling and prediction of fine particulate matter emissions. *Build. Environ.* **2020**, *176*, 106865. [CrossRef]
90. Giunta, M.; Lo Bosco, D.; Leonardi, G.; Scopelliti, F. Estimation of Gas and Dust Emissions in Construction Sites of a Motorway Project. *Sustainability* **2019**, *11*, 7218. [CrossRef]

91. Thai, A.; McKendry, I.; Brauer, M. Particulate matter exposure along designated bicycle routes in Vancouver, British Columbia. *Sci. Total Environ.* **2008**, *405*, 26–35. [CrossRef]
92. Yan, H.; Ding, G.; Li, H.; Wang, Y.; Zhang, L.; Shen, Q.; Feng, K. Field Evaluation of the Dust Impacts from Construction Sites on Surrounding Areas: A City Case Study in China. *Sustainability* **2019**, *11*, 1906. [CrossRef]
93. Kim, S.-S.; Kang, D.-H.; Choi, D.-H.; Yeo, M.-S.; Kim, K.-W. Comparison of strategies to improve indoor air quality at the pre-occupancy stage in new apartment buildings. *Build. Environ.* **2008**, *43*, 320–328. [CrossRef]
94. Tang, X.; Ughetta, L.; Shannon, S.K.; Houzé de l'Aulnoit, S.; Chen, S.; Gould, R.A.T.; Russell, M.L.; Zhang, J.; Ban-Weiss, G.; Everman, R.L.A.; et al. De-pollution efficacy of photocatalytic roofing granules. *Build. Environ.* **2019**, *160*, 106058. [CrossRef]
95. Bossa, N.; Chaurand, P.; Levard, C.; Borschneck, D.; Miche, H.; Vicente, J.; Geantet, C.; Aguerre-Chariol, O.; Michel, F.M.; Rose, J. Environmental exposure to TiO_2 nanomaterials incorporated in building material. *Environ. Pollut.* **2017**, *220*, 1160–1170. [CrossRef] [PubMed]
96. Bai, Z.; Dong, Y.; Wang, Z.; Zhu, T. Emission of ammonia from indoor concrete wall and assessment of human exposure. *Environ. Int.* **2006**, *32*, 303–311. [CrossRef] [PubMed]
97. Schripp, T.; Langer, S.; Salthammer, T. Interaction of ozone with wooden building products, treated wood samples and exotic wood species. *Atmos. Environ.* **2012**, *54*, 365–372. [CrossRef]
98. George, C.; Beeldens, A.; Barmpas, F.; Doussin, J.-F.; Manganelli, G.; Herrmann, H.; Kleffmann, J.; Mellouki, A. Impact of photocatalytic remediation of pollutants on urban air quality. *Front. Environ. Sci. Eng.* **2016**, *10*, 2. [CrossRef]
99. Hutter, H.-P.; Moshammer, H.; Wallner, P.; Damberger, B.; Tappler, P.; Kundi, M. Health complaints and annoyances after moving into a new office building: A multidisciplinary approach including analysis of questionnaires, air and house dust samples. *Int. J. Hyg. Environ. Health* **2006**, *209*, 65–68. [CrossRef]
100. Du, T.; Sun, Y. Correlation of Building Heating and Air Qualities in Typical Cities of China. *Energy Procedia* **2019**, *158*, 6532–6537. [CrossRef]
101. Sun, Y.; Wang, P.; Zhang, Q.; Ma, H.; Hou, J.; Kong, X. Indoor Air Pollution and Human Perception in Public Buildings in Tianjin, China. *Procedia Eng.* **2015**, *121*, 552–557. [CrossRef]
102. Shaw, C.; Boulic, M.; Longley, I.; Mitchell, T.; Pierse, N.; Howden-Chapman, P. The association between indoor and outdoor NO_2 levels: A case study in 50 residences in an urban neighbourhood in New Zealand. *Sustain. Cities Soc.* **2020**, *56*, 102093. [CrossRef]
103. Fan, S.; Wong, Y.; Shen, L.; Lu, W.; Wang, T.; Yu, A.; Shen, Q. The effectiveness of DustBubbles on dust control in the process of concrete drilling. *Saf. Sci.* **2012**, *50*, 1284–1289. [CrossRef]
104. Faber, P.; Drewnick, F.; Borrmann, S. Aerosol particle and trace gas emissions from earthworks, road construction, and asphalt paving in Germany: Emission factors and influence on local air quality. *Atmos. Environ.* **2015**, *122*, 662–671. [CrossRef]
105. Fuller, G.W.; Green, D. The impact of local fugitive PM_{10} from building works and road works on the assessment of the European Union Limit Value. *Atmos. Environ.* **2004**, *38*, 4993–5002. [CrossRef]
106. Gabbe, C.J.; Oxlaj, E.; Wang, J. Residential development and near-roadway air pollution: Assessing risk and mitigation in San Jose, California. *J. Transp. Health* **2019**, *13*, 78–89. [CrossRef]
107. Wang, Y.; Chen, C.; Wang, P.; Wan, Y.; Chen, Z.; Zhao, L. Experimental Investigation on Indoor/Outdoor $PM_{2.5}$ Concentrations of an Office Building Located in Guangzhou. *Procedia Eng.* **2015**, *121*, 333–340. [CrossRef]
108. Jing, R.; Wang, M.; Brandon, N.; Zhao, Y. Multi-criteria evaluation of solid oxide fuel cell based combined cooling heating and power (SOFC-CCHP) applications for public buildings in China. *Energy* **2017**, *141*, 273–289. [CrossRef]
109. Aung, W.-Y.; Noguchi, M.; Pan-Nu Yi, E.-E.; Thant, Z.; Uchiyama, S.; Win-Shwe, T.-T.; Kunugita, N.; Mar, O. Preliminary assessment of outdoor and indoor air quality in Yangon city, Myanmar. *Atmos. Pollut. Res.* **2019**, *10*, 722–730. [CrossRef]
110. Rella, R.; Sturaro, A.; Vianello, A. Incorrect installation and use of materials as the cause of a severe air pollution incident in a school building. *Sci. Total Environ.* **2014**, *487*, 255–259. [CrossRef]
111. Vervoort, R.; Blocken, B.; van Hooff, T. Reduction of particulate matter concentrations by local removal in a building courtyard: Case study for the Delhi American Embassy School. *Sci. Total Environ.* **2019**, *686*, 657–680. [CrossRef]
112. Kozlovtseva, E.Y.; Loboyko, V.F.; Nikolenko, D.A. Monitoring of Fine Dust Pollution of Multistory Buildings Air Environment as an Adoption Factor of Town-planning Decisions. *Procedia Eng.* **2016**, *150*, 1954–1959. [CrossRef]
113. Bozkurt, Z.; Doğan, G.; Arslanbaş, D.; Pekey, B.; Pekey, H.; Dumanoglu, Y.; Bayram, A.; Tuncel, G. Determination of the personal, indoor and outdoor exposure levels of inorganic gaseous pollutants in different microenvironments in an industrial city. *Environ. Monit. Assess.* **2015**, *187*, 4816. [CrossRef]
114. Chan, C.Y.; Xu, X.D.; Li, Y.S.; Wong, K.H.; Ding, G.A.; Chan, L.Y.; Cheng, X.H. Characteristics of vertical profiles and sources of $PM_{2.5}$, PM_{10} and carbonaceous species in Beijing. *Atmos. Environ.* **2005**, *39*, 5113–5124. [CrossRef]
115. Heidari, B.; Marr, L. Real-time emissions from construction equipment compared with model predictions. *J. Air Waste Manag. Assoc.* **2015**, *65*. [CrossRef]
116. Schleicher, N.; Norra, S.; Dietze, V.; Yu, Y.; Fricker, M.; Kaminski, U.; Chen, Y.; Cen, K. The effect of mitigation measures on size distributed mass concentrations of atmospheric particles and black carbon concentrations during the Olympic Summer Games 2008 in Beijing. *Sci. Total Environ.* **2011**, *412–413*, 185–193. [CrossRef] [PubMed]
117. Alvanchi, A.; Rahimi, M.; Mousavi, M.; Alikhani, H. Construction schedule, an influential factor on air pollution in urban infrastructure projects. *J. Clean. Prod.* **2020**, *255*, 120222. [CrossRef]

118. Liu, Y.-S.; Cao, Y.; Hou, J.-J.; Zhang, J.-T.; Yang, Y.-O.; Liu, L.-C. Identifying common paths of CO_2 and air pollutants emissions in China. *J. Clean. Prod.* **2020**, *256*, 120599. [CrossRef]
119. Azuma, K.; Ikeda, K.; Kagi, N.; Yanagi, U.; Osawa, H. Physicochemical risk factors for building-related symptoms in air-conditioned office buildings: Ambient particles and combined exposure to indoor air pollutants. *Sci. Total Environ.* **2018**, *616–617*, 1649–1655. [CrossRef] [PubMed]
120. Asere, L.; Mols, T.; Blumberga, A. Assessment of Energy Efficiency Measures on Indoor Air Quality and Microclimate in Buildings of Liepaja Municipality. *Energy Procedia* **2016**, *95*, 37–42. [CrossRef]
121. Spiru, P.; Simona, P.L. A review on interactions between energy performance of the buildings, outdoor air pollution and the indoor air quality. *Energy Procedia* **2017**, *128*, 179–186. [CrossRef]
122. Jiang, C.; Li, D.; Zhang, P.; Li, J.; Wang, J.; Yu, J. Formaldehyde and volatile organic compound (VOC) emissions from particleboard: Identification of odorous compounds and effects of heat treatment. *Build. Environ.* **2017**, *117*, 118–126. [CrossRef]
123. Šenitková, I.J.; Kraus, M. Assessment of Selected Interior Flooring Materials on Indoor Air Quality. *Procedia Eng.* **2016**, *161*, 1527–1531. [CrossRef]
124. Khodakarami, J.; Ghobadi, P. Urban pollution and solar radiation impacts. *Renew. Sustain. Energy Rev.* **2016**, *57*, 965–976. [CrossRef]
125. Asim, N.; Alghoul, M.; Mohammad, M.; Amin, M.H.; Akhtaruzzaman, M.; Amin, N.; Sopian, K. Emerging sustainable solutions for depollution: Geopolymers. *Constr. Build. Mater.* **2019**, *199*, 540–548. [CrossRef]
126. Guttikunda, S.K.; Goel, R.; Pant, P. Nature of air pollution, emission sources, and management in the Indian cities. *Atmos. Environ.* **2014**, *95*, 501–510. [CrossRef]
127. Juda-Rezler, K.; Reizer, M.; Maciejewska, K.; Błaszczak, B.; Klejnowski, K. Characterization of atmospheric $PM_{2.5}$ sources at a Central European urban background site. *Sci. Total Environ.* **2020**, *713*, 136729. [CrossRef] [PubMed]
128. Ahmed, S.; Arocho, I. Emission of particulate matters during construction: A comparative study on a Cross Laminated Timber (CLT) and a steel building construction project. *J. Build. Eng.* **2019**, *22*, 281–294. [CrossRef]
129. Guttikunda, S.K.; Nishadh, K.A.; Gota, S.; Singh, P.; Chanda, A.; Jawahar, P.; Asundi, J. Air quality, emissions, and source contributions analysis for the Greater Bengaluru region of India. *Atmos. Pollut. Res.* **2019**, *10*, 941–953. [CrossRef]
130. Järnström, H.; Saarela, K.; Kalliokoski, P.; Pasanen, A.-L. Reference values for indoor air pollutant concentrations in new, residential buildings in Finland. *Atmos. Environ.* **2006**, *40*, 7178–7191. [CrossRef]
131. Guariso, G.; Sangiorgio, M. Multi-objective planning of building stock renovation. *Energy Policy* **2019**, *130*, 101–110. [CrossRef]
132. Tunno, B.; Longley, I.; Somervell, E.; Edwards, S.; Olivares, G.; Gray, S.; Cambal, L.; Chubb, L.; Roper, C.; Coulson, G.; et al. Separating spatial patterns in pollution attributable to woodsmoke and other sources, during daytime and nighttime hours, in Christchurch, New Zealand. *Environ. Res.* **2019**, *171*, 228–238. [CrossRef]
133. Tong, Z.; Yang, B.; Hopke, P.K.; Zhang, K.M. Microenvironmental air quality impact of a commercial-scale biomass heating system. *Environ. Pollut.* **2017**, *220*, 1112–1120. [CrossRef]
134. Shafique, M.; Xue, X.; Luo, X. An overview of carbon sequestration of green roofs in urban areas. *Urban For. Urban Green.* **2020**, *47*, 126515. [CrossRef]
135. Karteris, M.; Theodoridou, I.; Mallinis, G.; Tsiros, E.; Karteris, A. Towards a green sustainable strategy for Mediterranean cities: Assessing the benefits of large-scale green roofs implementation in Thessaloniki, Northern Greece, using environmental modelling, GIS and very high spatial resolution remote sensing data. *Renew. Sustain. Energy Rev.* **2016**, *58*, 510–525. [CrossRef]
136. Muir, D.; Longhurst, J.W.S.; Tubb, A. Characterisation and quantification of the sources of PM_{10} during air pollution episodes in the UK. *Sci. Total Environ.* **2006**, *358*, 188–205. [CrossRef]
137. Saliba, N.A.; El Jam, F.; El Tayar, G.; Obeid, W.; Roumie, M. Origin and variability of particulate matter (PM_{10} and $PM_{2.5}$) mass concentrations over an Eastern Mediterranean city. *Atmos. Res.* **2010**, *97*, 106–114. [CrossRef]
138. Wieser, A.A.; Scherz, M.; Maier, S.; Passer, A.; Kreiner, H. Implementation of Sustainable Development Goals in construction industry—A systemic consideration of synergies and trade-offs. *IOP Conf. Ser. Earth Environ. Sci.* **2019**, *323*, 012177. [CrossRef]
139. Scherz, M.; Zunk, B.M.; Passer, A.; Kreiner, H. Visualizing interdependencies between sustainability criteria to support multicriteria decision-making processes in building design. *Procedia CIRP* **2018**, *69*, 200–205. [CrossRef]
140. Kreiner, H.; Scherz, M.; Passer, A. How to make decision-makers aware of sustainable construction? In *Proceedings of the Life-Cycle Analysis and Assessment in Civil Engineering, Ghent, Belgium, 28–31 October 2018*; Caspeele, R., Taerwe, L., Frangopol, D., Eds.; CRC Press: Boca Raton, FL, USA, 2018.
141. Scherz, M.; Passer, A.; Kreiner, H. Challenges in the achievement of a Net Zero Carbon Built Environment—A systemic approach to support the decision-aiding process in the design stage of buildings. *IOP Conf. Ser. Earth Environ. Sci.* **2020**, *588*, 32034. [CrossRef]
142. Körfgen, A.; Glatz, I.; Maier, S.; Scherz, M.; Kreiner, H.; Passer, A.; Allerberger, F.; Kromp-Kolb, H.; Stötter, J. Austrian Universities and the Sustainable Development Goals. *IOP Conf. Ser. Earth Environ. Sci.* **2019**, *323*, 012156. [CrossRef]

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Evaluation of PM2.5 Particulate Matter and Noise Pollution in Tikrit University Based on GIS and Statistical Modeling

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Abstract: In this paper, we assess the extent of environmental pollution in terms of PM2.5 particulate matter and noise in Tikrit University, located in Tikrit City of Iraq. The geographic information systems (GIS) technology was used for data analysis. Moreover, we built two multiple linear regression models (based on two different data inputs) for the prediction of PM2.5 particulate matter, which were based on the explanatory variables of maximum and minimum noise, temperature, and humidity. Furthermore, the maximum prediction coefficient R^2 of the best models was 0.82, with a validated (via testing data) coefficient R^2 of 0.94. From the actual total distribution of PM2.5 particulate values ranging from 35–58 $\mu g/m^3$, our best model managed to predict values between 34.9–60.6 $\mu g/m^3$. At the end of the study, the overall air quality was determined between moderate and harmful. In addition, the overall detected noise ranged from 49.30–85.79 dB, which inevitably designated the study area to be categorized as a noisy zone, despite being an educational institution.

Keywords: PM2.5; air quality; noise; silence zone area; GIS; linear regression

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1. Introduction

Air pollution is one of the major issues plaguing the world today, which highly correlates with vast industrialization, in addition to the already existing particulate matter pollutants [1–3]. There are a variety of air pollution compositions, but the majority contain PM2.5 and PM10 particulate matter. PM2.5 in particular (with a diameter of 2.5 μm), has been shown to be harmful to humans based on several epidemiological studies [3–6]. Due to this, experts put an emphasis on PM2.5 when performing air quality monitoring.

In general, particulate concentration measurements are done by dedicated monitoring stations that are geographically dispersed [7–9]. Jumaah et al. [10] found such dispersions to be problematic as insufficient samples might be collected to come up with any meaningful analysis. This is supported by Zhao et al. [11] and Hsu et al. [12], where both assert the importance of more comprehensive area coverage to allow reliable and continuous sampling.

In addition to location, gauging pollution levels in the chronological structure of a particular pollutant, such as PM2.5, is highly influenced by atmospheric factors and noise. Studying the influence or correlation of such variables on particulate matter can provide insights for better pollution monitoring [13]. The work in [14], for instance, asserts that the correlation between particulate matter and traffic noise should be looked into for better air pollution insights. This is supported by [15], where their work demonstrated how various air contaminants along with noise led to worsened air quality. In addition to traffic (as the main cause of noise pollution), weather can be an influential periodic factor that produces seasonal variations of noise [16].

1.1. Noise Pollution Mapping

Chandrappa and Das [17] define noise as undesired sound. As of 2016, the World Health Organization (WHO) puts noise contamination as the third greatest environmental contamination after air and water [18]. Studies have shown the adverse impacts of noise on human health, such as being destructive to human hearing [19]. Therefore, it is sensible to reduce (or even eliminate) unnecessary noise for the overall well-being of humanity [20,21].

Advancements in noise pollution mapping has facilitated in noise pollution assessment. Since such maps display the spatial distributions of noise, one can map noise at different times of the day such as in the morning, mid-day, evening, and night [22]. This allows researchers and authorities to evaluate locations containing possible noise pollutions and decide on necessary actions. One practical application is the analysis and assessment of traffic noise contamination [23]. In other research, noise mapping is performed through interpolating data from different monitoring stations where noise pollution can then be assessed through equivalent sound pressure data [24]. An example of such work was done by Harman et al. [25] where the noise map of Isparta city was generated using inverse distance weighted (IDW), Kriging, and multiquadric interpolation methods using various parameters. Location-wise noise analysis was then assessed based on national environmental noise thresholds. The most applied methodology has always been getting information on the features of various sample points as much as possible in the particular geographic region, as well as predicting the value of the unobserved point from the value of the known point over spatial interpolation [26].

1.2. Geographical Information Systems (GIS)

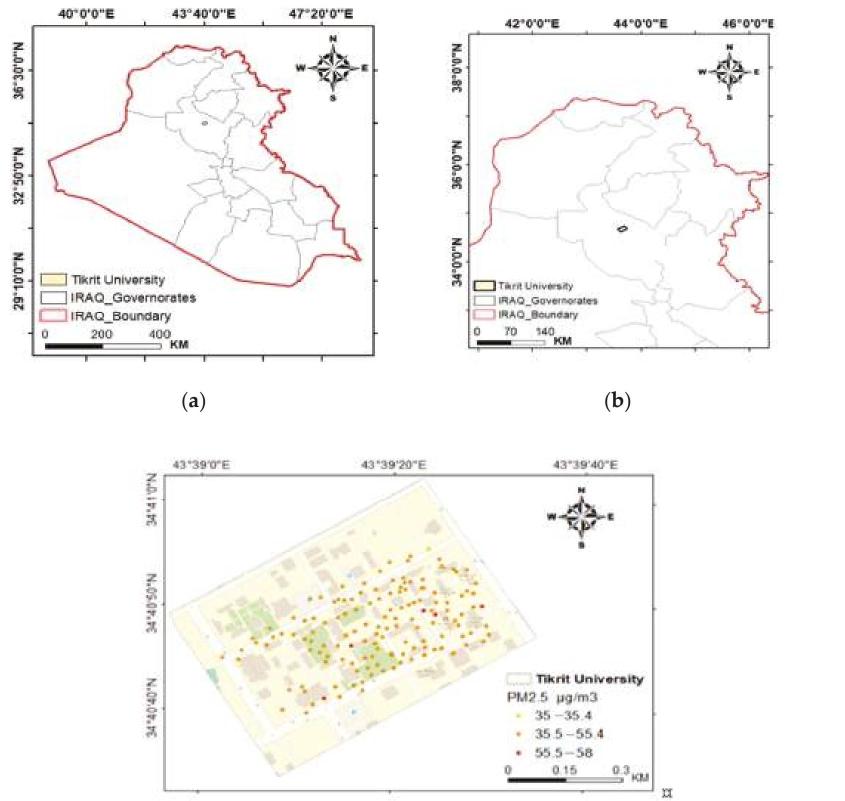
Environmental modeling possesses significant history and progress, and has many applications in problems related to ecology [27]. Urban ecological problems relate to studying wide areas that take advantage of geographical information systems (GISs) [28]. GISs are able to incorporate various information sources allowing data interpretation through various modeling and visualization techniques [29]. Hence, GISs can be considered decision support systems for the relevant authorities to perform assessments and decision making [30–33]. The use of spatial modeling and statistics has risen up-to-date [34]. Multiple new techniques for the statistical assessment and model patterns have been developed currently [35]. For example, modeling air quality is helpful in air pollution problems controlling [36].

In this study, we evaluate air quality and determine noise distributions in silent zones inside Tikrit University, Tikrit, Iraq. Building upon GIS techniques, we apply the least-square model to investigate the impact of noise and meteorological factors on air pollution and PM2.5 prediction. Specifically, the correlation between noise with climatic parameters (i.e., as independent variables) is examined in a multivariate regression model for the PM2.5 particulate quantity estimation. Our data consist of daily manually measured data around Tikrit University (during July 2019) as well as NASA satellite remotely sensed data of PM2.5. The month of July is characterized by high temperatures throughout Iraq, and the university is devoid of students. Therefore, it is possible to determine the extent of noise pollution with the least amount of sound and the extent of the impact of atmospheric factors at peak times. Moreover, we can determine the extent of noise from the university's surroundings. We expect this study to offer insights for the proposal of future air quality management protocols in the study area and the city of Tikrit.

2. Materials and Methods

2.1. Study Area

Tikrit University is chosen as the study area. It is located in Tikrit city, situated in the Salahuddin province of Iraq, which is 155 km from the capital city of Baghdad [37]. The study area (Figure 1) lies between 43°38′56.4″–43°39′35.5″ E and 34°40′33.3″–34°41′2.4″ N. The main goal of this study is to evaluate the environmental impacts of air and noise pollution occurring inside the university area. Tikrit University is selected due to the fact that it is an important educational region.



(**a**) (**b**)

(**c**)

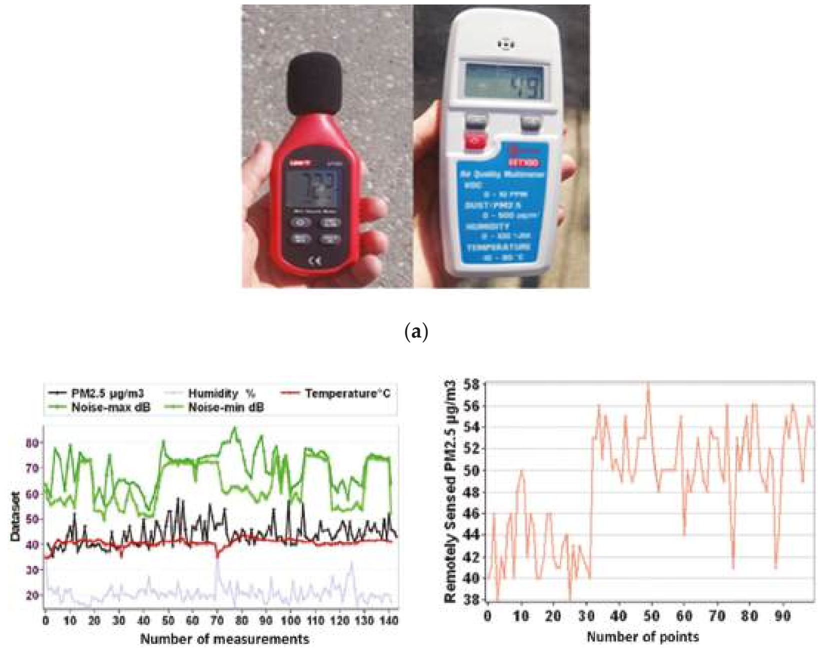
Figure 1. The Tikrit University study area. (**a**) Map of Iraq; (**b**) map of Salahuddin; (**c**) map of University of Tikrit.

2.2. Data Acquisition and GIS Techniques

Measurements were taken along the study area, which consist of the following:

1. PM2.5 particulate mass (µg/m^3). Source: NASA Worldview data;
2. Maximum and minimum noise (dB);
3. Humidity percentage;
4. Temperature (°C).

The overall amassed dataset was then processed using ArcGIS10.3. Two methods were used to represent the data distribution, namely the IDW and least square modeling (LSM). Figure 2 shows the details of data acquisition/data types, along with the measuring devices that were used (i.e., mini sound meter and air quality multimeter).



(**a**)

(**b**) (**c**)

Figure 2. Data acquisition details. (**a**) Left to right—mini sound meter and air quality multimeter; (**b**) the field dataset distribution; and (**c**) the remotely sensed PM2.5 data.

In this study, noise levels were measured using the mini sound meter. Fieldwork involved measuring the maximum noise and minimum noise pollutions inside the university and surrounding areas, which were conducted throughout July 2019. For each sampling site, noise measurements were continuously taken for 30 days. The data collected from each location were processed for statistical analysis.

The data that belong to noise pollution are shown in Figure 2b, which depict the average values of maximum and minimum noise levels in the silence zone of Tikrit city at various time intervals (i.e., 9:00 a.m., 11:00 a.m., 2:30 p.m., and 4:30 p.m.). Weather data (temperature and humidity) were measured by the air quality multimeter. To validate our results, historical data of PM2.5 levels were obtained from air matter, which was provided by the Global Air Quality Service Provider and downloaded from https://air-matters.com/ (accessed on 20 September 2019).

To assess and evaluate the influence of noise and air pollution, the IDW interpolation technique was employed. This method was chosen due to its suitability in flat lands where there is uniformity between the variables. As IDW is a statistical technique, each known point is assumed to affect the magnitude of unknown points. Therefore, the values of points near the known points can be calculated [4,38]. Note that the unknown points' values can be deduced, but with the risk of low accuracy. This is due to the fact that values of converging points searched by IDW can vary significantly. Therefore, interpolated point values were collected in small and closely adjacent areas, ensuring higher point distribution accuracy. The equation for IDW and estimation of z at (x) can be written as Equation (1):

$$\hat{z}(\mathrm{x}) = \frac{\sum_i^n w_i z_i}{\sum_i^n w_i} \tag{1}$$

where z_i denotes the control value for the ith sample point, and w_i is a weight that defines the relative importance of the specific control point z_i in the interpolation process [30]. The IDW analysis is generated based on the concept of spatial dependence making it a reliable interpolation process for air pollution status prediction. IDW also measures the ratio of the dependency relationships between adjacent and discrete features and specifies the result of the cell in the segment that requires metadata.

After performing IDW, two empirical linear models are applied to the results where the first model is constructed based on 100 points from the field data, whereas the second model is constructed based on remotely sensed PM2.5 data. As for the image properties, moderate resolution imaging spectroradiometer (MODIS) images were downloaded at a 30 m resolution per pixel, since 7 July 2019 with WGS 84 projections.

2.3. Linear Regression

Linear regression is a statistical prediction technique that models the linear dependence/relationship between a variable with other variables (known as explanatory variables). Based on training/observed data, a linear fit (i.e., the linear model) is estimated through an iterative process of parameter/coefficient updates. These parameters are updated based on the concept of error reduction between each iteration's predicted value (i.e., hypotheses) and the respective known value in the dataset. Once the overall error is minimized, the linear model is considered converged and ready to be deployed. The model we generated correlates PM2.5 to the noise and weather data (i.e., the two explanatory variables) to predict PM2.5 values in the specified region inside the university. This means that the model takes in as input, real-world (previously unseen by the model during training) values of the explanatory variables to estimate the PM2.5 response. If the purpose is to interpret the changes in the response features that can be related to changes in the explanatory features, linear regressions can be used to determine the power of the correlation within the dependent and the explanatory features. Moreover, particularly to ascertain if some of the explanatory features may not have a linear relation with the response ever or to distinguish if any subset of explanatory features may include irrelevant information of the response [39].

Since we consider two explanatory variables (factors), the multiple linear regression (least-squares) is used. Additionally, we used Cook and Weisberg [4], Weisberg [40], Sen and Srivastava [41], and Jumaah et al. [42]. The multiple least-squares regression can be represented by Equation (2).

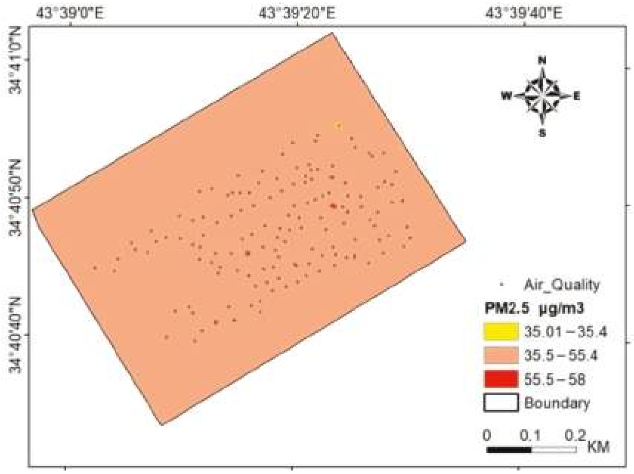
$$z_i = \beta_0 + \beta_1\, x_{1i} + \ldots + \beta_k\, x_{ki} + \varepsilon \tag{2}$$

where i represents a point location, z_i is the estimated factor at i, $x_{1i} \ldots x_{ki}$ are the explanatory factors at i, β_0 is the intercept term, $\beta_1, \ldots, \beta_k$ are the factor coefficients, and ε is the error term.

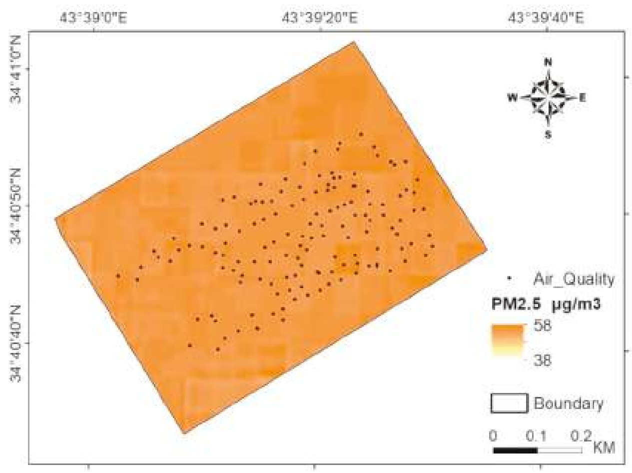
3. Results

3.1. Resultant Distribution Maps

We generated the map for the PM2.5 distribution in the study area and the PM2.5 concentration (as air quality evaluation) was in the range of moderate to unhealthy/harmful. Figure 3a,b shows the PM2.5 distribution maps in Tikrit University, indicating field dataset values between 35.01 to 58 μg/m^3. Moreover, the satellite imagery distribution validated this dataset, which ranged between 38–58 μg/m^3.



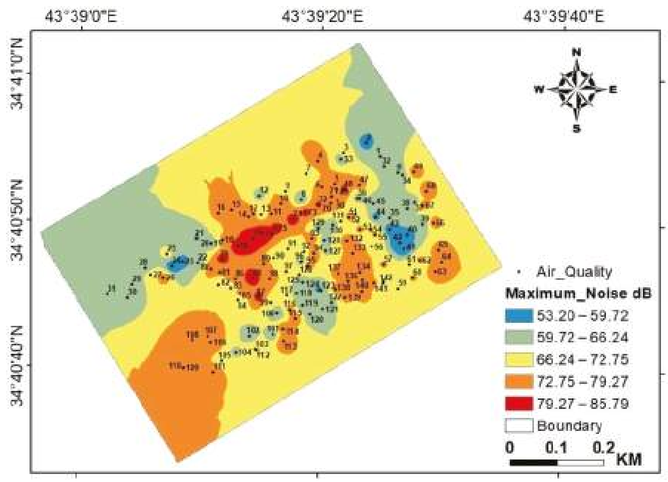
(**a**)



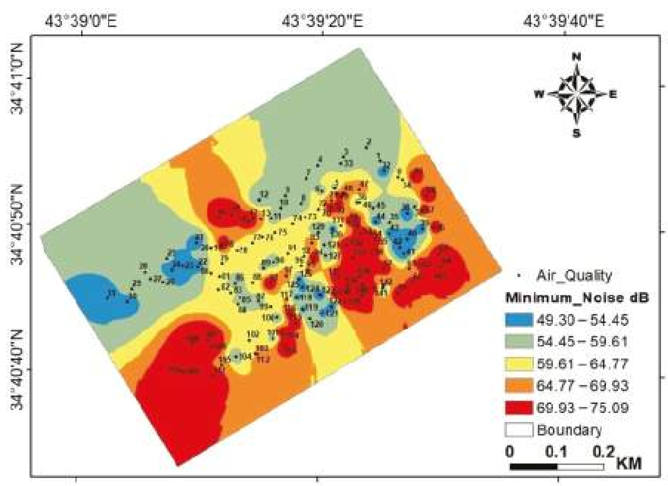
(**b**)

Figure 3. The PM2.5 distribution maps in Tikrit University. (**a**) Field measurements distribution; (**b**) remotely sensed PM2.5 distribution.

The analyzed noise dataset is subsequently mapped to visualize clusters that exhibit different levels of noise (in dB). Two maps of maximum and minimum noise distributions were produced for Tikrit University, as shown in Figure 4.



(**a**)



(**b**)

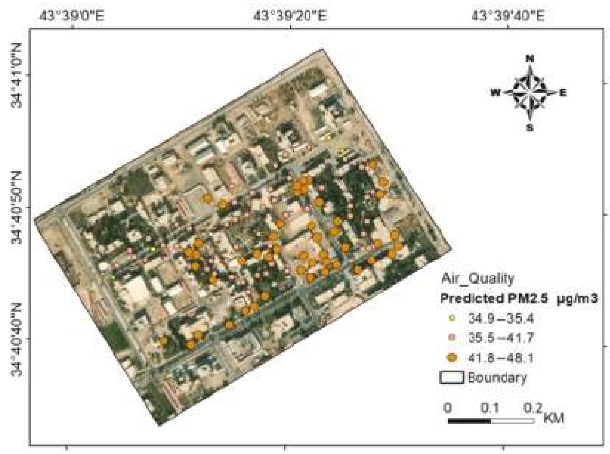
Figure 4. Noise distribution maps in Tikrit University. (**a**) Maximum noise distribution map; (**b**) minimum noise distribution map.

It is important to note that these maps were produced through field measurements at pre-defined sites. Maximum noise levels ranged from 53.20–85.79 dB. In particular, higher maximum noise was observed at location points 48, 76, 77, 78, 79, and 88. Point 48, for example, is near the engineering college laboratories, where loud noise can be due to the electrical generator present in the premises. Points 76 and 77 are near a pharmacy college and a restaurant. Point 78 is located at the sub road between the pharmacy and the science colleges, where a generator set is accompanied by road noise. Points 79 and 88 are near the science colleges. Some collected points are positioned near the abandoned buildings in the university, which might explain why low maximum noise levels were recorded at these locations (i.e., points 41 and 42).

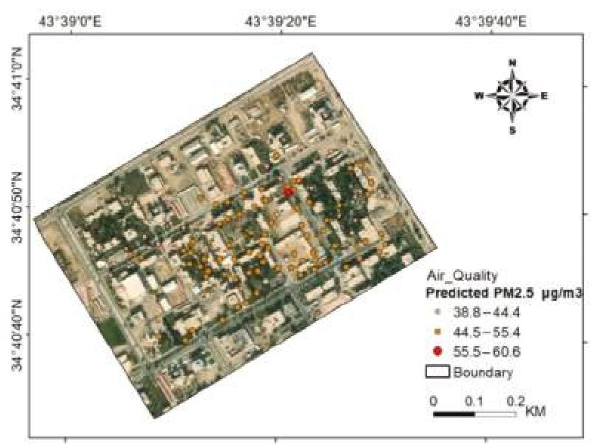
Minimum noise levels were recorded between 49.30 and 75.09 dB. Higher minimum noise levels were recorded at locations 94, 106, 107, and 108. For point 94, the louder minimum noise is due to its location near construction laboratories. Point 106 is on the main road of the university. Point 107 was in the sub-road between the veterinary and science colleges. Point 108 is located near the sports hall and education college lecture rooms. Low minimum noise levels are noticed at points 24, 38, 41,42, 43, and, 44, which were in open space areas and near abandoned buildings.

3.2. Generated Regression Maps

The regression results and model performance are shown in Figure 5. This figure presents the PM2.5 prediction maps at Tikrit University.



(**a**)



(**b**)

Figure 5. The PM2.5 prediction maps at Tikrit University. (**a**) PM2.5 prediction map based on field dataset; (**b**) PM2.5 prediction map based on remotely sensed data.

The multiple linear regression model estimates the dependent factor (i.e., PM2.5 particulate mass) from the explanatory variables, in this case: Noise and meteorological parameters. The PM2.5 predicted values ranged between 34.9 and 48.1 μg/m^3 based on 100 measured points in the study area. On the other hand, the predicted PM2.5 values based on satellite imagery ranged between 38.8 and 60.6 μg/m^3. Table 1 shows the regression statistics and Table 2 shows the modeling synopsis outputs.

Table 1. The regression statistics.

Regression Statistics	Based on the Field Dataset	Based on Remotely Sensed Data
Multiple R	0.71	0.90
R Square	0.51	0.82
Adjusted R Square	0.49	0.82
Standard Error	3.22	2.21
Observation	100	100

Table 2. The modeling synopsis outputs.

Modeling Synopsis	Based on the Field Dataset		Based on Remotely Sensed Data	
	Coefficients (C)	*p*-Value	Coefficients (C)	*p*-Value
Intercept (I)	−21.741	0.051	−49.732	2.76×10^{-9}
Humidity	0.455	4.14×10^{-5}	0.750	3.32×10^{-17}
Temperature	0.764	0.002	1.118	1.3×10^{-9}
Noise max	0.036	0.542	0.127	0.002
Noise min	0.350	2.04×10^{-9}	0.450	1.46×10^{-21}

From Table 1, Multiple R refers to the correlation coefficient of the estimated equation. This output is equal to 0.71 and 0.90 for field dataset and remotely sensed data, respectively. Previous studies indicate that a good correlation has a Multiple R value of 0.70 or greater [43]. R square (R^2) values are 0.51 and 0.82, respectively for field dataset and remotely sensed data. R^2 refers to the variance ratio for PM2.5, which is explained by the other parameters in the regression equation. In our study, the remotely sensed data show more potential in variance interpretation between variables, where the model correlates PM2.5 to the noise and weather data to predict PM2.5 values in the specified region within the university area. The Adjusted R squared is similar to R^2, but adjusted for the number of predictors in the regression model. The Standard Error is the average estimation error of the model.

One of the synopsis outputs in Table 2 is the *p*-value. In our work, we determined that a variable's *p*-value must not exceed 0.05 or that particular variable will be excluded from the model (i.e., deemed statistically insignificant). As a result, the Noise max variable is not included in the regression equation for the field dataset, as expressed in Equation (3), but included in the equation for the remotely sensed data (Equation (4)). On the other hand, each coefficient isolates the role of the respective variable from all of the other variables. The intercept term is simply the y-intercept where the fitted regression line crosses the *y*-axis.

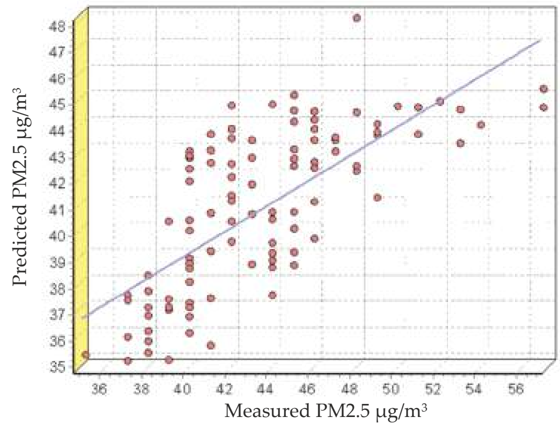
$$\text{PM2.5}_{\text{ Predicted}} = -\text{I} + \text{C}_H \times \text{H} + \text{C}_T \times \text{T} + \text{C}_{\text{N}_{min}} \times \text{N}_{min} \tag{3}$$

$$\text{PM2.5}_{\text{Predicted}} = -\text{I} + \text{C}_H \times \text{H} + \text{C}_T \times \text{T} + \text{C}_{\text{N}_{max}} \times \text{N}_{max} + \text{C}_{\text{N}_{min}} \times \text{N}_{min} \tag{4}$$

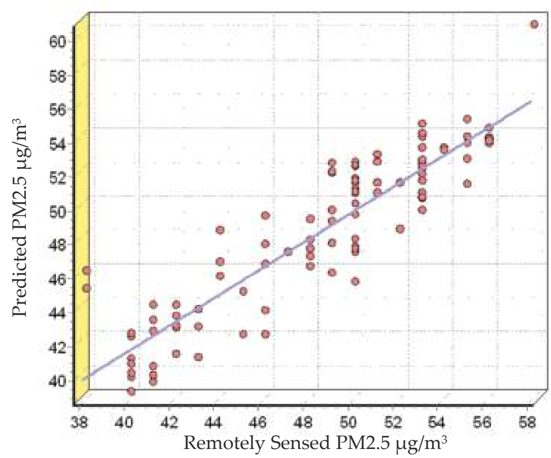
where I is the intercept term, C_H is the humidity coefficient, C_T is the temperature coefficient, $\text{C}_{\text{N}_{max}}$ is the maximum noise coefficient, $\text{C}_{\text{N}_{min}}$ is the minimum noise coefficient, H is humidity, T is temperature, N_{max} is the maximum noise, and N_{min} is the minimum noise.

3.3. Validation

Figure 6a,b shows the linear regression model generated using the field and remotely sensed datasets, respectively. For Figure 6a, the resultant R^2 based on the field dataset is 0.51. This indicates a low description of the variability, i.e., 51% as the maximum. On the other hand, the R^2 based on remotely sensed dataset is 0.82, indicating a maximum variability description of 82%, which also indicates higher prediction prowess.



(**a**)

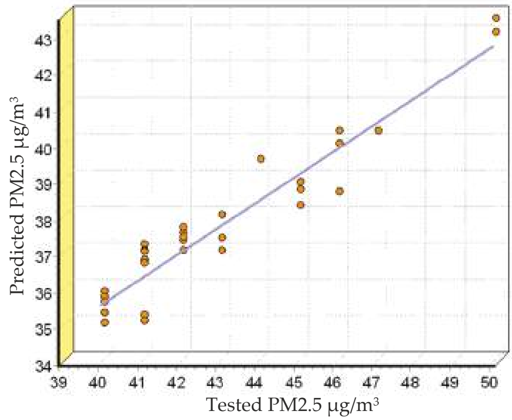


(b)

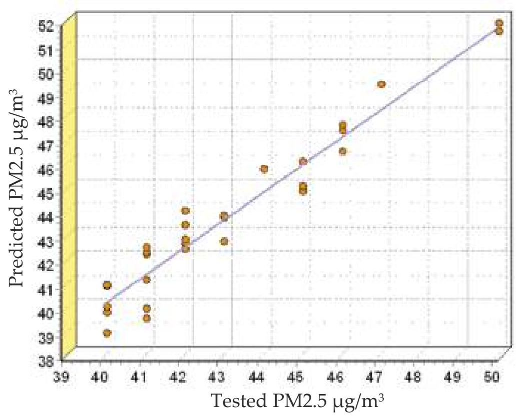
Figure 6. Validation. (**a**) Validation by measured points; (**b**) validation by remotely sensed points.

3.4. Model Testing

We present the model testing results for both datasets, as shown in Figure 7. R^2 were 0.91 and 0.94 for the model based on field data and model based on the remotely sensed points, respectively. The results indicate that both models fit the test data well and fall within the confidence range.



(**a**)



(**b**)

Figure 7. Model testing. (**a**) Testing of measured points; (**b**) testing of remotely sensed points.

4. Discussion

Based on both validated models (Figure 5a,b), the predicted PM2.5 levels were between 34.9–48.1 µg/m^3 and 38.8–60.6 µg/m^3, respectively. This indicates moderate to harmful air quality (as suggested by the model based on field data) and harmful to unsafe (as suggested by the model based on remotely sensed data). Although both models differed slightly in the predicted values, the air quality seems to be within an unsafe and non-standard safety level, as mentioned in [44,45].

The model in Figure 5a had a low maximum accuracy of 51% obtained by field data fitting. However, increasing the sampling can potentially increase the accuracy. On the other hand, the fitting for the model based on remotely sensed data had a maximum accuracy of 82%. This study tried to attain, at least, a minimum correlation of the noise in the PM2.5 prediction.

The geospatial analysis by GIS technology is one of the important and effective methods for determining emissions of pollutants into the air. At the heart of statistical processes, the regression and estimation models are decision-making tools [46].

This study also looked at noise pollution. Environmental noise in Tikrit University was measured and then compared with the recommended health standards from WHO. Figure 4 shows that overall maximum noise levels ranged from 53.20 to 85.79 dB, while minimum noise levels were from 49.30 to 75.09 dB. Note that the WHO guidelines state that noise pollution occurs when levels are above 65 dB [15]. Moreover, according to [47], silent zones should not exceed 45 dB. Based on these standards, the results clearly show that the University of Tikrit is categorized as *noisy*, which is opposite to what a university should be (i.e., a silent zone). Based on conclusions derived from [48,49], university noise levels should be within 35–45 dB. Our findings are crucial as high nose levels can cause non-auditory impacts on students, lecturers, and others alike [50]. Moreover, this can lead to attention deficits and impaired learning and communication [51]. The overall outcomes on noise pollution in different areas of Tikrit University indicate that noise levels were high in the different sampling locations. We posit that this was due to the relevant surrounding activities involved, large number of motor vehicles, and the existence of generators.

5. Conclusions

Undoubtedly, air and noise pollution have harmful effects on human health. However, they are unavoidable environmental elements in most urban settings. Researchers are now actively measuring and analyzing both pollutions to gain insight on the causes, as well as to possibly propose solutions where possible. Remotely sensed information and distribution maps can be useful tools for such tasks.

In this paper, air (PM2.5 particulate matter) and noise pollutions are investigated. Specifically, two multiple linear prediction models are generated based on PM2.5 particulate matter measurements and environmental variables (i.e., humidity, temperature, maximum noise, and minimum noise). This study applied the IDW technique and regression analysis based on field measurements and remotely sensed data. Both trained regression models indicate that the PM2.5 particulate and noise pollutions are at undesirable levels in Tikrit University, which could lead to negative consequences if not mitigated. Moreover, and worryingly, this study designated the university as a noisy zone, rather than its supposed designation of being a silent zone.

In terms of the generated linear models, the remotely sensed data-based model had a higher validation accuracy at 82%. Furthermore, model testing showed a 94% accuracy. However, the final prediction values did not differ significantly from the field data-model (at 51% accuracy and 91% testing accuracy).

In conclusion, we believe that mitigative measures can be taken to decrease noise pollutions through planting more trees on both sides of the roads, proper maintenance of the roads, and ensuring that road pavement is based on standard specifications. Moreover, the electrical generators can be covered by silencers to further reduce noise.

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References

1. Bolaño-Truyol, J.; Schneider, I.L.; Cuadro, H.C.; Bolaño-Truyol, J.D.; Oliveira, M.L.S. Estimation of the impact of biomass burning based on regional transport of PM2.5 in the Colombian Caribbean. *Geosci. Front.* **2021**, 101152, in press. [CrossRef]
2. Somvanshi, S.S.; Vashisht, A.; Chandra, U.; Kaushik, G. Delhi Air Pollution Modeling Using Remote Sensing Technique. *Handb. Environ. Mater. Manag.* **2019**, 1–27. [CrossRef]
3. Duarte, A.L.; Schneider, I.L.; Artaxo, P.; Oliveira, M.L.S. Spatiotemporal assessment of particulate matter (PM10 and PM2.5) and ozone in a Caribbean urban coastal city. *Geosci. Front.* **2021**, 101168, in press. [CrossRef]
4. Jumaah, H.J.; Ameen, M.H.; Kalantar, B.; Rizeei, H.M.; Jumaah, S.J. Air quality index prediction using IDW geostatistical technique and OLS-based GIS technique in Kuala Lumpur, Malaysia. *Geomat. Nat. Hazards Risk* **2019**, *10*, 2185–2199. [CrossRef]
5. Huang, K.; Bi, J.; Meng, X.; Geng, G.; Lyapustin, A.; Lane, K.J.; Gu, D.; Kinney, P.L.; Liu, Y. Estimating daily PM2.5 concentrations in New York City at the neighborhood-scale: Implications for integrating non-regulatory measurements. *Sci. Total Environ.* **2019**, *697*, 134094. [CrossRef] [PubMed]
6. Huang, G.; Brown, P.E. Since January 2020 Elsevier Has Created a COVID-19 Resource Centre with Free Information in English and Mandarin on the Novel Coronavirus COVID-19. The COVID-19 Resource Centre Is Hosted on Elsesvier Connect, the Company's Public News and Information. Available online: https://www.google.com.hk/url?sa=t&rct=j&q=&esrc=s&source=web&cd=&ved=2ahUKEwiykMzcncvyAhUFCqYKHRZNA5AQFnoECAMQAQ&url=https%3A%2F%2Fstacks.cdc.gov%2Fview%2Fcdc%2F87050%2Fcdc_87050_DS1.pdf&usg=AOvVaw0Hl4VYJGwTsEXCu9XpbWI7 (accessed on 20 August 2021).
7. Yi, X.; Zhang, J.; Wang, Z.; Li, T.; Zheng, Y. Deep distributed fusion network for air quality prediction. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, London, UK, 19–23 August 2018; pp. 965–973. [CrossRef]
8. Luo, H.; Guan, Q.; Lin, J.; Wang, Q.; Yang, L.; Tan, Z.; Wang, N. Air pollution characteristics and human health risks in key cities of northwest China. *J. Environ. Manag.* **2020**, *269*, 110791. [CrossRef] [PubMed]
9. Patel, C.J.; Kerr, J.; Thomas, D.C.; Mukherjee, B.; Ritz, B.; Chatterjee, N.; Amos, C.I. Opportunities and challenges for environmental exposure assessment in population-based studies. *Cancer Epidemiol. Prev. Biomark.* **2017**, *26*, 1370–1380. [CrossRef] [PubMed]
10. Jumaah, H.J.; Mansor, S.; Pradhan, B.; Adam, S.N. UAV-based PM2.5 Monitoring for Small-scale Urban Areas. Available online: https://www.researchgate.net/publication/333378629_UAVbasedPM25monitoring_forsmall-scaleurbanareas (accessed on 20 August 2021).
11. Zhao, C.; Wang, Q.; Ban, J.; Liu, Z.; Zhang, Y.; Ma, R.; Li, S.; Li, T. Estimating the daily PM2.5 concentration in the Beijing-Tianjin-Hebei region using a random forest model with a $0.01° \times 0.01°$ spatial resolution. *Environ. Int.* **2020**, *134*, 105297. [CrossRef] [PubMed]
12. Hsu, Y.-C.; Chang, S.-H.; Chang, M.B. Efficacy of the novel continuous sampling system for PCDD/Fs and unintentional persistent organic pollutants. *Chemosphere* **2020**, *243*, 125443. [CrossRef] [PubMed]
13. Pérez, P.; Trier, A.; Reyes, J. Prediction of PM2.5 concentrations several hours in advance using neural networks in Santiago, Chile. *Atmos. Environ.* **2000**, *34*, 1189–1196. [CrossRef]
14. Chowdhury, A.K.; Debsarkar, A.; Chakrabarty, S. Novel methods for assessing urban air quality: Combined air and noise pollution approach. *J. Atmos. Pollut.* **2015**, *3*, 1–8.
15. Singh, D.; Kumar, A.; Kumar, K.; Singh, B.; Mina, U.; Singh, B.B.; Jain, V.K. Statistical modeling of O3, NOx, CO, PM2.5, VOCs and noise levels in commercial complex and associated health risk assessment in an academic institution. *Sci. Total Environ.* **2016**, *572*, 586–594. [CrossRef] [PubMed]
16. Munir, S.; Khan, S.; Nazneen, S.; Ahmad, S.S. Temporal and seasonal variations of noise pollution in urban zones: A case study in Pakistan. *Environ. Sci. Pollut. Res.* **2021**, *28*, 29581–29589. [CrossRef] [PubMed]
17. Chandrappa, R.; Das, D.B. Noise Pollution. In *Environmental Health-theory and Practice*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 141–148.
18. Ozyavuz, M.; Sisman, E.E. Determination of traffic noise pollution of the city of tekirdag. *J. Environ. Prot. Ecol.* **2017**, *17*, 1276–1284.
19. Wang, L.K.; Pereira, N.C.; Hung, Y.-T. *Advanced Air and Noise Pollution Control*; Springer: Berlin/Heidelberg, Germany, 2005; ISBN 1592597793.
20. Murphy, E.; King, E. *Environmental Noise Pollution: Noise Mapping, Public Health, and Policy*; Newnes: London, UK, 2014; ISBN 0124116140.
21. Bello, J.P.; Silva, C.; Nov, O.; Dubois, R.L.; Arora, A.; Salamon, J.; Mydlarz, C.; Doraiswamy, H. Sonyc. *Commun. ACM* **2019**, *62*, 68–77. [CrossRef]
22. Di, H.; Liu, X.; Zhang, J.; Tong, Z.; Ji, M.; Li, F.; Feng, T.; Ma, Q. Estimation of the quality of an urban acoustic environment based on traffic noise evaluation models. *Appl. Acoust.* **2018**, *141*, 115–124. [CrossRef]
23. Lagonigro, R.; Martori, J.C.; Apparicio, P. Environmental noise inequity in the city of Barcelona. *Transp. Res. Part D Transp. Environ.* **2018**, *63*, 309–319. [CrossRef]
24. Yang, W.; Park, J.; Cho, M.; Lee, C.; Lee, J.; Lee, C. Environmental health surveillance system for a population using advanced exposure assessment. *Toxics* **2020**, *8*, 74. [CrossRef]
25. Harman, B.I.; Koseoglu, H.; Yigit, C.O. Performance evaluation of IDW, Kriging and multiquadric interpolation methods in producing noise mapping: A case study at the city of Isparta, Turkey. *Appl. Acoust.* **2016**, *112*, 147–157. [CrossRef]

26. Ikechukwu, M.N.; Ebinne, E.; Idorenyin, U.; Raphael, N.I. Accuracy Assessment and Comparative Analysis of IDW, Spline and Kriging in Spatial Interpolation of Landform (Topography): An Experimental Study. *J. Geogr. Inf. Syst.* **2017**, *9*, 354–371. [CrossRef]
27. Fedra, K. GIS and Environmental Modeling. *Environ. Model. GIS* **1993**, 35–50. Available online: http://pure.iiasa.ac.at/id/eprint/3730/1/RR-94-02.pdf (accessed on 20 August 2021).
28. Fedra, K. Urban environmental management: Monitoring, GIS, and modeling. *Comput. Environ. Urban Syst.* **1999**, *23*, 443–457. [CrossRef]
29. Kalantar, B.; Ueda, N.; Al-Najjar, H.A.H.; Moayedi, H.; Halin, A.A.; Mansor, S. Uav and lidar image registration: A surf-based approach for ground control points selection. In Proceedings of the International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences—ISPRS Archives, Enschede, The Netherlands, 10–14 June 2019; Volume 42.
30. Ajaj, Q.M.; Shareef, M.A.; Hassan, N.D.; Noori, A.M.; Hasan, S.F. GIS based spatial modeling to mapping and estimation relative risk of different diseases using inverse distance weighting (IDW) interpolation algorithm and evidential belief function (EBF)(Case study: Minor Part of Kirkuk City, Iraq). *Int. J. Eng. Technol.* **2018**, *7*, 185–191. [CrossRef]
31. Kalantar, B.; Ameen, M.H.; Jumaah, H.J.; Jumaah, S.J.; Halin, A.A. Zab River (IRAQ) Sinuosity and Meandering Analysis Based on the Remote Sensing Data. Available online: https://www.researchgate.net/publication/343799487_ZAB_RIVER_IRAQ_SINUOSITY_AND_MEANDERING_ANALYSIS_BASED_ON_THE_REMOTE_SENSING_DATA (accessed on 20 August 2021).
32. Al-Najjar, H.A.H.; Kalantar, B.; Pradhan, B.; Saeidi, V.; Halin, A.A.; Ueda, N.; Mansor, S. Land cover classification from fused DSM and UAV images using convolutional neural networks. *Remote Sens.* **2019**, *11*, 1461. [CrossRef]
33. Jebur, A.K. Uses and Applications of Geographic Information Systems. *Saudi J. Civ. Eng.* **2021**, *5*, 18–25. [CrossRef]
34. Sarkar, M.; Das, A.; Mukhopadhyay, S. Assessing the immediate impact of COVID-19 lockdown on the air quality of Kolkata and Howrah, West Bengal, India. *Environ. Dev. Sustain.* **2021**, *23*, 8613–8642. [CrossRef]
35. Stillwell, J.; Clarke, G. *Applied GIS and Spatial Analysis*; Wiley: Hoboken, NJ, USA, 2006; ISBN 9780470871331.
36. Hossain, E.; Shariff, M.A.U.; Hossain, M.S.; Andersson, K. A novel deep learning approach to predict air quality index. *Adv. Intell. Syst. Comput.* **2021**, *1309*, 367–381. [CrossRef]
37. Hadi, S.J.; Shafri, H.Z.M.; Mahir, M.D. Factors Affecting the Eco-Environment Identification Through Change Detection Analysis by Using Remote Sensing and GIS: A Case Study of Tikrit, Iraq. *Arab. J. Sci. Eng.* **2014**, *39*, 395–405. [CrossRef]
38. Li, T.; Zhou, X.C.; Ikhumhen, H.O.; Difei, A. Research on the optimization of air quality monitoring station layout based on spatial grid statistical analysis method. *Environ. Technol.* **2018**, *39*, 1271–1283. [CrossRef] [PubMed]
39. Brook, R.J.; Arnold, G.C. *Applied Regression Analysis and Experimental Design*; CRC Press: Boca Raton, FL, USA, 2018; ISBN 1351465899.
40. Cook, R.D.; Weisberg, S. Criticism and influence analysis in regression. *Sociol. Methodol.* **1982**, *13*, 313–361. [CrossRef]
41. Weisberg, S. *Applied Linear Regression*; John Wiley & Sons: Hoboken, NJ, USA, 2005; Volume 528, ISBN 0471704083.
42. Sen, A.; Srivastava, M. *Regression Analysis: Theory, Methods, and Applications*; Springer Science & Business Media: Berlin/Heidelberg, Germany, 2012; ISBN 1461244706.
43. Shareef, M.A.; Toumi, A.; Khenchaf, A. Prediction of water quality parameters from SAR images by using multivariate and texture analysis models. *SAR Image Anal. Model. Tech. XIV* **2014**, *9243*, 924319. [CrossRef]
44. Al-jarakh, T.E.; Hussein, O.A.; Al-azzawi, A.K.; Mosleh, M.F. Design and implementation of IoT based environment pollution monitoring system: A case study of Iraq. *IOP Conf. Ser. Mater. Sci. Eng.* **2021**, *1105*, 012037. [CrossRef]
45. Hamed, H.H.; Jumaah, H.J.; Kalantar, B.; Ueda, N.; Saeidi, V.; Mansor, S.; Khalaf, Z.A. Predicting PM2.5 levels over the north of Iraq using regression analysis and geographical information system (GIS) techniques. *Geomat. Nat. Hazards Risk* **2021**, *12*, 1778–1796. [CrossRef]
46. Caraka, R.E.; Yusra, Y.; Toharudin, T.; Chen, R.C.; Basyuni, M.; Juned, V.; Gio, P.U.; Pardamean, B. Did Noise Pollution Really Improve during COVID-19? Evidence from Taiwan. *Sustainability* **2021**, *13*, 5946. [CrossRef]
47. Chauhan, A.; Pawar, M.; Kumar, D.; Kumar, N.; Kumar, R. Assessment of Noise Level Status in Different Areas of Moradabad City. *Researcher* **2010**, *2*, 88–90.
48. Mahmoud, R.M.; Abbas, A.H.; Yaseen, R.H. Assessment of Noise Pollution and Architectural Solutions for The Colleges and Universities. *AUS* **2019**, *26*, 445–453.
49. Al-Samarrie, M.S.; Mohanad, F.; Salman, A.H. A Study of some Noise Pollution Variables in Sport Halls and Classrooms for College of Sport Education–Tikrit University–Iraq. *Int. J. Adv. Sport Sci. Res.* **2014**, *2*, 417–428.
50. Chijioke, A.M.; Mathias, U.U.; Nwokolo, V.I.; George, I.C. Noise in a Nigerian University. *J. Environ. Pollut. Hum. Health* **2019**, *7*, 53–61. [CrossRef]
51. Ibrahim, S.A. Study Noise Effects on The Students of The Faculty of Engineering/Mustansiriyah University. *Al-Nahrain J. Eng. Sci.* **2018**, *21*, 178–186.

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Did Haze Pollution Harm the Quality of Economic Development?—An Empirical Study Based on China's PM2.5 Concentrations

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Abstract: Based on the PM2.5 haze data of China's provinces between 2004–2016, this paper systematically explores the impact of haze pollution on the quality of China's economic development, as well as its transmission mechanisms. This is achieved by measuring the quality of economic development with total factor productivity. Furthermore, this paper innovatively uses precipitation as an instrumental variable for mitigating the endogeneity of the haze pollution variable, by which the impact of haze pollution on the quality of China's economic development is estimated within the framework of two-stage least squares. It is found that: the haze pollution has degraded the quality of China's economic development significantly; the labor supply loss, counter urbanization and human capital disruption are the three major transmission channels through which haze pollution affects the quality of China's economic development; strengthening government's environmental management is effective in mitigating the adverse impact of haze pollution on the economic development quality; and that China's unique fiscal decentralization system has exacerbated the negative economic effect of haze pollution. The policy implications of this paper are as follows: Improvement of economic development quality is a prerequisite for the transition of economic development mode; and the governmental management of haze is conducive to enhancing the quality of atmospheric environment and economic development, and to promoting the high-quality development of the Chinese economy.

Keywords: haze pollution; economic development quality; environmental management; PM2.5 concentration

1. Introduction

Since the reform and opening up policies were implemented, China's economy has grown continuously at a high pace for many years, with its economic aggregate leaping up to become the world's second largest. In terms of per capita income, China has also been ranked as a middle- and high-income economy. Nevertheless, the extensive rapid growth over the years and the traditional idea of GDP predominance have also led to a series of problems in China's economic growth, such as input factor wastage, low economic efficiency and severe environmental pollution. In particular, the quality of atmospheric environment has declined, and the occurrence of haze has become frequent. In 2013, the "haze from all sides" spread to more than 100 large- and medium-sized cities in 25 provinces, which has threatened people's daily lives severely. In the 2018 Global Environmental Performance Index rankings, China ranked 120th among 180 countries and regions. What is worse, the air quality indicator for China ranked fourth from the bottom. In the meantime, China's economic growth rate has fallen to around 6% since 2012, signaling a transition towards a stage of high-quality development. Consequently, the conflicts between economic growth and environment have become ever more complicated and fiercer. The severe haze pollution is the red flag raised by nature towards the extensive growth mode that has been utilized. The only way of improving the environment and enhancing the quality of economic development is to thoroughly manage various forms of environmental pollution like haze. Its significance not only lies in the haze itself, but is also linked to the fundamental transformation of the economic development mode and sustainable high-quality development in China. This paper attempts to answer the following key questions that have not yet been well answered: Did China's aggravating haze pollution harm the quality of its economic development, and what is the mechanism behind it? Can a win-win be achieved for environmental and economic dividends? Beyond doubt, the answers to these questions are of profound theoretical and practical significance for China to achieve the sustainable development path of 'valuing both the economy and the environment'.

Concerning the relationship between economic development and environmental pollution, the majority of extant literatures have focused on the unidirectional relationship of how economic development affects environmental pollution by using the Environmental Kuznets Curve (EKC) model as the main framework, while the reverse impact of environmental pollution on economic development has scarcely been studied [1–5]. As a matter of fact, economic growth and the environment constitute a large interactive system, so it is possible that the environmental degradation affects economic growth as well. Lopez [6] regarded the environment as an important factor for production input. According to the *Report on Losses from Environmental Pollution in China* released by the World Bank in 2007, the losses arising from air and water pollution in China were equivalent to 5.8% of its actual GDP that year. An empirical study covering 59 countries by Despina Giannadakia et al. [7] revealed that cutting agricultural emissions by 50% each year could reduce 200,000 deaths, especially in Europe, Russia, Turkey, the United States, Canada and China. This was accompanied by billions of dollars in economic benefits. The research on the economic consequences of environmental pollution has concentrated on the impact of pollution on residents' health [8,9]. In contrast, there are few literature articles on the impact of environmental pollution on economic development, and those on the impact of haze pollution on economic development are even more scarce [10]. According to Zhang et al. [11], haze pollution produces a tremendous negative impact on stock returns through the emotional channels of investors. A static model-based estimation by Jibo et al. [12] showed that the indirect economic losses caused by haze pollution in Beijing to the transportation sector amounted up to 23.7 million yuan in 2013. In light of this, the present paper carries out a systematic empirical investigation around the impact of haze pollution on the economic development quality and its relevant mechanism based on the provincial panel data of China between 2004–2016. This is achieved by taking the total factor productivity as a measure of economic development quality, and by characterizing the degree of haze pollution with satellite-monitored PM2.5 concentrations. To be specific, the marginal contribution of this paper is reflected in the following three aspects: First of all, unlike most research which examined the impact of economic development on haze pollution, this paper systematically studies the impact of haze pollution on China's economic development, and reveals the importance of environmental surveillance and management, thereby offering an empirical evidence for local governments who seek a win-win between environmental protection and economic growth. Secondly, a major challenge in exploring the impact of haze pollution on China's economic development is endogeneity. In rainy and snowy weathers, haze pollution tends to decline prominently. Meanwhile, both the rainfall and snowfall are determined by meteorological system and are well exogenous. Accordingly, this paper innovatively uses the annual precipitation converted by rain and snow as an instrumental variable of haze pollution, in order to mitigate the potential endogeneity problem. Thirdly, despite the discussion on the extent of harm caused by air pollution to the economic development, Yu Hao [10] failed to analyze the specific path via which the haze pollution harmed the quality of economic development. After a review of extant literature, this paper puts forward that the air pollution affects economic development mainly through the "labor supply loss effect", "counter urbanization effect" and "human capital disruption effect", thereby enriching the theoretical literature on the economic consequences of environmental pollution.

The reminder of this paper is organized as follows: Section 2 reviews the literature and proposes research hypotheses; Section 3 presents the econometric models and relevant variables; Section 4 analyzes the empirical results; and Section 5 summarizes research conclusions and policy recommendations.

2. Literature Review and Hypothesis Formulation

Unregulated pollutant emissions affect the economic growth in two ways. One way is to give play to the natural environment's role of absorbing and depositing wastes. Where other input factors are given, the economic establishments can increase their output level through depletion of the natural environment, thereby bringing about an overall positive impact on economic growth. The problem is that although individual economic establishments can improve their output by increasing pollutant emissions, the ongoing accumulation of emissions will reduce the environmental carrying capacity of the entire society continuously, as well as the quality of the natural environment. This will eventually bring about negative externalities to the output or quality of various economic establishments, and even the macroeconomy. The ultimate impact of such unregulated pollutant emissions on economic development depends on the relative changes between positive and negative effects. Specific to haze pollution, its negative impact on economic development has been discussed in the extant literature covering at least three aspects. Firstly, air pollution harms the health of individuals and lowers the supply of labor. Secondly, haze pollution reduces the attractiveness of cities significantly, thereby limiting the effective exertion of the urban agglomeration effect and ultimately slowing down economic development [13]. Thirdly, haze pollution damages the accumulation of human capital, which is one of the foremost drivers of economic development. Thus, clearly, haze pollution can also suppress economic development by slowing down human capital accumulation [14]. In view of this, this paper analyzes the specific transmission mechanisms whereby haze pollution affects China's economic development quality from the perspectives of labor supply, urbanization and human capital.

2.1. Air Pollution and Loss of Labor Supply

Air pollution has been proven by extensive pathological and sociological studies to have a variety of negative effects on human health, such as shortening average life expectancy [15], increasing morbidities of respiratory diseases and lung cancer [16] as well as causing more premature deaths amongst the working population [17–19]. Therefore, air pollution may reduce the supply of labor by harming human health. As early as in 1983, Bart conducted a quantitative research on relevant U.S. data by employing the ordinary least squares model. He claimed that for every 10% increase in total suspended particulates in the air, the number of lost labor days increased by 4.4%. Utilizing the same data by controlling the inter-city differences, Hausman et al. [20] reported that the number of lost labor days increased by 0.1 for each standard deviation of particulate pollutants. Based on the observation of the external pollution variation resulting from the shutdown of a large Mexican oil refinery, Hanna and Oliva [21] calculated the SO_2 levels as the pollutant. They concluded that the closure of the refinery has led to a pollution reduction in the surrounding communities by 19.7%, as well as an increase of weekly working time by 1.3 h (3.5%). Bosi [22] studied the short- and long-term effects of pollution in the Ramsey model. They determined the sufficient conditions for the existence and uniqueness of long-term equilibrium based on an argument that the "pollution and labor supply are inseparable in household preferences". Furthermore, through the flip branch research model, they proved that a tremendous negative impact of pollution on labor supply would cause macroeconomic fluctuations, thereby providing a theoretical basis for the eco-friendly fiscal policies. Carson et al. [23] found from a survey of 4259 households made by the Bangladesh Bureau of Statistics in 2000 that in rural areas with severe arsenic exposure, the labor supply level was 7.9% lower than that in non-exposed areas. Aside from damaging the health of laborers themselves, the long-term exposure to severe air pollution may also compel the adult laborers to spend more time caring for infected children and elders, thereby resulting in an increased absenteeism and shortened working hours. Kim et al. [24] studied the medium- and long-term effects of air pollution on labor supply based on a natural experiment of the 1997 Indonesian forest fires. They found that the exposure to air pollution shortened the working hours of laborers, and that the parents with children were more prone to working hour reductions during severe pollution incidents. In addition, the medium- and long-term effects of pollution were more drastic. Hence, haze pollution may reduce the labor supply in heavily polluted areas, thereby endangering the quality of economic development.

2.2. Air Pollution and Counter Urbanization

Tending to benefits and avoiding harms are an instinctual stress response of living organisms. During the 1960s and 1970s, severe haze pollution broke out in the Los Angeles area of California, United States. After the 1970s, the state government decided to implement a haze removal plan, which resulted in a significant increase in population with the reduction of haze, especially in the underprivileged districts. On the one hand, the settlement of haze problem enhanced people's residential willingness remarkably, thereby lowering the population outflow rate. On the other hand, the demand for labor increased, and the number of immigrants grew accordingly, so that the area turned from a population outflow region into an inflow region. This implies that people can avoid harsh living environments through migration. With continuous intensification of urban environmental pollution, some susceptible people in poor physical conditions have chosen to leave the heavily polluted cities, since they were worried about the pollution-induced health damage. Chen et al. [25] examined the migration effect of air pollution from an emigration place perspective. Based on the China census sampling data, they calculated the population emigration rate at the county level, who found that the air pollution promoted the outflow of population. A research based on city-level data by Qin and Zhu [26] confirmed that the frequency of people searching for immigration via the Internet was elevated during periods of exacerbated air pollution. Unlike the foregoing studies which were from the perspective of emigration to another place, Kahn [27] investigated the impact of air quality on population growth by utilizing the California county-level sample data. They found that the improvement of air quality led to a substantial regional inflow of immigrants, as well as a rapid growth of population. Urbanization, as a major force driving the improvement of economic quality, has effectively reduced the surplus rural labor, thereby providing sufficient labor for the development of manufacturing and service industries while enhancing the efficiency of agricultural production, which has ultimately driven the overall economy forward. Haze pollution, however, has lowered the attractiveness of cities. As a result, the migrants' willingness to stay declined, which further limited the effect of increasing returns to urban scale and the agglomeration effect, ultimately slowing down economic development [13].

2.3. Air Pollution and Human Capital Disruption

Air pollution increases the probability of labor migration, and when making migration decisions, highly qualified laborers are more sensitive to air pollution. This is attributable to the wider choices and job alternatives offered to these laborers. So they can bear the economic consequences of leaving the workplace temporarily or reducing working hours when faced with the dangers of air pollution. In contrast, low-quality laborers have a lower human capital reserve, which reduces the flexibility of their work choices. Therefore, they will not easily quit existing jobs even in the face of severe air pollution. Cole et al. [14] found that the high-skilled employees had a stronger ability to avoid air pollution, who were capable of bearing the corresponding switching costs, and were more inclined to work in the low polluted industries or regions. As a result, highly polluted cities can hardly retain high-skilled employees. In fact, some companies already tried to prevent the outflow of employees by increasing their medical insurance expenses and paying additional "welfare subsidies" for air pollution [28]. Additionally, air pollution damages the health of individuals, which traps them into negative emotions to weaken their creativity and work motivation, thereby reducing the output capacity of human capital. Targeting the Chinese manufacturing firms between 1998–2007, Fu et al. [29]

estimated the impact of air pollution on the corporate output per capita by using the IV method. Furthermore, they explained the mechanism whereby air pollution suppressed the corporate output per capita from the perspective of internal production relationships. Human capital is one of foremost factors promoting the improvement of economic quality, especially with the consideration that the economic development has fully entered the era of the knowledge economy. Haze pollution may be notably detrimental to the accumulation of local human capital.

Based on the above analyses, this paper proposes that the haze pollution hinders the sustainable development of economy through the "labor supply loss effect", "counter urbanization effect" and "human capital disruption effect".

3. Model Building and Indicator Selection

To investigate the impact of haze pollution on the quality of China's economic development, this paper builds the following benchmark regression model:

$$TFP_{it} = a_0 + a_1 PM2.5_{it} + a_2 Density_{it} + a_3 FDI_{it} + a_4 Innov_{it} + a_5 Indus_{it} + \gamma_i + \mu_t + \varepsilon_{it}. \quad (1)$$

3.1. Dependent Variable

Where TFP stands for total factor productivity of economy, and is used for measuring the quality of economic growth. The core of economic growth quality is efficiency. The economic total factor productivity has been recognized universally as a proxy variable. Organizations like the World Bank and the OECD have also listed total factor productivity as a crucial referential indicator for studying the quality of China's economic growth. Based on the DEA-Malmquist index model, we calculated the economic total factor productivities (TFPs) of various provinces over the studied years using DEAP 2.1. In this paper, the capital (unit: 100 million yuan), labor (unit: 10,000 people) and total energy consumption (unit: 10,000 tons of standard coal) were selected as the input variables. Meanwhile, the regional total output value (unit: 100 million yuan) was chosen as the desirable output; and the total discharge of industrial waste water (unit: 10,000 tons), total discharge of industrial waste gas (unit: 100 million cubic meters) and generation of industrial solid waste (unit: 10,000 tons) were used as the undesirable outputs.

3.2. Core Explanatory Variable

$PM2.5_{it}$ denotes the PM2.5 concentration of a certain province i in the year t, which was used for measuring the level of haze pollution. As its coefficient a_1 measures the impact of haze pollution on the economic development quality, it is the kernel parameter of concern in this paper. After controlling a series of regional characteristic variables, if a_1 remains significantly negative, it indicates that the haze pollution will degrade the quality of economic development, and vice versa. In addition, this paper also controls the regional and temporal fixed effects, in order to further alleviate the biases of missing variables. Finally, ε_{it} represents the error term. Regarding the haze pollution data, unlike the conventional haze pollutants like SO_2, CO_2, CO, TSP, API and PM10 used in the majority of the literature, this paper selects PM2.5 for empirical research, which is the culprit for haze pollution that is attracting the most attention from all sectors of society. This not only supplements the existing literature, but also contributes to the current policy discussions on haze pollution.

3.3. Control Variables

With reference to the extant literature, this paper also adopts four control variables in the benchmark regression model, namely the foreign direct investment (FDI), industrial structure (Indus), technological innovation (Innov) and population density (Density), so as to alleviate the biases of missing variables as much as possible. The level of FDI in a region affects its green TFP, and the primary reasons include the "pollution haven" hypothesis [30] and the opposite view of the "pollution halo" hypothesis [31]. Thus, the variable should be considered in the model. Indus is a comprehensive influencing factor of TFP proposed by reference [32], which can reflect the industrial layout. In this paper, Indus is calculated in terms of the output value of secondary industry in proportion to GDP. The higher the proportion of secondary industry, the more severe the pollution it brings, which will adversely affect the TFP. Presumably, Indus is negatively correlated with TFP. In addition, factors like Density and Innov are also common variables in the literature [33,34]. In this paper, Density is measured by the number of people per unit area, while Innov is calculated by the number of patents per capita. We presume that Innov is positively correlated with TFP. Meanwhile, a higher Density means there is a greater pressure imposed on the environment. Presumably, this variable is negatively correlated with TFP. Table 1 presents descriptions statistics for the main variables.

Table 1. Descriptive Statistics of Variables.

Variable	Min	Max	Mean	SD
TFP	0.500	2.249	1.095	0.296
PM2.5	4.8	82.67	32.122	16.843
Density	0.040	1.288	0.483	0.266
FDI	0.008	0.263	0.483	0.266
Innov	2.654	383.68	42.099	51.350
Indus	0.240	2.022	1.203	0.337

In analyzing how the haze pollution affects the quality of economic development through the transmission mechanisms, the endogeneity of haze pollution is not a serious issue. During direct analysis of the impact of haze pollution on the economic development quality based on the above benchmark model, however, the endogeneity of haze pollution variables becomes an inevitable issue to discuss. Specifically, on the one hand, environmental pollution may drag down the quality of economic development through channels like the "labor supply loss effect", "counter urbanization effect" and "human capital disruption effect". On the other hand, the quality of economic development itself also affects environmental pollution through the scale effect, technology effect and structure effect. An effective way of alleviating the aforementioned endogeneity problem is to find the appropriate instrumental variables for haze pollution, which is the core explanatory variable. The sought instrumental variables must be highly correlated with the endogenous variable (PM2.5 concentration), while not directly relevant to the explained variable (economic development quality). Precipitation can be used as an instrumental variable for haze pollution because on the one hand, a larger value of precipitation indicates more local rainwater. In the rainy and snowy weathers, air pollution tends to decline remarkably, which is negatively correlated with haze pollution, thus satisfying the correlation hypothesis of valid instrumental variables [35]. On the other hand, precipitation is affected by rainfall and snowfall, both of which are determined by complex meteorological systems and geographical conditions, thereby satisfying the exogeneity hypothesis of valid instrumental variables [36].

In summary, to quantitatively explore the impact of air pollution on the economic development quality, the two-stage least squares (2SLS) regression model in this paper is defined as follows:

$$\mathrm{PM2.5}_{it} = \beta_0 + \beta_1 \mathrm{Rainfall}_{it} + \gamma_i + \mu_t + \varepsilon_{it} \tag{2}$$

$$\mathrm{TFP}_{it} = y_0 + y_1 \mathrm{PM2.5}_{it} + y_2 \mathrm{Density}_{it} + y_3 \mathrm{FDI}_{it} + y_4 \mathrm{Innov}_{it} + y_5 \mathrm{Indus}_{it} + \gamma_i + \mu_t + \varepsilon_{it} \tag{3}$$

where $\mathrm{Rainfall}_{it}$ represents the annual rainfall of a certain province i in the year t. In the 2SLS model, it is an instrumental variable of PM2.5 concentration, the haze pollution variable. All the other variables are identical to those used in the benchmark model Formula (1).

In this paper, the panel data from 30 provinces, autonomous regions and municipalities (Tibetan region is excluded due to severe data missing) of China between 2004–2016 are utilized. Regarding haze pollution, we used the satellite raster data of global average PM concentration published by the Socioeconomic Data and Applications Center of Columbia University by referring to Van's methodology [37]. With the aid of ArcGIS software, the above data were analyzed into the average annual concentration of surface PM2.5 for China's 30 province-level administrative regions from 2004 to 2016. The rest of the raw data were from the *China Statistical Yearbooks*, *China Environmental Statistics Yearbooks*, the official websites of National Bureau of Statistics and the provincial, municipal statistics bureaus, as well as the GTA CSMAR database. All the value variables in this paper are processed for to account for inflation with 2004 as the base year.

4. Analyses of Empirical Results

4.1. Benchmark Regression

The columns (1), (2) in Table 2 present the fixed effect estimations for the designed model. The use of panel data fixed effect model is based primarily on the following two aspects: On the one hand, since the chi-square value in Hausman test report is 45.324, and its corresponding P value is 0.000, the random effect model is rejected; on the other hand, the random effect assumes that the individual fixed effect term is irrelevant to the explanatory variables, which often hardly holds in practice. According to the results in column 1, haze pollution is significantly negatively correlated with the quality of regional economic development. The results in column 2, after controlling a series of regional characteristic variables, still show a significant negative correlation of haze pollution with the quality of regional economic development. Considering that the economic development mode affects both the quality of economic development and the haze pollution, especially that the imbalance of industrial structure is a major reason for the intensification of haze pollution in China, failure to control these factors effectively may lead to biases of missing variables, which in turn affects the reliability of research results. In column 3, the proportion of secondary production is added, in order to control the impact of industrial structure. Its results demonstrate that a significant negative correlation remains between the haze pollution and the urban economic development quality.

Table 2. The impact of haze pollution on the quality of economic development.

	(1)	(2)	(3)	(4)	(5)	(6)
		Fixed Effect			2SLS	
	TFP	TFP	TFP	PM2.5 Stage One	TFP Stage Two	TFP
PM2.5	−0.006 **	−0.005 **	−0.005 **		−0.050 ***	−0.545
	(−2.58)	(−2.28)	(−2.45)		(−2.61)	(−1.23)
$PM2.5^2$						0.007
						(1.12)
Rainfall				−1.974 **		
				(−2.40)		
Density		−0.0401	−0.0960		−0.152	−0.160
		(−0.32)	(−0.77)		(−1.23)	(−1.29)
FDI		−1.381 ***	−1.263 ***		−1.311 ***	−1.381 ***
		(−2.83)	(−2.63)		(−2.73)	(−2.85)
Innov		0.008 ***	0.005 **		0.005 **	0.005 **
		(3.67)	(2.52)		(2.56)	(2.43)
Indus			−0.162 ***		−0.145 ***	−0.143 ***
			(−3.59)		(−3.20)	(−3.17)
_cons	1.301 ***	1.335 ***	1.571 ***	45.22 ***	3.003 ***	11.02
	(16.19)	(13.47)	(13.36)	(8.28)	(4.81)	(1.53)
R^2	0.0182	0.0752	0.1076	0.0158	0.1095	0.1126
N	390	390	390	390	390	390

t statistics in parentheses, ** $p < 0.05$, *** $p < 0.01$.

Columns (4) to (6) in Table 2 display the estimation results with the two-stage least squares (2SLS), since the endogeneity problem of haze pollution to TFP is taken into consideration. In this regard, the instrumental variables are subjected to rationality tests, including the underidentification test and the weak instrumental variable test. Initially, according to the LM statistic of 6.357 in the underidentification test, and its corresponding p value of 0.0117, the hypothesis of non-correlation between instrumental and endogenous variables can be rejected at the 5% level. Next, the selected instrumental variables are tested for weak variables. The reported Cragg-Donald F statistic is 6.382, and its corresponding 10% critical value is 16.38. Therefore, it is impossible to reject the null hypothesis of strong correlations between instrumental and endogenous variables. This suggests that the selected instrumental variables are correlated strongly with the endogenous variables. Finally, Sargan's results demonstrate that the model conforms to the exact identification and does not require an overidentification test. To sum up, the instrumental variables selected in this paper are rather reasonable. On the whole, the results of first-stage regression suggest that the precipitation reduces the haze pollution at a 1% significance level. According to the results of second-stage regression, the impact of haze pollution on the quality of China's economic development resembles the benchmark regression reported in Table 2, both in terms of direction and significance. This further verifies the adverse effect of haze pollution on the quality of China's economic development. However, from a quantitative point of view, the absolute estimated coefficient of haze pollution has increased nearly ten times compared to the benchmark regression. This suggests that the potential endogeneity problem tends to cause underestimation of the adverse effect of haze pollution on China's economic development quality. According to the linear regression results of the benchmark model, on the whole, haze pollution has degraded the quality of China's economic development strikingly. This leaves us with a question: did haze pollution adversely impact the quality of China's economic development just from the beginning, or did this negative impact appear gradually after the haze pollution reached a certain level? Extensive studies have found that the destructiveness of environmental pollution depends on its severity to a large extent, and that there may be a Kuznets curve effect regarding its impact on economic development. In this respect, we empirically tested the above assumption by further adding the quadratic term of PM2.5 concentration into the benchmark regression model. According to our findings, there is no inverted U-shaped relationship between PM2.5 concentration and quality of economic development, and the impact of haze pollution has been only linear to the economic development quality for China in recent years. This is probably linked to the time interval selected in this paper.

Regarding control variables, regional FDI has a significant negative correlation with TFP, which agrees with the "pollution haven" hypothesis. This hypothesis has been prevailing in FDI academia [38]. Given the high environmental pollution costs, developed countries will transfer some pollution-intensive firms to those developing countries with loose environmental regulations, so as to cut the pollution control costs. Developing countries, on the other hand, will introduce some pollution-intensive industries and low-tech industries by lowering the level of environmental regulations, so as to increase their competitiveness in attracting foreign investment. As a result, the environmental pollution will be exacerbated to hinder the enhancement of green TFP. This paper provides evidence for the "pollution haven" hypothesis from China. In terms of other aspects, Indus is significantly negatively correlated with TFP; Innov is significantly positively correlated with TFP; and Density is insignificantly negatively correlated with TFP, all of which are basically consistent with the predictions.

4.2. Analysis of Transmission Mechanisms

Results of the foregoing studies show that the haze pollution is negatively influential to the quality of China's economic development. So, what caused this phenomenon? In other words, what are the transmission mechanisms for haze pollution that affect the quality of China's economic development? Based on the foregoing hypotheses, this paper studies the transmission mechanisms whereby haze pollution affects China's economic development quality from three aspects: Labor loss, counter urbanization and human capital disruption. First of all, haze pollution can affect China's economic development through a loss of labor. To verify this mechanism, we selected the proportion of employed population to total population as the proxy variable for labor (Labor). In Table 3, the corresponding empirical regressions are reported. As can be seen, the regression coefficient of labor variable in column 1 is significantly positive, indicating that the labor force promotes the enhancement of economic quality. To alleviate the endogeneity problem, its impact on the quality of economic development is examined in column 2 of Table 3 by using the quantity of one-phase lagging labor. The two-stage least squares estimation in column 3 reveals a significant negative correlation of the haze pollution with the labor, indicating that the haze pollution has caused drastic depletion of the local labor supply. Secondly, haze pollution can affect China's economic development through counter urbanization. To verify this mechanism, the proportion of non-agricultural population to total population is selected as a proxy variable for urbanization (Urban). In Table 3, the corresponding empirical regressions are reported. As can be seen, the regression coefficient of urbanization variable in column 4 is significantly positive, indicating that the urbanization promotes the enhancement of economic quality. Noteworthy is that the higher the quality of economic development, the more likely it is to attract population agglomeration, which may adversely affect the urbanization process. To alleviate this endogeneity problem, the impact of urbanization on the economic development quality is examined in column 4 of Table 3 by using the one-phase lagging urbanization. For column 5, the 2SLS estimation is still used. The significantly negative coefficient of urbanization variable indicates that the haze pollution has slowed down the process of urbanization. Finally, another major mechanism for haze pollution to affect the quality of China's economic development is by impacting the human capital accumulation. In this paper, the average years of education widely used in the literature is chosen as a proxy variable for human capital (Capital). With this variable, the human capital mechanism through which the haze pollution affects the quality of China's economic development is examined empirically. As shown in Table 3, the human capital transmission mechanism can be verified effectively. That is, the accumulation of human capital has enhanced the quality of economic development, while the haze pollution has lowered the human capital strikingly.

Table 3. Verification of Transmission Mechanisms.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	TFP	TFP	Labor	TFP	TFP	Urban	TFP	TFP	Capital
	Labor Supply Loss			Counter Urbanization			Human Capital Disruption		
PM2.5			−0.005 ***			−0.028 *			−0.181 ***
			(−2.74)			(−1.66)			(−2.62)
Labor	2.534 ***								
	(5.14)								
l.Labor		2.854 ***							
		(5.76)							
Urban				0.433 ***					
				(7.83)					
L.Urban					0.381***				
					(7.46)				
Capital							0.149 ***		
							(11.92)		
l.Capital								0.151 ***	
								(12.60)	
Density	−0.211 *	−0.195	0.019	−0.424 ***	−0.260 **	0.661 ***	−0.462 ***	−0.357 ***	2.133 ***
	(−1.74)	(−1.63)	(1.57)	(−3.50)	(−2.22)	(5.98)	(−4.23)	(−3.43)	(4.80)
FDI	−0.940 **	−0.875 *	−0.267 ***	−0.906 **	−0.796 *	−0.906 **	−0.179	−0.174	−7.539 ***
	(−1.99)	(−1.94)	(−5.05)	(−2.01)	(−1.82)	(−2.11)	(−0.43)	(−0.44)	(−4.38)
Innov	0.003	0.004 *	0.009 ***	0.00351 *	0.004 *	0.006 ***	0.001	0.0021	0.002 ***
	(1.51)	(1.80)	(4.27)	(1.65)	(1.86)	(3.01)	(0.88)	(1.09)	(3.55)
Indus	−0.098 **	−0.071	−0.020 ***	−0.095 **	−0.113 ***	−0.137 ***	−0.0423	0.0141	−0.728 ***
	(−2.17)	(−1.56)	(−4.48)	(−2.23)	(−2.68)	(−3.38)	(−1.07)	(0.36)	(−4.48)
_cons	1.057 ***	0.985 ***	0.299 ***	1.754 ***	1.664 ***	0.0817	0.00136	−0.120	15.13 ***
	(9.50)	(8.71)	(4.66)	(17.93)	(18.38)	(0.15)	(0.01)	(−0.84)	(6.76)
F			25.67			31.27			17.94
R^2	0.2175	0.2248	0.2770	0.2261	0.2181	0.3520	0.3520	0.4029	0.2708
N	390	360	390	390	360	390	390	360	390

t statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.3. Robustness Analysis

To further guarantee the reliability of research conclusions, we also performed a series of robustness tests based on the instrumental variable regression reported in column 5 of Table 2. Table 4 details the corresponding results. Since the aforementioned variables only target the core explanatory variables, a related concern is the probable endogeneity problems with the control variables caused by "reverse causality". To eliminate this adverse effect, all the control variables are lagged by one phase in column 1 of Table 4, and the regression results are basically unchanged as well. For a better comparability of study samples, the municipality samples are excluded, and only the provincial-level samples are retained. The regression results are reported in column 2 of Table 4, which show high consistency with the benchmark scenario. Another potential problem is the close correlation of PM2.5 concentration, a core explanatory variable, with the SO_2 and soot emissions. As pollutants, SO_2 and soot may also produce an impact on the quality of economic development, thereby leading to biases of missing variables. To this end, we further controlled the SO_2 and soot emissions per unit area, in order to identify the impact of PM2.5 pollution on the quality of China's economic development accurately. Compared to the column 5 in Table 2, the coefficient and significance in the column 3 of Table 4 are basically unchanged. To examine the sensitivity of the regression results to the model settings, an empirical analysis is carried out using a logarithmic model, which finds that the negative impact of haze pollution on the economic development quality still exists at significant levels. Furthermore, 0.5% of samples with the highest and lowest PM2.5 concentrations are excluded from the column 5 of Table 4, in order to examine the influence of haze pollution outliers on the regression results. Again, the research results basically remain unchanged. Finally, GDP per capita is also used by some research for measuring the quality of economic development. As shown in the column 6 of Table 4, the haze pollution remains negatively correlated with the GDP per capita.

Table 4. Robustness Tests.

	(1)	(2)	(3)	(4)	(5)	(6)
	TFP	**TFP**	**TFP**	**ln TFP**	**TFP**	**GDP**
	Lag Control Variable	**Delete Municipality**	**Control SO_2**	**Absolute Value**	**Delete 0.5%**	**GDP as Explained Variable**
PM2.5	−0.068 ***	−0.054 ***	−0.047 ***		−0.059 ***	−0.598 ***
	(−3.62)	(−2.67)	(−2.61)		(−2.61)	(−4.27)
lnPM2.5				−1.499 **		
				(−2.51)		
Density	0.028	−0.240 *	−0.247 **	−0.094	−0.152	5.668 ***
	(0.22)	(−1.82)	(−2.03)	(−0.90)	(−1.23)	(6.30)
FDI	−1.564 ***	−1.698 ***	−1.077 **	−1.049 **	−1.311 ***	−18.89 ***
	(−3.31)	(−3.10)	(−2.39)	(−2.58)	(−2.73)	(−5.41)
Innov	0.004 **	0.004 *	0.003	0.005 ***	0.005 **	0.010 ***
	(2.14)	(1.71)	(1.65)	(2.65)	(2.56)	(6.30)
Indus	−0.061	−0.152 ***	−0.103 **	−0.111 ***	−0.145 ***	−2.173 ***
	(−1.25)	(−3.16)	(−2.31)	(−2.90)	(−3.20)	(−6.61)
L.x16			−0.003 ***			
			(−4.47)			
_cons	3.419 ***	3.223 ***	3.164 ***	5.222 ***	3.293 ***	23.16 ***
	(5.58)	(4.84)	(5.44)	(2.64)	(4.48)	(5.11)
F	33.71	22.79	37.58	27.38	27.53	16.69
R^2	0.1048	0.1139	0.1882	0.1018	0.1095	0.4426
N	360	338	360	390	390	390

t statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.4. Heterogeneity Analysis

The Chinese Government has taken environmental management to an unprecedented level, and made pollution prevention one of the three major battles for winning a well-off society in an all-round way. The government called for efforts to address prominent environmental issues, continue to implement the atmospheric pollution control campaigns and to win the battle for the defense of the blue sky, so as to promote green development. Given China's vast territory, local governments show distinct differences in the enforcement of environmental regulations, which may affect the relationship between the haze pollution and the economic development quality. With reference to previous research [39], this paper classifies the environmental regulations into the investment type and the expense type depending on the perspective of capital investment. Initially, the proportion of industrial pollution control investment and emission charges in GDP was calculated for various provinces, followed by the calculation of the median value of the proportion. Using this median as the boundary, regions were divided into those with high environmental management efforts and low environmental management efforts. Afterwards, econometric regression was performed on them separately. The columns (1)–(4) in Table 5 present the regression results. Clearly, the destructive effect of haze pollution on the economic development quality is present only in the regions with low environmental management efforts.

Under the Chinese-style fiscal decentralization system, local governments are facing both the core task of developing economy and the sustainability goal of protecting the environment. The local governments' awareness and behavior of environmental protection are affected by fiscal decentralization. The impact of haze pollution on the quality of economic development may vary by the degree of fiscal decentralization. In this paper, the proportion of a region's total budgetary fiscal expenditure in the country's total budgetary fiscal expenditure is taken as a measure of fiscal decentralization degree, and then the median value of the proportion is calculated. Using this median as the boundary, regions are divided into those with high fiscal decentralization and low fiscal decentralization. Afterwards, econometric regression is performed on them separately. The columns (5)–(6) in Table 5 present the regression results. As can be seen, the destructive effect of haze pollution on economic development quality is present only in the regions with high fiscal decentralization.

Table 5. Heterogeneity Analysis.

	(1)	(2)	(3)	(4)	(5)	(6)
	Low Pollutant Discharge	**High Pollutant Discharge**	**Small Investment**	**Large Investment**	**Great Fiscal Decentralization**	**Small Fiscal Decentralization**
PM2.5	−0.080 ***	−0.016	−0.067 ***	−0.008	−0.088 ***	0.046
	(−3.72)	(−0.66)	(−2.89)	(−0.31)	(−3.48)	(1.61)
Density	−0.0543	−0.165	−0.320 **	0.139	−0.282 *	0.661 **
	(−0.40)	(−0.87)	(−2.22)	(0.65)	(−1.90)	(2.48)
FDI	−0.529	−5.818 ***	−0.348	−3.981 ***	−1.435 **	0.077
	(−1.20)	(−4.09)	(−0.66)	(−4.35)	(−2.26)	(0.10)
Innov	0.005 **	−0.003	0.004 *	0.001 *	0.005 *	0.005
	(2.31)	(−0.48)	(1.80)	(1.98)	(1.82)	(1.62)
Indus	−0.164 ***	−0.220 ***	−0.124 **	−0.167 **	−0.135 **	−0.128
	(−3.27)	(−3.04)	(−2.37)	(−2.14)	(−2.35)	(−1.58)
_cons	3.924 ***	2.178 ***	3.514 ***	1.668 *	4.331 ***	−0.559
	(5.64)	(2.68)	(4.68)	(1.87)	(5.26)	(−0.59)
F	35.45	11.49	27.91	11.78	17.53	41.49
R^2	0.1795	0.1832	0.1200	0.2412	0.1223	0.2169
N	244	146	254	136	251	139

t statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The above empirical results indicate that the environmental regulations can mitigate the damaging effect of haze pollution on the economic development quality. So through what mechanisms do environmental regulations play their positive role? This paper next explores the relevant principles through the effects of environmental regulations on the three transmission channels of haze pollution. Depending on the aforementioned proportion of emission charges in GDP, various provinces were classified into regions with high environmental management efforts and low environmental management efforts. Then, econometric regression was performed separately on the three channels. As shown in Table 6, in regions with low environmental management efforts, haze pollution is significantly negatively correlated with all the three variables of Labor, Urban and Capital, while in regions with high environmental management efforts, such negative correlations are all insignificant. It has been widely recognized by academia that strict environmental regulations can improve the eco-environment and the health of residents [40]. Strengthening of environmental regulations not only can impact the quality of economic growth by influencing the health and effective labor input of residents, but also can attract more high-end talented individuals through the improvement of eco-environment. As the above results suggest, environmental regulations promote the sustainable economic growth precisely by mitigating the "labor supply loss effect", "counter urbanization effect" and "human capital disruption effect" of the haze pollution.

Table 6. Environmental Regulations and Conduction Mechanism.

	(1)	(2)	(3)	(4)	(5)	(6)
	Less Sewage Charge			Large Sewage Charge		
	Labor	Urban	Capital	Labor	Urban	Capital
PM2.5	−0.010 ***	−0.022 *	−0.280 **	−0.001	−0.003	−0.010
	(−3.37)	(−2.26)	(−3.17)	(−0.36)	(−0.52)	(−0.09)
Density	0.022	0.269 ***	1.258 *	0.023	0.302 ***	2.658 **
	(1.21)	(4.41)	(2.30)	(1.55)	(5.30)	(3.16)
FDI	−0.169 *	−0.483 *	−6.149 **	−0.202 **	−0.987 ***	−13.12 ***
	(−2.45)	(−2.17)	(−3.07)	(−3.11)	(−4.06)	(−3.66)
Innov	0.008 *	0.001 **	0.003 **	0.002 ***	0.006 **	0.007 *
	(2.58)	(2.66)	(3.12)	(4.60)	(3.38)	(2.28)
Indus	−0.025 ***	−0.064 **	−0.522 **	−0.010	−0.070 **	−0.931 **
	(−3.70)	(−2.93)	(−2.62)	(−1.93)	(−3.38)	(−3.03)
_cons	0.474 ***	1.214 ***	18.55 ***	0.128 *	0.545 *	9.345 **
	(4.83)	(3.82)	(6.49)	(2.04)	(2.31)	(2.68)
R^2	0.2286	0.2458	0.2326	0.3132	0.5144	0.3603
N	254	254	254	136	136	136

t statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

According to the empirical results in Table 5, the degree of fiscal decentralization is an important influencing factor of the haze pollution effects. Similarly, to clarify the relevant mechanisms, econometric regression was performed separately on the three channels of haze pollution. As shown in Table 7, in the regions with high fiscal decentralization, the haze pollution is significantly negatively correlated with Labor and Capital, while in the regions with low fiscal decentralization, such negative correlations are insignificant. The core of Chinese-style fiscal decentralization is the economic decentralization and political centralization. Encouraged by the political promotion, the central government uses local GDP growth as a standard for assessing local officials, with the aim of stimulating the economic growth. Meanwhile, the local officials have made economic construction their main priority, which has led to the "promotion tournament" phenomenon that is unique to China. The extensive growth mode of factor input expansion is prone to problems, such as compromised environmental quality, insufficient public service supply and declining human capital stock. Such negative effects may be stronger with a heightening degree of fiscal decentralization, where the haze pollution produces a more severe negative impact on the quality of economic development.

Table 7. Fiscal Decentralization and Conduction Mechanism.

	(1)	(2)	(3)	(4)	(5)	(6)
	High Fiscal Decentralization			Low Fiscal Decentralization		
	Labor	Urban	Capital	Labor	Urban	Capital
PM2.5	−0.006 *	−0.002	−0.092 *	−0.001	−0.011	−0.049
	(−2.08)	(−1.22)	(−2.35)	(−0.79)	(−0.48)	(−0.50)
Density	0.051 *	0.429 ***	2.306 ***	0.006	0.226 ***	2.349 ***
	(2.13)	(6.25)	(4.53)	(0.57)	(4.09)	(3.37)
FDI	−0.08	−0.421	−0.637	−0.045	−0.266	−6.691 **
	(−0.98)	(−1.65)	(−0.34)	(−1.10)	(−1.41)	(−2.80)
Innov	0.002 ***	0.005 ***	0.008 ***	0.001	0.001	0.002
	(3.93)	(3.37)	(8.34)	(0.93)	(1.63)	(0.21)
Indus	−0.028 ***	−0.076 **	−0.722 ***	0.006	0.027	0.550 *
	(−3.35)	(−3.16)	(−4.00)	(1.27)	(1.25)	(2.01)
_cons	0.370 ***	0.590	12.32 ***	0.118 *	0.628 *	8.169 *
	(3.47)	(1.96)	(5.51)	(2.07)	(2.43)	(2.50)
R^2	0.3788	0.4668	0.6201	0.1255	0.1262	0.1238
N	206	206	206	184	184	184

t statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5. Conclusions and Policy Recommendations

Environmental protection and economic development are eternal concerns for all of mankind. In particular, with the entry of China's development into a new era, the issue has attracted wider attention from all walks of life. How can we fight the battle against pollution? How should we promote the high-quality development of economy through governmental management of environment? Achieving such a win-win goal is inseparable from a systematic grasp of the relationship between environmental pollution and economic development. The majority of extant studies, however, focus only on the unidirectional relationship of the impact of economic development on haze pollution, while ignoring the feedback mechanism of the impact of haze pollution on economic development. In a literature study closest in scope to this paper [10], the potential endogeneity problems were not resolved effectively, because of a failure to find the instrumental variables for haze pollution. In addition, the literature lacked discussion of the mechanism whereby the haze pollution affected the economic development. To this end, this paper systematically investigates the impact of haze pollution on the quality of China's economic development, as well as its transmission mechanisms. This is accomplished by taking total factor productivity as a proxy variable for the economic development quality, and by using China's PM2.5 haze data at the provincial level over a span of 13 years from 2004 to 2016. Furthermore, this paper innovatively uses precipitation as an instrumental variable for mitigating the endogeneity of haze pollution, and employs 2SLS for estimating the impact of haze pollution on the quality of economic development. The main conclusions of this paper are as follows: The intensification of haze pollution degrades the quality of China's economic development strikingly; the loss of labor supply, counter urbanization and human capital disruption are the three major transmission channels through which haze pollution affects the quality of China's economic development; strengthening government's environmental management is effective in reducing the haze pollution to upgrade the quality of economic development; and Chinese-style fiscal decentralization is a major reason for the negative economic effect of haze pollution. These research conclusions have profound policy implications. For a long time, in the grand context of economic construction centricity, a common view on the relationship between economic development and haze pollution has been that the reduction of haze pollution inevitably harms economic development. As a result, some places have adopted a "laissez-faire attitude" towards haze pollution. Given the limited carrying capacity of the environment, however, boosting the economy persistently through continuous pollutant emissions is destined to be unsustainable. Today, China is already confronting the dual challenges of severe environmental deterioration and the urgent need for enhancement of economic development quality. Extensive economic growth is the culprit, leading to the exacerbating haze pollution. Haze pollution in turn further affects the quality of China's economic development through channels like labor loss, counter urbanization and human capital disruption. To resolve such a vicious circle and dilemma fundamentally, the sole measure is the implementation of a reasonable and effective governmental policy on environmental management. By doing so, the production factors can flow continuously away from inefficient high energy consumption, from high emission sectors to the efficient low energy consumption, low emission sectors. In addition, the economic structure can be optimized continuously and the total factor productivity and economic development quality can be improved constantly. In this way, the win-win goal of continuous reduction of haze pollution and the transformation of economic development mode to high-quality development can be attained. Also, this is precisely the core implication of China's supply-side structural reform in dealing with the eternal relationship between environmental protection and economic development.

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References

1. Shafik, N. Economic development and environmental quality: An econometric analysis. *Oxf. Econ. Pap.* **1994**, *46*, 757–773. [CrossRef]
2. Friedl, B.; Getiner, M. Determinants of CO_2, emissions in a small open economy. *Ecol. Econ.* **2003**, *45*, 133–148. [CrossRef]
3. Ebenstein, A.; Fan, M.; Greenstore, M.; He, G.; Yin, P.; Zhou, M. Growth, pollution and life expectancy: China from 1991–2012. *Am. Econ. Rev.* **2015**, *105*, 226–231. [CrossRef]
4. Ouyanga, X.; Shao, Q.; Zhu, X.; Hea, Q.; Xianga, C.; Weia, G. Environmental regulation, economic growth and air pollution: Panel threshold analysis for OECD countries. *Sci. Total Environ.* **2019**, *657*, 234–241. [CrossRef] [PubMed]
5. Su, Y.; Lu, C.; Lin, X.; Zhong, L.; Gao, Y.; Lei, Y. Analysis of Spatio-temporal Characteristics and Driving Forces of Air Quality in the Northern Coastal Comprehensive Economic Zone, China. *Sustainability* **2020**, *12*, 536. [CrossRef]
6. Lopez, R. The environment as a factor of production: The effects of economic growth and trade liberalization. *J. Environ. Econ. Manag.* **1994**, *27*, 163–184. [CrossRef]
7. Giannadaki, D.; Giannakis, E.; Pozzer, A.; Lelieveld, J. Estimating health and economic benefits of reductions in air pollution from agriculture. *Sci. Total Environ.* **2018**, *622–623*, 1304–1316. [CrossRef]
8. Kampa, M.; Castanas, E. Human Health Effects of Air Pollution. *Environ. Pollut.* **2008**, *151*, 362–367. [CrossRef]
9. Yang, G.; Wang, Y.; Zeng, Y. Rapid health transition in China, 1990–2010: Findings from the Global Burden of Disease Study 2010. *Lancet* **2013**, *381*, 1987–2015. [CrossRef]
10. Hao, Y.; Peng, H.; Temulun, T.; Liu, L.; Mao, J.; Lu, Z.; Chen, H. How harmful is air pollution to economic development? New evidence from PM2.5 concentrations of Chinese cities. *J. Clean Prod.* **2017**, *172*, 743–757. [CrossRef]
11. Zhang, Y.; Jiang, Y.; Guo, Y. The effects of haze pollution on stock performances: Evidence from China. *Appl. Econ.* **2017**, *49*, 2226–2237. [CrossRef]
12. Chen, J.C.; Wang, G.; Chen, R.; Liu, X.; Wei, G. Indirect Economic Impact Incurred by Haze Pollution: An Econometric and Input–Output Joint Model. *Public Health* **2019**, *16*, 2328. [CrossRef] [PubMed]
13. Hanlon, W.W. *Coal Smoke and the Costs of the Industrial Revolution*; NBER Working Paper No. 22921; National Bureau of Economic Research: Cambridge, MA, USA, 2016. [CrossRef]

14. Cole, M.A.; Elliott, R.J.; Okubo, T. Trade, Environmental Regulations and Industrial Mobility: An Industry-level Study of Japan. *Ecol. Econ.* **2010**, *69*, 1995–2002. [CrossRef]
15. Knittel, C.R.; Millera, D.L.; Sanders, N.J. Caution, Drivers! Children Present: Traffic, Pollution and Infant Health. *Rev. Econ. Stat.* **2016**, *98*, 350–366. [CrossRef]
16. Kenneth, Y.; Chay, M.G. The Impact of Air Pollution on Infant Mortality: Evidence from Geographic Variation in Pollution Shocks Induced by a Recession. *Q. J. Econ.* **2003**, *118*, 1121–1167.
17. He, J.; Liu, H.; Salvo, A. Severe Air Pollution and Labor Productivity: Evidence from Industrial Towns in China. *Am. Econ. J. Appl. Econ.* **2019**, *11*, 173–201. [CrossRef]
18. Deryugina, T.; Heutel, G.; Miller, N.H. The Mortality and Medical Costs of Air Pollution: Evidence from Changes in Wind Direction. *Am. Econ. Rev.* **2019**, *109*, 4178–4219. [CrossRef]
19. Lua, X.; Lin, C.; Li, W.; Chen, Y.; Huang, Y.; Funga, J.; Lau, C.H.; Alexis, K.H. Analysis of the adverse health effects of PM2.5 from 2001 to 2017 in China and the role of urbanization in aggravating the health burden. *Total Environ.* **2019**, *652*, 683–695. [CrossRef]
20. Hausman, J.A.; Ostro, B.D.; Wise, D.A. Air pollution and lost work. *Natl. Bureau Econ. Res.* **1984**, 1263. [CrossRef]
21. Rema, H.; Paulina, O. The effect of pollution on labor supply: Evidence from a natural experiment in Mexico City. *J. Public Econ.* **2015**, *122*, 68–79.
22. Bosi, S.; Desmarchelier, D.; Ragot, L. Pollution effects on labor supply and growth. *Int. J. Econ. Theory* **2015**, *11*, 371–388. [CrossRef]
23. Carson, R.T.; Koundouri, P.; Nauges, C. Arsenic mitigation in Bangladesh: A Household Labor market approach. *Am. J. Agric. Econ.* **2011**, *93*, 407–414. [CrossRef]
24. Kim, Y.; Manley, J.; Radoias, V. Medium and long-term consequences of pollution on labor supply: Evidence from Indonesia. *J. Labor Econ.* **2017**, *6*, 5. [CrossRef]
25. Chen, S.; Oliva, P.; Zhang, P. *The Effect of Air Pollution on Migration: Evidence from China*; NBER Working Paper No. 24036; National Bureau of Economic Research: Cambridge, MA, USA, 2017. [CrossRef]
26. Qin, Y.; Zhu, H. Run Away? Air Pollution and Emigration Interests in China. *Popul. Econ.* **2018**, *31*, 235–266. [CrossRef]
27. Kahn, M.E. Smog Reduction's Impact on California County Growth. *J. Reg. Sci.* **2000**, *40*, 565–582. [CrossRef]
28. Akpalu, W.; Ametefee, K.N. Gold Mining Pollution and the Cost of Private Healthcare: The Case of Ghana. *Ecol. Econ.* **2017**, *142*, 104–112. [CrossRef]
29. Fu, S.H.; Viard, V.B.; Zhang, P. Air Pollution and Manufacturing Firm Productivity: Nationwide Estimates for China. 2017. Available online: http://www.ckgsb.com/uploads/pollution_and_productivity.pdf (accessed on 19 February 2020).
30. Copeland, B.R.; Taylor, M.S. North-South Trade and the Environment. *Q. J. Econ.* **1994**, *9*, 755–787. [CrossRef]
31. Reppelin-Hill, V. Trade and Environment: An Empirical Analysis of the Technology Effect in the Steel Industry. *J. Environ. Econ. Manag.* **1999**, *38*, 283–301. [CrossRef]
32. Li, B.; Wu, S. Effects of local and civil environmental regulation on green total factor productivity in China: A spatial Durbin econometric analysis. *J. Clean Prod.* **2017**, *153*, 342–353. [CrossRef]
33. Song, T.; Zheng, T.G.; Tong, L.J. An empirical test of the environmental Kuznets curve in China: A panel cointegration approach China. *Am. Econ. Rev.* **2008**, *19*, 381–392. [CrossRef]
34. Tientao, A.; Legros, D.; Pichery, M.C. Technology spillover and TFP growth: A spatial Durbin model. *J. Int. Econ.* **2016**, *145*, 21–31. [CrossRef]
35. Hering, L.; Poncet, S. Environmental Policy and Exports: Evidence from Chinese Cities. *J. Environ. Econ. Manage.* **2014**, *68*, 296–318. [CrossRef]
36. Broner, F.; Bustos, P.; Carvalho, V. *Sources of Comparative Advantage in Polluting Industries*; NBER Working Paper No. 18337; National Bureau of Economic Research: Cambridge, MA, USA, 2012. [CrossRef]
37. Van, A.D.; Mar Tin, R.V.; Brauer, M. Use of satellite observations for long-term exposure assessment of global concentrations of fine particulate matter. *Environ. Health Perspect.* **2015**, *123*, 135–143.
38. Cole, M.A. Trade, the pollution haven hypothesis and the environmental Kuznets curve: Examining the linkages. *Ecol. Econ.* **2004**, *48*, 71–81. [CrossRef]

39. Berman, E.; Bui, L.T. Environmental Regulation and Productivity: Evidence from Oil Refineries. *Rev. Econ. Stat.* **2001**, *83*, 498–510. [CrossRef]
40. Shadbegian, R.J.; Gray, W.B. What determines environmental performance at paper mills: The roles of abatement spending, regulation, and efficiency. *E J. Econ. Anal. Policy* **2003**, *3*, 1144–1163. [CrossRef]

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Study on Coupled Relationship between Urban Air Quality and Land Use in Lanzhou, China

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Abstract: The intensification of global urbanization has exacerbated the negative impact of atmospheric environmental factors in urban areas, thus threatening the sustainability of future urban development. In order to ensure the sustainability of urban atmospheric environments, exploring the changing laws of urban air quality, identifying highly polluted areas in cities, and studying the relationship between air quality and land use have become issues of great concern. Based on AQI data from 340 air quality monitoring stations and urban land use data, this paper uses inverse distance weight (IDW), Getis-Ord Gi*, and a negative binomial regression model to discuss the spatiotemporal variation of air quality in the main urban area of Lanzhou and its relationship with urban land use. The results show that urban air quality has characteristics of temporal and spatial differentiation and spatially has characteristics of agglomeration of cold and hot spots. There is a close relationship between urban land use and air quality. Industrial activities, traffic pollution, and urban construction activities are the most important factors affecting urban air quality. Green spaces can reduce urban pollution. The impact of land use on air quality has a seasonal effect.

Keywords: air quality; spatiotemporal characteristics; urban land use; coupled relationship; Lanzhou City

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1. Introduction

Over 40 years of reform and opening up, China's urbanization rate increased from 17.92% in 1978 to 60.60% in 2019. According to United Nations statistics and projections, the global urbanization rate will reach 68% by 2050, China's urbanization rate will reach 80%, and about 1.1 billion people will live in cities [1]. Rapid urbanization has led to coal-fired energy consumption and an increased number of vehicles, resulting in increasingly serious air pollution [2]. Air pollution can lead to respiratory diseases, strokes, cancer, and cardiovascular diseases; it is one of the main environmental problems affecting people's quality of life and physical and mental health [3]. A World Health Organization report shows that about 4.2 million people died due to health problems caused by air pollution in 2020 [4], and 1.24 million people died due to air pollution in China, accounting for about 30% of global deaths [5]. Air pollution has become an important factor that hinders the sustainable development of Chinese cities. Understanding the changes in air pollution, identifying its driving factors, and proposing effective optimization strategies have become important for geographic, urban, and rural planning and environmental science.

Air quality reflects the degree of air pollution, which is judged based on the concentrations of pollutants in the air. At present, SO_2, NO_2, CO, O_3, $PM_{2.5}$, and PM_{10} are defined as the six standard pollutants that quantify the level of air pollution in the world. The concentrations of pollutants may differ by orders of magnitude, and the impact of the unit concentration on health also differs significantly. It is difficult for the general public to directly use these concentrations to characterize air pollution levels. Therefore, two comprehensive air quality indicators, AQI and API, are often used to reflect the degree of air pollution. API is calculated by PM_{10}, SO_2, and NO_2. PM_{10} is the main pollutant of API, accounting for more than 90% [6]. AQI is calculated by PM_{10}, SO_2, NO_2, $PM_{2.5}$, O_3, and CO, and $PM_{2.5}$ is the main pollutant [7]. AQI can better express the impact of human activities on air quality than API [8]. In 2012, China issued a new ambient air quality standard, and air quality monitoring data were changed from API to AQI. The AQI is the most widely used index in the world [9]. According to the Ambient Air Quality Index (AQI) Technical Regulations (Trial) (HJ 633~2012), the air quality index is divided into six levels: level 1, excellent, 0–50; level 2, good, 51–100; level 3, slight pollution, 101–150; level 4, moderate pollution, 151–200; level 5, severe pollution, 201–300; and level 6, severe pollution, >300 [10].

The research on air quality from the geographical perspective mainly focuses on its spatiotemporal distribution characteristics and driving factors. Studies are mostly based on single indicators such as $PM_{2.5}$ [11] and comprehensive indicators such as AQI [12] and API [13] using global/local autocorrelation [11], inverse distance weight (IDW) [14], and statistical analysis methods [15], on spatial scales such as the whole country [11], provinces [16], urban agglomerations [6], and typical regions [17] and key cities [18], and time scales such as year, season, month, hour, etc. Scholars have found that China's air quality is showing a tendency to change for the better [19]. There are obvious seasonal characteristics over time, mainly manifested as serious pollution in winter and spring and lighter pollution in summer and autumn [19]. In terms of space, studies show the coexistence of high-pollution and low-pollution areas. Air pollution presents a spatial pattern of high in the north and low in the south [11,14], heavy in the east and light in the west [11,15], and high inland and low on the coast [20]. Within cities, it also has the characteristics of seasonal and spatial differentiation [3,21]. Affected by urban forms and land use characteristics [22,23], the air quality in the suburbs is better than in central cities, and residential areas with more greenery are better than other areas [24]. Natural factors such as geomorphology, meteorological elements, sand and dust transportation, and hazy weather and human factors such as industrial emissions, energy structure, motor vehicle emissions, and the level of urbanization development have jointly caused air pollution [24–28].

In recent years, many studies have focused on the relationship between urban land use and air quality [29]. The purpose of urban land use is to provide land with a suitable scale and a reasonable location based on urban planning according to the specific requirements of various activities in the city: work, residence, recreation, and transportation. Changes in urban land use are caused by the substitution and vitality of internal urban functions, and they are more significant on a long-term scale [30,31]. In China, urban planning has a legal effect once it is approved. Changing land use requires a series of complicated procedures. Therefore, land use does not change much on an annual or seasonal scale during the year. To a certain extent, it determines the locations of industrial zones, industrial enterprises, and heating boilers. Some land-use types can directly cause air pollution, while others do not but produce air pollutants as a result of human activities connected to land use; for example, automobile exhaust connected to traffic is an important factor that affects the air quality [32,33].

Studies have used spatial analysis and statistical methods (e.g., based on 170 regression models [34]), private air quality monitoring smart sensors [35], stepwise linear regression models [36,37], and a land use regression (LUR) model [38] to examine the relationship between urban land use and air quality. In such studies, the air quality data can be refined to the hourly scale, but the land use data are basically static, even in the LUR model [39,40]. Those studies show that the level of urban land expansion and the proportion of construction land are positively correlated with the degree of air pollution [29,41,42]. The expansion of urban construction land and the increase of impervious areas have enhanced the urban heat island effect, thereby exacerbating urban air pollution. A larger proportion of natural land coverage, especially water, woodland, farmland, and green space, is helpful to reduce the concentration of pollutants [29,34,42,43]. Air pollution in cities is mainly caused by human factors such as industrial pollution and traffic emissions [26]. From the perspective of urban land use structure, the proportion and layout of roads and industrial land will increase air pollution. Urban thermal power plants and steel plants are the biggest sources of pollution [23,25,44]. Therefore, formulating a strategy for optimizing urban land use from the perspective of policy guarantees will help to improve urban air quality [45]. Łapko's research shows that reducing pollution in cities can contribute to increasing their attractiveness as tourist destinations [46].

The typical geographical features and special industrial structure of Lanzhou City have attracted the attention of academics, and a great deal of research on the characteristics, sources, and causes of air pollution has emerged. The research perspective is focused more on the impact of dust, heating, and motor vehicle emissions on air quality, as well as the characteristics of air pollution and effectiveness of governance [46–49]. However, there is no comprehensive and systematic study on the relationship between the spatiotemporal distribution of air quality and land use in cities. Previous studies often chose PM_{10} or $PM_{2.5}$ to assess air quality [39,50], but a single pollutant cannot fully reflect the state of air quality in a certain place or represent the impact of air pollution on humans; it is more useful to apply a comprehensive index of air pollutants to the study of air quality [8].

Previous research results provide significant theoretical and practical experience with regard to air quality distribution and driving factors, but those studies pay more attention to large-scale air quality in the whole country, urban agglomerations, and typical regions; there are few studies on the differences in air quality within cities, because most of the air quality data needed for the research come from satellite measurements and national environmental air quality monitoring sites [51]. Satellite measurements are usually obtained at a fixed time of the day to obtain the spatial distribution of atmospheric pollutant concentrations. This method is limited by the imaging time, the spatial resolution is relatively coarse, and the time resolution is low [52]. It is generally difficult to capture intra-city variability due to the limited geographic coverage of national ambient air quality monitoring stations [53]. There are only five monitoring stations in Lanzhou. In studying the relationship between urban land use and air quality, the land use data mostly come from remote sensing images, and the interpretation of urban land use differences is not ideal due to the influence of the precision of remote sensing data and image interpretation [8,36]. Therefore, the purpose of this study was as follows: (1) to use IDW and Getis-Ord Gi* methods based on data from 340 monitoring locations in the city to explore air quality changes in the city and identify highly polluted areas and (2) to build a negative binomial regression model of air quality and land use within a 1000 m buffer zone around the monitoring site to study the relationship between air quality and land use. Our results are expected to help policymakers to improve air quality and promote sustainable urban development.

2. Materials and Methods

2.1. Study Area

Lanzhou City is located at 35°34′–37°07′ N and 102°36′–104°34′ E (Figure 1). It has a typical continental climate with average annual rainfall of 327 mm, which is mainly concentrated from June to September. The central city of Lanzhou has high terrain in the west and low terrain in the east, with two mountains in the north and south. The Yellow River runs through the entire territory from west to east, connecting the Xigu, Qilihe-Anning, and Chengguan Basins. The special river valley landform conditions and the meteorological and climatic conditions, in which the proportion of quiet windy days per year reaches more than 50%, make it difficult for air pollutants to spread; as a result, Lanzhou was classified as a severely polluted city by the World Health Organization [54]. As an important industrial base in Northwest China, Lanzhou has formed an industrial system dominated by oil refining, chemicals, electromechanics, metallurgy, military, energy, light and textile, and building materials after the construction of the First and Second Five-Year Plans and the Third Front. The industrial layout of the heavy petrochemical industry and the structure of coal-fired energy create mixed air pollution. With the launch of national air pollution prevention and control measures in 2012, the implementation of the Air Pollution Prevention and Control Plan in 2015, and the adjustment of the urban industrial structure, the urban air pollution situation has been significantly improved, with frequent occurrence of the "Lanzhou blue" phenomenon. Lanzhou City won a reform and progress award at the Paris Climate Conference in 2015.

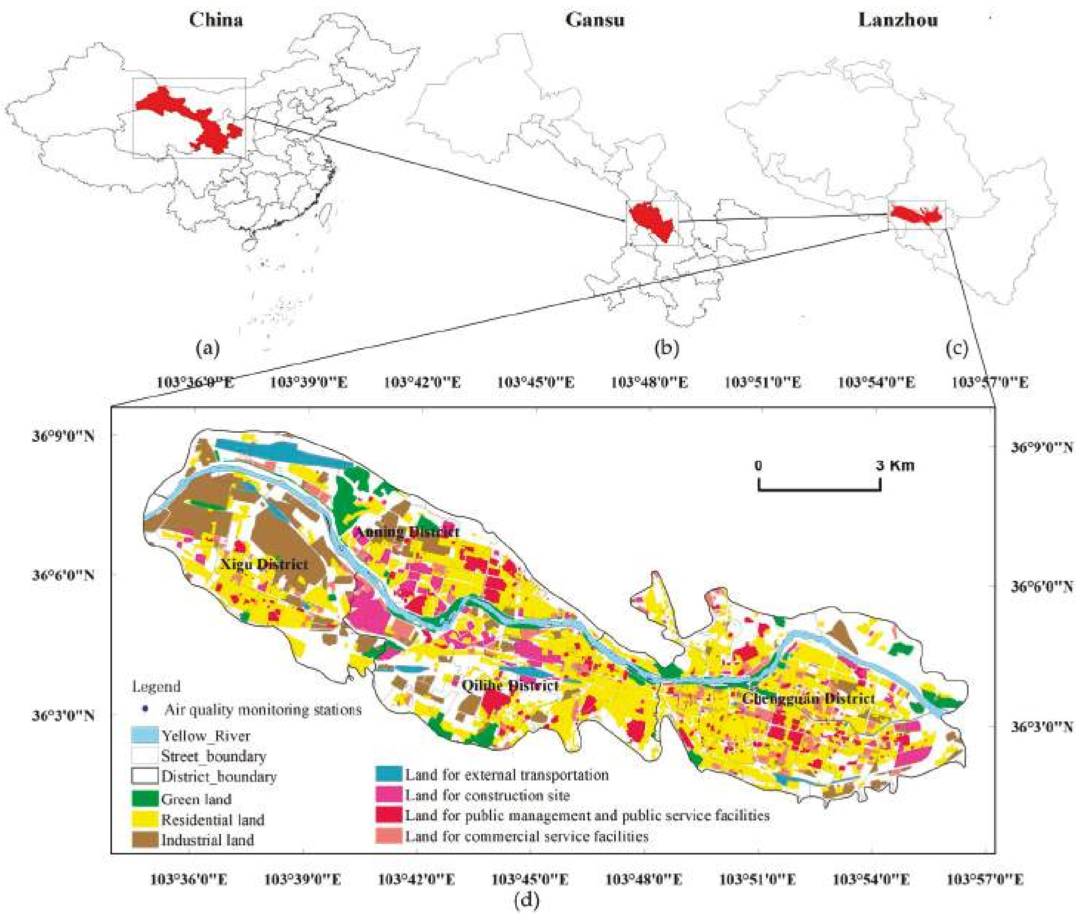


Figure 1. Distribution map of study area and air quality monitoring stations: (**a**) Gansu Province in China; (**b**) Lanzhou in Gansu Province; (**c**) study area in Lanzhou; (**d**) air quality monitoring stations and land use in the study area.

2.2. Data Sources

2.2.1. Air Quality Data

We selected AQI to quantitatively describe and comprehensively reflect air quality status. The higher the index, the more serious the air pollution. The AQI data come from the mobile phone app of the public version of the Lanzhou Urban Atmospheric Environment Grid Monitoring System (http://sthjj.lanzhou.gov.cn/col/col4210/index.html (accessed on 31 December 2020)). We obtained the location information and AQI data of 479 air quality monitoring stations in the central urban area of Lanzhou from 1 January to 31 December 2020. Excluding data outside the study area and incomplete data, data from 340 air quality monitoring stations were obtained. We transformed the location information of the monitoring site into longitude and latitude coordinates in a data format that could be analyzed by ArcGIS software for later analysis. The study area and air quality monitoring stations are shown in Figure 1.

2.2.2. Urban Land Use Data

Most of the land use data in previous studies came from 30 m resolution remote sensing images. According to the Classification of Land Use Status (GB/T 21010-2017), land use has been subdivided into agricultural, water use, urban construction, unused land, etc. [8]. Previous studies went beyond the urban built-up area or took the urban area as a whole, which makes it difficult to reflect differences in land use within a city, and does not consider the coupled relationship between air quality and land use. According to the Urban and Rural Land Classification and Planning and Construction Land Standards (GB50137-2011), this paper subdivides urban construction land into green, residential, and industrial land, and land for external transportation, public management and public service facilities, and commercial service facilities. The emission of building dust is an important part of the dust source [55]. Therefore, we added additional land for construction sites. The land use data come from the current urban land use and planning maps in the Lanzhou City master plan.

2.2.3. Other Data

Urban air pollution sources include fixed and mobile sources. Fixed pollution sources include factories and heating boilers, and the mobile pollution source is motor vehicle exhaust [56]. For this study, we selected industrial enterprises above a designated size to characterize industrial pollution sources. The data come from the Chinese industrial enterprises database and the directory of industrial and commercial enterprises registered in Lanzhou City, Gansu Province. Heating boiler data come from the Lanzhou directory of heating service companies for 2019–2020. There are 138 industrial enterprises and 288 heating boilers in total. Traffic pollution is the main source of mobile pollution in cities. There are more vehicles in areas with dense road networks, producing more air pollutants [57]. We used road network density within a 1000 m buffer zone around the air quality monitoring sites to express traffic emissions [39]. Road network data come from OpenStreetMap (OSM) (www.openstreetmap.org (accessed on 12 March 2021)).

In this paper, the dependent variables are average AQI for the whole year, spring, summer, autumn, winter, heating period, and non-heating period, which are labeled as Y1, Y2, Y3, Y4, Y5, Y6, and Y7, respectively. The independent variable is the land use factor within a 1000 m buffer zone around each air quality monitoring station (Table 1). A total of seven regression models were constructed for the seven variables.

Table 1. Descriptive statistics of variables.

	Factors	Variables (1000 m Buffer Zone)	Min	Max	Mean	Std. Dev.	VIF
X1	Heating emissions	Number of heating stations (pieces)	0	48	8.31	9	1.78
X2	Industrial emissions	Industrial enterprises above designated size (pieces)	0	14	2.28	2.34	1.33
X3	Traffic emissions	Road network density (km/km^2)	0.62	8.22	4.1	1.73	2.16
X4	Industrial land	Proportion of industrial land	0	0.73	0.07	0.11	1.87
X5	Land for construction sites	Proportion of land used for construction sites	0	0.58	0.04	0.08	1.19
X6	Land for public management and public service facilities	Proportion of land for public management and public service facilities	0	0.36	0.08	0.07	1.23
X7	Green land	Proportion of green land	0	0.35	0.03	0.05	1.32
X8	Residential land	Proportion of residential land	0.02	0.86	0.51	0.18	1.85
X9	Land for commercial service facilities	Proportion of land for commercial service facilities	0	0.3	0.07	0.06	1.36
X10	Land for external transportation	Proportion of land for external transportation	0	0.31	0.01	0.03	1.29

2.3. Research Methods

2.3.1. Correlation Analysis

The impact of land use on air quality has a scale effect [36]. The spatial scale is too large to identify differences in land use. Therefore, we first calculated that the maximum distance between the monitoring stations is 1971 m and the average distance is 323.49 m. Then, we built 5 buffer zones with a radius of 330, 500, 1000, 1500, and 2000 m. The Pearson correlation coefficient was used to investigate the correlation between air quality concentration and land use composition within these 5 buffer zones around the 340 monitoring stations. Its expression is as follows:

$$R_{xy} = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \overline{y})^2}}$$

where n is the number of samples, x_i is the observed value of point i corresponding to variable x, y_i is the observed value of point i corresponding to variable y, $\overline{x}$ is the average of x samples, and $\overline{y}$ is the average of y. Rxy is the Pearson correlation coefficient, and its range is between −1 and 1. There is a negative relationship between two variables (x and y) when $R_{xy} < 0$ and a positive relationship when $R_{xy} > 0$. If the absolute value of R_{xy} is close to 1, that indicates a strong correlation between variables x and y. If the absolute value of R_{xy} is close to 0, then the correlation relationship is weak.

It is found that within 1000 m, the correlation coefficient between land use and air quality is high and the explanatory power is good (Table 2). In subsequent research, the 1000 m buffer zone around the monitoring station was used as a spatial scale to explore the relationship between air quality and land use.

Table 2. Results of Pearson correlation coefficient analysis.

	Variable	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10
330 m buffer zone	Y1	−0.116 *	0.187 **	0.111 *	0.141 **	0.018	0.011	−0.123 *	−0.047	0.008	−0.04
	Y2	−0.201 **	0.173 **	0.142 **	0.161 **	0.038	0.033	−0.184 **	−0.092	0.029	−0.058
	Y3	−0.241 **	0.162 **	0.232 **	0.197 **	0.03	0.046	−0.297 **	−0.069	0.044	−0.05
	Y4	0.102	0.079	−0.049	0.006	0.003	0.023	0.073	0.034	−0.047	0.064
	Y5	0.145 **	0.091	0.129 *	0.043	−0.035	−0.055	0.221 **	0.027	−0.086	−0.039
	Y6	0.091	0.122 *	0.067	0.005	−0.004	−0.033	−0.125 *	0.013	−0.057	−0.032
	Y7	−0.203 **	0.176 **	0.183 **	0.181 **	0.026	0.032	−0.231 **	−0.069	0.022	−0.035
500 m buffer zone	Y1	−0.124 *	0.321 **	0.025	0.221 **	0.084	0.01	−0.171 **	−0.003	−0.058	0.016
	Y2	−0.208 **	0.332 **	0.037	0.265 **	0.129 *	0.008	−0.231 **	−0.077	−0.035	−0.04
	Y3	−0.295 **	0.244 **	0.153 **	0.233 **	0.138 *	0.053	−0.335 **	−0.089	0.045	0.004
	Y4	0.133 *	0.137 *	0.130 *	0.051	−0.048	0.016	0.071	0.142 **	−0.157 **	0.126 *
	Y5	0.191 **	0.168 **	0.260 **	0.009	−0.053	−0.059	0.184 **	0.097	−0.092	0.018
	Y6	0.134 *	0.245 **	0.198 **	0.1	−0.018	−0.04	−0.09	0.066	−0.126 *	0.034
	Y7	−0.237 **	0.281 **	0.079	0.232 **	0.119 *	0.036	−0.273 **	−0.041	−0.004	0.002
1000 m buffer zone	Y1	−0.281 **	0.588 **	0.151 **	0.536 **	0.069	0.199 **	−0.317 **	−0.096	0.081	0.321 **
	Y2	−0.393 **	0.579 **	0.208 **	0.559 **	0.167 **	0.218 **	−0.375 **	0.174 **	0.043	0.360 **
	Y3	−0.499 **	0.496 **	0.389 **	0.500 **	0.260 **	0.222 **	−0.504 **	0.288 **	0.180 **	0.327 **
	Y4	0.170 **	0.293 **	−0.049	0.164 **	−0.088	0.014	−0.203 **	0.120 *	−0.294 **	0.068
	Y5	0.258 **	0.225 **	0.329 **	0.181 **	−0.302 **	−0.058	0.141 **	−0.245 **	−0.355 **	0.062
	Y6	0.180 **	0.369 **	0.174 **	0.306 **	−0.197 **	−0.097	−0.018	0.154 **	−0.306 **	0.161 **
	Y7	−0.428 **	0.560 **	0.295 **	0.528 **	0.201 **	0.205 **	−0.433 **	0.212 **	0.066	0.328 **
1500 m buffer zone	Y1	−0.207 **	0.430 **	0.079	0.329 **	0.075	0.102	−0.284 **	−0.011	−0.068	0.052
	Y2	−0.318 **	0.424 **	0.141 **	0.370 **	0.141 **	0.126 *	−0.332 **	0.065	−0.037	0.006
	Y3	−0.428 **	0.317 **	0.317 **	0.330 **	0.205 **	0.108 *	−0.439 **	−0.167 **	0.046	0.147 **
	Y4	0.138 *	0.181 **	−0.083	0.096	−0.042	0.047	−0.005	0.161 **	−0.161 **	0.098
	Y5	0.253 **	0.136 **	0.345 **	0.103	−0.204 **	−0.059	0.132 *	−0.242 **	−0.167 **	0.150 **
	Y6	0.146 **	0.265 **	0.210 **	0.113 **	−0.119 *	−0.062	0.033	0.188 **	−0.144 **	0.024
	Y7	−0.353 **	0.386 **	0.221 **	0.340 **	0.166 **	0.099	−0.380 **	0.091	−0.007	0.081
2000 m buffer zone	Y1	−0.133 *	0.306 **	0.002	0.172 **	0.067	0.05	−0.126 *	0.018	−0.033	0.058
	Y2	−0.241 **	0.325 **	0.061	0.124 **	0.116 *	0.067	−0.176 **	−0.08	0.006	0.013
	Y3	−0.350 **	0.221 **	0.218 **	0.120 **	0.152 **	0.025	−0.285 **	−0.112 *	0.09	0.119 *
	Y4	0.106	0.180 **	−0.108 *	0.101	−0.033	0.028	0.065	0.089	−0.111 *	0.087
	Y5	0.238 **	0.185 **	0.323 **	0.075	−0.125 *	−0.073	0.186 *	−0.134 *	−0.120 *	0.107 *
	Y6	0.110 *	0.175 **	0.223 **	0.006	−0.069	−0.06	0.006	0.075	−0.138 *	0.04
	Y7	−0.274 **	0.276 **	0.129 *	0.191 **	0.127 *	0.032	−0.131 *	0.066	0.034	0.099

** At the 0.01 level (two-tailed), the correlation is significant, * At the 0.05 level (two-tailed), the correlation is significant.

2.3.2. Inverse Distance Weight (IDW)

It can be seen from Figure 1 that the distribution of air quality monitoring points in the downtown area of Lanzhou cannot cover the entire city. This research attempts to analyze the temporal and spatial characteristics of the city's air quality through spatial interpolation.

Spatial interpolation is a method of estimating unknown points through known points. It is derived from the first law of geography, that is, the closer the points in space, the more similar their characteristics. It has been widely used in many fields, such as environment, soil, and digital terrain analysis. Commonly used spatial interpolation methods include inverse distance weight (IDW), kriging, spline, trend surface, and natural neighbor [58]. In order to accurately simulate the time and space distribution of air quality in the city, these four methods were used to obtain the city's AQI data, and then the interpolation results were cross-validated, and the best fit was compared. R^2 and root mean square error (RMSE) were used to determine the optimal interpolation method. The calculation method is as follows:

$$R^2 = \frac{\sum(\hat{y} - \overline{y})^2}{\sum y^2}$$

$$RMSE = \sqrt{\frac{\sum_i^n (\hat{y} - \overline{y})^2}{n}}$$

where n is the number of test sample points, y is the actual measured value corresponding to the test interpolation point, $\hat{y}$ is the estimated value corresponding to the test interpolation point, and $\overline{y}$ is the mean AQI value of the test interpolation point. R^2 represents the degree of fit between the interpolation result and the measured value; the closer to 1, the better the interpolation effect. *RMSE* represents the degree of deviation between the interpolation result and the measured value; the smaller the value, the higher the interpolation accuracy.

The calculation results (Table 3) show that the average R^2 of IDW is the highest and the *RMSE* is the smallest. This paper selected IDW to study the spatial distribution of AQI.

Table 3. Comparison of interpolation methods.

	IDW	Kriging	Trend Surface	Spline	Natural Neighbor
R^2	0.985383874	0.977285623	0.621729574	0.828676546	0.961090602
RMSE	2.914003447	2.902368713	2.488706625	2.827320784	2.927091981

When the set of points is dense enough to capture the extent of local surface variation needed for the analysis, IDW is used [58]. IDW interpolation has the advantages of a simple principle, convenient calculation, and conformity to the first law of geography. It is widely used in research of air quality spatial distribution characteristics [59]. IDW takes the distance between the interpolation points and the sample points as the weighted average; the closer the sample points to the interpolation points, the greater the weight given by the sample points [58]. It can model various scales when predicting air quality, which can reduce the uncertainty of prediction in exposure assessment and is more reliable than kriging.

Let a series of discrete points be distributed on the plane whose coordinates and values are called Xi, Yi, Zi (i = 1, 2, . . . , n); then, the value of Z points can be obtained by weighted distance. According to the value of the surrounding discrete points, the value of the Z point is calculated by the distance weighted value. Its expression is as follows:

$$Z_0 = \left[\sum_{i=1}^{n} \frac{Z_i}{d_i^k}\right] / \left[\sum_{i=1}^{n} \frac{1}{d_i^k}\right]$$

where Z_0 is the estimated value of point 0, Z_i is the value of control point i, d_i is the distance between control point i and point 0, n is the number of control points used in the estimation, and k is the specified power. In this paper, the inverse distance weighted difference method provided by ArcGIS10.2 was used to obtain all AQI values in the study area.

2.3.3. Getis-Ord Gi*

IDW can show the spatial distribution of AQI, but it has no statistical significance. Therefore, an optimized hot spot analysis was performed to show the statistical significance of highly polluted areas.

Getis-Ord Gi* is an effective method for calculating spatial autocorrelation that was proposed by mathematicians Getis and Ord in 1992. It is a statistic that identifies the specific locations of statistically significant point clusters with high data point density in the vicinity of a given point. Features with a high value density may not represent a statistically significant hot spot, and a hot spot can be determined if a feature with high value density is surrounded by other features with high values as well. It can qualitatively determine spatial hot or cold spot areas on a local scale and increase the confidence probability. Its expression is as follows [60]:

$$G_i^* = \frac{\sum_{j=1}^{n} W_{i,j}x_j - \overline{X}\sum_{j=1}^{n} w_{i,j}}{\sum_j^n W_{i,j}x_j}$$

where $W_{i,j}$ is the spatial weight between feature i and j. A positive G_i^* value shows that high values cluster around i; hence, the region is considered a hot spot. A negative value of G_i^* shows that low values cluster around i; hence, the region is considered a cold spot. Since the monitoring stations provide point data, this paper uses the inverse distance weighted difference method provided by ArcGIS 10.2 to obtain all AQI values in the study area, then constructs a 1000×1000 m fishing net using the extraction and analysis tool in ArcGIS to obtain the AQI value of each fishing net center, and then uses the spatial joint tool in the Overlay toolset to connect the point data to the fishing net data. Then, the 1000×1000 m fishing net is taken as the spatial scale for Getis-Ord Gi* visualization.

2.3.4. Negative Binomial Regression Model

Regression models such as ordinary linear regression, Poisson regression, negative binomial regression, and zero inflation models are usually used to analyze data where the dependent variable is numerical, and ordinary least squares (OLS) is used when the relationship between them is linear and assumptions are observed. The assumptions of linear regression modeling include normality, independence, homoscedasticity of errors, exclusion of spatial autocorrelation, and multicollinearity [61]. When the dependent variable has a large number of zero values, the zero-inflated Poisson regression model (ZIP) [62] is useful. The Poisson distribution assumes that the expected and variance values are equal [63], but this is not always true, causing dispersion of data when the variance is higher than average, such as in studies linking air quality. When over-dispersion happens, one way to estimate its parameter is to use negative binomial distribution [64]. The negative binomial regression model is a continuous mixed Poisson distribution [65] that allows the Poisson mean to follow the y distribution, and its expression is:

$$\begin{gathered}\Pr(Y=y)=\tfrac{\Gamma(y+\tau)}{y!\Gamma(\tau)}\left(\tfrac{\tau}{\lambda+\tau}\right)^{\tau}\left(\tfrac{\lambda}{\lambda+\tau}\right)^{y}\\ y=0,1,\ldots;\ \lambda,\ \lambda>0\\ \lambda=E(Y)\end{gathered}$$

where τ is the fuzzy parameter, and Y is the dependent variable, namely air quality, and the variance of Y is $\lambda + \lambda^2/\tau$. When τ tends to infinity, the negative binomial is close to the Poisson distribution. The negative binomial distribution has a very simple property:

the variance is greater than the mean. This paper uses a negative binomial regression model to explore the relationship between urban air quality and land use.

3. Results

3.1. Spatiotemporal Characteristics of Urban Air Quality

3.1.1. Temporal Distribution Characteristics

The annual AQI is represented by the continuous "valley–peak" interphase distribution characteristics of "low pollution–pollution peak–low pollution" (Figure 2a). The daily average of AQI fluctuated between 45 and 174, and the annual average was 85. There were 6 excellent days, 285 good days, 74 lightly polluted days, and 1 moderately polluted day. There was a total of 75 polluted days and 291 good days. The rate of excellent and good days was 79.5%, indicating that the air quality in Lanzhou was good.

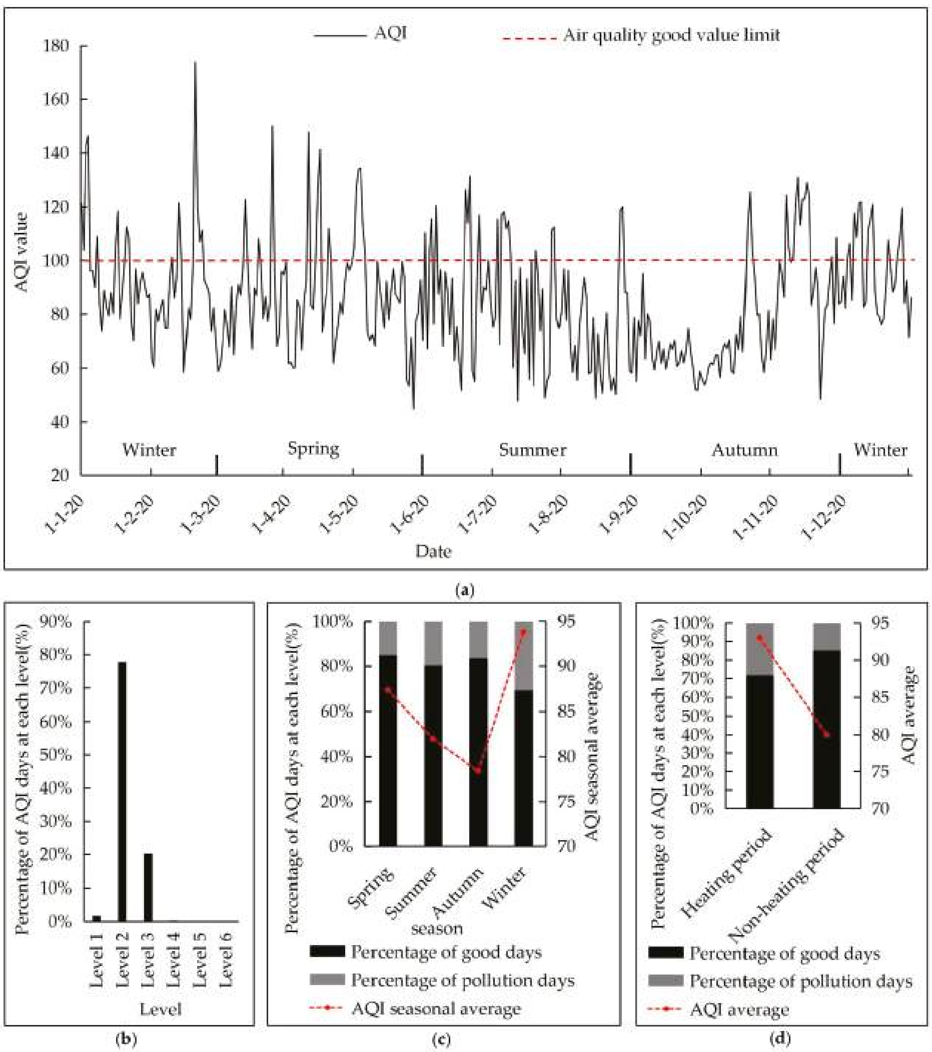


Figure 2. Temporal distribution characteristics of air quality: (**a**) trend of annual air quality change; (**b**) annual distribution of air quality by level; (**c**) seasonal characteristics of AQI; (**d**) heating and non-heating period characteristics of AQI.

We divided the year into four seasons, with March to May as spring, June to August as summer, September to November as autumn, and December to February as winter. In terms of the seasonal distribution of AQI (Figure 2c), the pollution degree was in the order of winter > spring > summer > autumn, but in terms of the rate of good air quality, it was in the order of winter > spring > autumn > summer. The air quality in summer and autumn was better than in winter and spring, showing the characteristics of a V-shaped change, and the seasonal average AQI value fluctuated between 74 and 96.

From the beginning of spring, the air quality slowly decreased to its lowest value in autumn and then rose rapidly to its highest value in winter. In spring, air quality was dominated by good days and light pollution, with a rate of excellent and good days of 84.78%. In summer, the number of good days with light pollution gradually increased and the number of good days gradually decreased, with a rate of excellent and good days of 80.43%. In autumn, atmospheric convection was strong and pollutants were diffuse, occurring relatively quickly, with significant precipitation, and the city's air quality was the best, with a rate of excellent and good days of 83.52%. In winter, the city's air quality was the worst, with a rate of excellent and good days of only 69.23% and a pollution rate of 30.77%.

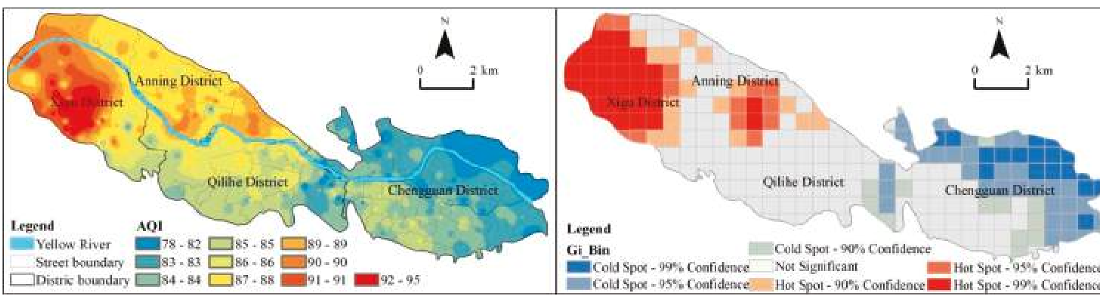
The fundamental reason lies in the atmospheric circulation and heating in winter. Northwest wind prevails in Lanzhou in spring. There is much dusty weather, the concentration of particulate matter obviously increases, precipitation and relative humidity are low, and there is more dust and floating dust on the surface. The superposition of the two causes 40% of air pollution in spring [54,57]. In summer and autumn, affected by the East Asian and South Asian monsoons, the atmosphere has good diffusion conditions, which is conducive to the dilution and diffusion of pollutants. Rainfall increases, vegetation coverage significantly increases, and dust from roads and construction is suppressed. In winter, there is little precipitation, dry climate, dry vegetation, stable atmospheric stratification, severe temperature inversion, and poor conditions for dilution and diffusion of pollutants [66], and the entire city enters a long heating period, so winter pollution is the most serious. From the perspective of changes in the heating and non-heating period (Figure 2d), air quality during the heating period is poor and the pollution rate reaches 27%, and air quality during the non-heating period is better. This is consistent with research conclusions in Balıkesir, Turkey, and in the Rhine–Ruhr area of Germany [67,68].

3.1.2. Spatial Clustering Features

AQI has obvious differentiation in space. In general, the degree of air pollution showed characteristics of heaviness in the west and lightness in the east, in the order of Xigu District > Anning District > Qilihe District > Chengguan District (Figure 3a). Hot spots are mainly concentrated in Xigu and Anning and cold spots mainly in Chengguan, while the agglomeration characteristics of Qilihe District are not significant (Figure 3b). This may be related to urban functions, land use structure, industrial enterprise layout, and energy consumption intensity. Xigu District forms the city's pollution core, dominated by Xiliugou, Sijiqing, Xigucheng, and Fuli Road Streets, with an AQI over 90. The main reason is that Xigu is the most important industrial area in Lanzhou, with nearly 50% of the land used for industry, and there are heavy and chemical industries such as Lanzhou Xigu Thermal Power Plant, Lanzhou Petrochemical Company, Lanzhou Petrochemical Company of PetroChina, Fanping Power Plant, Lanzhou Gas Plant, and so on. Most of these enterprises are in the thermal power, crude oil smelting, and petrochemical industries. Their emission of pollutants is in excess of the city's industrial emissions of 50%.

Anning is the cultural district of Lanzhou City, as well as the distribution area of the instrument and high-tech industries, so a number of point pollution cores have formed: Shilidian, Yintan Road, Xilu, and Shajingyi Streets. The AQI of the whole region is over 85, and the pollution degree decreases from the north bank of the Yellow River to Renshou Mountain. The main reason is that Anning is close to Xigu and the area along the river is susceptible to industrial pollution. The high AQI of Shilidian Street in the east is related to the waste gas emissions of the sewage treatment plant.

Qilihe District is bounded by Xihu Street, where pollution is heavy in the west and light in the east, high in the north (south bank of the Yellow River), and low in the south. Xiuchuan, Gongjiawan, Pengjiaping, and Jingangcheng are four low-pollution areas. Qilihe undertakes the city's commercial, living, and productive services and other functions and is also the most important construction and development zone in the built-up area. There are many construction sites in the "three beaches", the Matan, Cuijiadandatan, and Yingmentan areas. Dust has a certain amount of impact on air quality. The air quality in Chengguan District is better, and the AQI is below 85. The main reason is that Chengguan is the city's administrative office and commercial area and is located in the upwind direction with fewer pollution sources (especially industrial sources).



(**a**) (**b**)

Figure 3. Spatial distribution map of air quality throughout the year: (**a**) spatial distribution and (**b**) spatial agglomeration characteristics of AQI.

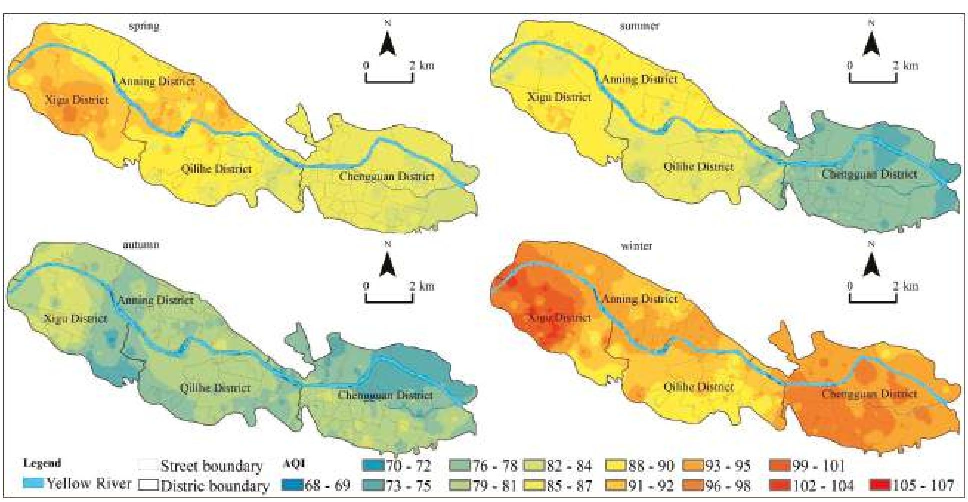
Air pollution forms an obvious spatial process of clustering–diffusion with seasonal changes (Figure 4a). The hot spot in spring and summer is Xigu District, and the cold spot in Anning is Chengguan District. Great changes take place in the hot spot areas in autumn and winter. The hot spot area in autumn is mainly concentrated in Xigu District and the central areas of Qilihe and Chengguan Districts, while the cold spot area is mainly concentrated in the mountainous part of Qilihe and along the river in the northern part of Chengguan. In winter, two hot spots are formed in Xigu and Chengguan, and Qilihe is a cold spot area (Figure 4b). In the spring, the AQI of the whole city is between 80 and 97.

Spatially, an industrial pollution area centered on Xigu District and an area around the central business district of Datan and Peili Square in Anning–Yingmentan–Qilihe District have formed. For lightly polluted centers, the AQI is above 90. The Anning central business district and the "Santan" area have been key construction areas in Lanzhou in recent years, with a distribution of many construction sites, and construction dust has made these areas highly polluted. The AQI of the eastern part of Qili River and Chengguan District is basically between 82 and 90, and the pollution level is heavy in the west and light in the east. In summer, the city's AQI is between 69 and 92. The low AQI area expands, and the high pollution area further shrinks in Xigu and Anning. The AQI is greater than 90.

Lightly polluted areas have formed in Anning District, such as Shajingyi, the central business district, and sewage treatment plants. Xiuchuan, Pengjiaping, and Xihu Streets in Qilihe District have even reached excellent grades. The whole area of Chengguan District is of excellent grade, with AQI below 80, and only light pollution occurs in the railway station, Yanchangbao, and Dongfanghong Square. In autumn, the city's AQI is between 64 and 91, with only slight pollution in the surrounding areas of Lanzhou Xigu Thermal Power Plant, Lanzhou Petrochemical Company, and Anning District Sewage Treatment Plant. In winter, the city's AQI is between 81 and 104.

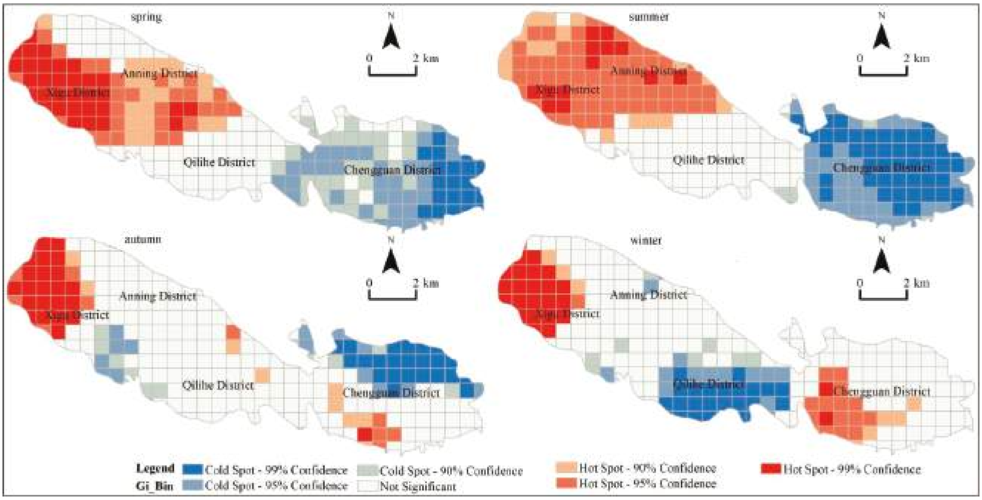
Two moderately polluted areas, Xigu District with mainly industrial emissions and Chengguan District with mainly heating emissions, have formed, with an AQI of over 95. A surface pollution area formed in Chengguan dominated by Zhangye Road, Guangwumen, Jiuquan Road, Gaolan Road, Wuquan, Railway East Village, Railway West Village, and other streets. The main reason is that 56.5% of heating stations are gathered in Chengguan. Boilers emit large amounts of dust and SO_2, forming low-altitude non-point-source pollution [69]. The air quality in Anning and Qilihe Districts is relatively good, and the AQI is basically between 90 and 95. Even marginal areas have low values, such as Chenping Street in the east of Xigu and Pengjiaping Town in Qilihe.

The heating period in Lanzhou is from the beginning of November to the end of March, and the non-heating period is from the beginning of April to the end of October. It can be seen from Figure 5 that air pollution during the heating period is obviously more serious than during the non-heating period. The AQI of the whole city during the heating period is between 82 and 104. The AQI of the whole city during the non-heating period is between 70 and 88. During the heating period, two pollution cores are formed in Xigu and Chengguan Districts (Figure 5). Anning District is also a heavily polluted area in the city due to the prevailing wind direction [52]. It is shown that the spatial variation of air pollutants is affected not only by local emission but also by meteorological conditions (such as wind), which cause secondary pollution near the emission source [36]. In terms of spatial agglomeration, the core areas of Xigu and Chengguan Districts are hot spots, the mountainous area in the south of Qilihe District is a cold spot area, and the agglomeration of Anning District is nonsignificant. The air quality of Lanzhou is gradually stable during the non-heating period, and the air pollution is heavy in the west and light in the east. The spatial agglomeration model shows that the stable hot spots of pollution are Xigu and Anning Districts, the cold spot is Chengguan District, and the spatial agglomeration characteristics of Qilihe District are not significant.



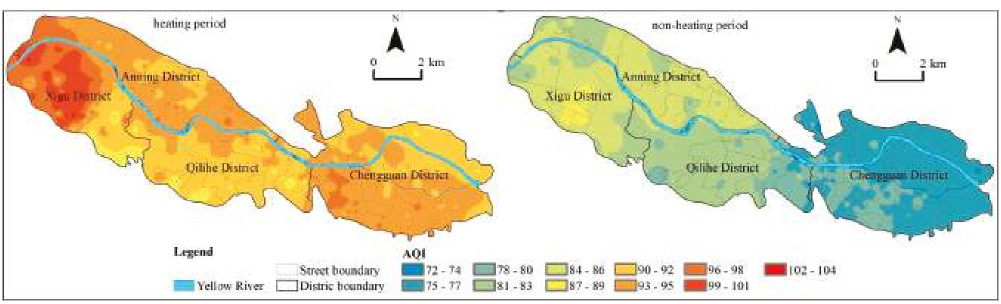
(**a**)

Figure 4. *Cont.*

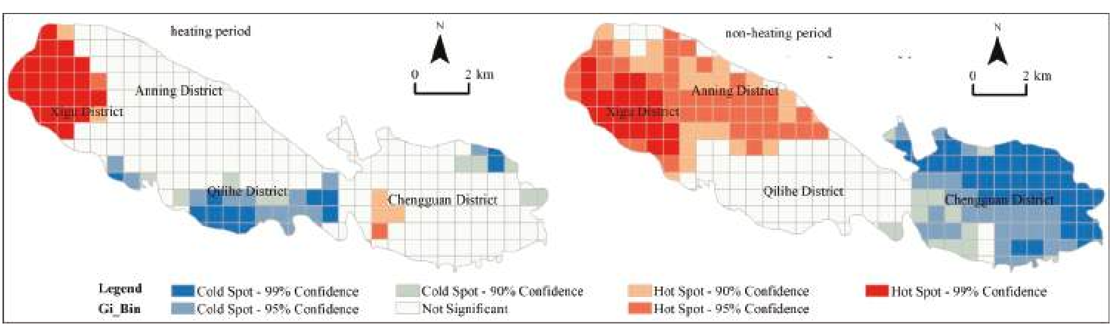


(**b**)

Figure 4. Seasonal spatial distribution map of air quality: (**a**) seasonal spatial distribution and (**b**) agglomeration characteristics of AQI.



(**a**)



(**b**)

Figure 5. Spatial distribution map of air quality during heating and non-heating periods: (**a**) spatial distribution and (**b**) agglomeration characteristics of AQI.

3.2. Relationship between Urban Air Quality and Land Use

Using SPSS software to test the normality of each dependent variable to determine whether it was discrete data (Table 4), we found that the significance level of Y1, Y2, Y3, Y4, Y6, and Y7 was less than 0.05, in a discrete distribution state. Only Y5 had a significance greater than 0.05 (0.222). The main reason is that Lanzhou has frequent static winds in winter, a high inversion rate of 99% [69], and poor diffusion conditions, resulting in seemingly distributed air quality data. Air quality is discrete data, and none of the data had a value less than 0. This paper used a negative binomial regression model for regression analysis.

Table 4. Normality test of data.

Variable	Mean	Variance	Wa	*p*
Y1	86	8.529	0.965	0
Y2	88	13.895	0.950	0
Y3	82	36.377	0.889	0
Y4	79	9.144	0.986	0.002
Y5	94	13.544	0.994	0.222
Y6	93	9.113	0.960	0
Y7	80	14.704	0.950	0

Note: Normality tested by Shapiro–Wilk test.

In order to improve the simulation accuracy of the model, it is necessary to check the collinearity of the respective variables. The analysis results (Table 4) show that the VIF of each variable is less than 3 and is far less than the critical value of 10, which indicates that the model has no multicollinearity problem and can be used for negative binomial regression analysis.

The negative binomial regression model analysis results (Table 5) show that all negative binomial regressions were statistically significant ($p < 0.01$) with high fitting precision.

The results of the annual regression model show that air quality is negatively correlated with green land and positively correlated with industrial emissions, traffic emissions, industrial land, and land for external transportation at the 0.01 significance level and residential land at the 0.05 significance level. It is positively correlated with land for construction sites at the 0.1 significance level, and the degree of impact shows the order of industrial land > land for external transportation > traffic emissions > heating emissions > residential land > land for construction sites. In spring, air quality is negatively correlated with heating emissions and green land at the 0.01 significance level, and the impact of green land is greater than heating emissions. It is positively correlated with industrial emissions, traffic emissions, and land for external transportation at the 0.01 significance level. It is positively correlated with industrial land at the 0.05 significance level. There is a positive correlation with land for construction sites and residential land at the 0.1 significance level, and the degree of influence shows the order of land for external transportation > industrial emissions > traffic emissions > industrial land > land for construction sites > residential land.

In summer, air quality is negatively correlated with heating emissions and green land at the 0.01 significance level, and the impact of green land is greater than heating emissions. It is positively correlated with industrial emissions, industrial land, land for construction sites, residential land, and land for external transportation at the 0.01 significance level. At the 0.05 significance level, it is positively correlated with land for public management and public service facilities, and land for commercial service facilities, and the degree of impact shows the order of industrial land > land for construction sites > land for external transportation > residential land > industrial emissions > land for public management and public service facilities > land for commercial service facilities.

In autumn, air quality is positively correlated with heating emissions, industrial emissions, and industrial land at the 0.01 significance level, and the degree of influence shows the order of industrial land > industrial emissions > heating emissions. In winter, air quality is positively correlated with traffic emissions at the 0.01 significance level, and positively correlated with heating emissions and industrial emissions and negatively correlated with land for public management and public service facilities at the 0.1 significance level. The degree of impact shows the order of traffic emissions > industrial emissions > heating emissions. During the heating period, air quality is positively correlated with heating, industrial, and traffic emissions at the 0.05 significance level, and the degree of influence shows the order of traffic emissions > industrial emissions > heating emissions. During the non-heating period, air quality is negatively correlated with green land and positively correlated with industrial emissions, industrial land, land for construction sites, residential land, and land for external transportation at the 0.01 significance level. There is a negative correlation with heating emissions at the 0.05 significance level. There is a positive correlation with traffic emissions, land for public management and public service facilities, and land for commercial service facilities at the 0.1 significance level, and the degree of impact is in the order of industrial land > land for construction sites > land for external transportation > residential land > industrial emissions > land for commercial service facilities > land for public management and public service facilities > traffic emissions.

Overall, there is a close relationship between urban land use and air quality. Industrial activities, traffic pollution, and urban construction activities are the most important factors affecting urban air quality. Green space can reduce urban pollution. Industrial land has a serious impact on the quality of the air environment in terms of area and spatial distribution. As the "green lung" of the city, green land can adsorb and settle most air pollutants; the larger the green land, the better the air quality. The impact of land use on air quality has a seasonal effect and shows a certain time coupling with local social and economic activities. There is not a clear positive or negative correlation between all urban construction land and air quality. Land for public management and public service facilities has a positive correlation with air quality in summer and non-heating periods, and a negative correlation in winter, and there is no obvious mathematical relationship in other models. The land used for commercial service facilities only shows a positive correlation with air quality in summer and non-heating periods, and there is no obvious mathematical relationship in other models.

Table 5. Negative binomial model results.

Variables	M1	M2	M3	M4	M5	M6	M7
X1	−0.00019816 (−0.92)	−0.0007814 *** (−3.51)	−0.00173062 *** (−4.47)	0.00107369 *** (3.32)	0.00053515 * (2.19)	0.00057556 ** (2.72)	−0.00086096 ** (−3.15)
X2	0.00429904 *** (5.19)	0.00540908 *** (5.48)	0.0066031 *** (4.59)	0.00310282 *** (3.84)	0.00224721 * (1.99)	0.00296906 ** (3.29)	0.00540177 *** (5.26)
X3	0.00414971 *** (3.31)	0.00534804 *** (3.47)	0.00410567 (1.70)	−0.00022114 (−0.14)	0.00664185 *** (4.04)	0.00421788 ** (3.18)	0.00407687 * (2.50)
X4	0.18057696 *** (4.76)	0.12480744 ** (2.63)	0.45315445 *** (5.19)	0.19876456 *** (3.53)	−0.02347487 (−0.54)	0.07403405 (1.91)	0.26899138 *** (4.73)
X5	0.05019174 * (2.42)	0.06809959 * (2.55)	0.16797907 *** (4.09)	−0.02767476 (1.05)	−0.05262646 (−1.82)	−0.00819725 (−0.36)	0.09824626 *** (3.63)
X6	0.02209244 (0.95)	0.01899393 (0.65)	0.13869561 ** (3.07)	0.02586483 (0.96)	−0.08079757 ** (−2.87)	−0.03109436 (−1.41)	0.06620023 * (2.18)
X7	−0.1662874 *** (−6.95)	−0.21372142 *** (−7.27)	−0.47167738 *** (−10.63)	−0.01679669 (−0.51)	0.01593301 (0.51)	−0.03059924 (−1.19)	−0.27981642 *** (−8.95)
X8	0.03085474 ** (2.66)	0.02762988 * (2.00)	0.09474067 *** (3.89)	0.01392373 (0.96)	−0.00599751 (−0.43)	0.00047415 (0.04)	0.05649607 *** (3.54)
X9	0.02789775 (0.67)	0.03558245 (0.76)	0.24589958 ** (3.29)	−0.08055354 (−1.84)	−0.08187814 (−1.52)	−0.06773554 (−1.57)	0.10692261 * (2.06)
X10	0.06640575 *** (3.45)	0.07624238 *** (3.49)	0.12397266 *** (3.44)	0.02951012 (1.35)	0.03569024 (1.24)	0.0450457 (1.84)	0.08384093 *** (3.43)
_cons	4.4093038 *** (553.85)	4.4330281 *** (466.38)	4.3374985 *** (233.47)	4.3384706 *** (404.55)	4.545 *** (474.31)	4.5089679 *** (552.08)	4.3316371 *** (366.43)
N	340	340	340	340	340	340	340

t statistics shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4. Discussion

Previous studies mostly obtained air quality data from five national air quality monitoring stations in Lanzhou [50,70]. Due to the lack of monitoring stations, it is difficult to truly and effectively describe the temporal and spatial evolution of air quality in the city [36]. There are some defects in the identification of polluted area inside the city [3]. In this study, AQI data from 340 air quality monitoring stations in Lanzhou were used to make up the deficiency of previous studies, which can clearly depict the spatiotemporal change law of air quality and identify high-pollution areas in the city. The modeling of the relationship between land use and air quality was mainly based on annual average air quality data, ignoring seasonal differences, and the research results show that construction land has a significant effect on urban air quality. There is no detailed classification of urban construction land, so this paper discusses the relationship between land use and air quality by using the refined land use data within the buffer zone of 1000 m around the air quality monitoring station. It is found that not all construction sites cause air pollution, and different types of land have different effects on air quality. The effect of land use on air quality also has seasonal differences under different model conditions, to a certain extent, and this conclusion extends the previous research and provides a practical case for micro-scale air quality distribution and its driving factors based on land use.

The study found that the rate of excellent and good air quality in Lanzhou reached 79.5%, which is consistent with the research conclusions of Sun, Ma, Guan, and others [46,49,50]. This is in line with the development trend of air quality in China [19], which cannot be separated from air pollution mitigation measures such as central heating, traffic restrictions, and street sprinkling [39]. In terms of time distribution, it has the characteristics of alternating high and low pollution and obvious seasonal changes throughout the year. Pollution in winter and spring is more serious than that in summer and autumn, which is consistent with the results of air quality research in China [12]. It is mainly affected by monsoon climate conditions and rain and heat conditions.

The air quality in Lanzhou City has spatial differentiation. Pollution in Xigu District is the most serious, which has been widely recognized by scholars [50,54,70]. The reason is that Xigu, as the largest heavy chemical industry zone in Lanzhou, has a large discharge of pollutants. In addition to the special geomorphic conditions of Lanzhou, air pollutants are not easily diffused, which leads to aggravation of pollution [70]. However, some scholars have found that there is no spatial heterogeneity in the air pollution in Lanzhou, which may be related to the research data [3]. Data from five national ambient air quality monitoring stations cannot identify differences in air quality within cities; a large quantity of data from monitoring stations is needed to clearly identify the differences in air quality within a city. The spatial distribution of air quality has seasonal differences, which is consistent with the conclusion of Shi [71]. However, Shi's research did not identify where the seasonal differences in air quality within cities are reflected. The research in this paper found that in addition to the core of pollution in Xigu District, the air pollution in Lanzhou during the heating period is mainly concentrated in Chengguan District, which deepens previous research conclusions.

The spatial changes of air pollution in cities are closely related to land use. Different types of land use have different effects on air quality, which is consistent with the results of Jo's research in Korea [35]. Industrial emissions, traffic emissions, industrial land, residential land, and land for external transportation cause air pollution, while green land can control air pollution, which is consistent with the previous yearly model [25,35,43]. Industrial and traffic emissions are the main causes of air pollution in Lanzhou [70]. Residential areas gather large numbers of people, and the high population density leads to deteriorated air quality [8].

The results of different seasonal models show that land for construction sites, heating emissions, and green land have seasonal effects on air quality. In winter and heating periods, only heating emissions, industrial emissions, and traffic emissions are positively correlated with the degree of air pollution, which is consistent with the research conclusions of Li.

As the weather gets colder in winter, the inhibitory effect of vegetation on air pollutants gradually decreases from 16.6% in spring to 10.8% in winter. Traffic emissions are increased due to the weakened impact of green space [72], and mobile sources such as traffic cause more pollution than power generation and industry [73].

The secondary pollution in Lanzhou is relatively serious in winter, and the proportion of pollutants emitted by motor vehicles is relatively large [47]. Therefore, Lanzhou should adopt different air pollution prevention and control measures according to seasonal variations. The impact of land for public management and public service facilities and land for commercial service facilities on air quality is not clear, which is inconsistent with the research conclusions of Korean scholars [35]. These two studies found that commercial areas increase the degree of air pollution through real-time big data of smart sensors. The above inconsistent results may be caused by the accuracy of the data. Future studies can use smart sensors, big data, and other means to clearly describe the differences between the two.

5. Conclusions

5.1. Conclusions

Identifying the areas of poor air quality inside cities and their driving factors in terms of land use is a prerequisite and basis for effective air environmental governance, which is of great practical significance in order to promote sustainable development of the urban environment. This study contributes to the research on air quality and land use at the micro-scale by examining the changing laws of air quality and the relationship between urban land use and air quality based on data from 340 air quality monitoring stations.

The air quality in Lanzhou has the characteristics of temporal and spatial differentiation. Air quality varies throughout the year with high and low pollution, with obvious seasonal changes; summer and autumn are better than winter and spring, and air pollution is the most serious during the heating period. Air pollution presents a spatial pattern of heavy weight in the west and light weight in the east, characterized by the order of Xigu > Anning > Qilihe > Chengguan District.

The results of identifying hot and cold spots of air pollution show that the hot spots are mainly concentrated in Xigu and Anning and the cold spots are mainly concentrated in Chengguan. With seasonal changes, air pollution undergoes a process of "concentration–diffusion" in space. During the heating period, two air pollution hot spots form a perennial pollution core in Xigu and a heating core in Chengguan.

Different land use categories have different effects on air quality with regard to either the direction, magnitude, or seasonal scale effect of correlation. In general, industrial activities, traffic pollution, and urban construction activities are the most important factors affecting urban air quality. Green spaces can reduce urban pollution. The impact of land use on air quality has a seasonal effect.

The land use types are directly related to pollution emissions, which indirectly affects air quality. However, due to the influence of regional transmission and secondary conversion, future research should combine primary pollutants such as SO_2, NOx, dust (PM_{10}, $PM_{2.5}$), etc., and AQI to study their relationships with land use types. The AQI is a comprehensive representation of air pollution. Different pollutants have different relative contributions to the AQI in different seasons. For example, O_3 contributes significantly in summer, while PM contributes significantly in winter, which may lead to differences in the analysis of the spatial distribution of the AQI. Urban land use is static data, while air quality is dynamic data. Although studies have found seasonal differences in the impact of land use on air quality, using only one year of data might affect the stability of the conclusion. In the future, we need to acquire long-term dynamic data using new methods such as big data, machine learning, and intelligent sensors and rebuild the air–LUR model to fully study the coupled relationship between urban air quality and land use.

5.2. Policy Suggestions

Based on the analysis results of this study, different types of land use have different impacts on air quality. Similarly, the impact of land use on air quality under different model conditions has seasonal differences. Therefore, discussing methods to curb the deterioration of air quality does not mean that, in order to control the scale of urban construction land, it is necessary to subdivide the types of land, identify the types that affect air quality, optimize and adjust the land structure, and formulate sustainable urban land use policies to control air pollution. Specifically, the following should be addressed: (1) In urban planning, when optimizing the layout of urban functions, we should try to avoid the "spreading pie" type of urban space expansion, adopt a compact and intensive development model, alleviate the commuter traffic demand caused by the separation of work and residence, and implement public transportation. The priority strategy is to build a complete public transportation system and guide individuals to transfer to using it, thereby slowing the growth of motor vehicles, reducing traffic emissions, and improving air quality. (2) In urban land use planning, we should control the scale of industrial land, construction site land, and foreign-use land; gradually transfer industries in the central area of the city to the suburbs; reduce the proportion of industrial land; and use water bodies and land between polluting factories and other land. It is essential to protect and isolate open spaces to prevent industrial pollution. (3) In the planning of the urban green space system, we should increase the coverage of urban green space, cover areas with high concentrations of air pollutants, absorb urban air pollutants, improve air quality, and reduce the concentration of pollutants in the entire city. (4) We should strengthen the management of dust from urban roads and construction sites; promote an improved mechanized road cleaning rate, install atmospheric environment monitoring equipment and atomization and dust suppression devices on construction sites, and network with the environmental protection and housing construction departments to improve the management level of construction dust. (5) We should further optimize the energy structure, replace coal with clean energy, and reduce air pollution caused by coal burning during the heating period.

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References

1. *World Urbanization Prospects: The 2018 RevisionUnited Nations*; Department of Economic and Social Affairs, Population Division: New York, NY, USA, 2018.
2. Tecer, L.H.; Tagil, S. Impact of Urbanization on Local Air Quality: Differences in Urban and Rural Areas of Balikesir, Turkey. *Clean Soil Air Water* **2014**, *42*, 1489–1499. [CrossRef]
3. Zhang, Y.; Li, M.; Bravo, M.A.; Jin, L.; Nori-Sarma, A.; Xu, Y.; Guan, D.; Wang, C.; Chen, M.; Wang, X.; et al. Air Quality in Lanzhou, a Major Industrial City in China: Characteristics of Air Pollution and Review of Existing Evidence from Air Pollution and Health Studies. *Water Air Soil Pollut.* **2014**, *225*, 2187. [CrossRef]
4. World Health Organization. Air Pollution. 2020. Available online: https://www.who.int/health-topics/air-pollution#tab=tab_2.2020-3-28 (accessed on 12 March 2021).
5. Yin, P.; Brauer, M.; Cohen, A.J.; Wang, H.; Li, J.; Burnett, R.T.; Stanaway, J.D.; Causey, K.; Larson, S.; Godwin, W.; et al. The effect of air pollution on deaths, disease burden, and life expectancy across China and its provinces, 1990–2017: An analysis for the Global Burden of Disease Study 2017. *Lancet Planet. Health* **2020**, *4*, 386–398. [CrossRef]

6. Abd Rani, N.L.; Azid, A.; Khalit, S.I.; Juahir, H.; Samsudin, M.S. Air Pollution Index Trend Analysis in Malaysia, 2010–15. *Pol. J. Environ. Stud.* **2018**, *27*, 801–807. [CrossRef]
7. Kanchan, K.; Gorai, A.K.; Goyal, P. A review on air quality indexing system. *Asian J. Atmos. Environ.* **2015**, *9*, 101–113. [CrossRef]
8. Tian, Y.; Jiang, Y.; Liu, Q.; Xu, D.; Zhao, S.; He, L.; Liu, H.; Xu, H. Temporal and spatial trends in air quality in Beijing. *Landsc. Urban Plan.* **2019**, *185*, 35–43. [CrossRef]
9. Hu, J.; Ying, Q.; Wang, Y.; Zhang, H. Characterizing multi-pollutant air pollution in China: Comparison of three air quality indices. *Environ. Int.* **2015**, *84*, 17–25. [CrossRef] [PubMed]
10. *HJ 633-2012, Ambient Air Quality Index (AQI) Technical Regulations (Trial)*; China Environmental Science Press: Beijing, China, 2012.
11. Wang, Z.B.; Liang, L.W.; Wang, X.J. Spatio-temporal evolution patterns and influencing factors of PM2.5 in Chinese urban agglomerations. *Acta Geogr. Sin.* **2019**, *74*, 2614–2630.
12. Zhang, X.M.; Luo, S.; Li, X.M.; Li, Z.F.; Fan, Y.; Sun, J.W. Spatio-temporal Variation Features of Air Quality in China. *Sci. Geogr. Sin.* **2020**, *40*, 190–199.
13. Nurul, A.M.; Ling, O.H.L.; Omar, D. Urban Air Quality and Human Health Effects in Selangor, Malaysia. *Procedia Soc. Behav. Sci.* **2015**, *170*, 282–291.
14. Liu, Q.; Yang, Y.C.; Liu, H.Y. Spatiotemporal evolution characteristics of air pollution degree in 366 cities of China. *Arid Land Geogr.* **2020**, *43*, 820–830.
15. Lin, X.Q.; Wang, D. Spatio-temporal variations and socio-economic driving forces of air quality in Chinese cities. *Acta Geogr. Sin.* **2016**, *71*, 1357–1371.
16. Germani, A.R.; Morone, P.; Testa, G. Environmental justice and air pollution: A case study on Italian provinces. *Ecol. Econ.* **2014**, *106*, 69–82. [CrossRef]
17. Kramer, A.L.; Campbell, L.; Donatuto, J.; Heidt, M.; Kile, M.; Simonich, S.L.M. Impact of local and regional sources of PAHs on tribal reservation air quality in the U.S. Pacific Northwest. *Sci. Total Environ.* **2020**, *710*, 136412. [CrossRef]
18. Oleniacz, R.; Gorzelnik, T. Assessment of the Variability of Air Pollutant Concentrations at Industrial, Traffic and Urban Background Stations in Krakow (Poland) Using Statistical Methods. *Sustainability* **2021**, *13*, 5623. [CrossRef]
19. Xiao, Y.; Tian, Y.; Xu, W.; Wu, J.; Tian, L.; Liu, J. Spatiotemporal Pattern Changes of Air Quality in China from 2005 to 2015. *Ecol. Environ. Sci.* **2017**, *26*, 243–252.
20. Steiner, A.L.; Tonse, S.; Cohen, R.C.; Goldstein, A.H.; Harley, R.A. Influence of future climate and emissions on regional air quality in california. *J. Geophys. Res. Atmos.* **2006**, *111*, 18303. [CrossRef]
21. Javanbakht, M.; Boloorani, A.D.; Kiavarz, M.; Samani, N.N.; Zangiabadi, M. Spatial-temporal analysis of urban environmental quality of tehran, iran. *Ecol. Indic.* **2020**, *120*, 106901. [CrossRef]
22. Mccarty, J.; Kaza, N. Urban form and air quality in the united states. *Landsc. Urban Plan.* **2015**, *139*, 168–179. [CrossRef]
23. Yu, J.; Shang, E.P. The Spacing Correspondence of PM2.5 to Factors of Urban Planning: A Case of Shen Yang. *Urban Dev. Stud.* **2013**, *20*, 9.
24. Wang, F.; Wu, K.Y.; Wang, H.H.; Zhang, S.Y. Correlations between PM2.5 with Land Use Types in Hefei and Constructive Solutions. *Environ. Sci. Manag.* **2014**, *39*, 73–79.
25. Xiao, J.N.; Du, G.M.; Shi, Y.Q.; Wen, Y.Y.; Yao, J.; Gao, Y.T.; Lin, J.Y. Spatiotemporal distribution pattern of ambient air pollution and its correlation with meteorological factors in Xiamen City. *Acta Sci. Circum.* **2016**, *36*, 3363–3371.
26. Li, X.F.; Zhang, M.J.; Wang, S.J.; Zhao, A.F.; Ma, Q. Variation Characteristics and Influencing Factors of Air Pollution Index in China. *Environ. Sci.* **2012**, *33*, 1936–1943.
27. Habermann, M.; Billger, M.; Haeger-Eugensson, M. Land use Regression as Method to Model Air Pollution. Previous Results for Gothenburg/Sweden. *Procedia Eng.* **2015**, *115*, 21–28. [CrossRef]
28. Aslan, A.; Altinoz, B.; Ozsolak, B. The link between urbanization and air pollution in turkey: Evidence from dynamic autoregressive distributed lag simulations. *Environ. Sci. Pollut. Res.* **2021**, 1–11. [CrossRef]
29. Xu, S.; Zou, B.; Pu, Q.; Guo, Y. Impact Analysis of Land Use/Cover on Air Pollution. *J. Geoinf. Sci.* **2015**, *17*, 290–299.
30. Yuan, L.L. Study on the Sustainable Use of Urban Land in the Process of Urbanization. Ph.D. Thesis, Huazhong Agricultural University, Wuhan, China, 2005.
31. Yang, Y.C.; Yang, X.J. Research on Urban Spatial Expansion and Land Use Inner Structure Transformation of the Large Valley-basin Cities in China from 1949 to 2005—A Case Study of Lanzhou. *J. Nat. Resour.* **2009**, *24*, 37–49.
32. Bandeira, J.M.; Coelho, M.C.; Sá, M.E.; Tavares, R.; Borrego, C. Impact of land use on urban mobility patterns, emissions and air quality in a Portuguese medium-sized city. *Sci. Total Environ.* **2011**, *409*, 1154–1163. [CrossRef] [PubMed]
33. Frank, L.D.; Sallis, J.F.; Conway, T.L.; Chapman, J.E.; Saelens, B.E.; Bachman, W. Many pathways from land use to health—Associations between neighborhood walkability and active transportation, body mass index, and air quality. *J. Am. Plan. Assoc.* **2006**, *72*, 75–87. [CrossRef]
34. Ku, C.A. Exploring the Spatial and Temporal Relationship between Air Quality and Urban Land-Use Patterns Based on an Integrated Method. *Sustainability* **2020**, *12*, 2964. [CrossRef]
35. Jo, S.S.; Sang, H.L.; Leem, Y. Temporal Changes in Air Quality According to Land-Use Using Real Time Big Data from Smart Sensors in Korea. *Sensors* **2020**, *20*, 6374. [CrossRef] [PubMed]
36. Xu, G.; Jiao, L.; Zhao, S.; Yuan, M.; Li, X.; Han, Y.; Zhang, B.; Dong, T. Examining the Impacts of Land Use on Air Quality from a Spatio-Temporal Perspective in Wuhan, China. *Atmosphere* **2016**, *7*, 62. [CrossRef]

37. Clark, L.P.; Millet, D.B.; Marshall, J.D. Air Quality and Urban Form in U.S. Urban Areas: Evidence from Regulatory Monitors. *Environ. Sci. Technol.* **2011**, *45*, 7028–7035. [CrossRef]
38. Wu, C.; Chen, Y.; Pan, W.; Zeng, Y.; Chen, M.; Guo, Y.L.; Lung, S.C. Land-use regression with long-term satellite-based greenness index and culture-specific sources to model PM2.5 spatial-temporal variability. *Environ. Pollut.* **2017**, *224*, 148–157. [CrossRef] [PubMed]
39. Zhou, X.; Zhang, T.; Li, Z.; Tao, Y.; Wang, F.; Zhang, X.; Xu, C.; Ma, S.; Huang, J. Particulate and gaseous pollutants in a petrochemical industrialized valley city, Western China during 2013–2016. *Environ. Sci. Pollut. Res.* **2018**, *25*, 1–17. [CrossRef]
40. Dons, E.; Van Poppel, M.; Kochan, B.; Wets, G.; Panis, L.I. Modeling temporal and spatial variability of traffic-related air pollution: Hourly land use regression models for black carbon. *Atmos. Environ.* **2013**, *74*, 237–246. [CrossRef]
41. Dadhich, A.P.; Goyal, R.; Dadhich, P.N. An assessment of urban space expansion and its impact on air quality using geospatial approach. *J. Urban Environ. Eng.* **2017**, *11*, 79–87. [CrossRef]
42. Halim, N.D.A.; Latif, M.T.; Mohamed, A.F.; Maulud, K.N.A.; Idrus, S.; Azhari, A.; Othman, M.; Sofwan, N.M. Spatial assessment of land use impact on air quality in mega urban regions, Malaysia. *Sustain. Cities Soc.* **2020**, *63*, 102436. [CrossRef]
43. Liu, H.L.; Shen, Y.S. The Impact of Green Space Changes on Air Pollution and Microclimates: A Case Study of the Taipei Metropolitan Area. *Sustainability* **2014**, *6*, 8827–8855. [CrossRef]
44. Michanowicz, D.R.; Shmool, J.L.; Tunno, B.J.; Tripathy, S.; Gillooly, S.; Kinnee, E.; Clougherty, J.E. A hybrid land use regression/aermod model for predicting intra-urban variation in pm2.5. *Atmos. Environ.* **2016**, *131*, 307–315. [CrossRef]
45. Ajtai, N.; Stefanie, H.; Botezan, C.; Ozunu, A.; Radovici, A.; Dumitrache, R.; Iriza-Burcă, A.; Diamandi, A.; Hirtl, M. Support tools for land use policies based on high resolution regional air quality modelling. *Land Use Policy* **2020**, *95*, 103909. [CrossRef]
46. Ma, M.J.; Tan, Z.Y.; Chen, Y.; Ding, F. Characteristics of air quality and impact of sand and dust weather in the recent 15 years in Lanzhou City. *J. Lanzhou Univ. (Nat. Sci.)* **2019**, *55*, 33–41.
47. Ma, S.; Li, Z.Q.; Chen, H.; Liu, H.; Yang, F.; Zhou, Q.; Xia, D.S. Analysis of air quality characteristics and sources of pollution during heating period in Lanzhou. *Environ. Chem.* **2019**, *38*, 344–353.
48. De Fatima Andrade, M.; Kumar, P.; de Freitas, E.D.; Ynoue, R.Y.; Martins, J.; Martins, L.D.; Nogueira, T.; Perez-Martinez, P.; de Miranda, R.M.; Albuquerque, T.; et al. Air quality in the megacity of so paulo: Evolution over the last 30 years and future perspectives. *Atmos. Environ.* **2017**, *159*, 66–68. [CrossRef]
49. Sun, W.J.; Liu, M.; Yin, Q.; Gong, J.L.; Huang, Z.Y. Changes of air pollution in Lanzhou in recent ten years and suggestions on its control. *Sci. Technol. Inf. Gansu* **2016**, *45*, 8–13.
50. Guan, Q.; Li, F.; Yang, L.; Zhao, R.; Yang, Y.; Luo, H. Spatial-temporal variations and mineral dust fractions in particulate matter mass concentrations in an urban area of northwestern China. *J. Environ. Manag.* **2018**, *222*, 95–103. [CrossRef] [PubMed]
51. An, J.; Shi, Y.; Wang, J.; Zhu, B. Temporal Variations of O3 and NOx in the Urban Background Atmosphere of Nanjing, East China. *Arch. Environ. Contam. Toxicol.* **2016**, *71*, 224–234. [CrossRef]
52. Zang, Z.; Wang, W.; You, W.; Li, Y.; Ye, F.; Wang, C. Estimating ground-level PM2.5 concentrations in Beijing, China using aerosol optical depth and parameters of the temperature inversion layer. *Sci. Total Environ.* **2017**, *575*, 1219–1227. [CrossRef]
53. West, J.J.; Cohen, A.; Dentener, F.; Brunekreef, B.; Zhu, T.; Armstrong, B.; Bell, M.L.; Brauer, M.; Carmichael, G.; Costa, D.L. What we breathe impacts our health: Improving understanding of the link between air pollution and health. *Environ. Sci. Technol.* **2016**, *50*, 4895–4904. [CrossRef]
54. Chen, T.T.; Li, Z.Q.; Zhou, Q.; Wang, F.L.; Zhang, X.; Wang, F.T. Air pollution characteristics, source analysis and cause of formation under the background of "Lanzhou blue". *Acta Sci. Circum.* **2020**, *40*, 1361–1373.
55. Dc, A.; Kyh, B.; Han, J.B.; Jhc, A. Assessing the distributional characteristics of pm 10, pm 2.5, and pm 1 exposure profile produced and propagated from a construction activity. *J. Clean. Prod.* **2020**, *276*, 124335.
56. Leng, H.; Kong, F.Q.; Yuan, Q. Research on Land Use Characteristics of Cold City based on Air Quality Analysis: Research Framework and Empirical Analysis. *Archit. J.* **2020**, *S1*, 6–11.
57. Li, X.; Peng, L.; Chi, T.H.; Li, H.C.; Xu, Y.Z. Spatial-temporal Features of Air Quality in Beijing City. *Bull. Surv. Map.* **2016**, *9*, 47–51.
58. Burrough, P.A.; McDonnell, R.A. *Principles of Geographical Information Systems*; Oxford University Press: Oxford, UK, 1998; pp. 321–345.
59. Salcedo, D.; Castro, T.; Ruiz-Suárez, L.G.; García-Reynoso, A.; Torres-Jardón, R.; Torres-Jaramillo, A.; Mar-Morales, B.E.; Salcido, A.; Celada, A.T.; Carreón-Sierra, S.; et al. Study of the regional air quality south of Mexico City (Morelos State). *Sci. Total Environ.* **2012**, *414*, 417–432. [CrossRef] [PubMed]
60. Getis, A.; Ord, J.K. The Analysis of Spatial Association by Use of Distance Statistics. *Geogr. Anal.* **2010**, *24*, 189–206. [CrossRef]
61. Kang, J.E.; Yoon, D.K.; Bae, H.J. Evaluating the effect of compact urban form on air quality in Korea. *Environ. Plan. B* **2019**, *46*, 179–200. [CrossRef]
62. Lambert, D. Zero-inflated Poisson Regression with an Application to Defects in Manufacturing. *Technometrics* **1992**, *34*, 1–14. [CrossRef]
63. Wong, S.C.; Sze, N.N.; Li, Y.C. Contributory factors to traffic crashes at signalized intersections in Hong Kong. *Accid. Anal. Prev.* **2007**, *39*, 1107–1113. [CrossRef]
64. Gwynn, R.C.; Burnett, R.T.; Thurston, G.D. A time-series analysis of acidic particulate matter and daily mortality and morbidity in the buffalo, New York, region. *Environ. Health Perspect.* **2000**, *108*, 125–133. [CrossRef]

65. Cameron, A.C.; Trivedi, P.K. *Regression Analysis of Count Data*; Cambridge University Press: Cambridge, UK, 1998; pp. 70–77.
66. Chu, P.C.; Chen, Y.; Lu, S. Atmospheric effects on winter SO2 pollution in Lanzhou, China. *Atmos. Res.* **2008**, *89*, 365–373. [CrossRef]
67. Tecer, L.H. A factor analysis study: Air pollution, meteorology, and hospital admissions for respiratory diseases. *Toxicol. Environ. Chem.* **2009**, *91*, 1399–1411. [CrossRef]
68. Gladtke, D. Air pollution in the Rhine–Ruhr-area. *Toxicol. Lett.* **1998**, *96–97*, 277–283. [CrossRef]
69. Cao, L.Y. A Study on Local Control Model of Urban Air Pollution—A Case Study of Lanzhou. Ph.D. Thesis, Lanzhou University, Lanzhou, China, 2015.
70. Filonchyk, M.; Yan, H.; Li, X. Temporal and spatial variation of particulate matter and its correlation with other criteria of air pollutants in Lanzhou, China, in spring-summer periods. *Atmos. Pollut. Res.* **2018**, *9*, 1100–1110. [CrossRef]
71. Shi, T.; Hu, Y.; Liu, M.; Li, C.; Zhang, C.; Liu, C. Land use regression modelling of $PM_{2.5}$ spatial variations in different seasons in urban areas. *Sci. Total Environ.* **2020**, *743*, 140744. [PubMed]
72. Li, C.; Zhang, K.; Dai, Z.; Ma, Z.; Liu, X. Investigation of the Impact of Land-Use Distribution on $PM_{2.5}$ in Weifang: Seasonal Variations. *Int. J. Environ. Res. Public Health* **2020**, *17*, 5135. [CrossRef] [PubMed]
73. Shen, N.C.; Zhou, B.F.; Li, S.S.; Zhao, W.H.; Wang, L.L.; Dong, J.; Zhao, W.J. Temporal and Spatial Variation Characteristics and Origin Analysis of Air Pollutants in Tianjin from 2015 to 2019. *Ecol. Environ. Sci.* **2020**, *29*, 1862–1873.

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Article

Experimental Analysis of CO_2 Concentration Changes in an Apartment Using a Residential Heat Recovery Ventilator

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Abstract: Korean law requires at least three levels of control for apartment ventilation systems, including 0.5 air change per hour (ACH). When this law was enacted, it was believed that a 0.5 ACH air flow rate would be sufficient for apartments following building completion. However, ventilation systems cause different air qualities in each space within a unit, depending on infiltration rate and number of occupants. In addition, the current ventilation rate standard is based on an apartment unit's total area, assuming that all room doors are open. In this study, changes in CO_2 concentration were experimentally analyzed based on the number of occupants and various ventilation frequencies with closed doors to analyze air quality differences among rooms in a typical 85 m^2 apartment unit in Korea. When the 0.5 ACH ventilation was performed, maintaining 1000 ppm or less was difficult if four people stayed for more than two hours in the living room or two people stayed for more than one hour in the bedroom with closed doors. Our results indicate that it is challenging to maintain a CO_2 concentration of 1000 ppm when doors are closed as standards are calculated based on a unit's total area. Therefore, ventilation systems should be required to provide different air volumes for each room.

Keywords: mechanical ventilation systems; minimum ventilation level; Korea housing; CO_2 concentration; apartment ventilation

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1. Introduction

According to the facility standard rules for buildings in Korea [1], housing ventilation systems must be able to provide a ventilation rate of at least 0.5 air change per hour (ACH). This corresponds to an air volume of approximately 100 m^3/h for the national housing scale with an area of 85 m^2 and ceiling height of 2.3 m, as defined in the Housing Law [2]. This air volume is similar to that calculated based on ASHRAE 62.2 [3]. Because the volume is based on all rooms in an apartment unit, it assumes that all room doors are open. However, when the room doors are closed, the appropriate ventilation rate can vary.

Although there are various methods to obtain the appropriate ventilation rate for maintaining indoor CO_2 concentration requirement, 1000 ppm [4–6], it can be calculated using the difference between the CO_2 concentration generated by the occupants and the external CO_2 concentration. According to the climate change monitoring information provided by the Korean Meteorological Administration, the external CO_2 concentration has been increasing since 1984 [7].

Applying the average CO_2 concentration in Anmyeondo, Korea in December 2019 (421 ppm) [7] and the CO_2 expiratory flow generated during the normal activities of one adult (18 L/h) [8], a ventilation rate of approximately 31 m^3/h was calculated. This means that approximately 124 m^3/h is required when a four-member family resides in an 85 m^2 house. In addition, the 0.5 ACH ventilation rate of a bedroom with an area of 9 m^2 [9] was calculated to be 10.4 m^3/h. A typical small room in Korean housing where a single bed and a wardrobe are installed has an area of 9 m^2 and a ceiling height of 2.3 m. This corresponds to 33.5% of 31 m^3/h, which is the ventilation rate required per person for one hour. Although the results could vary depending on the room's infiltration rate, the fact that CO_2 concentrations ranging from 2000 to 3000 ppm have been discovered in field surveys of existing houses indicates that this issue is difficult to solve by only considering infiltration differences [10,11].

In many previous studies related to CO_2 concentration control in residential buildings, various demand-controlled ventilation strategies were provided, and their results were analyzed through simulations [12–16]. Some studies presented control methods using CO_2, humidity, and occupancy sensors, and compared them through simulations [12–14]. Other work presented control methods using CO_2 and total volatile organic compounds sensors and compared them using a simulation [15]. There have also been studies that investigated control methods using only occupancy conditions and compared them to simulations [16,17]. Although various conditions can be analyzed using simulations, the results may differ from real-world situations.

In terms of field experiments, a study adjusted the ventilation rate in two steps by examining the presence of occupants using the difference between the indoor and outdoor CO_2 concentrations [18]. Field experiments were performed for a typical four-member family house in Denmark, but the target house had a larger area (140 m^2) than a typical house in Korea, and the standard ventilation rate applied in the experiment was also higher.

Mechanical ventilation systems installed in Korean apartments generally provide the same ACHs to all rooms in three steps. This is because Korean law requires at least three levels of control for mechanical ventilation system performance, including 0.5 ACH. When the law was enacted, it was believed that the risk of sick building syndrome would decrease following building completion. As such, at present the minimum ventilation level of 0.5 ACH is used as an intermediate step and a 20–100% smaller or larger air volume has been provided for the three-step control. However, it is challenging to determine whether an appropriate air volume is provided in each situation [19]. Therefore, such systems are highly likely to result in different air qualities within each space, depending on the infiltration rate and/or the number of occupants.

In this study, the CO_2 concentration was experimentally analyzed based on the number of occupants and various ventilation rates to analyze the differences among the rooms in an actual 84 m^2 apartment unit, which is the typical apartment size in Korea. In addition, case studies were conducted to investigate the effectiveness of apartment ventilation systems.

2. Materials and Methods

2.1. Experimental Sequence

An analysis was conducted in the following sequence to examine the CO_2 concentrations in 85 m^2 apartment units and the degree of CO_2 removal was assessed based on ventilation frequency.

Step 1: Analysis of residence time for each room

According to a 2019 survey conducted by Statistics Korea [20], a four-member family generally resides in an 85 m^2 house. Thus, in this study, the number of residents in the target house was assumed to be four, including a couple and two adult children, and the residence time for each room was analyzed thoroughly.

Step 2: Experimental analysis of the infiltration rate in each room

Because the infiltration rate affects the change in CO_2 concentration, the infiltration rate of each room in the target house was measured using the method proposed by KS F 2603 [21], when room doors were closed.

Step 3: Experimental analysis of the CO_2 increment for each room

The infiltration rates confirmed in the field experiments were applied to a formula that can obtain the pollutant removal results for each ventilation rate. Field experiments were performed for the residence time and the number of occupants classified in Step 1. The error range was identified through a comparison with the CO_2 concentrations obtained through the formula.

Step 4: CO_2 analysis at various ventilation frequencies

The CO_2 concentration was examined based on the number of occupants and various ventilation frequencies, using the formula and error range verified in Step 3.

2.2. Experiment Space and Measurement Equiptment

The experiment apartment in this study consisted of one living room and three additional rooms. The living room and two other rooms were placed on the southern side and one room was placed on the northern side.

Figure 1 shows the floor plan of the apartment unit used for the experiments. The volume of each room and the positions of the windows and doors are illustrated. R2 and R3 (children's bedrooms) had windows on the southern side, and R1 (couple's bedroom) had a small window on the northern side and a sliding door to the dressing room. The sliding door had a rail at the top and no frame at the bottom. All doors to the living room had a hinged structure with the top and bottom frames. An exhaust air duct system from the bathroom in Figure 1 is separate and not included in this experiment.

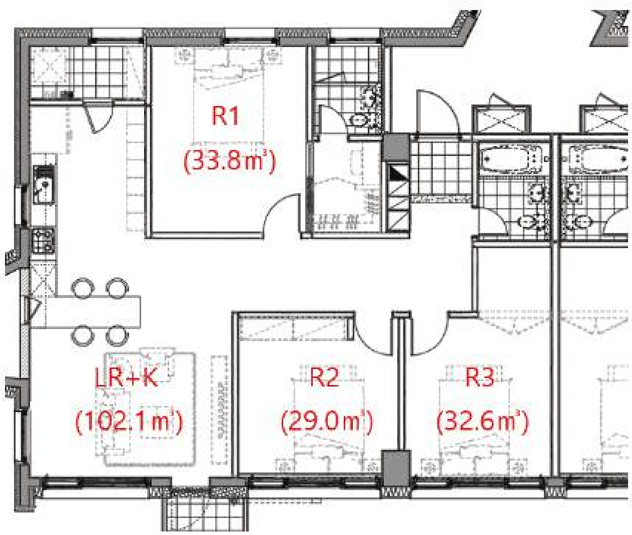


Figure 1. Apartment unit plan and room sizes for experiments.

Figure 2 shows the positions of the supply and return diffusers and the heat recovery ventilator as well as the flow metering system (FMS, Taehung M&C, Anyang-si, Korea) that measures the air volume for each room. The FMS measured the static pressure of the duct and calculated the air volume based on the value of the self-averaging multi-pitot tube. The diffusers were motorized and used to adjust the ventilation rate. They enabled multi-step adjustment from complete closing (an opening rate of zero) to complete opening (an opening rate of 3000).

The CO_2 concentration was measured by connecting the EE820 sensor (E + E Elektronik) for CO_2 (Figure 3a) to the Graphtec data logger (Figure 3b). The measurement range of the EE820 sensor provided by the manufacturer was 0–10,000 ppm, with error ranges of approximately 2%. The air volume measured at the end of each duct was divided by the room volume to calculate the air change per hour for each room. This was displayed on a separate monitor to minimize errors.

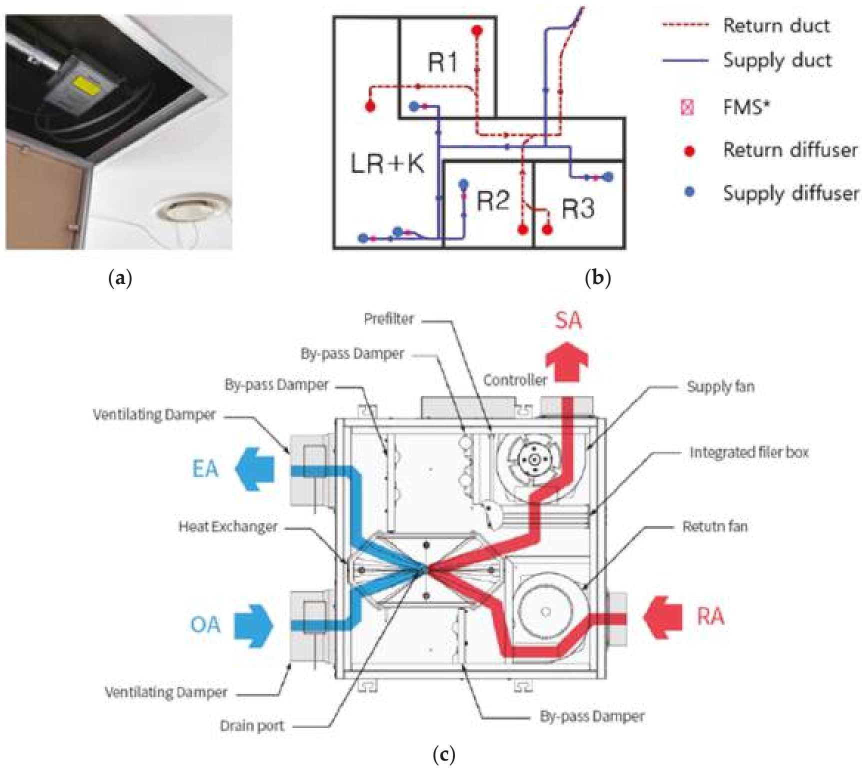


Figure 2. (**a**) Flow metering system (*FMS) and supply diffuser; (**b**) duct plan diagram; (**c**) heat recovery ventilator.

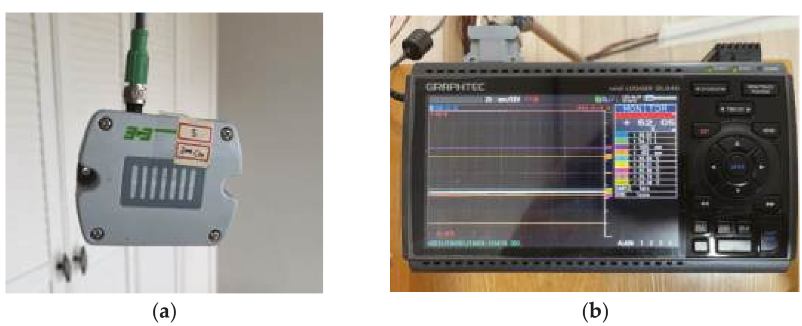


Figure 3. Equipment for experiments: (**a**) CO_2 Sensor; (**b**) data logger.

3. Results

3.1. Analysis of the Residence Time for Each Room

To construct experimental cases, the actual usage schedule was examined based on the results of the 2019 Residential Status Survey conducted by Statistics Korea [21]. For the convenience of analysis, the time unit of behavior was divided into 30 min. Key survey results incorporated in this study included:

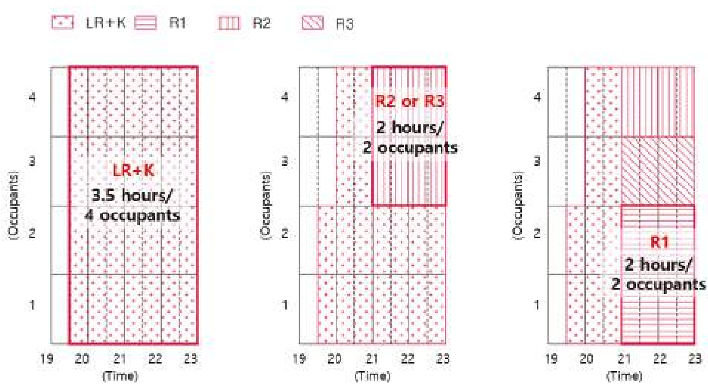
- The average bedtime for Korean people was 23:22 and the average wake-up time was 06:55, resulting in an average sleeping time of 7 h and 27 min. The average sleeping time of people older than 40 was 1 h less than that of their children. In other words, in the case of a four-member family, it was assumed that the couple slept for 7 h and the two children for 8 h each.

- Meal time ranged from 25 to 35 min, resulting in an average of 30 min. The preparation time for dressing and a shower before meals was assumed to be 30 min.
- School and working hours were from 09:00 to 18:00, and the average commute time was 1 h and 16 min. In this study, the commute time was assumed to be 1 h and 30 min.

Reflecting the results of the Residential Status Survey we also assumed:

- The couple goes to bed at 23:00 and wakes up at 06:00; the children wakes up at 07:00.
- The family leaves from home at 07:30 and works or studies from 09:00 to 18:00. They return to home at 19:30.
- The family has dinner for 30 min after a 30-min preparation allotment for dressing, and shower by approximately 20:30.
- Assuming that they spend 30 min to 1 h out of 2 h and 30 min before bedtime (23:00) with other family members, the practical continuous residence time in each room was estimated to be less than 2 h.
- As the target space is indoors, only light activities were assumed.

Based on the various schedules from 19:30 to 23:00 considered using the above conditions, the maximum number of occupants and residence time in each room could be obtained, as shown in Figure 4. The maximum residence time that occurred most frequently was 2 h, and the maximum number of occupants was four people in the living room, one person in R2 and R3, and two people in R1.



(**a**) (**b**) (**c**)

Figure 4. Maximum residence for three cases: (**a**) LR + K; (**b**) R2 + R3; (**c**) R1.

3.2. Analysis of the Infiltration Rate of Each Room

To calculate the infiltration rates of the living room + kitchen (LR + K), couple bedroom (R1), room 2 (R2), and room 3 (R3) (Figure 1), measurements were performed in accordance with KS F 2603 [22]. Equation (1) was specified in KS F 2603 (2016) to calculate the infiltration rate of a space using CO_2 reduction data.

$$Q = 2.303\frac{V}{t}\log_{10}\frac{C_1 - C_0}{C_t - C_0} \quad (1)$$

where Q is the supply air volume (m^3/h), V is the space volume (m^3), t is the time (h), C_1 is the initial CO_2 level (m^3/m^3), C_t is the CO_2 concentration after hours (m^3/m^3), and C_0 is the CO_2 concentration in supply air (m^3/m^3).

Notably, the infiltration rate may vary depending on the season [23]; the infiltration rate calculation experiment in this study was conducted in March and April when the CO_2

experiment was performed for each occupant. To examine the infiltration rate of each room with the door closed, CO_2 gas was injected until its concentration reached 2000 ppm, and then natural attenuation was allowed. The experiment was repeated five times within 30 min, in accordance with KS F 2603 (2016). Table 1 shows experiment results for the maximum, minimum, and average infiltration rates of each room.

Table 1. Infiltration rate analyzed by measurements.

Case	LR + K	R1	R2	R3
Max	0.37	0.61	0.25	0.41
Min	0.25	0.23	0.15	0.23
Average	0.33	0.41	0.20	0.30
Volume (m^3)	102.1	33.8	29.0	32.6

3.3. Mass Conservation Equation to Examine Indoor Air Pollution

Based on the mass balance equation, the indoor pollution concentration after time t can be obtained using Equation (2): The error from the experimental values was analyzed as follows:

- With no separate ventilation, Q can be considered as the infiltration volume.
- When mechanical ventilation was performed, the value obtained by adding the mechanical ventilation rate to the natural infiltration volume by the heat recovery ventilator was applied to Q. In this instance, the supply and return volumes were set to be equal by adjusting the speed of the supply and return fans before the start of the experiment. The values were examined using FMS in each room to minimize the influence of additional pressurization or decompression.
- In Equation (2), the amount of CO_2 generated (G) was calculated to be 18 L/h for adult males and 16 L/h for adult females, in accordance with ASHRAE 62.1 (2019) and KS F 2603 (2016).

$$V\frac{\partial C}{\partial T} = QC_0 - QC_i + G \tag{2}$$

where V is the space volume (m^3), T is the time (h), Q is the air change volume (m^3/h), C represents CO_2 level (mg/m^3), C_0 represents CO_2 level outside (mg/m^3), Ci represents CO_2 level inside (mg/m^3), and G is the CO_2 generation (mg/h).

Three cases of ventilation rates were set as follows:

1. No ventilation
2. 0.5 ACH, which is the minimum ventilation frequency required by law
3. 1.0 ACH, which is twice as high as the minimum required ventilation frequency

Each LR + K, R1, R2, and R3 with different infiltration rates was occupied by occupants for 2 h; the experiment was conducted based on the above three ventilation rates and the number of occupants as variables. In addition, the measured CO_2 concentrations (E.V.s) were compared to the calculated values (C.V.). The data are summarized in Table 2.

Table 2. Experimental results.

ACH_O *	LR + K E.V. (C.V.) (ppm)	Dif. (%)	R1 E.V. (C.V.)[2] (ppm)	Dif. (%)	R2 E.V. (C.V.) (ppm)	Dif. (%)	R3 E.V. (C.V.) (ppm)	Dif. (%)
0ACH_1	602(669)	−6	1002(1066)	−6	1459(1396)	+5	1231(1326)	−7
0ACH_2	931(966)	−1	1875(1873)	−1	2385(2372)	+1	2389(2458)	−3
0.5ACH_1	582(603)	−3	806(856)	−6	980(1088)	−10	982(1096)	−10
0.5ACH_2	710(756)	−6	1488(1400)	+6	1732(1757)	−1	1651(1772)	−7
1.0ACH_1	520(530)	−2	693(736)	−6	747(838)	−11	860(903)	−5
1.0ACH_2	630(667)	−5	1002(1130)	−11	1476(1361)	+6	1361(1385)	−2

* ACH: air change per hour, O: occupants (person), E.V.: experimental values, C.V.: calculated values, Dif.: difference between E.V. and C.V.

As shown in Table 2, the calculated values differed by −6 to +5% from the experimental values under the no ventilation condition. In the 0.5 and 1.0 ACH ventilation rates, which are the experimental results during mechanical ventilation, the experimental value also differed by −11 to +6% from the calculated values.

The maximum number of occupants was analyzed as four for LR + K and two for R1, R2, and R3, as shown in Figure 4.

As a result of the experimental case analyses, R1, 2, and 3 showed CO_2 concentrations exceeding 1000 ppm even with the highest ventilation case, 1.0 ACH. Accordingly, CO_2 concentrations in the 1.5 ACH cases were additionally analyzed according to the formula, and the possible error ranges were indicated. In addition, the calculation results that expanded the analysis range considering the maximum residence time and maximum number of occupants are shown in Figures 5 and 6 with the possible error ranges.

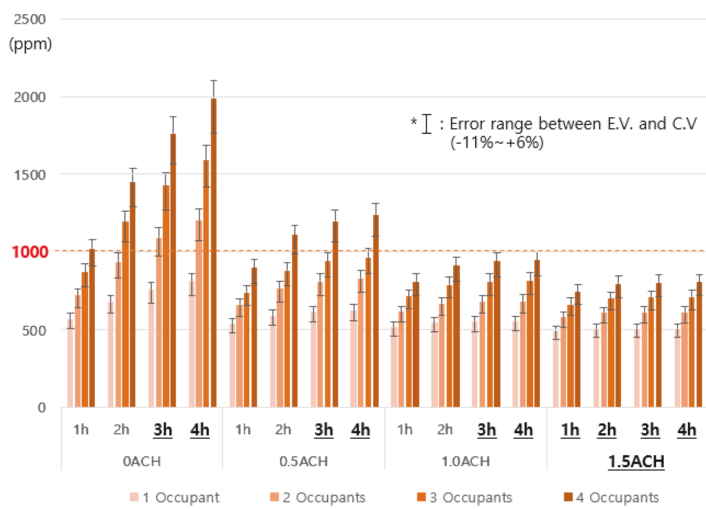


Figure 5. Calculated CO_2 concentration rates of LR + K, based on the experimental conditions with error ranges. * The **bold text** cases are analyzed by numerical calculations and error ranges without experiments in Table 2.

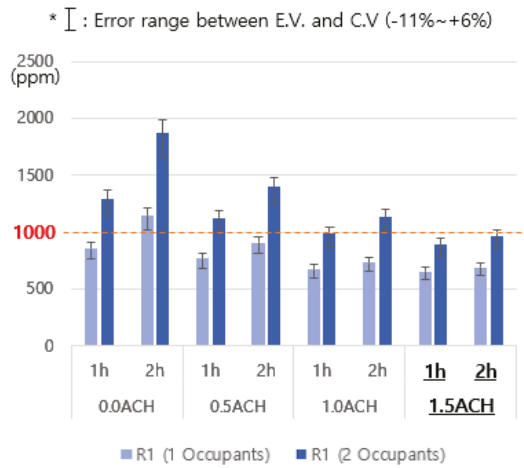
Figure 5 shows the increase in CO_2 concentration in LR + K depending on the number of occupants and ventilation frequency, and the error ranges considering the experimental values are also expressed. The analysis results that considered these error ranges were as follows:

- With no ventilation in LR + K (0 ACH), the CO_2 concentration could exceed 1000 ppm, if four people stayed for more than 1 h or two people stayed for more than 3 h.
- When a mechanical ventilation of 0.5 ACH was performed, the CO_2 concentration could also exceed 1000 ppm, if four people stayed for more than 2 h.

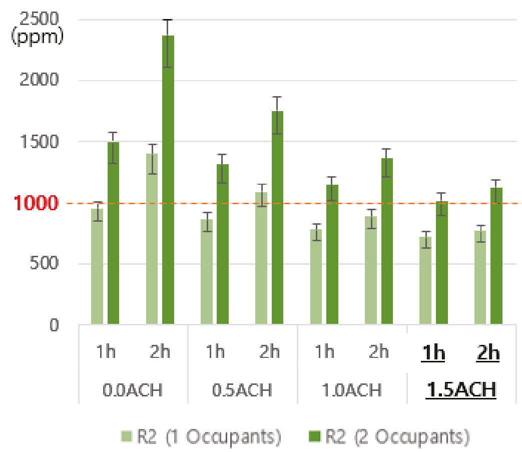
Figure 6 shows increases in the CO_2 concentration in R1, R2, and R3 based on the number of occupants and ventilation frequency. The key results were as follows:

- With no ventilation, the CO_2 concentration could exceed 1000 ppm under all conditions except when one person stayed for less than 1 h. In the case of R2 and R3, the CO_2 concentration could exceed 2000 ppm, if two adult males stayed for 2 h.
- When the minimum required 0.5 ACH ventilation was performed, the CO_2 concentration in R2 with the lowest infiltration rate increased to 1089 ppm if one adult male stayed for 2 h and to 1757 ppm if two adult males stayed for 2 h. In particular, the CO_2 concentration in R1, R2, and R3 exceeded 1000 ppm, if two adult males stayed for only 1 h.

- When a 1.5 ACH ventilation was performed, CO_2 concentration could be maintained at a level lower than 1000 ppm in R1, R2, and R3, even if one occupant stayed for more than 2 h. However, the CO_2 concentrations in R1, R2, and R3 exceeded 1000 ppm and reached 1130, 1361, and 1206 ppm, respectively, if two occupants stayed for 2 h.
- With a ventilation of 1.5 ACH, the indoor CO_2 concentration ranged from less than 1000 ppm to slightly higher than 1100 ppm. The latter values occurred if two occupants stayed for 2 h, the most severe among the experimental conditions.

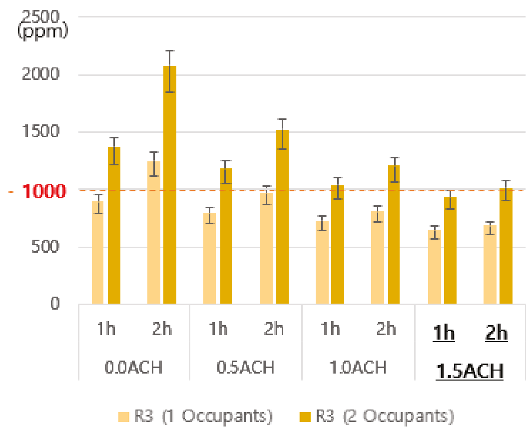


(**a**)



(**b**)

Figure 6. *Cont.*



(c)

Figure 6. Calculated CO_2 concentration rates of (**a**) R1, (**b**) R2, and (**c**) R3, based on the experimental conditions with error ranges. * The **bold text** cases are analyzed by numerical calculations and error ranges without experiments in Table 2.

4. Discussion

In this study, the occupancy conditions of residents were examined in an 85 m^2 apartment unit, which is the representative apartment size in South Korea. In addition, the improvement in indoor air quality based on occupancy condition and ventilation frequency was examined, with a focus on CO_2 concentration.

The experiment and analysis results of this study can be summarized as follows:

- The room occupancy scenarios of a four-member family living in an 85 m^2 apartment unit were examined using statistical data, and the residence time schedule for each room was prepared. The maximum number of occupants and the maximum residence time were found to be four people and 4 h, respectively, for LR + K, and two people and 2 h, respectively, for each of R1, R2, and R3.
- The infiltration rate for each room was obtained using the CO_2 reduction method in accordance with KS F 2603. The CO_2 concentration equation was then constructed for each case using the mass balance equation that combined these infiltration rates, and the error range was calculated by performing experiments under several conditions. In addition, the CO_2 concentration was analyzed for various cases using this equation.
- For the minimum required ventilation of 0.5 ACH, analysis results showed that it was difficult to maintain 1000 ppm or less if four people stay for more than 2 h in LR + K and if two people stay for more than 1 h in R1, R2, and R3, which is the minimum ventilation frequency by law.
- Ventilation of 1.0 ACH or more was required for two people to stay in a bedroom for more than 1 h. Furthermore, 1.5 ACH or more was required for two people to stay for more than 2 h while maintaining a CO_2 concentration of approximately 1000 ppm.

Overall, the findings from this study indicate that it is difficult to maintain a standard CO_2 concentration of 1000 ppm when doors are closed as housing ventilation rates in domestic and overseas standards were calculated based on an apartment unit's total area. In addition, results indicate that ventilation systems that can provide different air volumes for each room should be required in houses. However, increasing the capacity of fans or ventilating the total area at a high air volume for this purpose may result in high energy consumption. Therefore, research on energy-saving technologies is also required. In this study, only weekday results were analyzed, where residents have a general life pattern, and in cases except for other activities with higher emissions of CO_2 e.g., exercise.

During holidays, residence time tends to increase, which leads to a further increase in CO_2 concentration when compared to the results of the present study. Future research should include various scenarios, such as holidays and various activity cases, and analysis should be conducted through simulations and field experiments. In addition, strategies to maintain indoor air quality using individual room control should be presented to provide an optimal indoor air environment with minimal energy use.

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Conflicts of Interest: The authors declare no conflict of interest.

References

1. Ministry of Land, Infrastructure and Transport (MLIT). *Korean MLIT Decree No.704, Rules on the Facility Standards of Buildings*; MLIT: Seoul, Korea, 2020.
2. MLIT. *Law No. 17921, Law for Apartment Housing*; MLIT: Seoul, Korea, 2021.
3. American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE). *Ventilation and Acceptable Indoor Air Quality in Residential Buildings*; Standard 62.2; ASHRAE Inc.: Atlanta, GA, USA, 2019.
4. National Research Council. Carbon Dioxide. In *Spacecraft Maximum Allowable Concentrations for Selected Airborne Contaminants*; National Academies Press: Washington, DC, USA, 2008; pp. 112–124.
5. Health Canada. Indoor air quality in office buildings: A technical guide. In *A Report of the Federal-Provincial Advisory Committee on Environmental and Occupational Health*; Health Canada: Ottawa, ON, Canada, 1995.
6. Ministry of Environment (MOE). *Enforcement Rules of Indoor Air Quality Control*; Korean MOE Decree No.918; Ministry of Environment: Seoul, Korea, 2021.
7. Total Climate Change Monitoring Data, CO_2 Concentration in Korea. Available online: http://www.climate.go.kr/home/09_monitoring/ghg/co2_global_trend (accessed on 21 March 2021).
8. ASHRAE Inc. *Ventilation for Acceptable Indoor Air Quality*; ASHRAE Standard 62.1; ASHRAE Inc.: Atlanta, GA, USA, 2019.
9. Read by Area and Analyzed by Space. Available online: https://www.sciencetimes.co.kr/news (accessed on 24 April 2021).
10. Nam, K.; Lee, Y. An analysis on HCHO, TVOC, CO_2, concentration of existing housing indoor air in summer. *KIEAE J.* **2016**, *16*, 115–122. [CrossRef]
11. Nam, K.; Lee, Y.; Choi, B. A comparative analysis on concentration of pollutants in housing indoor air between winter and summer. *KIEAE J.* **2017**, *17*, 125–131. [CrossRef]
12. Pavlovas, V. Demand controlled ventilation: A case study for existing Swedish multifamily buildings, Energy Build. *REHVA Sci.* **2004**, *36*, 1029–1034.
13. Jreijiry, D.; Husaunndee, A.; Inard, C. Numerical study of a hybrid ventilation system for single family houses. *Sol. Energy* **2007**, *81*, 227–239. [CrossRef]
14. Laverge, J.; Bossche, N.V.D.; Heijmans, N.; Janssens, A. Energy saving potential and repercussions on indoor air quality of demand controlled residential ventilation strategies. *Build. Environ.* **2011**, *46*, 1497–1503. [CrossRef]
15. Seong, N. Energy requirements of a multi-sensor based demand control ventilation system in residential buildings. In Proceedings of the 31st AIVC Conference "Low Energy and Sustainable Ventilation Technologies for Green Buildings, Seoul, Korea, 26–28 October 2010.
16. Mortensen, D.K.; Walker, I.S.; Sherman, M.H. Optimization of Occupancy Based Demand Controlled Ventilation in Residences. *Int. J. Vent.* **2011**, *10*, 49–60. [CrossRef]
17. Hesaraki, A.; Holmberg, S. Demand-controlled ventilation in new residential buildings: Consequences on indoor air quality and energy savings. *Indoor Built Environ.* **2013**, *24*, 162–173. [CrossRef]
18. Nielsen, T.R.; Drivsholm, C. Energy efficient demand controlled ventilation in single family houses. *Energy Build.* **2010**, *42*, 1995–1998. [CrossRef]
19. Kim, K.; Kim, M.; Kwon, O.; Seok, Y.; Jeong, J. Application of Demand Controlled Ventilation in Multifamily Houses Meeting the Current Korean Ventilation Standards. *J. KIAEBS* **2009**, *3*, 192–200.
20. Statistics Korea. *Life Time Survey Results*; Social Statistics Bureau Social Statistics Planning Division: Seoul, Korea, 2019.

21. Statistics Korea. Residential Status Survey. 2019. Available online: https://kostat.go.kr (accessed on 5 February 2021).
22. Korean Standard. KS F 2603. In *Standard Test Method for Measuring Indoor Ventilation Rate (Carbon Dioxide Method)*; Korean Standard: Seoul, Korea, 2016.
23. Wallace, L.; Emmerich, S.; Howard-reed, C. Continuous measurements of air change rates in an occupied house for 1year: The effect of temperature, wind fans, and windows. *J. Exp. Anal. Environ. Epidemiol.* **2002**, *12*, 296–306. [CrossRef] [PubMed]

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The Adverse Impact of Air Pollution on China's Economic Growth

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Abstract: This study empirically evaluates the impact of air pollution on China's economic growth, based on a province-level sample for the period 2002–2017. Air pollution is measured by the concentration of fine particulate matter ($PM_{2.5}$), and economic growth is measured by the annual growth rate of gross domestic product (GDP) per capita. A panel data fixed-effects regression model is built, and the instrumental variables estimation method is utilized for quantitative analyses. The study reports a significant negative impact of air pollution on the macroeconomic growth of China. According to our instrumental variables estimation, holding other factors constant, if the concentration of $PM_{2.5}$ increases by 1%, then the GDP per capita growth rate will decline by 0.05818 percentage points. In addition, it is found that the adverse effect of atmospheric pollution is heterogeneous across different regions. The effect is stronger in the eastern region and in provinces with smaller state-owned enterprise shares, fewer governmental expenditures for public health services, and fewer medical resources. The study results reveal that air pollution poses a substantial threat to the sustainable economic growth of China. Taking actions to abate air pollution will generate great economic benefits, especially for those regions which are heavily damaged by pollution.

Keywords: air pollution; $PM_{2.5}$; economic growth rate; GDP per capita; China

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1. Introduction

Air pollution is a severe threat to sustainable development in many regions around the world [1–3]. Previous medical and environmental studies have solidly confirmed that air pollution damages human health heavily. Air pollution also has a series of considerable economic consequences. The literature has investigated the influences of air pollution on several aspects of economic activities, including labor productivity [4,5], housing prices [6], wage premiums [7], population mobility [8,9], and the tourism industry [10,11]. However, the impact of air pollution on the growth of the aggregate economy has not been well studied.

It is important to understand the linkage between air pollution and economic growth, as good air quality and economic growth are both essential components of sustainable development. Traditionally, studies on the link between environmental pollution and economic growth have been conducted within the framework of the environmental Kuznets curve (EKC). According to the EKC hypothesis, economic development initially leads to environmental degradation, but, after a certain income level, the degree of environmental pollution reduces. In the EKC model, changes in environmental quality are considered to be a consequence or byproduct of economic growth. However, the relationship between economic growth and pollution is not unidirectional. Given that many economic activities are influenced by the surrounding pollution, pollution likely affects the economic growth rate.

The research objective of this study is to empirically analyze whether and to what extent air pollution exerts impacts on macroeconomic growth in China. This research has an apparently realistic background. China is chosen as the target country of research, because China's high economic growth rate and severe air pollution problems are both worthy of attention. Although China had successfully maintained a high gross domestic product (GDP) growth rate for decades, the growth rate gradually diminished during the past decade. It is unsure whether China can hold its leading role as a growth engine of the world. Besides its economic sustainability issue, the environmental sustainability of China is also of interest. The poor air quality in some industrialized and population-dense Chinese cities is widely known. China has taken great efforts to prevent and control air pollution, and an improvement in air quality can be observed in recent years. However, China is currently still on the list of heavily polluted countries. What is the relation between these two phenomena (i.e., declining economic growth rate and severe air pollution in China)? This research will provide helpful insights.

This study offers marginal contributions to the literature in several aspects. (1) This study provides explicit evidence that air pollution has a substantial adverse influence on China's regional economic growth. On the basis of econometric regression estimates, this research offers a quantitative evaluation on the magnitude of air pollution's impact, which enables us to estimate the economic benefits of pollution abatement. (2) Our analysis focuses on the effect of atmospheric pollution on the growth rate of the economy. This feature distinguishes our research from the previous several studies that analyzed the effect of pollution on the level of GDP or GDP per capita. (3) This study also evaluates whether there are heterogeneities in different periods and across different districts. This study obtains a novel finding that the effect of air pollution is not uniform across all districts but dependent on the economic structures and features of the specific regions. (4) The regression analyses in this study confirm that the endogeneity issue of air pollution should be taken into account when using econometric models. Comparing the estimation result of a standard panel data fixed-effects estimation with that of an instrumental variables estimation shows that, if we incorrectly ignore the endogeneity of air pollution, the adverse impact of air pollution will be underestimated.

The remainder of this article is organized as follows. Section 2 develops the research hypothesis and reviews the existing literature. The empirical model and data are presented in Section 3. Section 4 provides the detailed estimation results. Finally, Section 5 discusses the research findings, concludes the paper, and offers information for future research directions.

2. Hypothesis Development and Literature Review

2.1. Hypothesis Development

It is widely known that air pollution poses public health risks. For instance, air pollution causes a higher incidence of many illnesses and unhealthy symptoms, including attention deficits [12,13], cardiovascular problems [14], cognitive impairment [15,16], headaches [17], irritability [18], mental depression [19], respiratory diseases [20,21], and so on. Air pollution results in a substantial global burden of diseases, higher morbidity, and increased mortality [22,23]. The health damages created by air pollution have severe economic consequences. In particular, previous studies have reported that air pollution reduces productivity, causes a loss of human capital, and strongly depresses some industries which are dependent on a clean environment.

As the health status of laborers becomes worse as a result of atmospheric pollution, productivity in economic activities declines. Laborers in poor health cannot work in a sufficiently efficient way. The previous labor economics literature has confirmed that air pollution has largely reduced the labor productivity in different industries across the world [4,5]. In addition, a recent study by Zhao and Yuan [24] reported that air pollution has an inhibitory effect on the total factor productivity (TFP) in China. As labor productivity and TFP are key determinants of economic growth [25–28], the damage of air pollution on productivity indicates that economic growth is harmed.

Air pollution also causes a loss of human capital, as some high-skilled laborers may choose to leave polluted areas and human cognitive abilities are damaged by pollution.

The environmental literature has found that the degree of perception and concern about atmospheric pollution rises with the increasing education level of individuals [29–31]. This implies that highly skilled laborers, such as scientists and technicians, who are usually well-educated on average, may be significantly responsive to the air pollution issue. Some of these individuals are likely to leave polluted regions, as previous studies have detected that air pollution affects people's mobility and residence decisions [6,8,9]. The leaving of laborers with high education levels results in a loss of human capital in the society. Moreover, the medical literature has identified that air pollution causes a decline in human cognitive abilities [15,16]. In consequence, pollution has an implicit damage on human capital in industries requiring high cognitive performance. For instance, Luo et al. [32] reported that air pollution in China reduces inventors' annual new patent output, reflecting a decrease in innovative abilities of researchers. Given the importance of human capital in sustainable economic growth [33–35], a loss of human capital induced by atmospheric pollution implies that economic growth is reduced.

Furthermore, air pollution directly depresses the development of certain industries that substantially rely on a clean environment. A particularly notable example is tourism. Given the fact that good environmental quality is an indispensable characteristic of attractive tourist destinations [36–40], tourism is heavily hurt by air pollution [10,11,41]. Air pollution inhibits sightseeing activities, damages the tourist experience, poses potential health risks, and, thus, reduces the competitiveness of a tourism destination [37–39,42–44]. The number of tourist arrivals and amount of tourism revenue both decline in air-polluted regions [45,46], as many tourists are unwilling to visit polluted areas. Potential tourists have explicitly been aware of and concerned with the air pollution in China [10,47]. The tourists' perception of air pollution has apparently reduced their willingness to visit China and the trip satisfaction [48–50]. As tourism is an economic growth engine in numerous districts [51,52], air pollution depresses economic growth through its damage to tourism. In addition to tourism, the sustainable development of agriculture is also severely hindered by air pollution [53–55], as crop yields and the diversification of wild species are adversely impacted.

In short, air pollution reduces economic productivity, causes human capital loss, and directly hampers the development of several environment-dependent industries. Although people might partially mitigate the damage of air pollution by taking some protective actions (e.g., building better infrastructure to prevent the indoor intrusion of outdoor pollution, using more air purifiers and masks, and being more informed to avoid staying in severely polluted areas and periods), these actions come at the cost of economic resources and daily inconvenience, while the harmfulness of pollution can hardly be eliminated completely. On the basis of the above analyses, it is reasonable to conjecture that air pollution impedes economic growth. Thus, the research hypothesis in this study was established as follows:

Hypothesis 1. *Air pollution has a negative impact on economic growth.*

2.2. Literature Review

Many previous studies, such as Atici [56], Dinda [57], Dong et al. [58], Farhani et al. [59], Gokmenoglu et al. [60], Luo et al. [61], Millimet et al. [62], and Zhang et al. [63], have analyzed the environmental Kuznets curve, which discusses the variations of pollutant emissions and environmental quality at different economic development states, reflected by the levels of per capita income. However, the impact of pollution on economic growth has not been sufficiently investigated in the literature.

Some studies have analyzed the influence of carbon dioxide (CO_2) emissions on economic growth; however, the findings were inconclusive. For instance, Abdouli and Hammami [64] investigated the situation in 17 Middle Eastern and North African (MENA) countries, Omri et al. [65] explored a global panel of 54 countries, and Omri et al. [66] analyzed 12 MENA countries. They all reported a significant negative impact of CO_2

emissions on economic growth. Differing from their findings, the study by Ghosh [67] focused on India and reported that no statistically significant long-term effect of carbon emissions on economic growth was detected. Similar conclusions were obtained by Ozturk and Acaravci [68] for Turkey, Zhang and Cheng [69] for China, and so on. Some studies have reported a positive effect of carbon emissions on economic growth. For example, Azam et al. [70] found that the impact of CO_2 emissions on economic growth was positive in the US, China, and Japan, although it was negative in India. Ahmad and Du [71] reported a positive influence of carbon emissions on economic growth in Iran. Muhammad [72] found that carbon emissions stimulated economic growth in developed and MENA countries.

It is notable that the scale of CO_2 emissions may not perfectly reflect the degree of ambient air pollution affecting human lives, as the actual concentration of air pollutants is greatly shaped by meteorological and geographical conditions. The volume of carbon emissions is tightly relevant to the intensity of energy use and the degree of energy efficiency in one region but may not be a satisfactory indicator of the density of pollutants in ambient air.

A few studies have explicitly used the measured density of atmospheric pollutants to denote the degree of air pollution. Dechezleprêtre et al. [73] took a sample of European regions over the period 2000–2015 and reported that a 1 $\mu g/m^3$ increase in the density of fine particulate matter ($PM_{2.5}$) caused a 0.8% reduction in real GDP. Sinha [74] reported that nitrogen dioxide (NO_2) and sulfur dioxide (SO_2) emissions significantly harmed the regional income levels for a panel of 139 Indian cities during the period 2001–2013. Hao et al. [75] estimated the impact of $PM_{2.5}$ pollution on the level of GDP per capita in Chinese cities between 2013 and 2015. They reported a significant negative impact: a 1% increase in $PM_{2.5}$ concentration was found to trigger the GDP per capita to decline by around 0.3–0.8%, depending on the model specifications used. Zhao and Sing [76] further reported that dust and SO_2 emissions in neighboring cities generated a negative spillover effect on the GDP of local Chinese cities. On the other hand, Gan et al. [77] reported that the spatial spillover effect of atmospheric pollution is positive. Jiang et al. [78] found no significant impact of SO_2 emissions on local GDP but reported a positive impact of air pollution in neighboring cities, based on the data for 28 cities in China during 2006–2015. These six studies provided findings that air pollution affects the level of economic development. However, we cannot simply say that the impact of air pollution on economic growth has been confirmed by these above-mentioned studies. It should be noted that the dependent variable used in these studies was the level of GDP or GDP per capita. Thus, the estimated regression coefficient of air pollution essentially evaluated its contemporaneous impact on economic scale, rather than the long-run effect on economic growth [73]. Taking the economic growth rate as the dependent variable in the regression equation is more consistent with that used in the economic growth literature (e.g., [79–85]). In our study, we use this kind of model setup and examine the effect of air pollution on the regional economic growth rate in Chinese provinces.

In brief, the existing literature has several gaps. (1) Based on the prior studies, although it is not difficult to infer intuitively that air pollution might negatively affect economic growth, there is not enough empirical evidence to directly verify this intuition. Particularly, we lack detailed studies to quantify the effect of air pollution. (2) As mentioned before, several previous studies used the level of GDP (per capita) as the dependent variable in regression models. However, the theory of economic growth pointed out the importance of inspecting the growth rate of GDP (per capita). The several above-mentioned studies did not consider this. (3) Different districts may own disparate macroeconomic structures and features, which influence the magnitude of air pollution's impact. The existing literature did not pay sufficient attention to the heterogeneous effects of air pollution.

2.3. Key Feature of This Study

The key feature of this study, which differentiates ours from the previous research, is that we use the GDP (per capita) growth rate, instead of the GDP (per capita), as the dependent variable in the econometric regression model. This point is crucial, as models using different dependent variables tell different stories. To clarify this, let us consider the following two simplified models:

$$\text{Model I:} \qquad GDP_t = a_0 + a_1 \times AirPollution_t \qquad (a_0 > 0,\, a_1 < 0),$$

$$\text{Model II:} \qquad GDPGrowthRate_t = b_0 + b_1 \times AirPollution_t \qquad (b_0 > 0,\, b_1 < 0)$$
$$\text{and} \qquad GDP_t = GDP_{t-1} \times (1 + GDPGrowthRate_t),$$

where GDP_t refers to the scale of GDP in period t, $GDPGrowthRate_t$ is the growth rate of the GDP, and $AirPollution_t$ is the degree of air pollution which negatively affects GDP or its growth rate.

First, we consider the scenario described by Model I. In this scenario, a change in the degree of air pollution alters the scale of the GDP but not the growth rate. This scenario has at least two important implications regarding economic growth. (1) Holding other things constant, in order to continuously increase the GDP, the region has to reduce its air pollution endlessly. If air quality reaches a level that the region can hardly further improve, the growth of the GDP will stop. (2) Another important implication is that the GDP in regions with bad air quality can quickly catch up with that in regions with good air quality by reducing air pollution. This is because variations in air pollution cause corresponding shifts in the scale of GDP, as reflected by Model I. We use Figure 1 to illustrate these two implications visually.

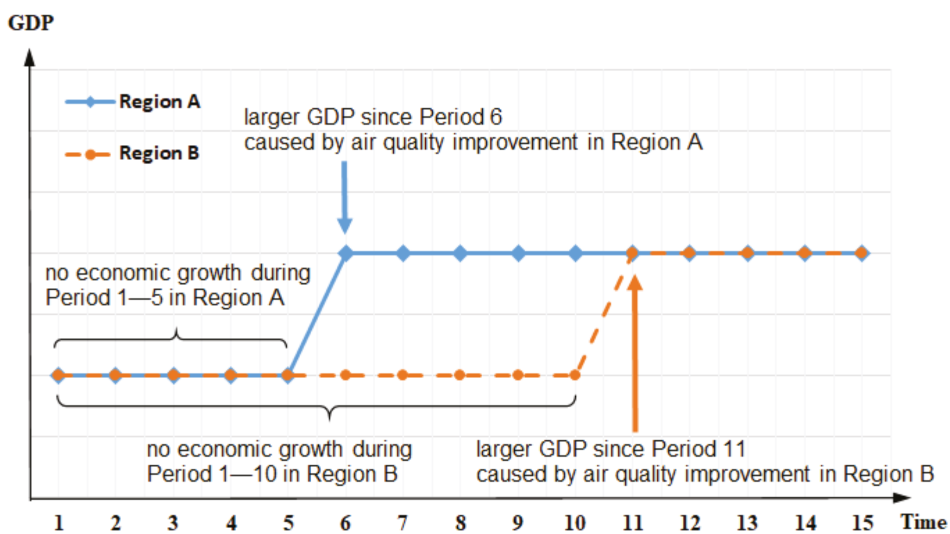

Figure 1. An illustrative case of a world in which air pollution affects the GDP scale. Abbreviation: GDP (gross domestic product).

Suppose that there are two regions (A and B) and fifteen periods. These two regions are identical in the beginning, and Regions A and B improve their air quality in Periods 6 and 11, respectively. As shown in the figure, these two regions are totally the same and unchanged in the first five periods. In Period 6, Region A reduces its air pollution and maintains improved air quality afterwards. Thus, from Period 6, the GDP size of Region A is constant and larger than that in Periods 1–5. The air quality in Region B is not improved until Period 11. From Period 11, Region B has good air quality, analogous to that in Region A. Therefore, the GDP of Region B catches up with Region A in Period 11 and keeps a constant scale afterwards. Overall, in the world of Model I, a reduction in air pollution contemporaneously expands the GDP scale, but sequential growth of the economy is not guaranteed.

Next, we consider the scenario described by Model II. In this scenario, a change in the degree of air pollution alters not only the scale of the GDP but also its development trend. This circumstance has two important implications regarding economic growth. (1) Holding other things constant, in order to continuously increase the GDP, the region should maintain air quality at a satisfactory level, such that the economic growth rate is positive. Different from the world of Model I, the region does not need to reduce air pollution endlessly. Even though the local air quality cannot be further improved in the future, the GDP will still grow. (2) As air pollution changes the economic growth rate, which has an accumulative effect, the gap of GDP scale between regions with different air qualities will expand increasingly over time. This indicates that regions which reduce air pollution earlier can establish an advantage in GDP expansion, compared to other regions which reduce their air pollution later. The earlier the regions improve their air quality, the better. The GDP of regions with relatively severe air pollution cannot easily catch up with the regions which reduce pollution earlier. We use Figure 2 as a visual example of these two implications.

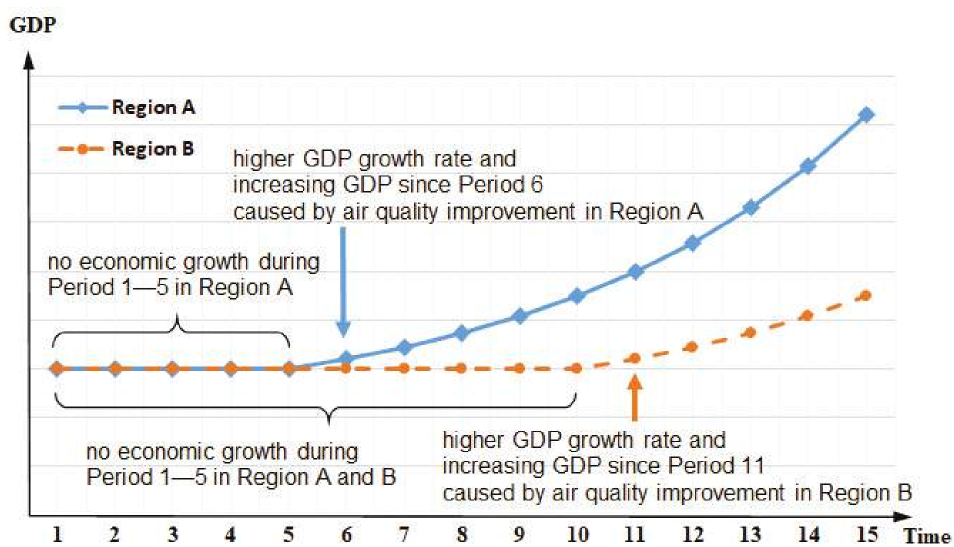

Figure 2. An illustrative case of a world in which air pollution affects the GDP growth rate. Abbreviation: GDP (gross domestic product).

We assume that there are two regions (A and B) and fifteen periods. The two regions are completely identical in the beginning. Region A and B ameliorate their air quality in Periods 6 and 11, respectively. As demonstrated by the graph, during Periods 1–5, the situations in the two regions are the same and invariant. In Period 6, Region A improves its air quality and maintains better air quality afterwards. Hence, from Period 6, Region A has a higher GDP growth rate and its GDP scale increasingly expands. The air quality in Region B is not made better until Period 11. From Period 11, Region B also has good air quality, similar to that in Region A. In consequence, during Periods 11–15, the GDP growth rate of Region B is as high as that of Region A. However, because the GDP scale of Region A is significantly larger than Region B, the same GDP growth rate in two regions implies that Region B cannot catch up with Region A, in terms of GDP scale. Overall, in the world of Model II, a reduction in air pollution not only enlarges the GDP scale, but also has a persistent impact on future economic growth.

The discussion above makes it clear that it is important to distinguish whether air pollution affects GDP scale or GDP growth rate. As the previous literature has analyzed the impact of air pollution on the Chinese GDP [75–78], we focus on the influence of pollution on GDP growth rate in this study.

3. Model and Data

3.1. Model

Our research sample has a panel data structure with two dimensions: the time and the cross-region dimension. Thus, our empirical analyses utilize a classical regression model with two-way fixed-effects, which is standard in panel data econometrics. The model is formulated by the equation

$$Growth_{it} = \alpha AirPollution_{it} + X_{it}\beta + s_i + v_t + \varepsilon_{it}, \tag{1}$$

where the dependent variable $Growth_{it}$ refers to the annual economic growth rate in province i in year t. The core explanatory variable of interest is $AirPollution_{it}$, the level of air pollution. The vector X_{it} is a vector of control variables; s_i and v_t refer to the province- and time-fixed effects, respectively; and ε_{it} is the error term. The coefficients α and β will be estimated using regression methods. Based on these coefficients, we can evaluate the effects of different explanatory variables. In particular, we concentrate on the impact of air pollution, captured by the coefficient α.

3.2. Variable

3.2.1. Dependent Variable

This study intends to assess the influence of atmospheric pollution on economic growth. Thus, following the empirical literature on economic growth, such as the studies of Alesina et al. [79], Chikalipah and Makina [80], Davis and Hopkins [81], Feeny et al. [82], Hermes and Lensink [83], Njikam [84], and Rioja and Valev [85], we take the annual growth rate of the real GDP per capita as the dependent variable. In the robustness analysis section, we consider the growth rate of the GDP as an alternative dependent variable.

It is notable that the dependent variable is the growth rate of GDP per capita, not the level of GDP per capita. This distinguishes our model setup from that of Dechezleprêtre et al. [73], Gan et al. [77], Hao et al. [75], Jiang et al. [78], Sinha [74], and Zhao and Sing [76], who took the logarithmic value of GDP or GDP per capita as the dependent variable. From a long-run perspective, it is even more important to examine the influence of air pollution on the growth potential of an economy, compared to its effect on the contemporary level of economic development. Therefore, focusing on the rate of growth is prevalent in the economic growth literature. We follow this tradition.

3.2.2. Core Explanatory Variable of Interest

The core explanatory variable in this study is $AirPollution$, the level of air pollution. Previous studies have verified that $PM_{2.5}$ is one of the most crucial atmospheric pollutants in Chinese regions [86,87]. Therefore, we use the annual population-weighted average concentration of $PM_{2.5}$ ($\mu g/m^3$) in each Chinese province to denote the degree of pollution. To address the scaling problem, the logarithmic value of $PM_{2.5}$ concentration is used as the explanatory variable. Thus, the changes in air pollution are expressed in percentage points.

The sample average $PM_{2.5}$ concentration is 45.993 $\mu g/m^3$. This pollution level is substantially higher than the desirable level of 10 $\mu g/m^3$ as suggested by the World Health Organization (WHO)'s Air Quality Guidelines. The standard deviation of pollution level is 18.029 $\mu g/m^3$, indicating apparent differences among different provinces. The minimum value is 5.7 μg/m^3, observed in Tibet in 2003. The maximum is 88.8 μg/m^3, recorded in Beijing in 2006.

We use Figure 3 to briefly demonstrate the distribution of $PM_{2.5}$ pollution among different provinces in Mainland China. We calculate the average $PM_{2.5}$ concentration during the sample period 2002–2017 for every province and use different colors in the graph to indicate different severities of pollution. As shown in the figure, two areas have the highest degree of pollution, with average $PM_{2.5}$ concentration exceeding 60 μg/m^3. One area consists of several provinces around Beijing City, which is located in North China and features high population density; the other area is Xinjiang, which is located in the most northwest part of China and contains some vast deserts. The area with the best air quality, with average $PM_{2.5}$ concentration below 20 μg/m^3, includes three provinces located in Southwest and South China. These three provinces are Tibet, Yunnan, and Hainan, which are all famous for their beautiful natural sceneries.

3.2.3. Control Variable

There are 11 important control variables included in the vector X: $Education$, $CapitalFormation$, $FinancialDevelopment$, $FinancialOpenness$, $TradeOpenness$, $Road$, $GovernmentSize$, $Population$, $GDPPerCapita$, $IndustrialStructure$, and $SolidWasteEmission$.

$Education$ is an indicator of the average education level of laborers. Human capital, majorly accumulated through education and training, is crucial for sustainable economic growth [88–91]. Thus, it is expected that education level has a positive effect on economic growth. We use the average value of schooling years of laborers as a proxy for the level of education.

$CapitalFormation$ refers to the value of the capital formation rate, namely the ratio of fixed capital investment to GDP. As capital is a kind of indispensable production input, we expect that capital formation boosts economic growth in China. Previous studies, such as those of Adams [92], Bal et al. [93], and Uneze [94], have also reported a positive effect of capital formation on economic growth in different countries.

$FinancialDevelopment$ is an indicator for financial development, indexed by the ratio of bank credits to GDP. Although some studies have reported a positive impact of financial development on economic growth, many researchers have found that the impact may be non-linear or dependent on the specific economic environment [85,95–97]. Thus, we do not have a specific expectation for the sign of this variable's coefficient.

$FinancialOpenness$ is an indicator of financial openness. We use the foreign direct investment (FDI) per capita (CNY, in constant 2010 price) as a proxy for this variable. The literature has reported inconsistent findings about the impact of financial openness [84,98]. Almfraji and Almsafir [99] conducted a literature review and found that the estimated impact of FDI was positive in some studies but was negative or null in other research.

$TradeOpenness$ is an indicator of trade openness, which is measured by the ratio of international trade volume to GDP. Given the fact that China has a great volume of international trade with many countries, trade openness may affect China's economic growth and, thus, should be considered as a control variable. The previous literature has reported mixed evidence about the impact of trade openness on GDP growth [100–103].

$Road$ is an indicator of the abundance of the transportation infrastructure, proxied by the road length (km) per area (km^2). It has been widely confirmed that infrastructure plays an beneficial role in regional economic development [104–107]. We expect that the estimated coefficient of this variable will have a positive sign.

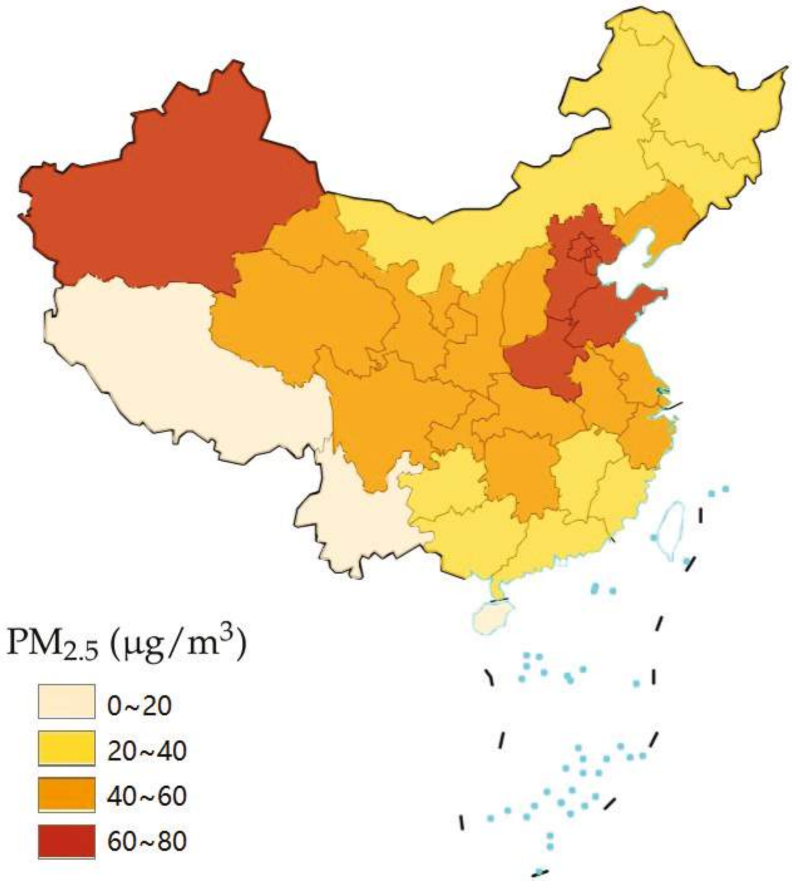

Figure 3. Average $PM_{2.5}$ concentration (2002–2017) in different provinces of Mainland China. Abbreviation: $PM_{2.5}$ (fine particulate matter). Data source of $PM_{2.5}$ concentration: Atmospheric Composition Analysis Group at Dalhousie University, Canada.

GovernmentSize refers to government size, measured by the ratio of fiscal expenditures to local GDP. This variable captures the role of the local government in regional economic growth. According to the literature, the impact of government size on economic growth is not clear-cut [108]. While some studies, such as those of Afonso and Furceri [109] and DiPeitro and Anoruo [110], have reported a negative impact, Asimakopoulos and Karavias [111] and Chiou-Wei et al. [112] reported a non-linear relationship. Given the importance of government in making macroeconomic and development policies in China, it is possible that government size has a positive influence on China's economic growth.

Population is the size of population within the province. Population change has important impacts on economic growth [113,114]. On the one hand, the agglomeration effects arising from a large population size may promote economic growth. On the other hand, numerically, population growth reduces the value of GDP per capita, if the scale of GDP cannot expand faster than the population. Thus, the effect of population on economic growth is ambiguous.

In addition, we control the variables describing the general economic status of each region. Two variables are included as control variables: *GDPPerCapita*, the logarithmic value of real GDP per capita (CNY, in constant 2010 price), and *IndustrialStructure*, the industrial structure proxied by the share of non-agricultural value added in GDP.

Finally, we consider that other types of pollutants may also affect economic growth. In the model, we control the pollution of solid wastes by using the variable *SolidWaste-Emission*, which measures the solid waste emissions (tons) per capita.

3.3. Data

The air pollution data were derived from the Atmospheric Composition Analysis Group at Dalhousie University, Canada. The data file is available at the web page: http://fizz.phys.dal.ca/~atmos/martin/?page_id=140, accessed on 1 March 2021. van Donkelaar et al. [115,116] and Hammer et al. [117] provided details about the methodology used to calculate the value of annual average $PM_{2.5}$ concentration within an area. The data of dependent variables and control variables were obtained from the database of the EPS China Data, accessible at its website: http://www.epschinadata.com, accessed on 1 March 2021. The EPS platform has collected and stored numerous data from different statistical reports and yearbooks offered by the official statistical departments.

The research sample covers all 31 provinces in Mainland China. Based on the data availability, the sample spans a time interval of 16 years, between 2002 and 2017. There are 496 observations in total. Table 1 reports the definitions and summary statistics of variables employed in this study.

Table 1. Summary statistics.

Variable	Definition	Obs	Mean	SD	Min	Max
Growth	Annual growth rate (%) of real GDP per capita	496	10.253	2.951	−2.300	23.600
AirPollution	Air pollution, measured by logarithmic value of the annual population-weighted average $PM_{2.5}$ concentration (μg/m^3)	496	3.719	0.533	1.740	4.486
Education	Education level, measured by the average schooling years of laborers	496	8.495	1.225	3.738	12.503
CapitalFormation	Capital formation rate, measured by the ratio of fixed capital investment to GDP	496	0.646	0.248	0.237	1.507
FinancialDevelopment	Financial development, measured by the ratio of bank credits to GDP	496	1.639	0.719	0.751	5.587
FinancialOpenness	Financial openness, measured by foreign direct investment per capita (CNY, in constant 2010 price)	496	1.661	2.660	0.063	20.469
TradeOpenness	Trade openness, measured by the ratio of international trade volume to GDP	496	0.298	0.349	0.012	1.668
Road	Transport infrastructure, measured by road length (km) per area (km^2)	496	7.285	4.850	0.324	21.146
GovernmentSize	Government size, measured by the ratio of fiscal expenditures to GDP	496	0.232	0.180	0.079	1.379
Population	Logarithmic value of population (10,000 persons)	496	8.076	0.863	5.576	9.306
GDPPerCapita	Logarithmic value of GDP per capita (CNY, in constant 2010 price)	496	10.107	0.674	8.407	11.661
IndustrialStructure	Industrial structure, measured by the share (%) of non-agricultural value added in GDP	496	88.053	6.272	62.100	99.638
SolidWasteEmission	Solid waste emissions (tons) per capita	496	2.079	3.022	0.017	25.267

Abbreviations: CNY (Chinese Yuan), GDP (gross domestic product), Max (maximum), Min (minimum), Obs (observations), $PM_{2.5}$ (fine particulate matter), SD (standard deviation).

4. Results

In this section, we report the estimated impact of air pollution on GDP growth. In Section 4.1, the estimation results of the fixed-effects model are reported. In Section 4.2, we deal with the endogeneity issue by utilizing the instrumental variables approach, which provides more reliable estimates. In Section 4.3, we explore the heterogeneous effects of air pollution in different periods and regions.

4.1. Results of Fixed-Effects Estimation

4.1.1. Baseline

The estimation result of Equation (1) is shown in column (i) of Table 2. The coefficient of $AirPollution$ was -2.108 and statistically significant at the 5% level. In other words, it was found that air pollution significantly harmed economic growth. According to the estimated coefficient, holding other factors constant, if the concentration of $PM_{2.5}$ rises by 1%, then the annual growth rate of GDP per capita will decline by 0.02108 percentage points.

Some of the control variables also help explain economic growth in China. As expected, the level of education ($Education$) had a positive coefficient, although it was not statistically significant. Capital investment ($CapitalFormation$) significantly promoted economic growth. This reflects the importance of investment in China's rapid economic expansion. The expansion of bank credits ($FinancialDevelopment$) demonstrated a significant negative effect. The degree of financial openness ($FinancialOpenness$) had a significant positive effect. This supports the opinion that FDI benefits China's economic development. Trade openness ($TradeOpenness$) did not have a significant influence on economic growth. Transportation infrastructure ($Road$) had a positive coefficient; however, this coefficient was not statistically significant. Government size ($GovernmentSize$) demonstrated a significant positive impact, reflecting the active role of government in the Chinese economy. Population size ($Population$) has a significant negative effect, indicating that the economies with larger population scales tend to grow more slowly. GDP per capita ($GDPPerCapita$) had a negative coefficient, indicating the existence of economic convergence among different regions; namely, economies with relatively low per capita incomes tend to grow at faster rates than relatively rich economies. The proportion of non-agricultural value added in GDP ($IndustrialStructure$) had a significant positive correlation with economic growth rate, in line with the phenomenon that economic growth is accompanied by the process of industrial structure updating. The coefficient of solid waste emissions ($SolidWasteEmission$) was significantly negative, implying that solid waste pollution also harms economic growth.

4.1.2. Robustness Check

In this subsection, we check whether the estimated significant negative coefficient of $AirPollution$ in column (i) was robust to the selection of economic growth indicator, existence of possible outliers, and measurement of air pollution.

Previously, we used the annual growth rate of real GDP per capita to measure the economic growth. Here, we used the growth rate of real GDP as the dependent variable in Equation (1) and re-estimated the coefficients. The results are presented in column (ii). The estimated coefficient of $AirPollution$ was -1.972 and was still statistically significant at the 10% level. The coefficients of control variables were also similar to that in column (i).

In order to abate the disturbances from possible outliers, we winsorized the observations with the top 2.5% or bottom 2.5% values of economic growth rate. The estimation results for this winsorized sample are reported in column (iii). It is shown that this study's main finding about the adverse impact of air pollution held. The coefficient of $AirPollution$ was -1.505 and statistically significant at the 10% level.

In previous regressions, we used the concentration of $PM_{2.5}$ as the indicator of atmospheric pollution. Here, we examined whether our study result is sensitive to the selection of pollution indicator. Given that SO_2 is also a crucial pollutant in China, we used the SO_2 concentration to represent the severity of air pollution. The SO_2 data were downloaded from the platform of EPS China Data (http://www.epschinadata.com, accessed on 1 March 2021). As the governmental department of environmental protection only reported SO_2 concentration for a few cities, we failed to calculate the annual average value for the whole province. Thus, we used the value of SO_2 concentration in the capital city of a province to proxy the degree of pollution in that province, considering that the capital city is typically also the economic center and the city with the most population in the corresponding province. We reported the estimation result in column (iv). The estimated coefficient of $AirPollution$ was -1.375 and significant at the 1% level.

Table 2. Estimated impact of air pollution on economic growth rate based on fixed-effects estimation.

Variable	Baseline	Robustness Analysis		
		y = GDP Growth Rate	Based on Winsorized Sample	$AirPollution$ = SO_2 Concentration
	(i)	(ii)	(iii)	(iv)
$AirPollution$	−2.108 ** [0.953]	−1.972 * [0.994]	−1.505 * [0.783]	−1.375 *** [0.428]
$Education$	0.706 [0.536]	0.577 [0.478]	0.618 [0.504]	1.553 * [0.824]
$CapitalFormation$	6.583 *** [1.624]	7.148 *** [1.714]	4.471 *** [1.145]	6.291 *** [1.806]
$FinancialDevelopment$	−1.959 ** [0.936]	−1.380 [1.058]	−1.391 [0.862]	−1.978 [1.512]
$FinancialOpenness$	0.491 *** [0.146]	0.293 *** [0.102]	0.440 *** [0.144]	0.0964 [0.113]
$TradeOpenness$	−2.609 [1.779]	−1.969 [1.551]	−2.116 [1.688]	−1.998 [2.012]
$Road$	0.0184 [0.087]	0.0814 [0.099]	−0.038 [0.082]	−0.0302 [0.140]
$GovernmentSize$	10.42 *** [3.584]	9.498 ** [3.487]	8.733 ** [3.422]	23.43 ** [9.236]
$Population$	−14.92 *** [3.416]	−9.877 *** [3.005]	−14.14 *** [2.946]	−18.26 *** [5.227]
$GDPPerCapita$	−10.410 *** [2.241]	−7.110 *** [2.499]	−7.722 *** [1.779]	−13.80 ** [5.154]
$IndustrialStructure$	0.198 *** [0.071]	0.146 * [0.072]	0.174 *** [0.059]	0.00689 [0.127]
$SolidWasteEmission$	−0.116 ** [0.048]	−0.126** [0.054]	−0.0768 ** [0.028]	−0.0622 [0.073]
Province-fixed effect	Yes	Yes	Yes	Yes
Time-fixed effect	Yes	Yes	Yes	Yes
Observations	496	496	496	496
Provinces	31	31	31	31
R^2	0.770	0.784	0.773	0.564

Note: (1) ***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively. Heteroscedasticity-robust standard errors are reported in parentheses. (2) Abbreviation: GDP (gross domestic product), SO_2 (sulfur dioxide).

Overall, the robustness checks in columns (ii)–(iv) of Table 2 provide explicit and consistent evidence that air pollution had a significant negative correlation with economic growth in China.

4.2. Results of Instrumental Variables Estimation

4.2.1. Baseline

We intend to confirm the causal effect of air pollution on economic growth. Therefore, we need to make sure that the estimated coefficient of $AirPollution$ does not merely reflect a correlation between $AirPollution$ and $Growth$. One important thing is that we should control the influences of potential confounding factors (e.g., capital formation, FDI, level of GDP per capita, and industrial structure) which affect both $AirPollution$ and $Growth$. We have done this by including a set of important control variables in the regression model.

Although we excluded the influences of those control variables, the previous results of the fixed-effects model may still have suffered from the potential endogeneity issue. As the expansion of economic activities generates air pollutant emissions, there probably exists a reverse causality from economic growth to air pollution. For example, the reciprocal interaction between economic growth and air quality has been confirmed in the travel and tourism sector. While air pollution influences tourism, the development of tourism industries reversely affects air quality, because tourist activities consume resources and emit pollutants [118–122]. This results in the endogeneity of the explanatory variable in our regression model and causes a bias in the coefficient estimate. The instrumental variable (IV) estimation is an effective approach to mitigate the endogeneity problem. Credible IVs should meet two conditions: First, the IVs should strongly influence the endogenous explanatory variable. Second, the IVs should not have a direct correlation with the dependent variable, except through their links with the endogenous variable. In our research, three meteorological indicators—the annual average wind speed, vapor pressure, and humidity—are selected as useful IVs. First, the environmental literature has already confirmed that these meteorological conditions largely influence the concentration of pollutants in ambient air. For example, Alifa et al. [123], Calkins et al. [124], Koutrakis et al. [125], and Pearce et al. [126] analyzed the considerable influence of wind speed. Aw and Kleeman [127], Pearce et al. [126], and Seinfeld [128] discussed the significant correlation between vapor pressure and air pollution. He et al. [129], Koutrakis et al. [125], Wang and Ogawa [130], and Wise and Comrie [131] reported that humidity strongly affects air pollution. Second, there is no apparent evidence that economic growth is directly impacted by these meteorological conditions. Thus, both conditions for the selection of reliable IVs are met.

We instrumented $AirPollution$ by the meteorological variables and used the standard IV-2SLS (two-stage least squares) method to estimate Equation (1). (The meteorological data were obtained from the China Meteorological Data Service Center at http://data.cma.cn/en, accessed on 1 March 2021). The IV estimation result is demonstrated in column (i) of Table 3.

In the first-stage regression, the variables of wind speed and vapor pressure both had negative coefficients, and humidity had a positive coefficient. All three of these coefficients were statistically significant at least at the 10% level, indicating that the three IVs indeed had a significant influence on air pollution, as suggested by previous environmental research. The associated Cragg–Donald Wald F statistic and Kleibergen–Paap rk Wald F statistic were both significant at the 10% level, showing that the selected IVs were not "weak IVs". The Hansen J statistic was not statistically significant. The insignificant value of the Hansen J statistic suggests that the regression model was not overidentified. Overall, these statistics demonstrate that the IVs were valid instruments and properly used in the estimation.

In the second-stage regression, the estimated coefficient of $AirPollution$ was -5.818, which was statistically significant at the 5% level. This shows that air pollution, indeed, had a substantially adverse impact on the economic growth rate after we effectively tackled the endogeneity issue by employing the IV approach. The research hypothesis in this study was, therefore, validated. The number suggests that, holding other factors constant, if air pollution can be abated by 1%, the annual economic growth rate will increase by 0.05818 percentage points. It is notable that the magnitude of the coefficient (-5.818) from the IV estimation was much larger than that (-2.108) from the fixed-effects estimation without addressing the endogeneity issue. The endogeneity test χ^2 statistic of 2.892 was significant at the 10% level, clearly rejecting the null hypothesis that air pollution can be regarded as exogenous. This implies that the endogeneity problem, indeed, existed and that it was necessary to use the IV method to obtain a more reliable estimate for $AirPollution$. The coefficients of control variables were generally similar to those in Table 2, and not discussed here to save space.

Table 3. Estimated impact of air pollution on economic growth rate based on instrumental variables estimation.

Variable	Baseline (IV Estimation)	Robustness Analysis (IV Estimation)		
		y = GDP Growth Rate	Based on Winsorized Sample	$AirPollution$ = SO_2 Concentration
	(i)	(ii)	(iii)	(iv)
$AirPollution$	−5.818 ** [2.677]	−6.373 ** [2.579]	−5.258 ** [2.544]	−3.718 ** [1.467]
$Education$	0.445 [0.358]	0.267 [0.356]	0.353 [0.337]	1.482 *** [0.527]
$CapitalFormation$	6.335 *** [1.037]	6.854 *** [1.076]	4.220 *** [0.706]	5.659 *** [1.350]
$FinancialDevelopment$	−2.168 *** [0.695]	−1.627 ** [0.722]	−1.602 *** [0.613]	−2.259 ** [0.942]
$FinancialOpenness$	0.518 *** [0.093]	0.325 *** [0.085]	0.468 *** [0.083]	0.0483 [0.116]
$TradeOpenness$	−3.043 *** [0.968]	−2.484 *** [0.793]	−2.555 *** [0.929]	−3.009 ** [1.314]
$Road$	−0.00503 [0.050]	0.0536 [0.050]	−0.0617 [0.046]	−0.0903 [0.081]
$GovernmentSize$	11.67 *** [2.379]	10.97 *** [2.357]	9.989 *** [2.151]	34.27 *** [9.208]
$Population$	−16.07 *** [2.241]	−11.24 *** [2.332]	−15.30 *** [1.920]	−21.80 *** [3.834]
$GDPPerCapita$	−10.20 *** [1.308]	−6.861 *** [1.365]	−7.510 *** [1.006]	−14.09 *** [2.445]
$IndustrialStructure$	0.164 *** [0.053]	0.104 ** [0.053]	0.139 *** [0.046]	0.0369 [0.072]
$SolidWasteEmission$	−0.136 *** [0.034]	−0.150 *** [0.037]	−0.0973 *** [0.031]	0.0106 [0.086]
Province-fixed effect	Yes	Yes	Yes	Yes
Time-fixed effect	Yes	Yes	Yes	Yes
First-stage regression coefficient				
Wind Speed	−0.0960 *	−0.0960 *	−0.0960 *	−0.921 ***
Vapor Pressure	−0.0777 ***	−0.0777 ***	−0.0777 ***	-
Humidity	0.780 ***	0.780 ***	0.780 ***	-
Cragg-Donald Wald F statistic	10.001 *	10.001 *	10.001 *	18.456 *
Kleibergen-Paap rk Wald F statistic	10.700 *	10.700 *	10.700 *	17.610 *
Hansen J statistic	3.120	1.450	4.263	-
Endogeneity test χ^2 statistic	2.892 *	5.447 **	3.346 *	2.997 *
Observations	496	496	496	496
Provinces	31	31	31	31
R^2	0.800	0.792	0.799	0.602

Note: (1) ***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively. Heteroscedasticity-robust standard errors are reported in parentheses. (2) Abbreviations: GDP (gross domestic product), IV (instrumental variable), SO_2 (sulfur dioxide). (3) The first-stage regression coefficients, Cragg–Donald Wald F statistic, and Kleibergen–Paap rk Wald F statistic are the same in columns (i)–(iii).

4.2.2. Robustness Check

To further verify the IV estimation results, we also conducted several robustness checks, analogous to those in columns (ii)–(iv) of Table 2. In column (ii) of Table 3, we used the GDP growth rate as the dependent variable and repeated the IV estimation procedure. We obtained a coefficient of −6.373 for *AirPollution*, which was not far from that in column (i). In column (iii), we winsorized the sample at the cutoff point of GDP per capita growth rate of top or bottom 2.5%. The estimation using the winsorized sample provided a coefficient of −5.258 for *AirPollution*, quite close to that in column (i). In column (iv), we used the SO_2 concentration as air pollution indicator. In the first-stage regression, we only utilized the wind speed as instrument variable, because vapor pressure and humidity did not demonstrate a significant correlation with SO_2 concentration. Accordingly, we did not report the Hansen J statistic because the equation was exactly identified (i.e., the number of instrument variable equals the number of endogenous variable). Using SO_2 as the pollution indicator, the estimated coefficient of *AirPollution* became −3.718, which was also significantly negative.

All in all, the robustness checks for IV estimation in columns (ii)–(iv) of Table 3 all support our previous statement that air pollution impeded economic growth. The magnitudes of the estimated coefficients—−6.373, −5.258, and −3.718—were still much larger than those reported for the fixed-effects model.

4.3. Heterogeneity Analysis

The previous analyses have shown an overall adverse influence of air pollution on China's economic growth. However, the impact of air pollution may not be homogeneous during all periods in all regions. In this subsection, we analyze the heterogeneous effects of pollution in different periods and districts. We examine whether the situation differed before and after 2008; before and after 2014; in the eastern, central, and western regions; and in provinces with different shares of state-owned enterprises, different levels of government health expenditures, and different availability of medical resources. The results suggest no evident changes along the time dimension but substantial differences among different regions.

The heterogeneity analysis is based on the following regression model:

$$Growth_{it} = \alpha_1 AirPollution_{it} + \alpha_2 AirPollution_{it} \times D_{it} + X_{it}\beta + s_i + v_t + \varepsilon_{it}, \quad (2)$$

where D_{it} is a binary dummy variable that equals 1 or 0, contingent on some specific conditions which will be defined later. The equation is estimated using the instrumental variables method.

4.3.1. Before- versus after-2008 Period

First, we examine whether there was a difference between the before- and after-2008 periods. The global financial crisis in 2008 largely altered the economic structures of many countries. Thus, we conjecture that the effect of air pollution on economic growth might change after the crisis. In order to empirically examine that, we define the dummy variable in Equation (2) as follows: $D_{it}^{After2008}$ = 1 if $t \geq 2008$, and 0 otherwise. The effects of pollution before and after 2008 are measured by the parameter α_1 and (α_1 + α_2), respectively.

Column (i) of Table 4 shows the estimation result. The value of α_1 was −4.759 and statistically significant. The value of α_2 was 0.507, which was small in magnitude compared to the value of α_1. Moreover, α_2 was not statistically significant. Therefore, we can conclude that the effects of pollution before and after 2008 were essentially similar.

4.3.2. Before- versus after-2014 Period

Next, we check the difference between the before- and after-2014 periods. The year 2013 was a turning point in terms of the public awareness and concern for air pollution in China [132]. On 9 September 2013, the "Air Pollution Prevention and Control Action Plan" was announced by the State Council of China. Then, the whole country implemented stronger policies to deal with the air pollution problem. Therefore, we conjecture that the effects of pollution in periods before and after 2014 may not be the same. We define the dummy variable in Equation (2) as follows: $D_{it}^{After2014}$ = 1 if $t \geq 2014$, and 0 otherwise.

Column (ii) of Table 4 shows the estimation result. The value of α_1 was −5.854, which was statistically significant. The value of α_2 was −0.0209, which was quite small in magnitude and not statistically significant. Thus, it can be concluded that there was no difference between the before- and after-2014 periods.

Table 4. Heterogeneous effects of air pollution in different periods and regions.

Variable	Before or After 2008	Before or After 2014	East or Center and West Region	Smaller or Larger State-Owned Enterprises Share	Fewer or More Governmental Health Expenditures	Fewer or More Medical Resources
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
$AirPollution$	−4.759 * [2.620]	−5.854 ** [2.709]	−7.015 * [3.681]	−7.201 ** [2.987]	−7.408 ** [3.303]	−7.268 ** [2.874]
$AirPollution \times D^{After2008}$	0.507 [0.361]					
$AirPollution \times D^{After2014}$		−0.0209 [0.280]				
$AirPollution \times D^{Center\&West}$			5.019 * [3.040]			
$AirPollution \times D^{LargerSOEShare}$				4.349 * [2.353]		
$AirPollution \times D^{MoreGovHealthExpenditures}$					5.898 ** [2.368]	
$AirPollution \times D^{MoreMedicalResources}$						4.591 * [2.487]
Other control variables	Yes	Yes	Yes	Yes	Yes	Yes
Province-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	496	496	496	496	496	496
Provinces	31	31	31	31	31	31
R^2	0.807	0.800	0.809	0.800	0.802	0.801

Note: ** and * represent the significance levels of 5% and 10%, respectively. Heteroscedasticity-robust standard errors are reported in parentheses. In order to save space, the coefficients of control variables are not reported in the table.

4.3.3. Eastern versus Central and Western Region

Thirdly, we classify our sample provinces into two groups according to their geographical locations. The first group contains 11 provinces located in the eastern region. The second group contains 20 provinces located in the central and western regions. The grouping of provinces is based on the official classification of the National Bureau of Statistics of China. As the eastern region of China has significantly higher levels of economic development, urbanization, and population density, compared to the central and western regions, we expect to observe a stronger impact of atmospheric pollution in the eastern region. We define the dummy variable in Equation (2) as follows: $D_{it}^{Center\&West} = 1$ if the province i is in the central and western regions, and 0 if it is in the eastern region.

Column (iii) of Table 4 reports the estimated coefficients. The value of α_1 was −7.015, which was statistically significant. The value of α_2 was 5.019, which was also significant. These coefficients imply that there was a substantial difference between the eastern and other regions. If the $PM_{2.5}$ concentration rises by 1%, the economic growth rate will reduce by 0.07015 percentage points in the eastern region and 0.01996 (=0.07015 − 0.05019) percentage points in the central and western regions. Therefore, it is verified that the adverse influence of air pollution on macroeconomic growth is stronger in the eastern region.

4.3.4. Smaller versus Larger State-Owned Enterprises Share

Here, we examine whether the share of state-owned enterprises (SOEs) in the economy matters. In China, numerous economic activities are conducted or influenced by SOEs. Compared to non-SOEs, SOEs are generally less efficient and more heavily intervened in by governments. Thus, a smaller proportion of SOEs in the economy indicates a larger degree of marketization, resource mobility, and economic vitality. The linkage between air pollution and economic growth may be influenced by the share of SOEs. As the official data sources did not provide information about the aggregate output of SOEs and non-SOEs, we measured the share of SOEs by the ratio of annual investments of SOEs to total investments in the whole province. We define the dummy variable in Equation (2) as follows: $D_{it}^{LargerSOEShare} = 1$ if the average share of SOEs during the sample period in province i is equal to or above the sample median, and 0 otherwise.

Column (iv) of Table 4 reports the estimated coefficients. The values of α_1 and α_2 equaled -7.201 and 4.349, respectively. Both of them were statistically significant. These coefficients indicate an obvious difference between the regions with different shares of SOEs. In a province with a relatively small SOEs share, a 1% increase in $PM_{2.5}$ concentration makes the economic growth rate decline by 0.07201 percentage points. In a province with a relatively large SOEs share, the economic growth rate will reduce by 0.02852 (=0.07201 − 0.04349) percentage points. The negative effect of air pollution on economic growth is stronger in the regions with smaller SOEs shares.

4.3.5. Fewer versus More Governmental Health Expenditures

The impact of air pollution may not be homogeneous in all regions. As discussed previously, the negative influence of air pollution on economic growth is largely grounded in its harmfulness to human health. Therefore, it is natural to consider that an improvement in public health services may help mitigate the damage of air pollution to economic growth. For instance, suppose that pollution causes a higher incidence of respiratory diseases of laborers. The patients living in provinces with a better public health service system can get better medical treatments and be cured sooner. Thus, in these regions, the loss of labor productivity caused by air-pollution-induced respiratory diseases will be relatively small. Following this logic, we conjecture that the negative impact of air pollution on economic growth is weaker in regions with better public health services.

In China, the government plays a determinant role in the provision of public health services. Hence, we focus on the part of public health services financed by the government. We calculate the scale of public health spending from the fiscal budget as a ratio to total government expenditures. A high ratio indicates that the government spends a large proportion of fiscal budget on public health services, implying a strong willingness to provide good services to the public. Ceteris paribus, we can reasonably believe that the higher the ratio, the better the public health services in the corresponding region. The dummy variable in Equation (2) is defined as follows: $D_{it}^{MoreGovHealthExpenditures} = 1$ if the average ratio of public health spending to total government spending during the sample period in province i is equal to or above the sample median, and 0 otherwise.

Column (v) of Table 4 reports the estimation result. The values of α_1 and α_2 were -7.408 and 5.898, respectively. Both of them were statistically significant. These coefficients show an evident difference between the regions with different levels of public health services. In a province with the local government spending a small proportion of fiscal spending on public health services, a 1% rise in $PM_{2.5}$ concentration causes the economic growth rate to reduce by 0.07408 percentage points. In a province with the government spending a large share of fiscal budget on public health, the economic growth rate will decrease by 0.0151 (=0.07408 − 0.05898) percentage points. The negative impact of air pollution on economic growth is severer in the regions with fewer governmental expenditures for public health services.

4.3.6. Fewer versus More Medical Resources

Given that the adverse health effect of atmospheric pollution is a major reason of the negative air pollution–economic growth linkage, the availability of medical resources within the region matters. Holding other factors constant, in districts with more medical resources, residents can obtain better healthcare services and, thus, are less damaged by air pollution. Accordingly, we conjecture that the inhibitory impact of air pollution on macroeconomic growth is weaker in provinces with more medical resources.

We measure the availability of medical resources using the ratio of the number of beds in healthcare institutions to the local population. A higher ratio indicates more availability of medical resources. The dummy variable in Equation (2) is defined as follows: $D_{it}^{MoreMedicalResources} = 1$ if the average availability of medical resources during the sample period in province i is equal to or above the sample median, and 0 otherwise.

Column (vi) of Table 4 shows the estimated coefficients. The values of α_1 and α_2 equaled -7.268 and 4.591, respectively. Both coefficients were statistically significant. If $PM_{2.5}$ pollution increases by 1%, the economic growth rate in areas with fewer medical resources will decrease by 0.07268 percentage points, and that in areas with more medical resources will decrease by 0.02677 (=0.07268 − 0.04591) percentage points. An explicit quantitative distinction exists between the regions with a different abundance of medical resources. The inhibitory impact of air pollution is stronger in provinces with fewer healthcare resources.

The heterogeneity analyses discussed above provide three findings. (1) The impact of air pollution on economic growth was always negative. After we classified the samples into different periods and different regions, we observed a negative effect in all subsamples. (2) There is no significant heterogeneity along the time dimension. The estimated impacts of air pollution in before- and after-2008 periods are similar. The estimated impacts in before- and after-2014 periods are also similar. (3) There are some quantitative differences along the geographical dimension. The harmful influence of air pollution is stronger in China's eastern region and in provinces with smaller state-owned enterprises shares, fewer governmental expenditures for public health services, and fewer healthcare resources.

5. Discussion, Conclusions, and Directions for Future Research

5.1. Discussion

China's economic growth has gradually slowed down in recent years. The blue-solid curve in Figure 3 shows the annual growth rate of the real GDP per capita of China over the past ten years (2010–2019). As can be seen from the graph, an evident decline in economic growth rate has been observed. It is of widespread concern whether and to what extent China can maintain its economic growth miracle in the future. Our study suggests that the air pollution problem poses a substantial threat to the economic growth of China. This finding has a clear policy implication: even from a purely economic perspective, China should implement effective policies to mitigate the atmospheric pollution problem. The aim of promoting economic growth and the desire to have clean air are not contradictory. According to our IV estimation (column (i) of Table 3), if the concentration of $PM_{2.5}$ can be diminished by 10%—which is not an unrealistic target—the annual growth rate of GDP per capita will be improved by 0.5818 percentage points. This is, indeed, a large benefit. The actions of environmental protection have a substantial positive economic outcome. The orange-dashed curve in Figure 4 displays the estimated growth rate of GDP per capita after an imagined 10% reduction in air pollution, which is substantially higher than the actual level.

The estimated impact of air pollution on economic growth rate in this study allows us to appraise the accumulative benefits of air pollution abatement in terms of GDP and GDP per capita. For example, let us consider what would happen if China had reduced the concentration of $PM_{2.5}$ by 10% since 2010. As already demonstrated in Figure 4, in such a scenario, the annual growth rate of GDP per capita would be 0.5818 percentage points higher than its actual value observed in the data. Therefore, the level of GDP per capita in every year since 2010 would also be higher than the actual level. Figure 5 demonstrates the estimated GDP per capita under the air-pollution-reduction scenario versus the actual level during the period 2010–2019. It is notable from the graph that, as time goes on, the gap between the actual and the estimated levels becomes larger. In 2019, the actual GDP per capita of China was USD 8255 (in constant 2010 price), while the estimated value reached USD 8714, which is over 5.6% larger than the actual level. It is also convenient to calculate the variations of GDP. In 2019, China's actual GDP was around USD 11.5 trillion (in constant 2010 price). If $PM_{2.5}$ had been reduced by 10% since 2010, the GDP would have reached the scale of USD 12.1 trillion. The difference of USD 0.6 (=12.1 − 11.5) trillion is so large that it is close to the economic scale of Poland or Sweden. The more China abates air pollution, the larger are the benefits, in terms of GDP or GDP per capita, that can be acquired. Moreover, as demonstrated previously in Figure 2, the earlier the country reduces air pollution, the larger is the scale of GDP expansion that can be obtained. In other words, if China can effectively improve its air quality earlier, the benefits will be more substantial.

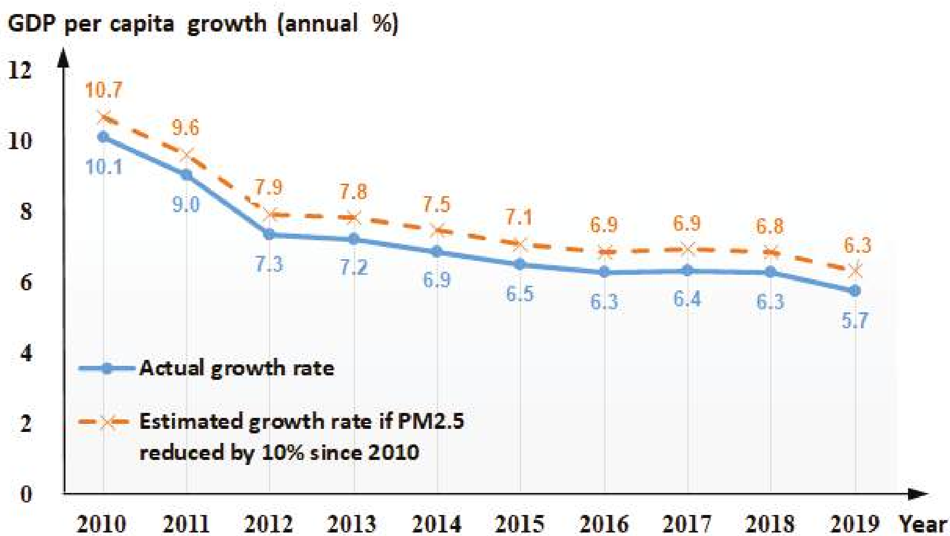

Figure 4. Annual growth rate of GDP per capita of China during 2010—2019. Abbreviation: GDP (gross domestic product). Data source of GDP per capita growth: World Bank's World Development Indicators database.

Prior studies have revealed that several Chinese economic sectors were greatly harmed by poor air quality in direct and indirect ways. A noticeable industry that garnered much attention is that of tourism. Becken et al. [10], Xu and Reed [48,49], and Yang and Chen [50], among others, emphasized the significant negative influences of atmospheric pollution on tourist arrivals and receipts in China. The agricultural losses due to air pollution are also substantial, as reported in the literature. For example, Wei et al. [133] estimated that, during the year of 2008, the damage costs in agriculture caused by industrial SO_2 pollution were around $1.43 billion, not to mention other kinds of air pollutants. As air pollution causes a great number of socioeconomic costs due to pollution-induced diseases, hospital admissions, mortality, and medical expenditures [134], there are observable reductions in the efficiency and productivity in a range of labor-intensive industries, such as call centers, garment processing, and textiles [5,135,136]. Some high-technology industries may also be affected because the accumulation of human capital and the advancement in innovation and R&D are impeded by pollution [32,137].

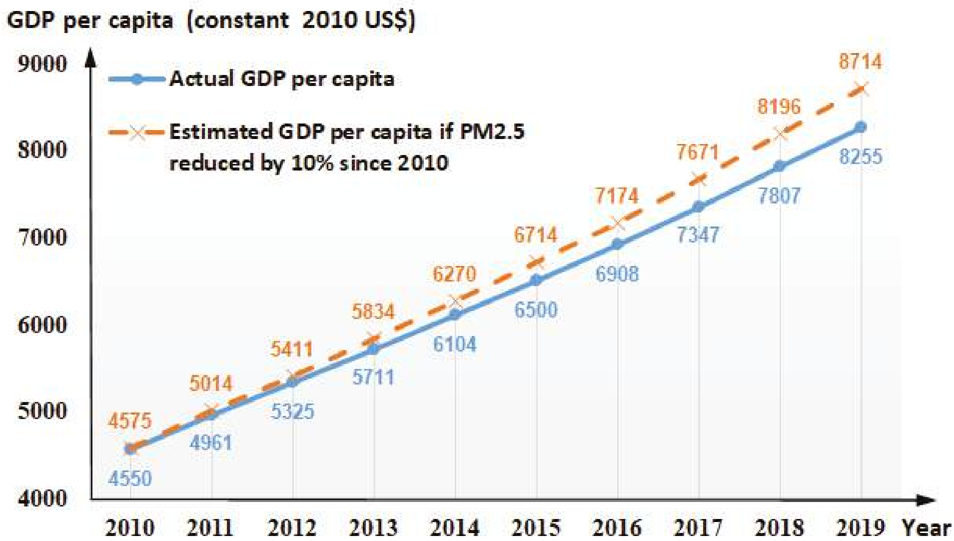

Figure 5. Level of GDP per capita of China during 2010–2019. Abbreviation: GDP (gross domestic product). Data source of GDP per capita: World Bank's World Development Indicators database.

China has undertaken much effort to reduce air pollution in recent years. Many actions, including technological innovation, citizen engagement, and top-down policy initiatives, have been implemented [138]. Chinese residents demonstrated a strong public willingness to pay for air pollution mitigation [139]. Although air pollution has been reduced, the current air quality remains unsatisfactory. According to the data from World Bank's World Development Indicators, in 2017, 99.998% of the Chinese population was exposed to $PM_{2.5}$ pollution levels exceeding the World Health Organization (WHO) guideline value (i.e., 10 $\mu g/m^3$), and 81.239% of the population was exposed to levels over the WHO Interim Target-1 value (i.e., 35 $\mu g/m^3$). While air pollution is especially serious in China's eastern areas, which have dense population, a high urbanization rate, and intensive economic production, significant pollution levels are also widespread across northern and central China [140–142]. Given the seriousness of the atmospheric pollution problem in China, the country has significant potential to improve its air quality. For instance, the deeper de-carbonization of the energy system will be very helpful [143]. Based on the results of our study, it is expected that, if China is able to reduce its air pollution effectively in the future, a great volume of economic activities can be stimulated and the country's economic development can reach a higher level. This study offers some useful policy implications, which are stated as follows.

First, it is economically beneficial for China to improve air quality as soon as possible. Abating air pollution can increase GDP growth rate and hence bring about large long-term accumulative welfare in terms of the expansion of economic scale. As long as the benefit of pollution abatement is greater than its cost, the government should make long-run plans for industrial structure adjustment and upgrade, implement regulations on high pollution enterprises, and develop environmentally friendly sectors and a circular economy in order to reduce pollution.

Second, different regions should strengthen the cross-regional coordination and take cooperative measures to prevent and control pollution. It is observed that the impact of air pollution on economic growth is always negative across different regions, although some heterogeneities are detected. Therefore, the adverse impact of pollution should be a concern of all Chinese regions. The efforts of a small number of districts are not enough to solve the problem in the whole country. The effective mechanism for cross-regional cooperation, such as those already built in the Beijing-Tianjin-Hebei region and the Yangtze River Delta, is indispensable.

Third, stronger policy supports should be provided to the provinces in which the damage of air pollution is severer. For instance, more favorable tax policies, greater public subsidies, and deeper green finance reforms aimed to develop renewable and clean energies and environmental protection industries could be encouraged. The analyses on different subsamples of this study suggest that the influence of atmospheric pollution on regional macroeconomic growth is substantially stronger in the eastern provinces and in provinces where the shares of state-owned enterprises are smaller, the local governments spend a smaller portion of the fiscal budgets on providing public health services, and medical resources are less abundant. The areas with a stronger impact of air pollution should pay more attention and bear more responsibility. Our analyses also indicate that, in order to mitigate the adverse effect of air pollution, the governments should increase the budget of public health service expenditures and provide supports to expand the local medical resources. These actions will not only benefit residents' health but also promote local economic growth. These are important, especially when there are difficulties in improving air quality in the short run.

5.2. Conclusions and Directions for Future Research

In summary, this study empirically examined the influence of air pollution on the regional economic growth in Chinese provinces, on the basis of a sample during 2002–2017. The results showed the significant negative impact of air pollution on economic growth, and thus, the research hypothesis in this study was confirmed. It was estimated that the annual growth rate of real GDP per capita declines by 0.05818 percentage points as a result of a 1% increase in $PM_{2.5}$ concentration. Therefore, the purpose of promoting economic growth actually requires the government to tackle the air pollution issue. In addition, it is found that the adverse effect of atmospheric pollution is qualitatively consistent but quantitatively heterogeneous across different regions.

This research has several limitations, which provide opportunities for future studies. (1) This research selected China as the target country and conducted an analysis on the basis of a Chinese sample. It is also very important to investigate similar scenarios in some other highly polluted developing countries, such as Bangladesh, India, Mongolia, and Pakistan. Lessons and experience from these countries will definitely be valuable. In future studies, scholars can investigate the influences of air pollution on economic growth in other countries and examine whether our findings based on Chinese data are also applicable to other regions. (2) This research analyzed the influence of air pollution at the province level. Given the fact that China has a vast territory, the different cities and counties may be highly heterogeneous even within one specific province. Thus, the effect of air pollution may not be uniform over a whole province. In the future, researchers can collect more detailed city- or county-level data, in order to provide deeper insights into how regional characteristics mediate the impact of pollution on economic growth. (3) In this study, we considered the regional macroeconomy as a whole without inspecting individual industries and sectors separately. It is possible that air pollution influences the growth of different industries unequally. Future studies could distinguish different industrial sectors to evaluate the impact of pollution. This can provide a more accurate understanding and help us identify the most crucial industries. (4) This study focused on the pollution in air and did not compare the relative importance of different pollution types. Some useful implications might be obtained if diverse pollution categories, such as air pollution, water pollution, solid wastes, and noise, can be included in a more complete model. By utilizing such a model, future researchers can provide a list of priorities to abate different pollutants. (5) The regression model in this study did not consider the possibility of cross-sectional dependence. As air pollution and economic activities might have spatial spillover effects, ignoring cross-sectional dependence possibly results in inaccurate estimates. In the future, researchers can construct a more sophisticated model, which incorporates cross-sectional dependence and instrumental variables estimation, to re-examine the impact of pollution.

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Abbreviations

The following abbreviations are used in this manuscript:

CNY	Chinese Yuan
CO_2	Carbon dioxide
GDP	Gross domestic product
IV	Instrumental variable
Max	Maximum
Min	Minimum
NO_2	Nitrogen dioxide
Obs	Observations
$PM_{2.5}$	Fine particulate matter
SD	Standard deviation
SO_2	Sulfur dioxide

References

1. Amegah, A.K.; Jaakkola, J.J. Household air pollution and the sustainable development goals. *Bull. World Health Organ.* **2016**, *94*, 215–221. [CrossRef]
2. Guo, D.; Cao, Z.; DeFrancia, K.; Yeo, J.W.G.; Hardadi, G.; Chai, S. Awareness, perceptions and determinants of urban sustainable development concerns—Evidence from a central province in China. *Sustain. Dev.* **2018**, *26*, 652–662. [CrossRef]
3. Rafaj, P.; Kiesewetter, G.; Gül, T.; Schöpp, W.; Cofala, J.; Klimont, Z.; Purohit, P.; Heyes, C.; Amann, M.; Borken-Kleefeld, J.; et al. Outlook for clean air in the context of sustainable development goals. *Glob. Environ. Chang.* **2018**, *53*. [CrossRef]
4. Chang, T.; Graff Zivin, J.; Gross, T.; Neidell, M. Particulate Pollution and the Productivity of Pear Packers. *Am. Econ. J. Econ. Policy* **2016**, *8*, 141–169. [CrossRef]
5. He, J.; Liu, H.; Salvo, A. Severe Air Pollution and Labor Productivity: Evidence from Industrial Towns in China. *Am. Econ. J. Appl. Econ.* **2019**, *11*, 173–201. [CrossRef]
6. Huang, X.; Lanz, B. The Value of Air Quality in Chinese Cities: Evidence from Labor and Property Market Outcomes. *Environ. Resour. Econ.* **2018**, *71*, 849–874. [CrossRef]
7. Cole, M.A.; Elliott, R.J.R.; Lindley, J.K. Dirty money: Is there a wage premium for working in a pollution intensive industry? *J. Risk Uncertain.* **2009**, *39*, 161–180. [CrossRef]
8. Cui, C.; Wang, Z.; He, P.; Yuan, S.; Niu, B.; Kang, P.; Kang, C. Escaping from pollution: The effect of air quality on inter-city population mobility in China. *Environ. Res. Lett.* **2019**, *14*, 124025. [CrossRef]
9. Qin, Y.; Zhu, H. Run away? Air pollution and emigration interests in China. *J. Popul. Econ.* **2018**, *31*, 235–266. [CrossRef]
10. Becken, S.; Jin, X.; Zhang, C.; Gao, J. Urban air pollution in China: Destination image and risk perceptions. *J. Sustain. Tour.* **2017**, *25*, 130–147. [CrossRef]
11. Xu, B.; Dong, D. Evaluating the Impact of Air Pollution on China's Inbound Tourism: A Gravity Model Approach. *Sustainability* **2020**, *12*, 1456. [CrossRef]

12. Myhre, O.; Låg, M.; Villanger, G.D.; Oftedal, B.; Øvrevik, J.; Holme, J.A.; Aase, H.; Paulsen, R.E.; Bal-Price, A.; Dirven, H. Early life exposure to air pollution particulate matter (PM) as risk factor for attention deficit/hyperactivity disorder (ADHD): Need for novel strategies for mechanisms and causalities. *Toxicol. Appl. Pharmacol.* **2018**, *354*, 196–214. [CrossRef] [PubMed]
13. Tzivian, L.; Winkler, A.; Dlugaj, M.; Schikowski, T.; Vossoughi, M.; Fuks, K.; Weinmayr, G.; Hoffmann, B. Effect of long-term outdoor air pollution and noise on cognitive and psychological functions in adults. *Int. J. Hyg. Environ. Health* **2015**, *218*. [CrossRef]
14. Khajavi, A.; Khalili, D.; Azizi, F.; Hadaegh, F. Impact of temperature and air pollution on cardiovascular disease and death in Iran: A 15-year follow-up of Tehran Lipid and Glucose Study. *Sci. Total Environ.* **2019**, *661*, 243–250. [CrossRef]
15. Chen, J.C.; Schwartz, J. Neurobehavioral effects of ambient air pollution on cognitive performance in US adults. *NeuroToxicology* **2009**, *30*, 231–239. [CrossRef] [PubMed]
16. Gatto, N.M.; Henderson, V.W.; Hodis, H.N.; St. John, J.A.; Lurmann, F.; Chen, J.C.; Mack, W.J. Components of air pollution and cognitive function in middle-aged and older adults in Los Angeles. *NeuroToxicology* **2014**, *40*, 1–7. [CrossRef] [PubMed]
17. Szyszkowicz, M.; Stieb, D.M.; Rowe, B.H. Air pollution and daily ED visits for migraine and headache in Edmonton, Canada. *Am. J. Emerg. Med.* **2009**, *27*, 391–396. [CrossRef]
18. Ghorani-Azam, A.; Riahi-Zanjani, B.; Balali-Mood, M. Effects of air pollution on human health and practical measures for prevention in Iran. *J. Res. Med. Sci.* **2016**, *21*, 65. [CrossRef]
19. Szyszkowicz, M.; Kousha, T.; Kingsbury, M.; Colman, I. Air Pollution and Emergency Department Visits for Depression: A Multicity Case-Crossover Study. *Environ. Health Insights* **2016**, *10*, 155–161. [CrossRef]
20. Ji, M.; Cohan, D.S.; Bell, M.L. Meta-analysis of the association between short-term exposure to ambient ozone and respiratory hospital admissions. *Environ. Res. Lett.* **2011**, *6*, 024006. [CrossRef]
21. Kowalska, M.; Skrzypek, M.; Kowalski, M.; Cyrys, J. Effect of NOx and NO_2 Concentration Increase in Ambient Air to Daily Bronchitis and Asthma Exacerbation, Silesian Voivodeship in Poland. *Int. J. Environ. Res. Public Health* **2020**, *17*, 754. [CrossRef]
22. Cohen, A.J.; Brauer, M.; Burnett, R.; Anderson, H.R.; Frostad, J.; Estep, K.; Balakrishnan, K.; Brunekreef, B.; Dandona, L.; Dandona, R.; et al. Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: An analysis of data from the Global Burden of Diseases Study 2015. *Lancet* **2017**, *389*, 1907–1918. [CrossRef]
23. Zhou, M.; Wang, H.; Zeng, X.; Yin, P.; Zhu, J.; Chen, W.; Li, X.; Wang, L.; Wang, L.; Liu, Y.; et al. Mortality, morbidity, and risk factors in China and its provinces, 1990–2017: A systematic analysis for the Global Burden of Disease Study 2017. *Lancet* **2019**, *394*, 1145–1158. [CrossRef]
24. Zhao, Q.; Yuan, C.H. Did Haze Pollution Harm the Quality of Economic Development?—An Empirical Study Based on China's $PM_{2.5}$ Concentrations. *Sustainability* **2020**, *12*, 1607. [CrossRef]
25. Atesoglu, H.S.; Smithin, J. Real wages, productivity and economic growth in the G7, 1960–2002. *Rev. Political Econ.* **2006**, *18*, 223–233. [CrossRef]
26. Cao, K.H.; Birchenall, J.A. Agricultural productivity, structural change, and economic growth in post-reform China. *J. Dev. Econ.* **2013**, *104*, 165–180. [CrossRef]
27. Lee, J.W.; McKibbin, W.J. Service sector productivity and economic growth in Asia. *Econ. Model.* **2018**, *74*, 247–263. [CrossRef]
28. Turner, C.; Tamura, R.; Mulholland, S.E. How important are human capital, physical capital and total factor productivity for determining state economic growth in the United States, 1840–2000? *J. Econ. Growth* **2013**, *18*, 319–371. [CrossRef]
29. Kim, M.; Yi, O.; Kim, H. The role of differences in individual and community attributes in perceived air quality. *Sci. Total Environ.* **2012**, *425*, 20–26. [CrossRef]
30. Pu, S.; Shao, Z.; Fang, M.; Yang, L.; Liu, R.; Bi, J.; Ma, Z. Spatial distribution of the public's risk perception for air pollution: A nationwide study in China. *Sci. Total Environ.* **2019**, *655*, 454–462. [CrossRef]
31. Qian, X.; Xu, G.; Li, L.; Shen, Y.; He, T.; Liang, Y.; Yang, Z.; Zhou, W.W.; Xu, J. Knowledge and perceptions of air pollution in Ningbo, China. *BMC Public Health* **2016**, *16*, 1138. [CrossRef]
32. Luo, Y.; Yang, J.; Chen, S. Air Pollution, Human Capital Flow and Innovative Vitality–Evidence from Individual Patent Inventions. *China Ind. Econ.* **2019**, *10*, 99–117.
33. Ahsan, H.; Haque, M.E. Threshold effects of human capital: Schooling and economic growth. *Econ. Lett.* **2017**, *156*, 48–52. [CrossRef]
34. Su, Y.; Liu, Z. The impact of foreign direct investment and human capital on economic growth: Evidence from Chinese cities. *China Econ. Rev.* **2016**, *37*, 97–109. [CrossRef]
35. Teixeira, A.A.C.; Queirós, A.S.S. Economic growth, human capital and structural change: A dynamic panel data analysis. *Res. Policy* **2016**, *45*, 1636–1648. [CrossRef]
36. Kirillova, K.; Fu, X.; Lehto, X.; Cai, L. What makes a destination beautiful? Dimensions of tourist aesthetic judgment. *Tour. Manag.* **2014**, *42*, 282–293. [CrossRef]
37. Łapko, A.; Panasiuk, A.; Strulak-Wójcikiewicz, R.; Landowski, M. The State of Air Pollution as a Factor Determining the Assessment of a City's Tourist Attractiveness—Based on the Opinions of Polish Respondents. *Sustainability* **2020**, *12*, 1466. [CrossRef]
38. Łapko, A.; Strulak-Wójcikiewicz, R.; Panasiuk, A. Air quality as a factor affecting urban tourism. *Stud. Perieget.* **2020**, *30*, 109–123. [CrossRef]

39. Salinas Fernández, J.A.; Serdeira Azevedo, P.; Martín Martín, J.M.; Rodríguez Martín, J.A. Determinants of tourism destination competitiveness in the countries most visited by international tourists: Proposal of a synthetic index. *Tour. Manag. Perspect.* **2020**, *33*, 100582. [CrossRef]
40. Torres-Delgado, A.; López Palomeque, F. The ISOST index: A tool for studying sustainable tourism. *J. Destin. Mark. Manag.* **2018**, *8*, 281–289. [CrossRef]
41. Anaman, K.A.; Looi, C.N. Economic Impact of Haze-Related Air Pollution on the Tourism Industry in Brunei Darussalam. *Econ. Anal. Policy* **2000**, *30*, 133–143. [CrossRef]
42. Pulido-Fernández, J.I.; Rodríguez-Díaz, B. Reinterpreting the World Economic Forum's global tourism competitiveness index. *Tour. Manag. Perspect.* **2016**, *20*, 131–140. [CrossRef]
43. Rodríguez-Díaz, B.; Pulido-Fernández, J.I. Sustainability as a Key Factor in Tourism Competitiveness: A Global Analysis. *Sustainability* **2020**, *12*, 51. [CrossRef]
44. Usman, O.; Bekun, F.V.; Ike, G.N. Democracy and tourism demand in European countries: Does environmental performance matter? *Environ. Sci. Pollut. Res.* **2020**, *27*, 38353–38359. [CrossRef] [PubMed]
45. Robaina, M.; Madaleno, M.; Silva, S.; Eusébio, C.; Carneiro, M.J.; Gama, C.; Oliveira, K.; Russo, M.A.; Monteiro, A. The relationship between tourism and air quality in five European countries. *Econ. Anal. Policy* **2020**, *67*, 261–272. [CrossRef]
46. Xu, X.; Dong, D.; Wang, Y.; Wang, S. The Impacts of Different Air Pollutants on Domestic and Inbound Tourism in China. *Int. J. Environ. Res. Public Health* **2019**, *16*, 5127. [CrossRef] [PubMed]
47. Law, R.; Cheung, C. Air Quality in Hong Kong: A Study of the Perception of International Visitors. *J. Sustain. Tour.* **2007**, *15*, 390–401. [CrossRef]
48. Xu, X.; Reed, M. Perceived pollution and inbound tourism in China. *Tour. Manag. Perspect.* **2017**, *21*, 109–112. [CrossRef]
49. Xu, X.; Reed, M. Perceived pollution and inbound tourism for Shanghai: A panel VAR approach. *Curr. Issues Tour.* **2019**, *22*, 601–614. [CrossRef]
50. Yang, Y.; Chen, G. In search of fresher air: The influence of relative air quality on vacationers' perceptions of destinations' restorative qualities. *Int. J. Tour. Res.* **2021**, *23*, 504–516. [CrossRef]
51. Brida, J.G.; Cortes-Jimenez, I.; Pulina, M. Has the tourism-led growth hypothesis been validated? A literature review. *Curr. Issues Tour.* **2016**, *19*, 394–430. [CrossRef]
52. Li, K.X.; Jin, M.; Shi, W. Tourism as an important impetus to promoting economic growth: A critical review. *Tour. Manag. Perspect.* **2018**, *26*, 135–142. [CrossRef]
53. Agrawal, M.; Singh, B.; Rajput, M.; Marshall, F.; Bell, J.N.B. Effect of air pollution on peri-urban agriculture: A case study. *Environ. Pollut.* **2003**, *126*, 323–329. [CrossRef]
54. Bell, J.N.B.; Power, S.A.; Jarraud, N.; Agrawal, M.; Davies, C. The effects of air pollution on urban ecosystems and agriculture. *Int. J. Sustain. Dev. World Ecol.* **2011**, *18*, 226–235. [CrossRef]
55. Gu, Y.; Wong, T.W.; Law, C.K.; Dong, G.H.; Ho, K.F.; Yang, Y.; Yim, S.H.L. Impacts of sectoral emissions in China and the implications: Air quality, public health, crop production, and economic costs. *Environ. Res. Lett.* **2018**, *13*, 084008. [CrossRef]
56. Atici, C. Carbon emissions in Central and Eastern Europe: Environmental Kuznets curve and implications for sustainable development. *Sustain. Dev.* **2009**, *17*, 155–160. [CrossRef]
57. Dinda, S. Environmental Kuznets Curve Hypothesis: A Survey. *Ecol. Econ.* **2004**, *49*, 431–455. [CrossRef]
58. Dong, K.; Sun, R.; Dong, C.; Li, H.; Zeng, X.; Ni, G. Environmental Kuznets curve for $PM_{2.5}$ emissions in Beijing, China: What role can natural gas consumption play? *Ecol. Indic.* **2018**, *93*, 591–601. [CrossRef]
59. Farhani, S.; Mrizak, S.; Chaibi, A.; Rault, C. The environmental Kuznets curve and sustainability: A panel data analysis. *Energy Policy* **2014**, *71*, 189–198. [CrossRef]
60. Gokmenoglu, K.K.; Taspinar, N.; Kaakeh, M. Agriculture-induced environmental Kuznets curve: The case of China. *Environ. Sci. Pollut. Res.* **2019**, *26*, 37137–37151. [CrossRef] [PubMed]
61. Luo, Y.; Chen, H.; Zhu, Q.; Peng, C.; Yang, G.; Yang, Y.; Zhang, Y. Relationship between Air Pollutants and Economic Development of the Provincial Capital Cities in China during the Past Decade. *PLoS ONE* **2014**, *9*, e104013. [CrossRef]
62. Millimet, D.L.; List, J.A.; Stengos, T. The Environmental Kuznets Curve: Real Progress or Misspecified Models? *Rev. Econ. Stat.* **2003**, *85*, 1038–1047. [CrossRef]
63. Zhang, J.; Zhang, K.; Zhao, F. Spatial effects of economic growth, energy consumption and environmental pollution in the provinces of China—An empirical study of a spatial econometrics model. *Sustain. Dev.* **2020**, *28*, 868–879. [CrossRef]
64. Abdouli, M.; Hammami, S. The Impact of FDI Inflows and Environmental Quality on Economic Growth: An Empirical Study for the MENA Countries. *J. Knowl. Econ.* **2017**, *8*, 254–278. [CrossRef]
65. Omri, A.; Nguyen, D.K.; Rault, C. Causal interactions between CO_2 emissions, FDI, and economic growth: Evidence from dynamic simultaneous-equation models. *Econ. Model.* **2014**, *42*, 382–389. [CrossRef]
66. Omri, A.; Daly, S.; Rault, C.; Chaibi, A. Financial development, environmental quality, trade and economic growth: What causes what in MENA countries. *Energy Econ.* **2015**, *48*, 242–252. [CrossRef]
67. Ghosh, S. Examining carbon emissions economic growth nexus for India: A multivariate cointegration approach. *Energy Policy* **2010**, *38*, 3008–3014. [CrossRef]
68. Ozturk, I.; Acaravci, A. CO_2 emissions, energy consumption and economic growth in Turkey. *Renew. Sustain. Energy Rev.* **2010**, *14*, 3220–3225. [CrossRef]

69. Zhang, X.P.; Cheng, X.M. Energy consumption, carbon emissions, and economic growth in China. *Ecol. Econ.* **2009**, *68*, 2706–2712. [CrossRef]
70. Azam, M.; Khan, A.Q.; Abdullah, H.B.; Qureshi, M.E. The impact of CO_2 emissions on economic growth: Evidence from selected higher CO_2 emissions economies. *Environ. Sci. Pollut. Res.* **2016**, *23*, 6376–6389. [CrossRef] [PubMed]
71. Ahmad, N.; Du, L. Effects of energy production and CO_2 emissions on economic growth in Iran: ARDL approach. *Energy* **2017**, *123*, 521–537. [CrossRef]
72. Muhammad, B. Energy consumption, CO_2 emissions and economic growth in developed, emerging and Middle East and North Africa countries. *Energy* **2019**, *179*, 232–245. [CrossRef]
73. Dechezleprêtre, A.; Rivers, N.; Stadler, B. The economic cost of air pollution: Evidence from Europe. In *OECD Economics Department Working Papers, No. 1584*; **2019**, OECD Economics Department, Paris, Franc . [CrossRef]
74. Sinha, A. Trilateral association between SO_2/NO_2 emission, inequality in energy intensity, and economic growth: A case of Indian cities. *Atmos. Pollut. Res.* **2016**, *7*, 647–658. [CrossRef]
75. Hao, Y.; Peng, H.; Temulun, T.; Liu, L.Q.; Mao, J.; Lu, Z.N.; Chen, H. How harmful is air pollution to economic development? New evidence from $PM_{2.5}$ concentrations of Chinese cities. *J. Clean. Prod.* **2018**, *172*, 743–757. [CrossRef]
76. Zhao, D.; Sing, T.F. Air pollution, economic spillovers, and urban growth in China. *Ann. Reg. Sci.* **2017**, *58*, 321–340. [CrossRef]
77. Gan, T.; Yang, H.; Liang, W. How do urban haze pollution and economic development affect each other? Empirical evidence from 287 Chinese cities during 2000–2016. *Sustain. Cities Soc.* **2021**, *65*, 102642. [CrossRef]
78. Jiang, S.; Wang, J.; Shi, L.; Ma, Z. Impact of Energy Consumption and Air Pollution on Economic Growth—An Empirical Study Based on Dynamic Spatial Durbin Model. *Energy Procedia* **2019**, *158*, 4011–4016. [CrossRef]
79. Alesina, A.; Özler, S.; Roubini, N.; Swagel, P. Political instability and economic growth. *J. Econ. Growth* **1996**, *1*, 189–211. [CrossRef]
80. Chikalipah, S.; Makina, D. Economic growth and human development: Evidence from Zambia. *Sustain. Dev.* **2019**, *27*, 1023–1033. [CrossRef]
81. Davis, L.; Hopkins, M. The Institutional Foundations of Inequality and Growth. *J. Dev. Stud.* **2011**, *47*, 977–997. [CrossRef]
82. Feeny, S.; Iamsiraroj, S.; McGillivray, M. Remittances and Economic Growth: Larger Impacts in Smaller Countries? *J. Dev. Stud.* **2014**, *50*, 1055–1066. [CrossRef]
83. Hermes, N.; Lensink, R. Foreign direct investment, financial development and economic growth. *J. Dev. Stud.* **2003**, *40*, 142–163. [CrossRef]
84. Njikam, O. Financial liberalization and growth in African economies: The role of policy complementarities. *Rev. Dev. Financ.* **2017**, *7*, 73–83. [CrossRef]
85. Rioja, F.; Valev, N. Does one size fit all?: A reexamination of the finance and growth relationship. *J. Dev. Econ.* **2004**, *74*, 429–447. [CrossRef]
86. Jin, Y.; Andersson, H.; Zhang, S. Air Pollution Control Policies in China: A Retrospective and Prospects. *Int. J. Environ. Res. Public Health* **2016**, *13*, 1219. [CrossRef]
87. Zeng, Y.; Cao, Y.; Qiao, X.; Seyler, B.C.; Tang, Y. Air pollution reduction in China: Recent success but great challenge for the future. *Sci. Total Environ.* **2019**, *663*, 329–337. [CrossRef] [PubMed]
88. Fleisher, B.; Li, H.; Zhao, M.Q. Human capital, economic growth, and regional inequality in China. *J. Dev. Econ.* **2010**, *92*, 215–231. [CrossRef]
89. Glewwe, P.; Maïga, E.; Zheng, H. The Contribution of Education to Economic Growth: A Review of the Evidence, with Special Attention and an Application to Sub-Saharan Africa. *World Dev.* **2014**, *59*, 379–393. [CrossRef]
90. Han, J.S.; Lee, J.W. Demographic change, human capital, and economic growth in Korea. *Jpn. World Econ.* **2020**, *53*, 100984. [CrossRef]
91. Li, Y.; Wang, X.; Westlund, H.; Liu, Y. Physical Capital, Human Capital, and Social Capital: The Changing Roles in China's Economic Growth. *Growth Chang.* **2015**, *46*, 133–149. [CrossRef]
92. Adams, S. Foreign Direct investment, domestic investment, and economic growth in Sub-Saharan Africa. *J. Policy Model.* **2009**, *31*, 939–949. [CrossRef]
93. Bal, D.P.; Dash, D.P.; Subhasish, B. The Effects of Capital Formation on Economic Growth in India: Evidence from ARDL-bound Testing Approach. *Glob. Bus. Rev.* **2016**, *17*, 1388–1400. [CrossRef]
94. Uneze, E. The relation between capital formation and economic growth: Evidence from sub-Saharan African countries. *J. Econ. Policy Reform* **2013**, *16*, 272–286. [CrossRef]
95. Adu, G.; Marbuah, G.; Mensah, J.T. Financial development and economic growth in Ghana: Does the measure of financial development matter? *Rev. Dev. Financ.* **2013**, *3*, 192–203. [CrossRef]
96. Arcand, J.L.; Berkes, E.; Panizza, U. Too much finance? *J. Econ. Growth* **2015**, *20*, 105–148. [CrossRef]
97. Hassan, M.K.; Sanchez, B.; Yu, J.S. Financial development and economic growth: New evidence from panel data. *Q. Rev. Econ. Financ.* **2011**, *51*, 88–104. [CrossRef]
98. Kim, D.H.; Lin, S.C.; Suen, Y.B. Dynamic Effects of Financial Openness on Economic Growth and Macroeconomic Uncertainty. *Emerg. Mark. Financ. Trade* **2012**, *48*, 25–54. [CrossRef]
99. Almfraji, M.A.; Almsafir, M.K. Foreign Direct Investment and Economic Growth Literature Review from 1994 to 2012. *Procedia Soc. Behav. Sci.* **2014**, *129*, 206–213. [CrossRef]

100. Huchet-Bourdon, M.; Le Mouël, C.; Vijil, M. The relationship between trade openness and economic growth: Some new insights on the openness measurement issue. *World Econ.* **2018**, *41*, 59–76. [CrossRef]
101. Keho, Y. The impact of trade openness on economic growth: The case of Cote d'Ivoire. *Cogent Econ. Financ.* **2017**, *5*, 1332820. [CrossRef]
102. Yanikkaya, H. Trade openness and economic growth: A cross-country empirical investigation. *J. Dev. Econ.* **2003**, *72*, 57–89. [CrossRef]
103. Zahonogo, P. Trade and economic growth in developing countries: Evidence from sub-Saharan Africa. *J. Afr. Trade* **2016**, *3*, 41–56. [CrossRef]
104. Canning, D.; Pedroni, P. Infrastructure, Long-Run Economic Growth and Causality Tests For Cointegrated PanelsI. *Manch. Sch.* **2008**, *76*, 504–527. [CrossRef]
105. Hong, J.; Chu, Z.; Wang, Q. Transport infrastructure and regional economic growth: Evidence from China. *Transportation* **2011**, *38*, 737–752. [CrossRef]
106. Kodongo, O.; Ojah, K. Does infrastructure really explain economic growth in Sub-Saharan Africa? *Rev. Dev. Financ.* **2016**, *6*, 105–125. [CrossRef]
107. Pradhan, R.P. Investigating the causal relationship between transportation infrastructure, financial penetration and economic growth in G-20 countries. *Res. Transp. Econ.* **2019**, *78*, 100766. [CrossRef]
108. Nyasha, S.; Odhiambo, N.M. Government Size and Economic Growth: A Review of International Literature. *SAGE Open* **2019**, *9*. [CrossRef]
109. Afonso, A.; Furceri, D. Government size, composition, volatility and economic growth. *Eur. J. Political Econ.* **2010**, *26*, 517–532. [CrossRef]
110. DiPeitro, W.R.; Anoruo, E. Government size, public debt and real economic growth: A panel analysis. *J. Econ. Stud.* **2012**, *39*, 410–419. [CrossRef]
111. Asimakopoulos, S.; Karavias, Y. The impact of government size on economic growth: A threshold analysis. *Econ. Lett.* **2016**, *139*, 65–68. [CrossRef]
112. Chiou-Wei, S.Z.; Zhu, Z.; Kuo, Y.H. Government size and economic growth: An application of the smooth transition regression model. *Appl. Econ. Lett.* **2010**, *17*, 1405–1415. [CrossRef]
113. Ahmed, R.N.; Ahmad, K. Impact of Population on Economic Growth: A Case Study of Pakistan. *Bull. Bus. Econ.* **2016**, *5*, 162–176.
114. Bucci, A. Population in Factor Accumulation-based Growth. *Riv. Ital. Degli Econ.* **2010**, 33–68. [CrossRef]
115. Van Donkelaar, A.; Martin Randall, V.; Brauer, M.; Boys Brian, L. Use of Satellite Observations for Long-Term Exposure Assessment of Global Concentrations of Fine Particulate Matter. *Environ. Health Perspect.* **2015**, *123*, 135–143. [CrossRef] [PubMed]
116. Van Donkelaar, A.; Martin, R.V.; Li, C.; Burnett, R.T. Regional Estimates of Chemical Composition of Fine Particulate Matter Using a Combined Geoscience-Statistical Method with Information from Satellites, Models, and Monitors. *Environ. Sci. Technol.* **2019**, *53*, 2595–2611. [CrossRef] [PubMed]
117. Hammer, M.S.; van Donkelaar, A.; Li, C.; Lyapustin, A.; Sayer, A.M.; Hsu, N.C.; Levy, R.C.; Garay, M.J.; Kalashnikova, O.V.; Kahn, R.A.; et al. Global Estimates and Long-Term Trends of Fine Particulate Matter Concentrations (1998–2018). *Environ. Sci. Technol.* **2020**, *54*, 7879–7890. [CrossRef]
118. Belsoy, J.; Korir, J.; Yego, J. Environmental Impacts of Tourism in Protected Areas. *J. Environ. Earth Sci.* **2012**, *2*, 64–73.
119. Danish.; Wang, Z. Dynamic relationship between tourism, economic growth, and environmental quality. *J. Sustain. Tour.* **2018**, *26*, 1928–1943. [CrossRef]
120. Sáenz-de Miera, O.; Rosselló, J. Tropospheric ozone, air pollution and tourism: A case study of Mallorca. *J. Sustain. Tour.* **2013**, *21*, 1232–1243. [CrossRef]
121. Sáenz-de Miera, O.; Rosselló, J. Modeling tourism impacts on air pollution: The case study of PM10 in Mallorca. *Tour. Manag.* **2014**, *40*, 273–281. [CrossRef]
122. Zhang, N.; Ren, R.; Zhang, Q.; Zhang, T. Air pollution and tourism development: An interplay. *Ann. Tour. Res.* **2020**, *85*, 103032. [CrossRef]
123. Alifa, M.; Bolster, D.; Mead, M.I.; Latif, M.T.; Crippa, P. The influence of meteorology and emissions on the spatio-temporal variability of PM10 in Malaysia. *Atmos. Res.* **2020**, *246*, 105107. [CrossRef]
124. Calkins, C.; Ge, C.; Wang, J.; Anderson, M.; Yang, K. Effects of meteorological conditions on sulfur dioxide air pollution in the North China plain during winters of 2006–2015. *Atmos. Environ.* **2016**, *147*, 296–309. [CrossRef]
125. Koutrakis, P.; Sax, S.N.; Sarnat, J.A.; Coull, B.; Demokritou, P.; Demokritou, P.; Oyola, P.; Garcia, J.; Gramsch, E. Analysis of PM10, $PM_{2.5}$, and $PM_{2.5}$–10Concentrations in Santiago, Chile, from 1989 to 2001. *J. Air Waste Manag. Assoc.* **2005**, *55*, 342–351. [CrossRef] [PubMed]
126. Pearce, J.L.; Beringer, J.; Nicholls, N.; Hyndman, R.J.; Tapper, N.J. Quantifying the influence of local meteorology on air quality using generalized additive models. *Atmos. Environ.* **2011**, *45*, 1328–1336. [CrossRef]
127. Aw, J.; Kleeman, M.J. Evaluating the first-order effect of intraannual temperature variability on urban air pollution. *J. Geophys. Res. Atmos.* **2003**, *108*. [CrossRef]
128. Seinfeld, J.H. Air pollution: A half century of progress. *AIChE J.* **2004**, *50*, 1096–1108. [CrossRef]

129. He, J.; Gong, S.; Yu, Y.; Yu, L.; Wu, L.; Mao, H.; Song, C.; Zhao, S.; Liu, H.; Li, X.; Li, R. Air pollution characteristics and their relation to meteorological conditions during 2014–2015 in major Chinese cities. *Environ. Pollut.* **2017**, *223*, 484–496. [CrossRef]
130. Wang, J.; Ogawa, S. Effects of Meteorological Conditions on $PM_{2.5}$ Concentrations in Nagasaki, Japan. *Int. J. Environ. Res. Public Health* **2015**, *12*, 9089–9101. [CrossRef]
131. Wise, E.K.; Comrie, A.C. Meteorologically adjusted urban air quality trends in the Southwestern United States. *Atmos. Environ.* **2005**, *39*, 2969–2980. [CrossRef]
132. Lu, Y.; Wang, Y.; Zuo, J.; Jiang, H.; Huang, D.; Rameezdeen, R. Characteristics of public concern on haze in China and its relationship with air quality in urban areas. *Sci. Total Environ.* **2018**, *637-638*, 1597–1606. [CrossRef]
133. Wei, J.; Guo, X.; Marinova, D.; Fan, J. Industrial SO_2 pollution and agricultural losses in China: Evidence from heavy air polluters. *J. Clean. Prod.* **2014**, *64*, 404–413. [CrossRef]
134. Xia, Y.; Guan, D.; Jiang, X.; Peng, L.; Schroeder, H.; Zhang, Q. Assessment of socioeconomic costs to China's air pollution. *Atmos. Environ.* **2016**, *139*, 147–156. [CrossRef]
135. Chang, T.Y.; Graff Zivin, J.; Gross, T.; Neidell, M. The Effect of Pollution on Worker Productivity: Evidence from Call Center Workers in China. *Am. Econ. J. Appl. Econ.* **2019**, *11*, 151–172. [CrossRef]
136. Chen, S.; Zhang, D. Impact of air pollution on labor productivity: Evidence from prison factory data. *China Econ. Q. Int.* **2021**, *1*, 148–159. [CrossRef]
137. Liu, P.; Dong, D.; Wang, Z. The impact of air pollution on R&D input and output in China. *Sci. Total Environ.* **2021**, *752*, 141313. [CrossRef] [PubMed]
138. Tilt, B. China's air pollution crisis: Science and policy perspectives. *Environ. Sci. Policy* **2019**, *92*, 275–280. [CrossRef]
139. Dong, K.; Zeng, X. Public willingness to pay for urban smog mitigation and its determinants: A case study of Beijing, China. *Atmos. Environ.* **2018**, *173*, 355–363. [CrossRef]
140. Aunan, K.; Hansen, M.H.; Wang, S. Introduction: Air Pollution in China. *China Q.* **2018**, *234*, 279–298. [CrossRef]
141. Fan, Y.; Ding, X.; Hang, J.; Ge, J. Characteristics of urban air pollution in different regions of China between 2015 and 2019. *Build. Environ.* **2020**, *180*, 107048. [CrossRef]
142. Rohde, R.A.; Muller, R.A. Air Pollution in China: Mapping of Concentrations and Sources. *PLoS ONE* **2015**, *10*, e0135749. [CrossRef] [PubMed]
143. Lu, X.; Zhang, S.; Xing, J.; Wang, Y.; Chen, W.; Ding, D.; Wu, Y.; Wang, S.; Duan, L.; Hao, J. Progress of Air Pollution Control in China and Its Challenges and Opportunities in the Ecological Civilization Era. *Engineering* **2020**, *6*, 1423–1431. [CrossRef]

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A Methodology for Designing Short-Term Stationary Air Quality Campaigns with Mobile Laboratories Using Different Possible Allocation Criteria

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Abstract: Air quality monitoring and control are key issues for environmental assessment and management in order to protect public health and the environment. Local and central authorities have developed strategies and tools to manage environmental protection, which, for air quality, consist of monitoring networks with fixed and portable instrumentation and mathematical models. This study develops a methodology for designing short-term air quality campaigns with mobile laboratories (laboratories fully housed within or transported by a vehicle and maintained in a fixed location for a period of time) as a decision support system for environmental management and protection authorities. In particular, the study provides a methodology to identify: (i) the most representative locations to place mobile laboratories and (ii) the best time period to carry out the measurements in the case of short-term air quality campaigns. The approach integrates atmospheric dispersion models and allocation algorithms specifically developed for optimizing the measuring campaigns. The methodology is organized in two phases, each of them divided into several steps. Fourteen allocation algorithms dedicated to three type of receptors (population, vegetation and physical cultural heritage) have been proposed. The methodology has been applied to four short-term air quality campaigns in the Emilia-Romagna region.

Keywords: design mobile laboratory campaign; air pollution concentration; population exposure to air pollutant

1. Introduction

Air quality monitoring and control are key issues for environmental assessment and management in order to protect public health, ecosystem services and physical cultural heritage (intended as physical artefacts in outdoor spaces). Therefore, local and central authorities have developed measuring systems to evaluate air pollution and to provide strategic indications to improve air quality and optimize its monitoring.

The most critical situations occur in urban areas, where emission sources (e.g., urban traffic, domestic heating) and sensitive receptors (e.g., population, physical cultural heritage) are concentrated. According to the data reported by the United Nations in its special edition on progress towards the Sustainable Development Goals [1], about 7 million people died as a result of high levels of air pollution, both ambient and household, in 2016. The same document reports that about 90% of people living in urban areas were still breathing air that did not meet the World Health Organization's air quality guideline values for particulate matter.

In such a context, governments and environmental protection agencies monitor ambient concentrations of air pollution in many parts of the world as part of regulatory programs designed to protect public health and the environment [2,3]. Historically, the most extensive monitoring systems were mainly developed in the United States and Western Europe, where regular monitoring of ambient air quality has been implemented since the mid-1970s [4]. Today, in Asia (especially Japan and China with a strong increase since the 2000s) there are extensive monitoring networks [5,6]. At the European level, the reference regulation for the monitoring and evaluation of air quality is set by Directive 2008/50/EC and subsequent amendments and additions [3]. This legislation establishes that fixed measurements shall be used to assess ambient air quality. These fixed measurements may be supplemented by modelling techniques and/or indicative measurements to provide adequate information on the spatial distribution of air pollutants.

Fixed monitoring stations represent the most conventional, consolidated and widespread approach for air quality monitoring and evaluation but have some limitations: (1) monitoring is usually limited to a small set of strategically placed locations and the assessment results are significant only for specific areas; (2) fixed monitoring stations have low flexibility. In the last ten years, the existing monitoring networks have been adjusted at European level in order to meet regulatory requirements (Directive 2008/50/CE) and cost efficiency. The following objectives are pursued: (1) to create a uniform and comparable network for wide areas (for example, all European States); (2) to reduce the number of stations, currently higher than required by the legislation [7]; (3) to optimize the spatial representativeness of the networks. In order to achieve these objectives and foster a thorough knowledge of an area even with a smaller number of fixed stations, mobile laboratories [8,9], mobile monitoring campaigns [10,11], low-cost sensors [12–14] and predictive mathematical models [15,16] have been applied. In order to maximize the effectiveness and efficiency of these alternative monitoring tools, it is necessary to adopt an appropriate allocation methodology, able to include spatial and temporal variables to design the short-term air quality campaigns. Recently, mobile laboratories for short-term stationary measurements (laboratories that are either fully housed within or transported by a vehicle and maintained in fixed location for a period of time) are spreading with good results (e.g., [17,18]).

Because operations research (OR) offers a structured method to solve complicated decision problems, several authors have proposed different OR approaches for air quality network design (see Table 1).

Table 1. Operation research approaches proposed to design air quality network: main characteristics.

Authors	Objectives	Variable/s of Action	Constraint/s	Sensitive Receptor/s
[19]	Number and placement	Pollution dosage	Exposure time to pollutant	Population
[20]		Maximum concentration values	Single source, pollutant and meteorological conditions	
[21]		Exceeding the law limits	Number of points defined before single pollutant	
[22–25]		Information associated to the signal	Previously measured data	
[26–29]		Spheres of influence	Data from air quality dispersion model	
[30]		Pollution exposure gradient	Previously measured data	

Table 1. *Cont.*

Authors	Objectives	Variable/s of Action	Constraint/s	Sensitive Receptor/s
[31]		Weighing function of maximum concentration values, exceeding the law limits, cost of the network and data validation	Previously measured data Economic aspect	
[32,33]		Site redundancy	Previous network	
[34]		Exceeding the law limits Protection capability Average daily concentration	Data from air quality dispersion model	
[35,36]		Information gain	Adding new stations	
[37–39]		Pollution exposure	Single pollutant Previously measured data	
[40]		Overall function of maximum concentration values, maximum dosage, maximum network coverage, maximum population protection	Applied to pollution from industrial districts	
[41–43]		Exceeding the law limits	Number of points defined before Number of points defined on the economic basis	
[44]		Cluster analysis procedure	Previously measured data	
[45]		Multiple criteria	Available budget	
[46]		Entropy-based Bayesian optimizing approach	Available budget	
[47]		Detection of higher pollutant concentrations "Protection capability" for areas with higher population density	Distribution of population, budget	
[48]		Population and emission sources		
[49]		Pollution exposure		

As it is possible to observe from Table 1, the objectives (typically: "choice of the optimal number of monitoring points and their spatial distribution") and constraints appear to be similar among the approaches. The studies differ in the choice and combination of the variables and in the formulation of the objective function: for example, Reference [49] applying population exposure as a decision variable, Reference [33] analyzing the redundancy of information provided by measuring stations and [29] using the spatial representativeness of the detected signal. The authors often propose a single objective function (e.g., [43,49]), always oriented towards the evaluation of the effects of air pollution on the resident population. Systematically, the authors deal with the placement of fixed air monitoring networks, considering the spatial aspect, but not the temporal one, as a decision parameter since fixed stations measure air quality continuously all year long (e.g., [19,25,48]). Conversely, algorithms to locate mobile stations must consider both spatial and temporal variables. In fact, mobile laboratories are used for short-term campaigns (a few days or a few weeks) and the temporal context must be given appropriate attention to maximize the representativeness of the campaign. To the best of our knowledge, there are no OR studies specifically developed to design mobile measurement campaigns for air quality, capable of simultaneously considering the spatial and temporal aspects in the sampling configuration.

This study aims to develop an OR methodological approach for optimizing the short-term air quality monitoring campaigns with mobile laboratories, by considering spatial and temporal variables in order to obtain measurements as representative as possible of the investigated area. The methodological approach has been structured using the typical scheme of the OR which, by using appropriate selection functions, is able to find the optimal (or suboptimal) solution to a decision problem. The proposed approach has been applied to four case studies. The study area is the province of Ravenna (northern Italy), made up of 18 municipalities that periodically sign a memorandum of understanding with Arpae (Regional Agency for Prevention, Environment and Energy of Emilia-Romagna) on monthly air quality monitoring campaigns by using a mobile laboratory. The four examples refer to areas with different features and extensions and with a significant difference: the Ravenna municipality is already largely covered (from the spatial point of view) by fixed monitoring stations, whereas the other areas are completely devoid of them.

2. Materials and Methods

2.1. Description of the Methodology Development through Operations Research

To be solved, a decision problem needs a question to answer, the data that contextualize the choice, and a criterion for making the choice [50]. As widely used in the literature, operations research (OR) is defined as "*a discipline that deals with the application of advanced analytical methods to help make better decisions*" and "*arrives at optimal or near-optimal solutions to complex decision-making problems*".

Through OR, a decision-making problem is mathematically described with functions that represent the logical relationships among the decision objectives, variables and constraints. A decision objective is the desired solution to which the decision-making process tends (e.g., minimum cost, maximum gain, etc.) (S in Equation (1) reported below). A variable of action is a quantity of the system, the value of which is unknown, and on which it is possible to act to determine different alternative solutions to the problem (e.g., the number of measuring points, items sold, etc.). The constraint(s) describe the conditions of admissibility of the solutions (e.g., technical constraints to indicate the maximum availability of resources, sign constraints). They are mathematical relationships that describe the conditions of admissibility of the solutions and are used to discriminate the combinations of values of the decision variables that represent acceptable solutions to the problem, from those that are not [51,52].

These three elements are formalized mathematically through a function (called "objective function") consisting of n variables and m constraints. It represents the objective to be maximized or minimized, mathematically formulated as a function of the decision variables and influenced in the resolution by the constrains.

$$\underset{x \in S}{Min\ (or\ max)\ f(x)} \tag{1}$$

where: $f(x)$ is the objective function to be minimized (or maximized); S is a set of possible values of the independent variables of the problem; x is n-dimensional vector variables. Solving an optimization problem formulated through an objective function consists in determining the values of the variables x that satisfy all the constraints and minimize (or maximize) the value of the objective function in S. The value of x that minimizes (or maximizes) $f(x)$ represents the optimal (or suboptimal) solution of the problem.

The decision problem studied by this work (where to measure the air quality by using mobile laboratories?) has been structured with the OR approach. The methodology integrates to the optimal spatial distribution another two fundamental aspects: (i) the best time period for carrying out the short-term monitoring campaign; (ii) the possibility of pursuing several objectives (e.g., monitoring the exposure of a group of residents, evaluating the impact of an emission source, evaluating the effectiveness of specific territorial policies, etc.).

The approach is structured in 2 distinct operational phases. Phase 1 is dedicated to the characterization of the study area through the collection of data and their processing. The result of phase 1 is a database that collects all the data. Phase 2 is the allocation procedure; its result is the identification of the optimal sites. It is noteworthy that phase 1 needs to be applied just once (obviously data may be updated), while phase 2 may be applied as many times as the number of the necessary measurement campaigns. In this way, numerous short-term air quality campaigns can be designed on the area of study, always applying the same database.

In the proposed methodological approach, phase 1 consists of the following four steps: (i) selection of the area of study; (ii) cell classification; (iii) quantification of air pollutant concentration; (iv) identification and distribution of sensitive receptors.

The first step consists of the identification of the study area and its division into square cells of equal size. Each cell is the basic assessment unit of each algorithm. All the information necessary for the allocation choice must be quantified for each cell (e.g., concentration of pollutants, sensitive receptors, type of cell, objective functions, and so on). A specific cell will be the final result of each allocation procedure.

The second step aims to classify each cell according to the type of prevalent emissive sources present inside it. What is interesting is the classification established by the European Directive 2008/50/EC [3]: (a) urban traffic (T): cells located in urban areas and near roads with heavy vehicle traffic; (b) industrial (I): cells located within or close to industrial areas; (c) urban background residential (BU-Res): cells located in urban areas with high population density and not crossed by roads with high traffic; (d) urban background (BU): cells located preferably within public green and/or pedestrian areas (parks, schools) and not directly subject to specific sources of pollution such as vehicle traffic and industrial emissions; (e) suburban background (B-SubU): cells located in suburban areas characterized by the transport phenomena from outside the city and phenomena produced inside the urban area; (f) rural background (BR): cells located outside the major cities, in predominantly rural/agricultural areas, also subject to phenomena of photochemical pollution, downwind of the direction of the wind field and most likely not in the immediate area of maximum emissions of pollutants; (g) remote background (B-Rem): cells located at natural areas (natural ecosystems, forests) at a great distance from urban and industrial areas.

The third step quantifies the air pollutant concentrations of interest. Many air quality mathematical models are suitable for this purpose, as explained previously. Whatever model is applied, a high-resolution estimation is necessary to answer the monitoring site allocation problem [30,47]. In the case of brief monitoring campaigns, as in this study, an adequate time resolution (preferably hourly or daily) is required, too. This aspect can be a problem for the management of a very large amount of data.

The fourth step enables the identification and spatial distribution of the sensitive receptors to air pollutants. It is necessary to define the spatial distribution of the resident population, the presence of sensitive vegetation and the presence of relevant physical cultural heritage.

Phase 2 consists of five steps. Each step allows for the selection of different elements of the monitoring campaign and the development of many different combinations, each of which determines a different configuration of the campaign. The graphical representation of phase 2 is shown in Figure 1. The first step is the selection of the spatial domain. The monitoring campaign could affect the entire study area selected during phase 1, or one of its subspatial domains. Using a square grid, it is possible to select only the cells of a subarea of interest. The second step is the selection of the temporal domain. This step allows for the identification of a specific time period in which to conduct the campaign (e.g., a day, a month, a season, a whole year). This is closely related to the temporal resolution used to define the pollutant concentration field during phase 1. The selection of the area type is the third phase, it helps to identify areas with homogeneous characteristics from the point of view of pollution and/or presence of emission sources. It allows the selection of cell type. The fourth step is the selection of one or more pollutants of interest, based on which the monitoring campaign will be designed. The last step is the selection of allocation criterion. This represents the mathematical expression of the purpose of the measurement campaign (e.g., evaluate the exceeding of legal limits, the exposure of the population, the damage to heritage). This study suggests fourteen objective functions that represent a large number of possible design criteria for short-term air monitoring campaigns, also considering the indications available in the bibliography (see Table S1 of Supplemental Material). Table 2 shows the list and the relative formulation of the proposed objective functions, while Table S1 of Supplementary Material shows any supplementary information necessary for their quantification. There are eleven allocation criteria dedicated to population protection, offering as a factor of choice the exposure of citizens to atmospheric pollutants, the highest concentration values, values above the legal limits, the correlation with the data measured by the AQMS, the spatial gradient of the concentration values. Five allocation criteria are dedicated to vegetation protection: exposure to pollution, values above the limits for the protection of vegetation, the quantities of pollutants that are deposited to the ground through dry and wet deposits. Finally, a specific damage index for physical cultural heritage has been proposed as a specific allocation criterion for its protection.

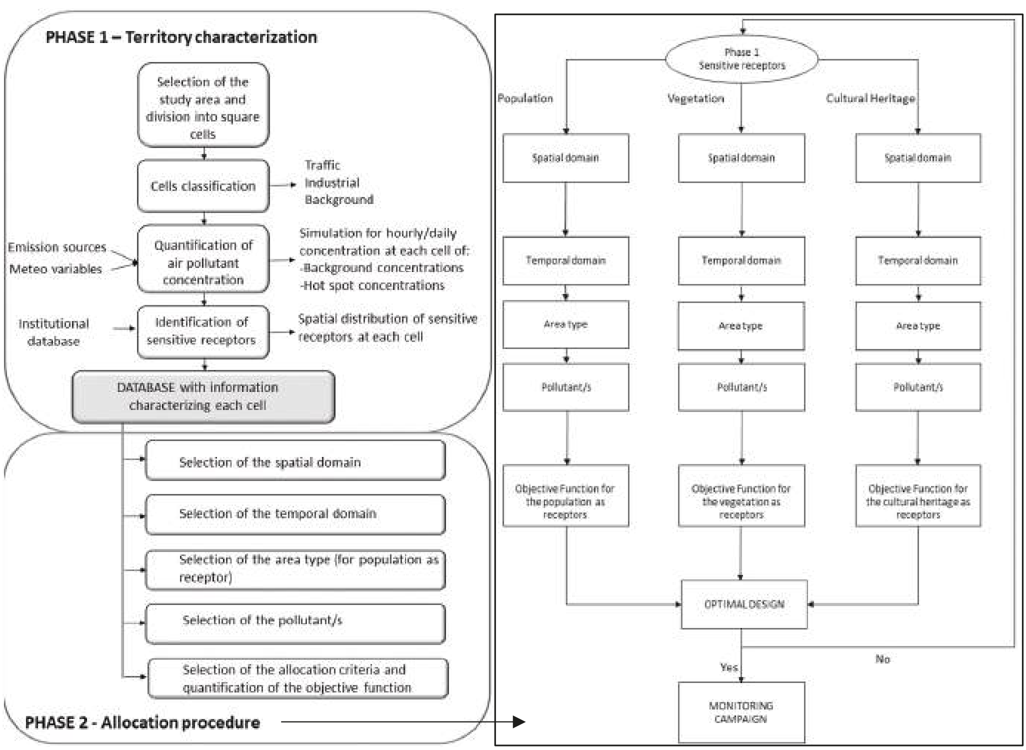
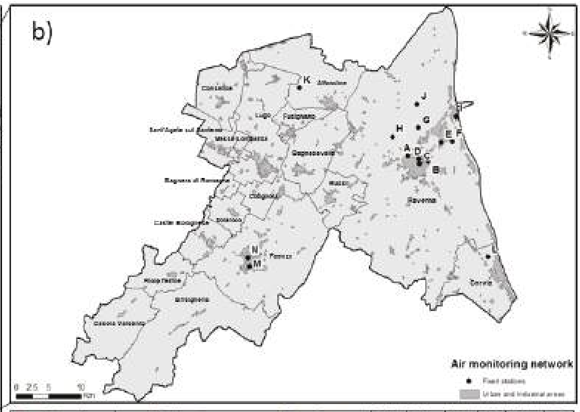


Figure 1. General schematic approach of the proposed design methodology and a specific focus of phase 2—allocation procedure.

2.2. Description of the Study Area

The study area is the Ravenna Province (northern Italy, Figure 2a); the area is 1860 km^2, the population is around 389,000 people [53] and the population density is about 200 inhabitants/km^2. The Ravenna Province is divided into 18 municipalities, each with a different size and features. The study area has a wide air quality monitoring network

(AQMN), mainly concentrated in the municipalities of Ravenna and Faenza (Figure 2b). In the urban centers, air quality is mostly affected by traffic-related air pollution [16] and domestic heating, while some suburban areas are affected by industrial pollution [54]. The study area has been divided into 250 × 250 m cells for a total of 30,618 cells, a compromise between high spatial resolution and computational resources.



ID	Station Name	Municipality	Station Type	PM_{10}	$PM_{2.5}$	NO_x	CO	BTX*	SO_2
A	Zalamella	Ravenna	Urban Traffic	x	-	x	x	x	-
B	Caorle	Ravenna	Urban Background - Residential	x	-	x	-	-	x
C	Rocca Brancaleone	Ravenna	Urban Industrial	x	-	x	x	-	x
D	SAPIR	Ravenna	Industrial	x	-	x	x	-	x
E	Via dei Germani	Ravenna	Industrial (private)	x	-	x	-	-	x
F	Azienda Marani	Ravenna	Industrial (private)	x	-	x	-	-	x
G	Agip29	Ravenna	Industrial (private)	x	-	-	-	-	-
H	Marina di Ravenna	Ravenna	Industrial (private)	-	-	x	-	-	x
I	Azienda Zorabini	Ravenna	Industrial (private)	-	-	x	-	-	x
J	Ballirana	Alfonsine	Residential Background	-	x	x	-	-	-
K	Delta Cervia	Cervia	SubUrban Background	x	-	x	-	-	-
L	Marconi	Faenza	Urban Traffic	x	-	x	x	x	-
M	Parco Bertozzi	Faenza	Urban Background	x	x	x	-	-	-
N	Giardini	Faenza	Urban Background	x	x	x	-	-	-

* Benzene, Toluene and Xylene

Figure 2. The area of study ((**a**) left) and its air quality monitoring network (capital letters) ((**b**) right).

As case study pollutants, PM_{10} and NO_2 have been chosen. The concentrations of PM_{10} (daily average values) and NO_2 (hourly average values) were estimated for each cell. Background concentrations and concentrations due to local sources were estimated and then combined. The background concentrations were quantified by the geostatistical PESCO (Post-processing and Evaluation with Statistical methods of a Chemistry-transport-model Output) model [55,56]. The package provides the functions to perform data fusion for air quality with hourly temporal resolution, correcting the output of a deterministic chemistry transport model with observed data, through a trans-Gaussian Kriging approach [57]. PESCO model results were provided by the Hydro-Weather-Climate service of Arpae with a spatial resolution of 1 × 1 km^2. The contribution of the local sources was quantified by the advanced Gaussian dispersion model ADMS-Urban [58]. The application of ADMS-Urban (made by the authors) required the identification and characterization of local air pollutant sources. This process was achieved through the spatial disaggregation of the provincial emissions inventory of industrial, road traffic and domestic heating [59] sources. The reference year of the inventory was 2015, the spatial resolution was 250 × 250 m. The pollutant concentrations estimated by PESCO and ADMS-Urban models were combined together using a multiple linear regression (Equation (2)).

$$Y = X\beta = \beta_0 x_{PESCO} + \beta_1 x_{ADMS-URBAN} + \varepsilon \tag{2}$$

where Y is the matrix identifying the dependent variables; it is composed of the values recorded by specific air quality monitoring stations; β are the regression coefficients; x are the pollutant concentrations estimated by PESCO and ADMS models, respectively; ε is the residue. The overall concentration field was then verified by comparing the simulated data and the values measured by the air quality monitoring network, applying specific comparison statistical indices [60,61]. Pearson's product moment correlation coefficient (COR), normalized mean square error (NMSE), fractional bias (FB), factor 2 (FA2) and index of agreement (IA) were employed. They are defined according to the following formulas:

$$COR = \overline{\left(Co - \overline{Co}\right)\left(Cp - \overline{Cp}\right)}/\sigma_o\sigma_p \tag{3}$$

$$NMSE = \overline{(Co - Cp)^2}/\overline{Cp}\,\overline{Co} \tag{4}$$

$$FB = 2\left(\overline{Cp} - \overline{Co}\right)/\left(\overline{Cp} + \overline{Co}\right) \tag{5}$$

$$FA2 = fraction\ of\ data\ for\ which\ 0.5\ \leq Cp/Co \leq 2 \tag{6}$$

$$IA = 1 - (Cp - Co)^2/\left(Cp - \overline{Cp}\right)\left(Co - \overline{Co}\right)^2 \tag{7}$$

where: CO and CP are the predicted and observed concentrations, respectively; σ_o and σ_p are the standard deviations of observations and predictions, respectively. *IA*, *COR* and *NMSE* measure the correlation between predicted and measured concentration values, *FB* measures the agreement of the mean concentration values and *FA2* is the fraction of predicted concentrations within a factor of two of the equivalent measured values. Under ideal conditions, *FB* and *NMSE* should be zero, while *COR*, *IA* and *FA2* should be one.

In this study three types of receptors that are sensitive to airborne pollution were selected: resident population, vegetation (natural areas, parks and forests) and physical cultural heritage. Resident population and vegetation were selected as they are the reference receptors in the legislation (e.g., Directive 2008/50/CE). Physical cultural heritage located outdoors was selected as these items are very sensitive to air pollution and have been severely damaged for the last century [62,63]. The spatial distribution of each type of receptor was disaggregated over the territory (250 × 250 m cells) starting from the following aggregated databases: census data of the National Institute of Statistics [53] for the resident population in 2011 (last complete population census available), Emilia-Romagna Region open-data for vegetation [64] and the database of the Italian Ministry of Cultural Heritage for cultural heritage [65].

Table 2. Proposed allocation criteria.

Allocation Criteria	Sensitive Receptors	Note
Individual exposition to the *i*-th pollutant in the *k*-th cell [$\mu g \cdot m^{-3} \cdot h$]	Population Vegetation	Quantifies the exposure of an individual to a specific outdoor pollutant [20,66–68]
Overall exposition to the *i*-th pollutant in the *k*-th cell [$\mu g \cdot m^{-3} \cdot h \cdot n$]	Population	Quantifies the overall exposure of all individuals present in a given cell [30,40]
Overall risk to all thepollutants in the *k*-th cell [$\mu g \cdot m^{-3} \cdot h$]	Population Vegetation	Quantifies the individual risk as the contribution of all the considered pollutants
Correlation between simulated and measured data of the *i*-th pollutant in the *k*-th cell	Population	Identifies areas with a good match between the measured data from fixed air quality monitoring stations and concentration data estimated [35,69]
Exceedance of the legal limits of the *i*-th pollutant in the *k*-th cell [n.]	Population Vegetation	Identifies the probability of exceeding the legal limits for a specific pollutant [24,31,34–36,41,42,47,68,70]
Maximum concentration value of the *i*-th pollutant in the *k*-th cell [$\mu g \cdot m^{-3}$]	Population Vegetation	Identifies the probability of measuring an elevated concentration value for a specific pollutant [34,71,72]

Table 2. *Cont.*

Allocation Criteria	Sensitive Receptors	Note
Minimum index of agreement (IOA) for the *i*-th pollutant in the *k*-th cell	Population	Assess how the values simulated by the model deviate from the values measured by the fixed air monitoring stations
Minimum index of agreement normalized with the resident population ($IOAP_r$) for the *i*-th pollutant in the *k*-th cell	Population	Assess how the values simulated by the model deviate from the values measured by the fixed air monitoring stations, considering also the presence of resident population.
Maximum concentration gradient for the *i*-th pollutant in the *k*-th cell	Population	Assesses how changing the concentration field at a specific point compared to neighboring points [30,39,73]
Maximum air quality index in the *k*-th cell	Population	Assesses the contribution of all the pollutants at the same time [24,74,75]
Minimum concentration difference in the *k*-th cell	Population	Assesses how changing the concentration field at a specific point compared to whole study area [31,73]
Maximum pollutant deposition in the *k*-th cell	Vegetation	Assess the total deposition of the selected pollutants [76]
Maximum PM_{10} deposition in the *k*-th cell	Vegetation	Assess the total deposition of the selected pollutants [76]
Maximum damage index in the *k*-th cell	Physical cultural heritage	Assess the total damage due to erosion blackening pollutants [76–78]

3. Results and Discussion

The results describe the application of the methodological approach developed for the reference study area, presenting some representative case studies of the design of air quality monitoring campaigns aimed at protecting the three types of sensitive receptor selected in the study: population, vegetation, physical cultural heritage.

3.1. Phase 1 Application

The developed methodology was applied in the study area to four specific short-term air quality campaigns. Phase 1 is the same for all campaigns.

As explained in the previous section, all the steps of phase 1 were applied, characterizing each 250 × 250 m cell with the necessary information and with average values of pollutant concentrations. The campaigns described in this paper use NO_2 and PM_{10} as specific pollutants.

Three sets of regression coefficients (β and ε) were calculated: one specific set for cells classified as traffic oriented (category T), one set for industrial cells (category I) and one set for background cells (category BU) (see Section 3.1). Three air quality monitoring stations, one for each cell category, were chosen to provide the values of dependent variable (Y in Equation (2)): (a) one traffic oriented station (A-Zalamella); (b) one industrial oriented station (E-Via dei Germani); (c) one background oriented station (K-Delta Cervia) (see Figure 2).

The multiple linear regression analysis applied to NO_2 overall concentration field provided the beta coefficients and constants shown below. One dataset consisting of 8760 values each (average concentration data per hour for an entire year) was used to calculate the regression coefficients: the data measured by the fixed air quality monitoring station chosen, the data simulated by the PESCO model and those simulated by the ADMS-Urban model.

$$\text{Traffic area}: \ C_{tot} = (0.60C_{PESCO} + 0.27C_{ADMS}) + 13.52 \quad (8)$$

$$\text{Industrial area}: \ C_{tot} = (0.70C_{PESCO} + 0.62C_{ADMS}) + 5.59 \tag{9}$$

$$\text{Background area}: \ C_{tot} = (0.87C_{PESCO} + 0.11C_{ADMS}) + 1.36 \tag{10}$$

For PM_{10}, the coefficients calculated using three datasets of 365 data each (daily average values) are as follows:

$$\text{Traffic area}: \ C_{tot} = (0.55C_{PESCO} + 1.99C_{ADMS}) + 6.89 \tag{11}$$

$$\text{Industrial area}: \ C_{tot} = (0.45C_{PESCO} + 1.65C_{ADMS}) + 4.62 \tag{12}$$

$$\text{Background area}: \ C_{tot} = (0.89C_{PESCO} + 0.58C_{ADMS}) + 1.58 \tag{13}$$

where: C_{tot} is the total concentration; C_{PESCO} and C_{ADMS} are the concentration values simulated by PESCO and ADMS-Urban models, respectively.

The multiple linear regression analysis results for NO_2 show a standard deviation of 10.60, 11.08 and 4.57 and a coefficient of determination (R^2) of 0.52, 0.39 and 0.85, respectively for the stations classified as "traffic", "industrial" and "background". For PM_{10} the values of the standard deviation are 15.07, 13.88 and 11.40, while for R^2 the values are 0.70, 0.61 and 0.83.

The p-values for all variables are less than 0.05, showing their statistical significance.

The statistical analysis comparing the measured and predicted total values is shown in Table 3. The correlations between measured and simulated data are always higher than 0.57. In particular for NO_2, there are values that often exceed 0.8. For PM_{10}, the values are between 0.58 and 0.68. The simulated and observed data have small differences in the concentrations values and, consequently, the resulting FB index assume values close to the next optimal results (which corresponds to the value 0). There are some situations with more significant differences (e.g., station "D"), but they are limited to few cases and often linked to areas characterized by highly variable pollution situations due to the proximity of very complex emission sources (the station "D" is inside the industrial and harbor area of Ravenna's city). The FA2 and IOA indices assume values close to ideal performance in many cases. Similarly, also the NMSE index assumes values that are almost ideal (which corresponds to the value 0) in the majority of the considered comparison points.

Table 3. Statistical analysis comparing the measured and predicted NO_2 and PM_{10} concentration values.

Fixed Air Quality Monitoring Stations	Measured MEAN (μg/m^3)	Predicted MEAN (μg/m^3)	CORR	NMSE	FA2	FB	IOA
NO_2							
B—Caorle	25.35	24.49	0.81	0.20	0.85	0.03	0.90
C—Rocca Brancaleone	32.23	32.15	0.77	0.13	0.92	0.00	0.86
D—SAPIR	47.12	26.64	0.63	0.43	0.58	0.56	0.62
F—Azienda Marani	32.81	26.26	0.60	0.46	0.67	0.22	0.67
H—Marina di Ravenna	21.77	18.90	0.65	0.36	0.73	0.14	0.78
I—Azienda Zorabini	15.72	21.16	0.57	0.75	0.51	0.29	0.71
J—Ballirana	22.63	20.10	0.80	0.18	0.90	0.12	0.88
L—Marconi	34.20	29.98	0.98	0.03	0.99	0.13	0.95
M—Parco Bertozzi	28.54	28.60	0.87	0.14	0.90	0.00	0.93
N—Giardini	21.45	21.27	0.94	0.06	0.95	0.01	0.97
PM_{10}							
B—Caorle	30.83	35.6	0.58	0.30	81.36	−0.14	0.72

Table 3. *Cont.*

Fixed Air Quality Monitoring Stations	Measured MEAN ($\mu g/m^3$)	Predicted MEAN ($\mu g/m^3$)	CORR	NMSE	FA2	FB	IOA
C—Rocca Brancaleone	29.89	34.09	0.67	0.16	89.75	−0.13	0.79
D—SAPIR	44.77	25.71	0.59	0.72	63.46	0.54	0.52
F—Azienda Marani	26.66	21.00	0.60	0.29	83.71	0.24	0.79
L—Marconi	30.90	30.39	0.67	0.15	94.66	0.02	0.79
M—Parco Bertozzi	23.64	27.25	0.68	0.27	88.14	−0.14	0.78
N—Giardini	25.05	32.04	0.61	0.32	78.33	−0.24	0.69

The worst performances were recorded for the stations classified as "industrial", due to the difficulty in characterizing (temporally and spatially) the emissions sources in areas of strong industrial vocation. On the other hand, the best performances were recorded for control stations classified as "background" or "urban".

Because of the good results of the comparative analysis between measured and predicted values, the equations obtained by regression analysis were applied to define the entire concentration fields of NO_2 and PM_{10} concentration in the study area, according to the classification of each cell. Finally, the resident population, vegetation and physical cultural heritage were spatially disaggregated for each cell.

3.2. Phase 2 Application

The four campaigns chosen in order to test the proposed methodology, called Examples n.1–n.4 are described below. Each example simulates the design of a measurement campaign with a mobile laboratory according to the following characteristics (Table 4).

Table 4. Main characteristics of each example.

Decision Criteria	Example n.1	Example n.2	Example n.3	Example n.4
Spatial domain	Territory of the municipality of Ravenna	Territory of the municipality's union of the lower Romagna	Territory of the municipality's union of the Romagna Faentina	Territory of the municipality of Ravenna
Temporal domain	Month of October	Month of July	Month of June	Month of December
Area type	Urban traffic (T)	Urban background residential (BU-Res)	Rural background (BR)	All
Pollutant	NO_2	NO_2	PM_{10}	PM_{10}
Allocation criteria and objective function	Overall exposition to NO_2 of the residential population	Maximum concentration values of NO_2	Maximum PM_{10} deposition	Maximum damage index

3.2.1. Campaign n.1

The objective of this example was to analyze the exposure of the urban population of Ravenna municipality to NO_2. Figure 3 shows the application of phase 2 to the spatial domain (a), temporal domain (b), area type (c) and pollutant (d) identification. These allowed the potential cells for the monitoring activities to be reduced numerically and spatially.

The selected criterion in the first case study was the "overall exposure of the residential population to NO_2". The maximization of the objective function that expressed this allocation criterion (operationally the function is calculated for all the cells resulting from the selection of the first 4 steps of phase 2 and then by selecting those with the maximum values) allowed the identification of only a few cells (Figure 3e). Keeping all the decision variables unchanged and changing only the month of monitoring, Figure 3 shows the different distribution of the points identified for monitoring. This is due to the different weather conditions and pollutant concentration values.

3.2.2. Campaign n.2

The objective of this example was to analyze the exposure of the population of an urban background area to NO_2. The selection of the spatial domain (a), temporal domain (b), area type (c) and pollutant (d) of the second campaign is shown in Figure 4. The selected criterion in the second case study was the "maximum NO_2 concentration values". Analogous to the previous case, the selection criteria values were calculated on the selection reported in Figure 4d and the optimal points where to place the mobile laboratories were identified among the cells with the highest values (Figure 4e).

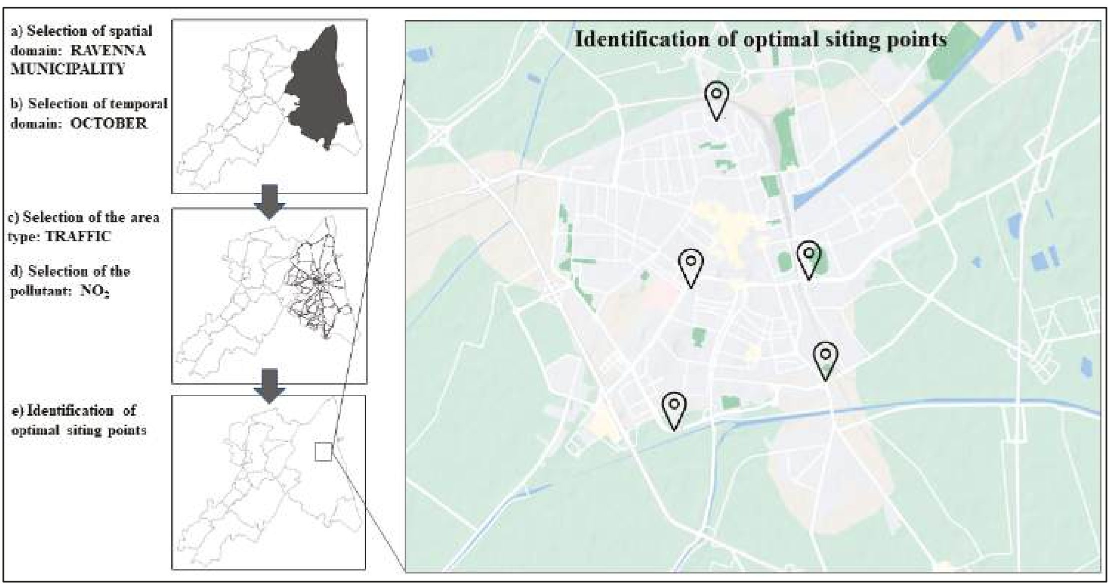


Figure 3. *Cont.*

Figure 3. *Cont.*

Figure 3. Example n.1—spatial domain (**a**), temporal domain (**b**), area type (**c**), pollutant selection (**d**) and extremes of the exposure value that identify the optimal monitoring points (**e**). The other figures show how the distribution of optimal points changes as a function of time.

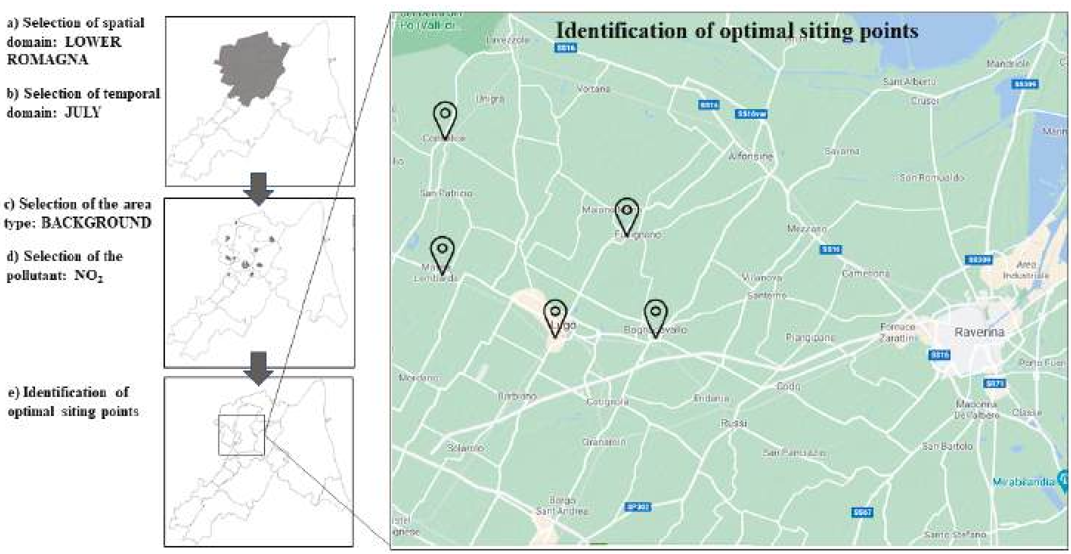


Figure 4. Example n.2—patial domain (**a**), temporal domain (**b**), area type (**c**), pollutant selection (**d**) and extremes of the exposure value that identify the optimal monitoring point (**e**).

3.2.3. Campaign n.3

The objective of this example was to analyze the PM_{10} deposition to assess the effect on sensitive vegetation. The selection of the spatial domain (a), temporal domain (b), area type (c) and pollutant (d) of the third campaign is shown in Figure 5. The selected criterion in the third case study was the "Maximum PM_{10} deposition". Analogous to the other case-studies, the selection criteria values were calculated on the selection reported in Figure 5d and the optimal points where to place the mobile laboratories were identified among the cells with the highest values (Figure 5e).

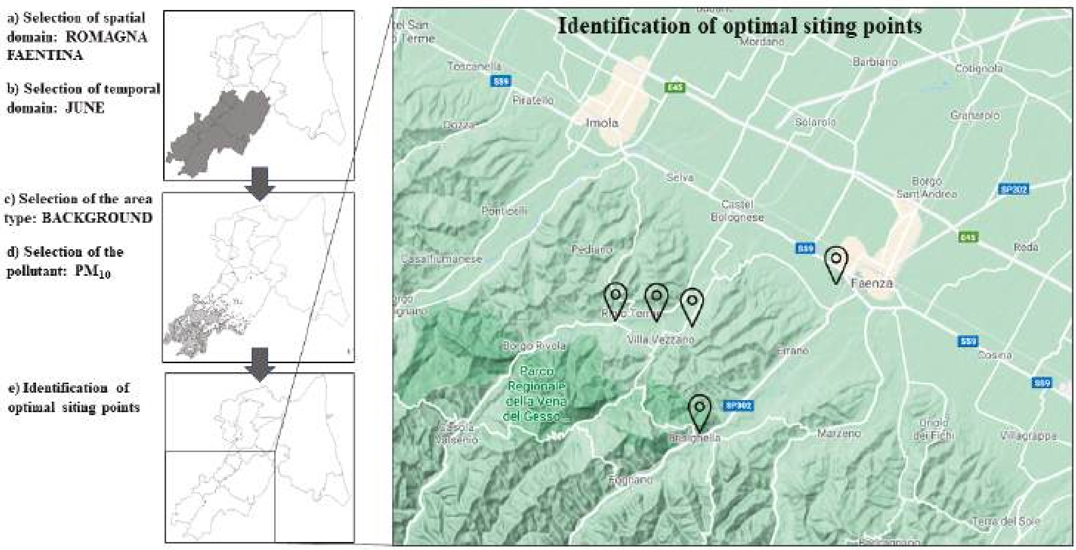


Figure 5. Example n.3—spatial domain (**a**), temporal domain (**b**), area type (**c**), pollutant selection (**d**) and extremes of the deposition value that identify the optimal monitoring points (**e**).

3.2.4. Campaign n.4

The last example that has been described used materials as a sensitive receptor and PM_{10} depositions (which contribute to determining the total damage index, see Table 3) as a choice criterion. The selection steps are shown in Figure 6.

As explained in Section 3, the proposed approach enables the allocation procedure of air monitoring stations including spatial and temporal variables. The inclusion of the temporal variable makes the approach particularly suitable for short-term air quality campaigns. The approach is structured as an actual procedure in phases and steps. This feature has several advantages. The procedural structure guarantees the respect of the principle of replicability that leads to the application of a coherent methodology for the various cases. The presence of two phases permits the simplification of the operations: the two phases are connected to each other, but each phase is able to operate independently from the other. The changes made in one phase determine the variation of the results of the next, but they do not cause a revision of the whole application procedure (which remains standardized). The subdivision in several steps permits transferability: the approach can be adapted to local peculiarity and different objectives. The possibility to choose among many objective functions and different sensitive receptors results in great versatility. Transferability and versatility make the proposed methodology applicable also to low-cost sensors used for air quality monitoring in areas with elevated variations from the spatial and temporal point of views and with low availability of financial resources [79,80].

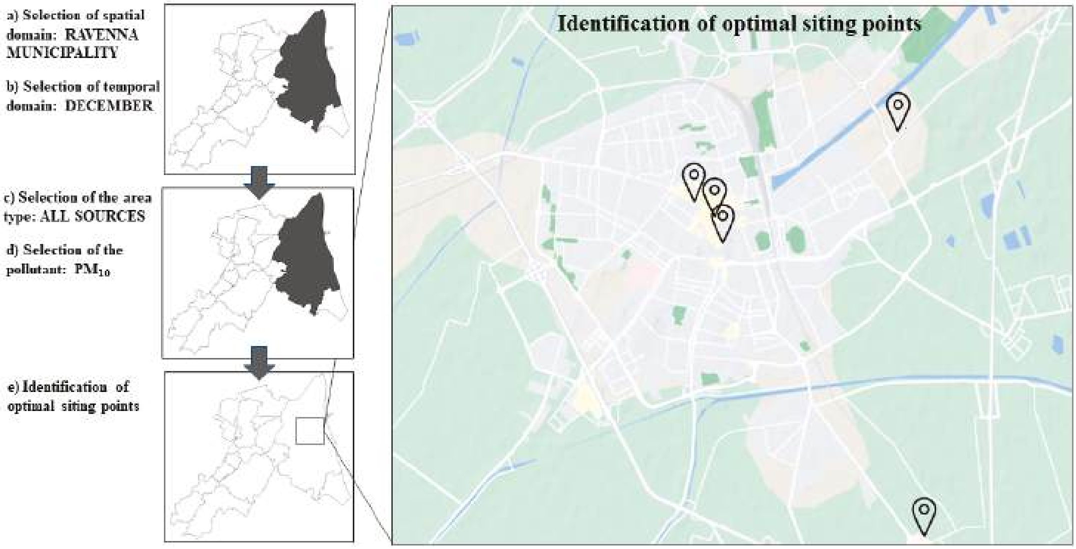


Figure 6. Example n.4—spatial domain (**a**), temporal domain (**b**), area type (**c**), pollutant selection (**d**) and extremes of the damage index values that identify the optimal monitoring point (**e**).

The experimental application of the methodological approach allowed the authors to test each step and to provide the following comments and observations. (i) The proposed methodology requires a preliminary pollutant concentration assessment. In the area of interest, a mathematical dispersion model to assess the background concentration was available (PESCO) and it was integrated by a model to evaluate the local source contributions (ADMS-Urban). Air pollution concentration data, maps and models are easily available in Europe and in other parts of the world [49,81] and the local source modeling requires information which is a part of local authority duties (see the EU Directives in European Union). (ii) Multiple linear regression appears to be a very interesting tool for combining data coming from different predictive models as it is cheap, easy to apply, effective and reliable. (iii) If data are available, the validation of simulated values vs. measured values is always recommended because it permits the adjustment of the assessment process and its strengths and weaknesses to be known. (iv) The spatial disaggregation of the residential population as a sensitive receptor has been done, starting from the national census of the population conducted by the National Institute of Statistics and representing the best available data. The population census is the most detailed information source on the population at different levels and it is very easily available. If the sensitive receptor is vegetation, easy and important sources of information could be lists and/or maps of protected areas, such as national parks, nature reserves and areas of special interest. Lists of national physical cultural heritage are also readily available in many countries. (v) Using all the collected information, processed and arranged through phase 1, the application of the allocation procedure, which constitutes phase 2 of the methodological developed approach, was very simple and fast.

The application of the proposed methodology highlights, also, some weaknesses. The more data used, the higher the resolution and the better the allocation choice, but to process and manage a high quantity of data requires substantial computing capacity that is not always available. Another weak point is that the database and information collection created by phase 1 have to be continuously updated for the approach to be effective. Finally, the allocation choice made by the proposed methodology might not be compatible with practical aspects (e.g., power requirements, security, site permissions, site access, etc.).

A refinement of the methodology could be provided by taking these weaknesses into account. It would be very useful to develop a software tool for the automatization of data loading and update activities. Moreover, it would be convenient to expand the list of objective functions in order to include other sensitive receptors (e.g., fauna) or to further detail the existing categories (population classified in increasing levels of sensitivity to pollutants, such as children and the elderly; cultural heritage classified according to the type of material, such as bronzes and carbonate materials).

4. Conclusions

In conclusion, a new methodology for designing short-term air quality monitoring campaigns has been proposed and tested on a case study area—situated in northeast Italy—through four short-term campaigns. The approach is designed especially for the environmental management and protection authorities but it is also usable by private entities. It is characterized by a high replicability (it is organized as a real procedure in phases and steps) and wide versatility, in fact, it can be adapted and contextualized for situations with very different characteristics (emission, sources, receptors, orography, etc.,) and it can answer very different questions (temporal aspects, different allocation criteria, different receptors, etc.).

Its experimental application has provided satisfactory results (both in terms of time and space) in regard to the objectives of this study by indicating suitable monitoring points.

Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.3390/su13137481/s1, Table S1. Proposed allocation criteria.

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References

1. United Nations Economic and Social Council. Special Edition: Progress Towards the Sustainable Development Goals Report of the Secretary-General. 2019. Available online: https://undocs.org/E/2019/68 (accessed on 9 November 2020).
2. USEPA. *Ambient Air Quality Surveillance Regulations*; USEPA: Washington, DC, USA, 1994.
3. European Commission. *Directive 2008/50/EC of the European Parliament and of the Council of 21 May 2008 on Ambient Air Quality and Cleaner Air for Europe*; European Commission: Brussels, Belgium, 2008.
4. Cohen, A.J.; Anderson, A.J.; Ostro, B.; Pandey, K.D.; Krzyzanowski, M.; Kuenzli, N.; Gutschmidt, K.; Pope, C.A.; Romieu, I.; Samet, J.M.; et al. *Mortality Impacts of Urban Air Pollution*; Taylor and Francis: New York, NY, USA, 2004.
5. Araki, S.; Shima, M.; Yamamoto, K. Estimating historical PM2.5 exposures for three decades (1987–2016) in Japan using measurements of associated air pollutants and land use regression. *Environ. Pollut.* **2020**, *263*, 114476. [CrossRef] [PubMed]
6. Zhang, F.; Shi, Y.; Fang, D.; Ma, G.; Nie, C.; Krafft, T.; He, L.; Wang, Y. Monitoring history and change trends of ambient air quality in China during the past four decades. *J. Environ. Manag.* **2020**, *260*, 110031. [CrossRef]
7. Jimmink, B.; de Leeuw, F.; Noordijk, E.; Ostatnická, J.; Coòková, M. *Reporting on Ambient Air Quality Assessment in the EU Member States*; ETC/ACM: Bilthoven, The Netherlands, 2010.
8. Hussein, T.; Saleh, S.; Dos Santos, V.; Abdullah, H.; Boor, B.E. Black Carbon and Particulate Matter Concentrations in Eastern Mediterranean Urban Conditions: An Assessment Based on Integrated Stationary and Mobile Observations. *Atmosphere* **2019**, *10*, 323. [CrossRef]
9. Kerckhoffs, J.; Hoek, G.; Vlaanderen, J.; van Nunen, E.; Messier, K.; Brunekreef, B.; Gulliver, J.; Vermeulen, R. Robustness of intra urban land-use regression models for ultrafine particles and black carbon based on mobile monitoring. *Environ. Res.* **2017**, *159*, 500–508. [CrossRef]

10. Crocchianti, S.; Del Sarto, S.; Ranalli, M.G.; Moroni, B.; Castellini, S.; Petroselli, C.; Cappelletti, D. Spatiotemporal correlation of urban pollutants by long-term measurements on a mobile observation platform. *Environ. Pollut.* **2021**, *268*, 115645. [CrossRef]
11. Sim, S.; Jeong, S.; Park, H.; Park, C.; Kwak, K.-H.; Lee, S.-B.; Kim, C.H.; Lee, S.; Chang, J.S.; Kang, H.; et al. Co-benefit potential of urban CO_2 and air quality monitoring: A study on the first mobile campaign and building monitoring experiments in Seoul during the winter. *Atmos. Pollut. Res.* **2020**, *11*, 1963–1970. [CrossRef]
12. Liu, X.; Jayaratne, R.; Thai, P.; Kuhn, T.; Zing, I.; Christensen, B.; Lamont, R.; Dunbabin, M.; Zhu, S.; Gao, J.; et al. Low-cost sensors as an alternative for long-term air quality monitoring. *Environ. Res.* **2020**, *185*, 109438. [CrossRef] [PubMed]
13. Andretta, M.; Coppola, F.; Pavlovic, A. New Technologies for Microclimatic and Indoor Air Quality Analysis for the Protection of Cultural Heritage: Case Studies of the Classense Library and "Tamo," The Museum of Mosaics at Ravenna. In *Advances in Applications of Industrial Biomaterials*; Pellicer, E., Ed.; Springer: Cham, Switzerland, 2017; pp. 161–178, ISBN 9783319627670.
14. Marinello, S.; Lolli, F.; Gamberini, R. Roadway tunnels: A critical review of air pollutant concentrations and vehicular emissions. *Transp. Res. Part D Transp. Environ.* **2020**, *86*, 102478. [CrossRef]
15. Chen, S.; Broday, D.M. Re-framing the Gaussian dispersion model as a nonlinear regression scheme for retrospective air quality assessment at a high spatial and temporal resolution. *Environ. Model. Softw.* **2020**, *125*, 104620. [CrossRef]
16. Righi, S.; Lucialli, P.; Pollini, E. Statistical and diagnostic evaluation of the ADMS-Urban model compared with an urban air quality monitoring network. *Atmos. Environ.* **2009**, *43*, 3850–3857. [CrossRef]
17. Liao, H.-T.; Yau, Y.-C.; Huang, C.-S.; Chen, N.; Chow, J.C.; Watson, J.G.; Tsai, S.-W.; Chou, C.C.-K.; Wu, C.-F. Source apportionment of urban air pollutants using constrained receptor models with a priori profile information. *Environ. Pollut.* **2017**, *227*, 323–333. [CrossRef]
18. Pirjola, L.; Paasonen, P.; Pfeiffer, D.U.; Hussein, T.; Hämeri, K.; Koskentalo, T.; Virtanen, A.; Rönkkö, T.; Keskinen, J.; Pakkanen, T.A. Dispersion of particles and trace gases nearby a city highway: Mobile laboratory measurements in Finland. *Atmos. Environ.* **2006**, *40*, 867–879. [CrossRef]
19. Denby, W.P.; Ossenbruggen, P.J.; Members, A. Optimization of urban air monitoring networks. *J. Environ. Eng. Div.* **1974**, *5*, 577–591.
20. Noll, K.E.; Miller, T.L.; Norco, J.E.; Raufer, R.K. An objective air monitoring site selection methodology for large point sources. *Atmos. Environ.* **1977**, *11*, 1051–1059. [CrossRef]
21. Noll, K.E.; Mitsutomi, S. Design methodology for optimum dosage air monitoring site selection. *Atmos. Environ.* **1983**, *17*, 2583–2590. [CrossRef]
22. Husain, T.; Khan, H.U. Shannon's entropy concept in optimum air monitoring network design. *Sci. Total Environ.* **1983**, *30*, 181–190. [CrossRef]
23. Husain, T.; Khan, S.M. Air monitoring network design using Fischer's information measure—A case study. *Atmos. Environ.* **1983**, *17*, 2591–2598. [CrossRef]
24. Modak, P.M.; Lohani, B.N. Optimization of ambient air quality monitoring networks. *Environ. Monit. Assess.* **1985**, *5*, 1–19. [CrossRef] [PubMed]
25. Silva, C.; Quiroz, A. Optimization of the atmospheric pollution monitoring network at Santiago de Chile. *Atmos. Environ.* **2003**, *37*, 2337–2345. [CrossRef]
26. Liu, M.K.; Avrin, J.; Pollack, R.I.; Behar, J.V.; McElroy, J.L. Methodology for designing air quality monitoring networks: I theorical aspects. *Environ. Monit. Assess.* **1986**, *6*, 1–11. [CrossRef]
27. McElroy, J.L.; Behar, J.V.; Meyers, T.C.; Liu, M.K. Methodology for designing air quality monitoring networks: II. Application to Las Vegas, Nevada, for carbon monoxide. *Environ. Monit. Assess.* **1986**, *6*, 13–34. [CrossRef] [PubMed]
28. Mofarrah, A.; Husain, T. A holistic approach for optimal design of air quality monitoring network expansion in an urban area. *Atmos. Environ.* **2010**, *44*, 432–440. [CrossRef]
29. Righini, G.; Cappelletti, A.; Ciucci, A.; Cremona, G.; Piersanti, A.; Vitali, L.; Ciancarella, L. GIS based assessment of the spatial representativeness of air quality monitoring stations using pollutant emissions data. *Atmos. Environ.* **2014**, *97*, 121–129. [CrossRef]
30. Langstaff, J.; Seigneur, C.; Mei-Kao, L.; Behar, J.; McElroy, J.L. Design of an optimum air monitoring network for exposure assessments. *Atmos. Environ.* **1967**, *21*, 1393–1410. [CrossRef]
31. Trujillo-Ventura, A.; Ellis, J.H. Multiobjective air pollution monitoring network design. *Atmos. Environ. Part. A Gen. Top.* **1991**, *25*, 469–479. [CrossRef]
32. Hwang, J.-S.; Chan, C.-C. Redundant Measurements of Urban Air Monitoring Networks in Air Quality Reporting. *J. Air Waste Manag. Assoc.* **1997**, *47*, 614–619. [CrossRef]
33. Wang, C.; Zhao, L.; Sun, W.; Xue, J.; Xie, Y. Identifying redundant monitoring stations in an air quality monitoring network. *Atmos. Environ.* **2018**, *190*, 256–268. [CrossRef]
34. Tseng, C.C.; Chang, N.-B. Assessing relocation strategies of urban air quality monitoring stations by GA-based compromise programming. *Environ. Int.* **2001**, *26*, 523–541. [CrossRef]
35. Saisana, M.; Sarigiannis, D.; Chaloulakou, A.; Spyrellis, N. Air Quality Monitoring Design: Optimization of Pm2.5 Networks Using Satellite Observations. In Proceedings of the 7th Conference on Environmental Science and Technology, Syros, Greece, 3–6 September 2001; pp. 3–6.
36. Sarigiannis, D.; Saisana, M. Multi-objective optimization of air quality monitoring. *Environ. Monit. Assess.* **2007**, *136*, 87–99. [CrossRef]

37. Chow, J.C.; Engelbrecht, J.P.; Freeman, N.C.; Hashim, J.H.; Jantunen, M.; Michaud, J.-P.; De Tejada, S.S.; Watson, J.G.; Wei, F.; Wilson, W.E.; et al. Chapter one: Exposure measurements. *Chemosphere* **2002**, *49*, 873–901. [CrossRef]
38. Chow, J.C.; Engelbrecht, J.P.; Watson, J.G.; Wilson, W.E.; Frank, N.H.; Zhu, T. Designing monitoring networks to represent outdoor human exposure. *Chemosphere* **2002**, *49*, 961–978. [CrossRef]
39. Kanaroglou, P.S.; Jerrett, M.; Morrison, J.; Beckerman, B.; Arain, M.A.; Gilbert, N.; Brook, J.R. Establishing an air pollution monitoring network for intra-urban population exposure assessment: A location-allocation approach. *Atmos. Environ.* **2005**, *39*, 2399–2409. [CrossRef]
40. Kao, J.-J.; Hsieh, M.-R. Utilizing multiobjective analysis to determine an air quality monitoring network in an industrial district. *Atmos. Environ.* **2006**, *40*, 1092–1103. [CrossRef]
41. Venegas, L.E.; Mazzeo, N.A. Design methodology for background air pollution monitoring site selection in an urban area. *Int. J. Environ. Pollut.* **2003**, *20*, 185. [CrossRef]
42. Elkamel, A.; Fatehifar, E.; Taheri, M.; Al-Rashidi, M.; Lohi, A. A heuristic optimization approach for Air Quality Monitoring Network design with the simultaneous consideration of multiple pollutants. *J. Environ. Manag.* **2008**, *88*, 507–516. [CrossRef] [PubMed]
43. Hao, Y.; Xie, S. Optimal redistribution of an urban air quality monitoring network using atmospheric dispersion model and genetic algorithm. *Atmos. Environ.* **2018**, *177*, 222–233. [CrossRef]
44. Gramsch, E.; Cereceda-Balic, F.; Oyola, P.; Vonbaer, D. Examination of pollution trends in Santiago de Chile with cluster analysis of PM10 and Ozone data. *Atmos. Environ.* **2006**, *40*, 5464–5475. [CrossRef]
45. Chen, C.-H.; Liu, W.-L.; Chen, C.-H. Development of a multiple objective planning theory and system for sustainable air quality monitoring networks. *Sci. Total Environ.* **2006**, *354*, 1–19. [CrossRef]
46. Ainslie, B.; Reuten, C.; Steyn, D.G.; Le, N.D.; Zidek, J.V. Application of an entropy-based Bayesian optimization technique to the redesign of an existing monitoring network for single air pollutants. *J. Environ. Manag.* **2009**, *90*, 2715–2729. [CrossRef]
47. Mazzeo, N.; Venegas, N.M.A.L. Development and Application of a Methodology for Designing a Multi-Objective and Multi-Pollutant Air Quality Monitoring Network for Urban Areas. *Air Quality* **2010**. [CrossRef]
48. Alsahli, M.M.; Al-Harbi, M. Allocating optimum sites for air quality monitoring stations using GIS suitability analysis. *Urban. Clim.* **2018**, *24*, 875–886. [CrossRef]
49. Munir, S.; Mayfield, M.; Coca, D.; Jubb, S.A. Structuring an integrated air quality monitoring network in large urban areas—Discussing the purpose, criteria and deployment strategy. *Atmos. Environ. X* **2019**, *2*, 100027. [CrossRef]
50. Lolli, F.; Ishizaka, A.; Gamberini, R. New AHP-based approaches for multi-criteria inventory classification. *Int. J. Prod. Econ.* **2014**, *156*, 62–74. [CrossRef]
51. Lolli, F.; Balugani, E.; Ishizaka, A.; Gamberini, R.; Butturi, M.A.; Marinello, S.; Rimini, B. On the elicitation of criteria weights in PROMETHEE-based ranking methods for a mobile application. *Expert Syst. Appl.* **2019**, *120*, 217–227. [CrossRef]
52. Jahan, A.; Edwards, K.L.; Bahraminasab, M. Multi-criteria decision-making for materials selection. In *Multi-Criteria Decision Analysis for Supporting the Selection of Engineering Materials in Product Design*; Elsevier BV: Amsterdam, The Netherlands, 2016; pp. 63–80.
53. ISTAT. Population Census. Available online: https://www.istat.it/it/archivio/104317#accordions (accessed on 4 May 2020).
54. Andretta, M.; Leonzio, B.; Lucialli, P.; Righi, S. Application of the ISCST3 model to an industrial area: Comparison between predicted and observed concentrations. *Water Pollut. VIII Model. Monit. Manag.* **2006**, *91*, 187–195. [CrossRef]
55. Bonafè, G.; Minguzzi, E.; Stortini, M.; Deserti, M. *Il Sistema Modellistico NINFA+PESCO per la Valutazione e la Previsione della Qualità dell'Aria in Emilia-Romagna*; Arpae Emilia-Romagna: Bologna, Italy, 2011.
56. Bonafè, G.; Stortini, M.; Minguzzi, E.; Deserti, M. Postprocessing of a CTM with Observed Data: Downscaling, Unbiasing and Estimation of the Subgrid Scale Pollution Variability. In Proceedings of the 14th International Conference on Harmonisation within Atmospheric Dispersion Modelling for Regulatory Purposes, Kos, Greece, 2–6 October 2001.
57. Arpae Pesco Model. Available online: https://github.com/ARPA-SIMC/pesco (accessed on 9 December 2019).
58. CERC ADMS-URBAN—User Guide. 2020. Available online: https://www.cerc.co.uk/environmental-software/assets/data/doc_userguides/CERC_ADMS-Urban5.0_User_Guide.pdf (accessed on 4 July 2021).
59. Righi, S.; Farina, F.; Marinello, S.; Andretta, M.; Lucialli, P.; Pollini, E. Development and evaluation of emission disaggregation models for the spatial distribution of non-industrial combustion atmospheric pollutants. *Atmos. Environ.* **2013**, *79*, 85–92. [CrossRef]
60. Karppinen, A.; Kukkonen, J.; Elolähde, T.; Konttinen, M.; Koskentalo, T. A modelling system for predicting urban air pollution: Comparison of model predictions with the data of an urban measurement network in Helsinki. *Atmos. Environ.* **2000**, *34*, 3735–3743. [CrossRef]
61. Kousa, A.; Kukkonen, J.; Karppinen, A.; Aarnio, P.; Koskentalo, T. Statistical and diagnostic evaluation of a new-generation urban dispersion modelling system against an extensive dataset in the Helsinki area. *Atmos. Environ.* **2001**, *35*, 4617–4628. [CrossRef]
62. Spezzano, P. Mapping the susceptibility of UNESCO World Cultural Heritage sites in Europe to ambient (outdoor) air pollution. *Sci. Total Environ.* **2021**, *754*, 142345. [CrossRef] [PubMed]
63. Di Turo, F.; Proietti, C.; Screpanti, A.; Fornasier, M.F.; Cionni, I.; Favero, G.; De Marco, A. Impacts of air pollution on cultural heritage corrosion at European level: What has been achieved and what are the future scenarios. *Environ. Pollut.* **2016**, *218*, 586–594. [CrossRef]

64. Emilia-Romagna, R. CMS (Content Management System) GIS with Data on the Spatial Distribution of Vegetation. Available online: http://www.mokagis.it/html/applicazioni_mappe.asp (accessed on 4 May 2020).
65. MIBACT. Territorial Information System to Support the Protection of Cultural Heritage. Available online: http://www.cartadelrischio.it/ (accessed on 4 May 2020).
66. Lozano, A.; Usero, J.; Vanderlinden, E.; Raez, J.; Contreras, J.; Navarrete, B. Air quality monitoring network design to control nitrogen dioxide and ozone, applied in Malaga, Spain. *Microchem. J.* **2009**, *93*, 164–172. [CrossRef]
67. Larsen, R.I.; Zimmer, C.E.; Lynn, D.A.; Blemel, K.G. Analyzing Air Pollutant Concentration and Dosage Data. *J. Air Pollut. Control Assoc.* **1967**, *17*, 85–93. [CrossRef] [PubMed]
68. Negri, A.; Sozzi, R. Optimization criteria in network configuration for air quality monitoring: Analysis of available facilities and possible development lines. *Environ. Softw.* **1988**, *3*, 174–179. [CrossRef]
69. Sajani, S.Z.; Scotto, F.; Lauriola, P.; Galassi, F.; Montanari, A. Urban air pollution monitoring and correlation properties between fixed-site stations. *J. Air Waste Manag. Assoc.* **2004**, *54*, 1236–1241. [CrossRef] [PubMed]
70. Lee, T.D.; Graves, R.J.; McGinnis, L.F. A Procedure for Air Monitoring Instrumentation Location. *Manag. Sci.* **1978**, *24*, 1451–1461. [CrossRef]
71. Corti, S.; Senatore, S. Project of an Air Quality Monitoring Network for Industrial Site in Italy. *Environ. Monit. Assess.* **2000**, *65*, 109–117. [CrossRef]
72. Munshi, U.; Patil, R.S. A method for selection of air quality monitoring sites for multiple sources. *Atmos. Environ.* **1982**, *16*, 1915–1918. [CrossRef]
73. Kumar, N.; Nixon, V.; Sinha, K.; Jiang, X.; Ziegenhorn, S.; Peters, T. An optimal spatial configuration of sample sites for air pollution monitoring. *J. Air Waste Manag. Assoc.* **2009**, *59*, 1308–1316. [CrossRef] [PubMed]
74. Ott, W.R.; Thorn, G.C. Air Pollution Index Systems in the United States and Canada. *J. Air Pollut. Control. Assoc.* **1976**, *26*, 460–470. [CrossRef]
75. Arpae Emilia Romagna. *Definizione di un Indice di Qualità dell'Aria per l'Emilia-Romagna*; Arpae Emilia Romagna: Bologna, Italy, 2008.
76. ARPAV. *Ottimizzazione Della Rete Regionale di Controllo Della Qualità dell'Aria del Veneto e Mappatura di Aree Remote*; ARPAV: Padova, Italy, 2006.
77. ISPRA. *Valutazione Degli Effetti dell'Inquinamento Atmosferico sui beni Culturali Architettonici di Roma*; ISPRA: Rome, Italy, 2011.
78. Lipfert, F.W. Dry Deposition Velocity as an Indicator for SO_2 Damage to Materials. *JAPCA* **1989**, *39*, 446–452. [CrossRef]
79. Gulia, S.; Prasad, P.; Goyal, S.; Kumar, R. Sensor-based Wireless Air Quality Monitoring Network (SWAQMN)—A smart tool for urban air quality management. *Atmos. Pollut. Res.* **2020**, *11*, 1588–1597. [CrossRef]
80. Singla, S.; Bansal, D.; Misra, A.; Raheja, G. Towards an integrated framework for air quality monitoring and exposure estimation—A review. *Environ. Monit. Assess.* **2018**, *190*, 562. [CrossRef] [PubMed]
81. EPA (Environmental Protection Agency). SPECIATE 4.4 Database. Available online: https://www.epa.gov/ (accessed on 1 June 2015).

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Joint Governance Regions and Major Prevention Periods of $PM_{2.5}$ Pollution in China Based on Wavelet Analysis and Concentration-Weighted Trajectory

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Abstract: China has made some progress in controlling $PM_{2.5}$ (particulate matter with an aerodynamic diameter of ≤2.5 µm) pollution, but there are still some key areas that need further strengthening. Considering that excessive prevention and control efforts affect economic development, this paper combined an empirical orthogonal function, a continuous wavelet transform, and a concentration-weighted trajectory method to study joint regional governance during key pollution periods to provide suggestions for the efficient control of $PM_{2.5}$. The results from our panel of data of $PM_{2.5}$ in China from 2016 to 2018 could be decomposed into two modes. In the first mode, the pollution center was in central Shaanxi Province, and the main eruption period was from November to January of the following year. As the center of this region, Xi'an should cooperate with the four cities in eastern Sichuan (Nanchong, Guangan, Bazhong, and Dazhou) to control $PM_{2.5}$, since the eruption occurred in this area. Moreover, governance should last for at least two cycles, where one cycle is at least 23 days. The pollution center of the second mode was in the western part of Xinjiang. Therefore, after the prevention and control efforts during the first mode are completed, the regional city of Kashgar should continue to build a joint governance zone for $PM_{2.5}$ along the Tianshan mountains in the east, focusing on prevention and control over two cycles (where one cycle is 28 days).

Keywords: $PM_{2.5}$; spatiotemporal variation; empirical orthogonal function; continuous wavelet transform; backward trajectory analysis; joint governance region

1. Introduction

The occurrence of haze and severe $PM_{2.5}$ (particulate matter with an aerodynamic diameter of ≤2.5 µm) pollution has attracted broad attention around the world. Increased $PM_{2.5}$ concentrations lead to a deterioration in human health [1], visibility [2], the regional climate [3], and economic development [4], causing urgent environmental problems that need to be solved. Developing countries that are experiencing rapid urbanization suffer from severe $PM_{2.5}$ pollution, and their inhabitants are exposed to high $PM_{2.5}$ concentrations. In January 2013, China suffered the most severe haze weather in its history (since haze has been recorded). The concentration of $PM_{2.5}$ in the Beijing–Tianjin–Hebei region (the most polluted region in China) was as high as 500 $\mu g \cdot m^{-3}$, which is much higher than the acceptable level of $PM_{2.5}$ concentrations (0–35 $\mu g \cdot m^{-3}$) in China [5]: This caused widespread concern across China. In 2013, the Chinese State Council released an *Atmosphere Pollution Prevention and Control Action Plan* [6], which required that by 2017, the respirable particle concentration in prefecture-level cities should be at least 10% lower than 2012 concentrations; moreover, the number of days with good air quality should increase every year. To achieve this goal, local governments in China have taken multiple measures. However, the high pollution levels in this severely polluted region do not breed confidence. In the fourth quarter of 2018, there were still 27 cities with $PM_{2.5}$ concentrations above the "lightly polluted" level (75–115 $\mu g \cdot m^{-3}$). Pollution control and the prevention of $PM_{2.5}$ still need further strengthening.

As for studies on $PM_{2.5}$ pollution, previous scholars have generally used descriptive statistical analyses and combined spatial autocorrelation analyses to study a spatial cluster of annual $PM_{2.5}$ concentrations [7–9]. However, concentrations change in space, which tends to change the means of local areas. In heavily polluted regions, $PM_{2.5}$ pollution is normally a superposition of pollutants from different sources. A quantitative analysis can only determine the overall distribution of $PM_{2.5}$ and the influencing factors of $PM_{2.5}$ pollution. When confronting a more specific situation, such as different pollution statuses in one polluted area or the pollution situation at different times on a shorter time scale, a metrology analysis is not suitable because short-term social and economic data are difficult to obtain: This also means that prevention recommendations are not possible.

The local control and prevention of pollution mainly focuses on the relocation of heavily polluted enterprises or on regulating cars. However, $PM_{2.5}$ pollution does not only come from local emissions, but is also influenced by meteorological conditions, such as wind direction and speed [10]. Local governments cannot mitigate pollution by themselves. Some common policies should be jointly developed by city governments in the most seriously polluted regions (instead of in traditional administrative regions) [11]. Considering the differences in $PM_{2.5}$ pollution levels and the characteristics of agglomeration, governments should implement differentiated regional pollution control strategies [7]: Prevention and control require cooperation [12]. Studies have already established hierarchical policies based on differentiated socioeconomic development conditions and requirements across Chinese cities [13,14]. Chen et al. [8] analyzed the socioeconomic factors of joint control using a geographically weighted regression method, establishing a strategy of joint control. Zhang et al. [15] built a $PM_{2.5}$ network correlation model to identify and demarcate regions with strong temporal intercorrelations using hourly $PM_{2.5}$ concentrations. These studies, however, have only analyzed the key aspects of joint control over $PM_{2.5}$ from the perspective of society and economics: They have not been focused on the sources of $PM_{2.5}$. $PM_{2.5}$ pollution is also closely related to atmospheric transportation. If heavily polluted regions could adopt joint control strategies for the sources of pollutants, the control of $PM_{2.5}$ would be more efficient.

Backward trajectory analysis is an important method for analyzing the sources of air pollution. Scholars have studied the regional transportation characteristics of atmospheric particles by analyzing their air mass trajectories [16–19]. Existing research has focused on descriptions of long-term pollution sources in a single region, which cannot distinguish between the air mass trajectory during a heavily polluted period and the air mass trajectory during a slightly polluted period. Considering that policies leading to $PM_{2.5}$ decreases in China have been implemented without taking economic costs into account (which might be unsustainable in the near future) [20], prevention should be primarily focused on heavily polluted periods in key regions to find a balance between the control of pollution and economic growth.

As for studies of polluted periods, previous researchers have mainly analyzed changes in $PM_{2.5}$ concentrations using statistical methods that include the year, quarter, or day to analyze variations in the concentration of $PM_{2.5}$ [7,9,15,21]. These researchers have used overall temporal information to analyze the evolutionary features of $PM_{2.5}$ based on a simple method, where temporal characteristics of $PM_{2.5}$ are evaluated with the assumption that the statistical properties of the time series do not vary over time. These types of studies can only uncover intense periods of high $PM_{2.5}$, ignoring the pollution cycle. Because of that, pertinent suggestions for control cannot be given. Meanwhile, $PM_{2.5}$ concentrations have a complex cyclical variation with several short and long periods, which makes it difficult to analyze the temporal changes in $PM_{2.5}$ concentrations. The wavelet transform method is a feasible and effective method for studying the laws of variation of air pollution time-series indexes [22]. Temporal variations are expressed well, and mutated signals of the $PM_{2.5}$ level can be identified through wavelet analysis [23]. Using the wavelet method, Chen et al. [24] discovered multiscale features that are indicated in the temporal evolution of $PM_{2.5}$. Huang et al. [25] used the wavelet transform method to obtain the characteristics of yearly changes and sudden changes in the $PM_{2.5}$ level. Liang et al. [26] utilized the wavelet approach to explore the potential association between $PM_{2.5}$ and influenza. In addition, the wavelet transform method is mainly used in $PM_{2.5}$ concentration predictions [27–31]. However, these studies have barely focused on the characteristics of periodic changes in the $PM_{2.5}$ concentration on a major scale.

The factors of time and space should both be considered in analyses of the period and location of heavy pollution. The empirical orthogonal function (EOF) method was originally introduced in meteorology as a method for extracting the dominant modes of spatial variability [32]: It has since been applied in climatological [33,34], hydrological [35,36], and geophysical studies [37]. This method can extract the main components of meteorological factors and temporal and spatial variations. This paper decomposes $PM_{2.5}$ concentrations and judges the pollution center through the $PM_{2.5}$ concentration distribution in different modes. Furthermore, it analyzes the counterpart time variation and cycle patterns, giving the foundation for an analysis of joint governance regions and control cycles.

Due to limitations with monitoring conditions, previous studies on the spatiotemporal distribution of $PM_{2.5}$ have mainly focused on the Yangtze River Delta [38], the Pearl River Delta [39,40], the Beijing–Tianjin–Hebei region [41], and other developed regions. Even if the scopes of these studies were national, pollutants in the western regions were characterized as missing or unpolluted due to missing data, which is not consistent with reality [7]. As the Chinese government has paid more attention to $PM_{2.5}$ issues, observation conditions across the country have improved. In 2013, there were only nearly 800 monitoring sites in the country [15], but as of December 2018, the number of sites exceeded 1600, covering the vast majority of the country. With these improvements in monitoring conditions, the pollution problem in the western region—which had not been studied before—has gradually come to light. Therefore, it is necessary to carry out a national $PM_{2.5}$ analysis of temporal and spatial variations according to existing conditions and to further expand previous research to create more accurate $PM_{2.5}$ studies in China.

First, this paper combines a spatiotemporal distribution of $PM_{2.5}$ with an analysis of the source of pollutants, studying the spatiotemporal distribution of $PM_{2.5}$ concentrations in China to identify seriously polluted areas and time coefficients. Moreover, we utilized a wavelet transform to analyze key pollution periods using time coefficients. Finally, a backward trajectory analysis and a concentration-weighted trajectory were utilized to study the joint prevention regions of seriously polluted areas at heavily polluted times, providing suggestions for the efficient control of $PM_{2.5}$. The main contributions of this work are summarized as follows:

- The study of the spatiotemporal distribution of $PM_{2.5}$ concentrations. We applied EOF decomposition to the spatiotemporal distribution of $PM_{2.5}$ concentrations, studying the time coefficients and vectors of $PM_{2.5}$ concentrations in different modes and analyzing the overall average state and local variation of $PM_{2.5}$. Thus, regions and periods of heavy pollution could be determined.
- An analysis of the duration of key prevention and control strategies. The time coefficient of $PM_{2.5}$ concentrations under different modalities was analyzed using a wavelet transform to judge

the length of time of serious pollution periods so as to provide suggestions for the duration of prevention and control policies.

- An investigation into the areas of joint protection and control. On the basis of the duration of key protection and control policies, $PM_{2.5}$ pollution in major cities in heavily polluted areas was analyzed using a backward trajectory analysis and a potential source analysis, with seriously polluted areas selected as the research object.

The rest of this paper is organized as follows (Figure 1): Chapter 2 describes our data sources and research methods. Chapter 3.1 presents a descriptive statistical analysis of the annual variation in $PM_{2.5}$ from 2016 to 2018, using EOF to decompose panel data of $PM_{2.5}$ concentrations to identify the periods of and areas with heavy pollution in different modes. Chapter 3.2 uses a continuous wavelet transform to analyze the duration of key protection and control policies. Using the above-mentioned pollution areas and prevention periods, Chapter 3.3 analyzes the joint prevention and control areas of the research object from the point of view of air mass trajectory. Chapter 4 is the conclusion.

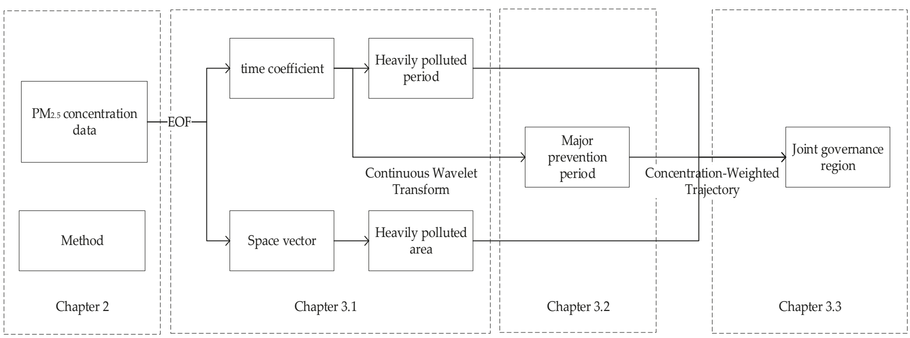


Figure 1. Research framework of this article.

2. Materials and Methods

2.1. Data Sources

2.1.1. $PM_{2.5}$ Data

The $PM_{2.5}$ data were collected from the PM25.in website [42] (estimated by the National Urban Air Quality Real-Time Release Platform of China's National Environmental Monitoring Center) [43]. The β-ray decay method and the tapered element oscillating microbalance (TEOM) method are commonly used as monitoring methods in China. Although these two methods are different in terms of measuring the concentration of $PM_{2.5}$ and although the TEOM is known to have seasonally dependent biases [44], there is no evidence that China's ground monitoring data are not valid. Therefore, this paper used the (valid) ground monitoring data of $PM_{2.5}$ concentrations released by official data sources, which are widely used in academic research [8,15,24], without considering errors in the measurements.

This paper collected 24 h monitoring data from 361 cities in China, and daily and annual data were obtained through averaging. The positions of the selected cities are shown in Figure 2. An inverse distance weight algorithm [45] was employed to interpolate the $PM_{2.5}$ concentration and a simulation of the spatial distribution of pollution. The results, combined with geographic data, are presented in ArcGIS 10.2.

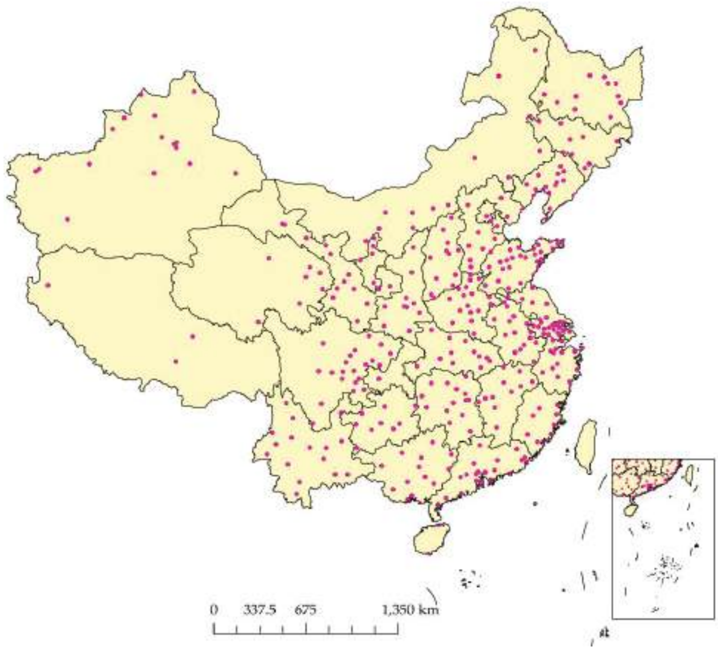


Figure 2. The distribution of the 361 cities used as data sources.

2.1.2. Backward Trajectory Analysis Data

The meteorological data, which were provided by the NCEP (National Environmental Forecasting Center), were exploited in backward trajectory mode (GDAS1 (Global Data Assimilation System) data). The meteorological element field included temperature, air pressure, relative humidity, ground precipitation, horizontal and vertical wind speed, etc., from 2016 to 2018. GADS1 has the capability of calculating trajectory directly using vertical wind speed, which is an advantage over other methods, whose vertical wind speed is calculated indirectly by calculating the vertical integration of horizontal wind speed divergence [46].

2.2. Method

2.2.1. Empirical Orthogonal Function

The empirical orthogonal function is a field analysis method widely used in the sphere of geosciences. Its principle is to decompose the spatiotemporal element field into several spatial basic modes and a linear combination of the time coefficient series, and then to objectively and quantitatively analyze the spatial structure and time changes of the element fields. The panel data of m observation points and n observations were expanded using the EOF and decomposed into the sum of the product of the orthogonal space matrix V and the orthogonal time matrix T:

$$X_{mn} = VT = \begin{pmatrix} v_{11} & \cdots & v_{1n} \\ \vdots & \ddots & \vdots \\ v_{m1} & \cdots & v_{mn} \end{pmatrix} \begin{pmatrix} t_{11} & \cdots & t_{1n} \\ \vdots & \ddots & \vdots \\ t_{m1} & \cdots & t_{mn} \end{pmatrix}. \tag{1}$$

Equation (1) is multiplied on the right to get Equation (2):

$$XX^T = VTT^TV^T = V\Lambda V^T, \tag{2}$$

where the superscript T represents the transpose of the matrix, Λ is a diagonal matrix composed of the eigenvalues of the matrix, and V is a matrix composed of the matrix eigenvectors.

Therefore, the time coefficient can be obtained from Equation (3):

$$T = V^T X. \tag{3}$$

North's Rule of Thumb assesses the uniqueness of EOF modes through assumptions of error of the eigenvalues. When adjacent eigenvalues match the condition $\lambda_{j+1} - \lambda_j \geq \lambda_j (\frac{2}{n})^{\frac{1}{2}}$, these two eigenvalues and their corresponding modes pass the sampling error test [47].

The variance contribution rate ρ of the eigenvalues and the cumulative variance contribution rate of the first p eigenvalues are calculated as follows:

$$\rho_i = \lambda_i / \sum_{i=1}^{m} \lambda_i, \tag{4}$$

$$p_i = \sum_{i=1}^{p} \lambda_i / \sum_{i=1}^{m} \lambda_i. \tag{5}$$

In the EOF, a set of eigenvalues, eigenvectors, and time coefficients represents a distribution mode. The first few eigenvectors passing the significance test represent the maximum distribution structure. The component of the eigenvector with the largest absolute value represents the intensity center. If the positive and negative signs in the eigenvector are consistent, the eigenvector reflects the features with the same change trend. If the component of a certain eigenvector is in a positive and negative phase distribution, then this eigenvector represents two opposite distribution types. The time coefficient represents the time variation characteristics of the spatial distribution form. When the time coefficient is positive, the year is consistent with the distribution form represented by the eigenvector, and vice versa. The larger the absolute value of the time coefficient is, the more significant the distribution form. The variance contribution rate ρ reflects the degree to which a mode explains the whole. The higher its cumulative value is, the more accurately the selected mode describes the overall situation.

2.2.2. Continuous Wavelet Transform

A continuous wavelet transform can clearly reveal the period of change hidden in nonstationary time series and can reflect its change trend in different time scales. A continuous wavelet transform can also extract multiple wave periods from the wave sequence at different scales to reflect its changing trend, which is suitable for signal feature extraction [48]. The principle is to shift the mother wavelet function $\psi(t)$ after the translation b, and then to make an inner product with the signal $f(t)$ for it to be analyzed at different scales a, as follows:

$$\psi_{ab} = \frac{1}{\sqrt{|a|}} \psi\left(\frac{t-b}{a}\right), \tag{6}$$

$$w_f(a,b) = \frac{1}{\sqrt{|a|}} \int_R f(t) \overline{\psi}\left(\frac{t-b}{a}\right) \mathrm{d}t, \tag{7}$$

where $b = 1, 2, \ldots, N$. N is the number of datapoints (1096 in this paper). According to the literature [49], for nonorthogonal wavelet analyses, one can use an arbitrary set of scales a to build a more complete picture. It is convenient to write the scales as fractional powers of two:

$$s_j = s_0 2^{j\delta j}, j = 0, 1 \ldots, J, \tag{8}$$

$$J = \delta j^{-1} \log_2(N\delta t / s_0), \tag{9}$$

where s_0 is the smallest resolvable scale and J determines the largest scale. Here, δt represents the sampling intervals of data in this paper, and s_0 should be chosen so that the equivalent Fourier period is approximately $2\delta t$. For the Morlet wavelet, a δj of about 0.5 is the largest value that can still give an adequate sampling scale. Parameter values from the literature [49] were used here: δj = 0.125. Therefore, the smallest and largest resolvable scales could be calculated as 2 and 512, respectively. Note that longer scales correspond to the most stretched-out wavelets. The more stretched-out the wavelet is, the longer the portion of the signal to which it is being compared (and the coarser the signal features measured by the wavelet coefficients) will be. In addition, a large scale also means a long period. The time between the adjacent maximum and minimum of wavelet coefficients is almost 7 months when the scale a is over 300 d (with similar data conditions) [24]. Because this article focuses on short-term trends in $PM_{2.5}$ concentration changes for efficient governance, the largest scale was set at 64, the same as in the literature [49].

The complex Morlet wavelet, which is a single-frequency complex sinusoidal function, which has symmetry, nonorthogonality, and an imaginary part [24], can simultaneously preserve the amplitude and phase information of the sequence signal of $PM_{2.5}$ concentrations. Therefore, a complex Morlet wavelet was selected as the mother wavelet. The complex Morlet wavelet function is as follows:

$$\psi(t) = (\pi \times f_b)^{-0.5} e^{2i \times f_c \times t} e^{-t^2/f_b}, \tag{10}$$

where t represents time and f_b represents the bandwidth controlling attenuation in the time domain and the corresponding bandwidth in the frequency domain. Here, f_b is the reciprocal of variance in the frequency domain. An increase in f_b will lead to the wavelet energy being concentrated around the center frequency and will slow down the attenuation speed in the time domain. On the other hand, a decrease in f_b will accelerate the decay rate in the time domain and reduce the energy of the frequency domain. Here, f_c denotes the center frequency and affects the frequency value when the time domain is converted into a frequency domain [24,50]. These two parameters can be adjusted to obtain appropriate time–frequency resolutions. In this paper, we set the f_b as 1 and the f_c as 1.5, in accordance with parameter settings from the literature [24] and parameter optimization from the literature [51].

Using the MatlabR2018a software platform, the wavemenu toolbox was selected to calculate the wavelet coefficients. Meanwhile, the wavelet variance of the EOF time coefficient was analyzed to find the main scale. Then, the coefficient modulus of the wavelet coefficients and the contour plots of the real part were plotted to find the main oscillation periods and periods of time series at major scales. The periodic variation of the real part of the wavelet coefficient on the main scale was the most significant period of the time series.

A continuous wavelet transform can expand one-dimensional signals in both the time and frequency directions to analyze the time–frequency structure of the data in detail and extract valuable information. A continuous wavelet transform can not only provide the relative contribution of different scales of the time series, but can also indicate changes in different scales, so it is very helpful for the study of time series.

2.2.3. Backward Trajectory Analysis and Concentration-Weighted Trajectory

Here, we convey the calculation of the air trajectory first. The backward trajectory mode adopts the Hybrid Single-Particle Lagrangian Integrated Trajectory Model (HYSPLIT) developed by the NOAA (National Oceanic and Atmospheric Administration) [52,53]. The HYSPLIT model uses gridding meteorological data to respond to emergencies in the atmosphere to diagnose issues and analyze the climate. This mode is Lagrangian, as is Euler's mixed diffusion mode: The processes of advection and diffusion are calculated using the Lagrangian method, and the concentration is calculated using the Euler Method [54]. HYSPLIT is considerably detailed in terms of the transportation, diffusion, and settling of pollutants, and its highest simulation accuracy can last hours. Thus, HYSPLIT is widely used in analyzing the source of pollutants and determining transmission and diffusion [55].

MeteoinfoMap is a geographic information system application that analyzes and visualizes multiple meteorological data formats [56]. Its plug-in, TrajStat, can use the backward trajectory analysis software adopted by the HYSPLIT Lagrangian diffusion module [57]. On the basis of the results from the EOF analysis, we selected cities with high pollution levels as the starting point and used the length of time of severe pollution as the pushback time. The air mass movement path at 500 m of altitude (the wind field at 500 m of altitude) can reflect the characteristics of the average flow field in the boundary layer [16,17,19]. Therefore, the height of the simulation was selected as 500 m, and we calculated the 48 h backward trajectory every 2 h.

After that, a grid was established based on the area covered by the atmospheric trajectory, with a resolution of 0.25° × 0.25°. The concentration-weighted trajectory (CWT) was used to analyze the source of pollution. The CWT is a mixed-trajectory receptor model that combines meteorological trajectory nodes (residence time) and pollutant concentrations to trace their contributions to the pollution of a recipient site [58]. After the study area was gridded, the CWT value of Grid (i, j) was as follows:

$$CWT_{ij} = \frac{1}{\sum\limits_{l=1}^{M} \tau_{ijl}} \sum_{l=1}^{M} c_l \tau_{ijl}, \tag{11}$$

where τ_{ijl} is the number of pollution trajectory nodes in the grid (i, j) in the area, and C_l is the pollutant concentration of the trajectory. The higher the grid CWT value is, the greater the probability that the pollution trajectory comes from that grid point.

When there are fewer trajectories within the grid, the residence time is shorter, so the x value is higher and there is greater uncertainty. When n_{ij} is less than three times its average value, we use the following weight function to reduce the uncertainty [58–60]:

$$WCWT_{ij} = W_{ij} \times CWT_{ij}, \tag{12}$$

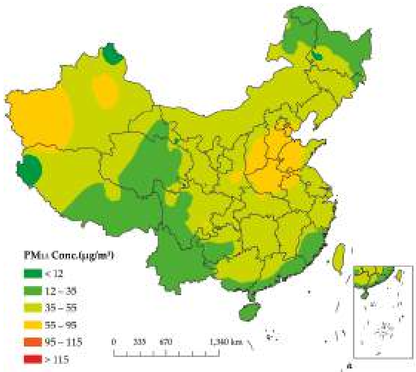
$$W_{ij} = \left\{ \begin{array}{c} 1.00 \quad 3n_{ave} < n_{ij} \\ 0.70 \quad n_{ave} < n_{ij} \leq 3n_{ave} \\ 0.42 \quad 0.4n_{ave} < n_{ij} \leq n_{ave} \\ 0.05 \quad n_{ij} \leq 0.4n_{ave} \end{array} \right\}. \tag{13}$$

3. Results

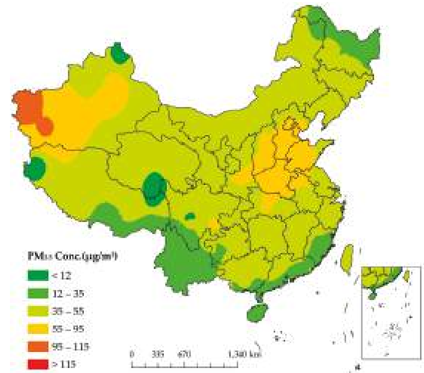
3.1. Spatiotemporal Features of $PM_{2.5}$ Concentrations

3.1.1. Descriptive Statistical Analyses

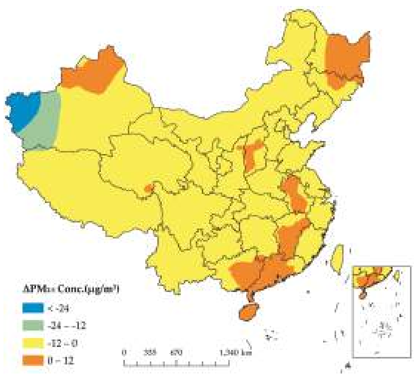
According to the $PM_{2.5}$ concentration data from 2016 to 2018, the annual mean of the $PM_{2.5}$ concentration across the country had a downward trend. The national average $PM_{2.5}$ concentration value was reduced by a total of 6.753 μg·m^{-3}, representing 14.6% of the former value. The mean value decreased from 46.15 μg·m^{-3} in 2016 to 43.76 μg·m^{-3} in 2017, and then declined to 39.39 μg·m^{-3}. As is shown in Figure 3, except for the North China Plain, southern Sichuan, and part of western Xinjiang, the three-year average $PM_{2.5}$ concentration value in most areas was less than 55 μ·m^{-3}, which indicates good-quality air. In 2016, heavily polluted areas (in terms of $PM_{2.5}$ pollution) were mainly concentrated in western Xinjiang, the Beijing–Tianjin–Hebei region, Shanxi, Henan, central Hubei, central Shanxi, and west Shandong. In 2017, the concentration of $PM_{2.5}$ in the Shanxi, Anhui, Guangxi, Guangdong, Hainan, and Northern Xinjiang areas increased. At the same time, the $PM_{2.5}$ concentration in western Xinjiang dropped significantly. However, due to the high $PM_{2.5}$ concentration in western Xinjiang, although the decline was large, the air quality in Xinjiang was still worrying. Although $PM_{2.5}$ concentrations in most parts of the country were under control in 2018, $PM_{2.5}$ concentrations in western Xinjiang and Tibet continued to rebound slightly, and $PM_{2.5}$ concentrations also increased in western Yunnan and northern Gansu, indicating that in these areas, regional $PM_{2.5}$ prevention and control policies were not effective. These results differ from previous studies of the $PM_{2.5}$ distribution in China (by Hu Line [41]).



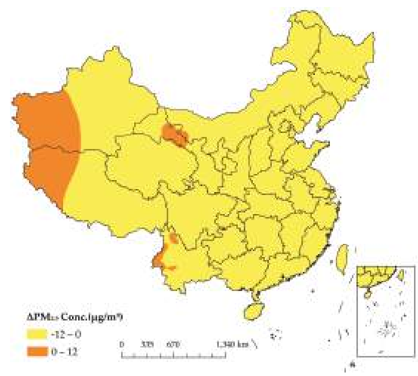
(a) Mean values over three years.



(b) Annual average concentration in 2016.



(c) Annual average increments in 2017.



(d) Annual average increments in 2018.

Figure 3. $PM_{2.5}$ (particulate matter with an aerodynamic diameter of $\leq$2.5 μm) annual average concentrations from 2016 to 2018.

These research results should alarm the Chinese government: Although $PM_{2.5}$ has been under control in most regions of the country under current policies, $PM_{2.5}$ pollution remains a major problem in some regions. $PM_{2.5}$ concentrations did not always continue to decrease over the three years. Therefore, $PM_{2.5}$ prevention and control work should focus on these problem areas by strengthening control policies further, improving governance policies, and making $PM_{2.5}$ governance more effective.

3.1.2. Heavily Polluted Areas and Periods

In order to further understand the spatial and temporal distribution of $PM_{2.5}$ pollution and to accurately determine the key areas and periods of $PM_{2.5}$ governance, this paper used EOF analysis. We employed a standardized matrix of monthly panel data of $PM_{2.5}$ concentrations in 361 cities from 2016 to 2018. The characteristic vector of EOF expansion demonstrated the spatial distribution of the $PM_{2.5}$ concentration in each province. The maximum value center of all eigenvector fields indicated the region that was the most sensitive to $PM_{2.5}$ concentration changes. The eigenvectors of $PM_{2.5}$ concentrations in China's provinces converged quickly, with eight eigenvalues passing North's Rule of Thumb. The variance contribution rates of each mode were 41.70%, 10.77%, 6.56%, 4.72%, 3.63%, 2.93%, 2.12%, and 1.78%. The contribution rates of the eigenvalue variance illustrated that the EOF analysis results were ideal. Compared to the first two modes, the third mode and the subsequent modes took up a small proportion of the EOF decomposition. Therefore, the first two eigenvectors could be used to represent the spatiotemporal structure of $PM_{2.5}$ concentrations.

The variance contribution of the first mode of EOF indicated the average state of the $PM_{2.5}$ concentration from 2016 to 2018, representing the distribution field of $PM_{2.5}$ concentrations in China. In Figure 4, it can be seen that the first eigenvector had a consistently positive value, indicating that the spatial variation trend of $PM_{2.5}$ concentrations in the first mode was synchronous. The distribution pattern of the eigenvector in the first mode was close to the mean distribution (Figure 3a). It can be concluded that the first mode was the average state of $PM_{2.5}$ concentration. The highest value area was located in the middle of Shaanxi Province. The eigenvalues of North China, central Sichuan, and parts of Xinjiang were also large. This indicates that the $PM_{2.5}$ concentration fluctuated greatly in these areas. When the time coefficient was positive, $PM_{2.5}$ pollution was more severe. In other areas, the eigenvalue was close to zero regardless of changes in the time coefficient, so the $PM_{2.5}$ concentration remained at a low level.

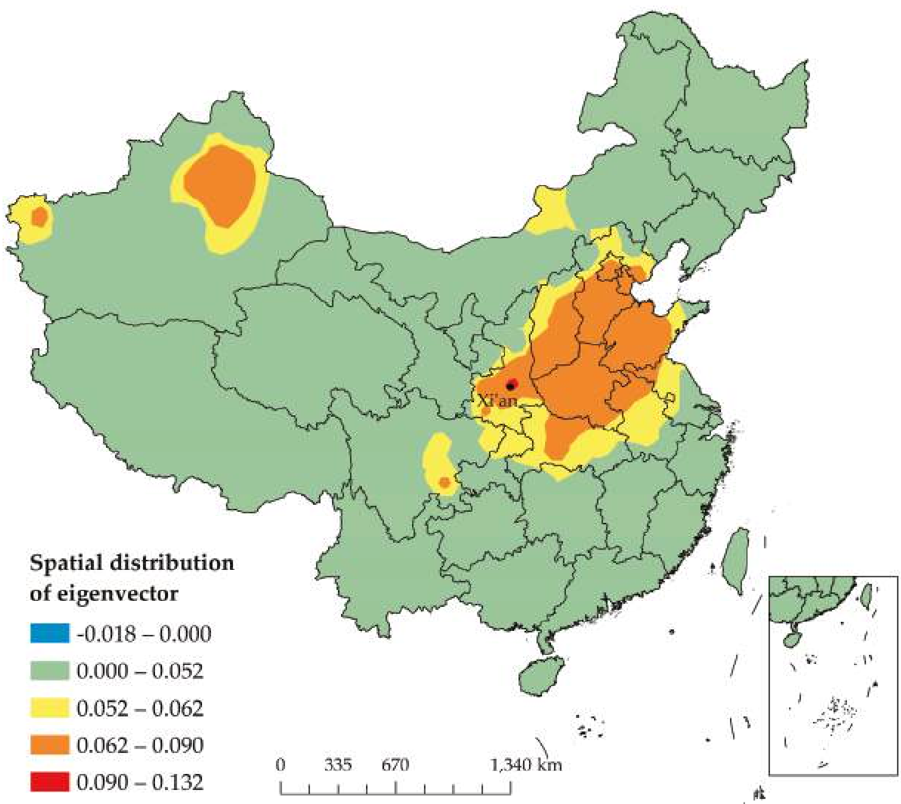


Figure 4. Spatial distribution of eigenvectors in the first empirical orthogonal function (EOF) mode.

From the distribution of the time coefficients in the first mode (Figure 5), it can be concluded that the $PM_{2.5}$ concentration change in the first mode had obvious seasonal characteristics. In the first and fourth quarters of each year, most $PM_{2.5}$ time coefficients were positive, and the maximum value each year appeared around December, which means that the high-value area of the eigenvector in the first and fourth quarters represented the $PM_{2.5}$ pollution problem getting worse and the pollution being the most serious from December to January. In the second and third quarters, the time coefficients were negative, so the $PM_{2.5}$ concentration gradually decreased. The dashed line in the figure is the linear regression of the time coefficients of the first mode, which had a downward trend, reflecting that in the long term, the pollution problems in the areas where the $PM_{2.5}$ concentrations changed after the first mode were alleviated.

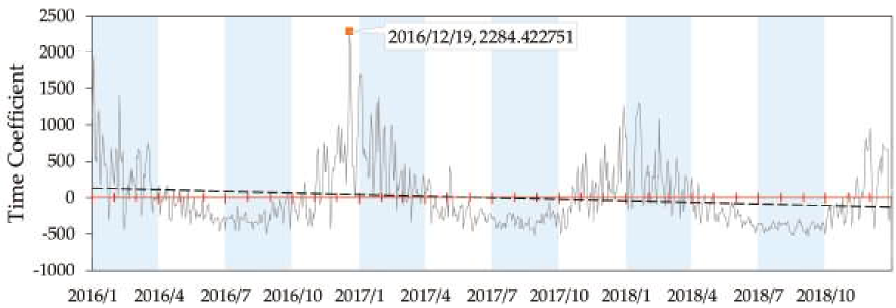


Figure 5. Time coefficients of the first EOF mode. The dashed line is the linear regression trend line. The maximum value is marked as a square.

According to the above analysis, in the first mode, the main pollution areas were Shaanxi, North China, Sichuan, and Xinjiang, and central Shaanxi. The main pollution periods were the first and fourth quarters of each year, and pollution was the most serious in December. Governments should focus on the above areas and pollution periods.

The second EOF mode reflected the spatial variation of regional $PM_{2.5}$ concentration differences; the spatiotemporal distributions are shown in Figure 6. Most of the eigenvalues exhibited in Figure 6 were close to zero, which meant that these regions contributed little to local pollution characteristics. However, the eigenvalues in Western Xinjiang had large negative values, suggesting dramatic changes in the $PM_{2.5}$ concentration.

It can be seen from Figure 7 that the time coefficients had large negative values from February to April each year, reaching a maximum on April 3, 2018. When looking at the eigenvectors of western Xinjiang in the second mode, in areas where the eigenvector is negative, negative time coefficients reflect a positive increase in the $PM_{2.5}$ concentration. The greater the absolute values of the time coefficients and eigenvalues are, the more severe the pollution is. It can be seen that the $PM_{2.5}$ pollution in the second mode was concentrated from February to April each year, and the pollution problem was extremely serious, especially in April (when there was an eruption of severe pollution). $PM_{2.5}$ governance in western Xinjiang should be strengthened during this period; the pollution problem in April is especially worthy of more attention.

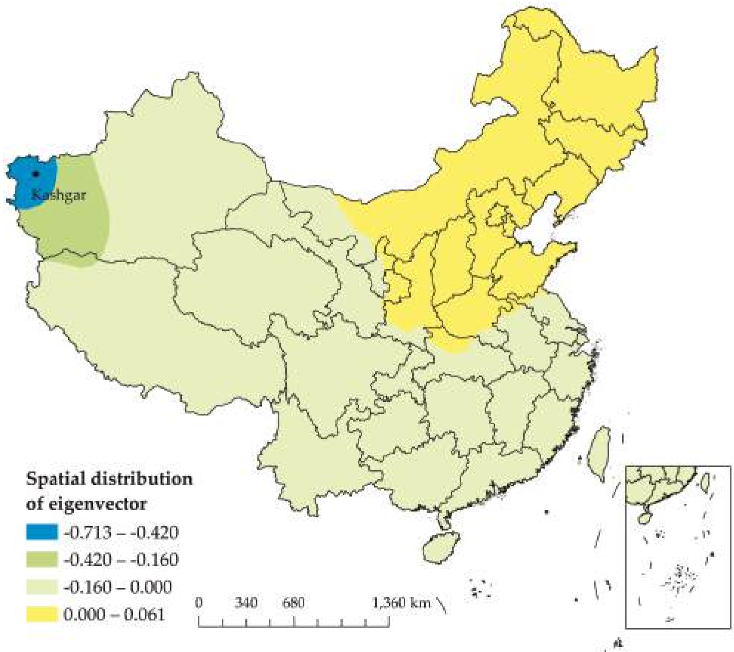


Figure 6. Spatial distribution of eigenvectors in the second EOF mode.

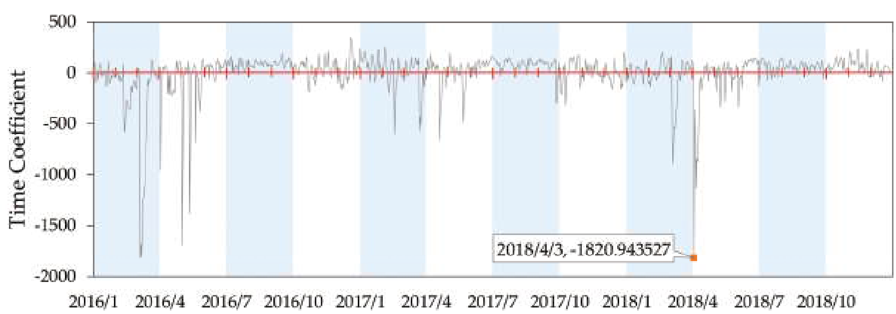


Figure 7. Time coefficients of the second EOF mode. The maximum value is marked as a square.

3.2. Major Prevention Period

The $PM_{2.5}$ pollution periods in different modes were analyzed above. Local governments should focus primarily on severely polluted periods, especially in the western region of China, to strictly control $PM_{2.5}$ and further strengthen prevention and control efforts. However, considering the economic costs brought on by strengthening prevention and control efforts, the periods that are the most polluted should be of higher priority to be the most efficient. Since changes in $PM_{2.5}$ levels also have high-intensity periods, we suggest carrying out at least one complete control cycle for polluted periods. Prevention during heavily polluted times is key to helping improve control efficiency. Therefore, a wavelet transform was performed on the time coefficients in the two modes to further study what the best prevention time periods were.

The variance of wavelet transform coefficients can determine the main scale of the wavelet transform, which is plotted in Figure 8. The line chart represents the relative intensity of each scale in a time series. The scale at the corresponding peak is called the main time scale of the wavelet transform, and the periodic oscillation at this scale is the most significant. It is clear from Figure 8 that the wavelet variance of the time coefficients in the first mode had two distinct peaks corresponding to the time scales of 37 and 23 d. The periodic oscillation of the time scale around 37 d was the largest, which could mean that this is the main scale. In the second mode, the time scale of about 44 d had the largest variance.

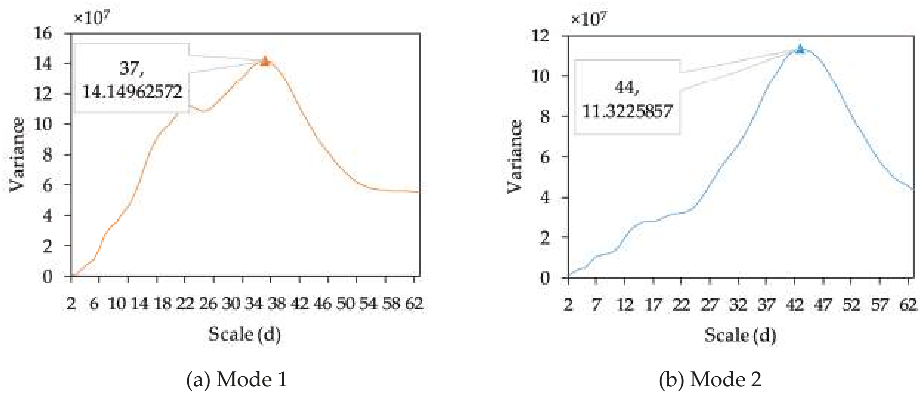


Figure 8. Wavelet variation variance. The maximum value is plotted as a triangle.

The modulus value of the wavelet coefficient is a reflection of the distribution of the energy density at different time scales, which corresponds to the period of change in the time domain. The larger the modulus value of the coefficient is, the stronger the periodicity of the corresponding period or scale is. A contour map of the modulus of the wavelet variation coefficient is plotted in Figure 9. The red area in the figure indicates a large wavelet coefficient modulus value. The corresponding abscissa indicates a time of strong oscillation, and the ordinate is the wavelet transform scale. As can be seen in the figure, in the first mode, the strong period corresponding to the main scale (37 d) was from December 2017 to January 2018. The strongest period in the second mode was from February to March 2016 (at 44 d).

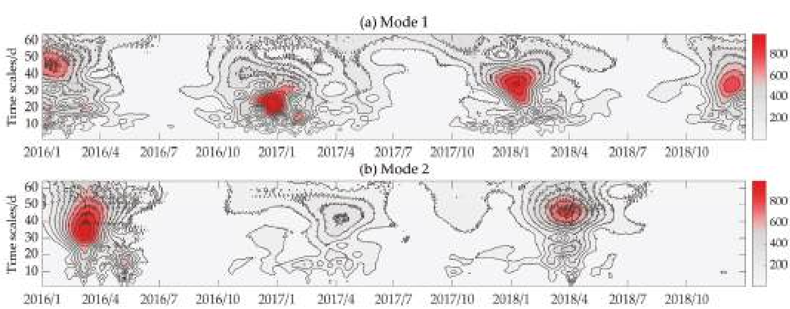


Figure 9. Contour map of the modulus of the wavelet variation coefficient.

On the basis of the wavelet coefficient modulus and variance, the main scale of the time coefficient of changes in $PM_{2.5}$ concentration in the two modes (and their corresponding time range) was found. The main scale was used in the frequency domain analysis to determine the time domain change at different frequencies, which has no practical meaning. Because we wanted to focus on the most polluted periods from 2016 to 2018, we selected the scale with the largest variance of wavelet coefficients and the time range of the corresponding maximum value of the wavelet coefficient modulus. In practical applications, other typical scales or periods can also be selected for analysis according to actual needs, or all periods corresponding to the main scales can be selected for a comprehensive analysis. This method is very flexible.

A contour plot of the real part of the wavelet transform coefficient can reflect the change in the data at different transform scales. The ordinate of the densely arranged region at the center of the positive and negative values is the characteristic time scale of the wave sequence, and the abscissa is the periodic time frame of changes. In Figure 10, there are four red and blue local oscillation regions in the first mode and two local oscillation regions in the second mode. The two types of oscillations at different scales reflect different periodic changes. Each time the regions alternate between red and blue is a pollution period. The above analysis was carried out by selecting areas located in the main time scale and within the strong oscillating periods. The first mode (Figure 10a, the 37 d scale) experienced two pronounced concentration bursts between December 2017 and January 2018. In the second mode (Figure 10b), the cold- and warm-colored alternation regions were mainly concentrated in the period between February and April in 2016, with two cycles of strength and weakness on a 44 d scale. It is worth noting that there was a slight increase in the concentration of $PM_{2.5}$ before the eruption of the two modes, which indicates the beginning of a serious eruption of $PM_{2.5}$ pollution, an important early warning sign for $PM_{2.5}$ prevention. After the second eruption, the $PM_{2.5}$ concentration decreased to normal levels, and we defined the end of the second eruption as the end time of major pollution.

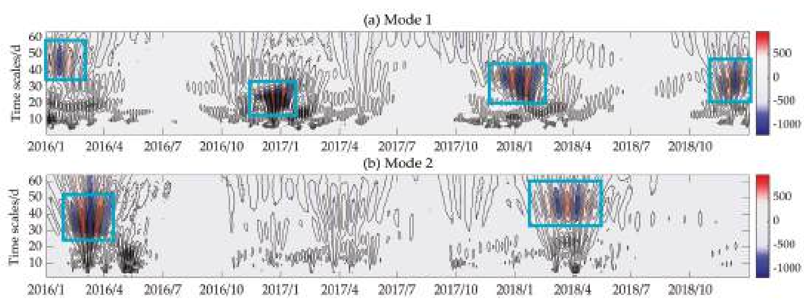


Figure 10. Contour map of the real part of the wavelet variation coefficients in (**a**) the first mode and (**b**) the second mode. The blue rectangles are areas with periodic oscillations.

The above analysis determined the main scales, strong oscillation periods, and cyclic changes in the corresponding time coefficients. For the purpose of determining the $PM_{2.5}$ pollution cycle in different modes, the real part of the wavelet transform coefficients of different modes (with their main scales) was drawn. A typical polluted period was calculated using the intervals between the $PM_{2.5}$ concentration peaks. In Figure 11, the peak is the eruption time, the start is the short eruption time before the intense eruption of pollution, and the end is the ending time of the major pollution period. With these calculations, we could find out that the typical pollution time under the first mode was between 27 November 2017 and 26 January 2018, the outbreak interval was 23 days, and there were two intense pollution eruptions of $PM_{2.5}$. Pollution in the second mode occurred between 27 January 2016 and 31 March 2016, the outbreak interval was 28 days, and there were two intense pollution eruptions of $PM_{2.5}$ here as well.

Autocorrelation was used to verify the wavelet transform results. The autocorrelation results from the first and second modes' time coefficients are shown in Figures A1 and A2, respectively. According to the literature [61,62], the time differences between peaks can be calculated—we did that here to find that there existed a long period of 22 days, a result very close to the wavelet transform results from the first mode. Though the autocorrelation of the second mode was weaker than that of the first mode, a long period of 25 days was found for the time coefficient of the second mode, which was only a three-day difference compared to the wavelet analysis results. The autocorrelation results certified that the continuous wavelet transform method could find periods of time series from weak autocorrelation and can be used reliably in $PM_{2.5}$ concentration research.

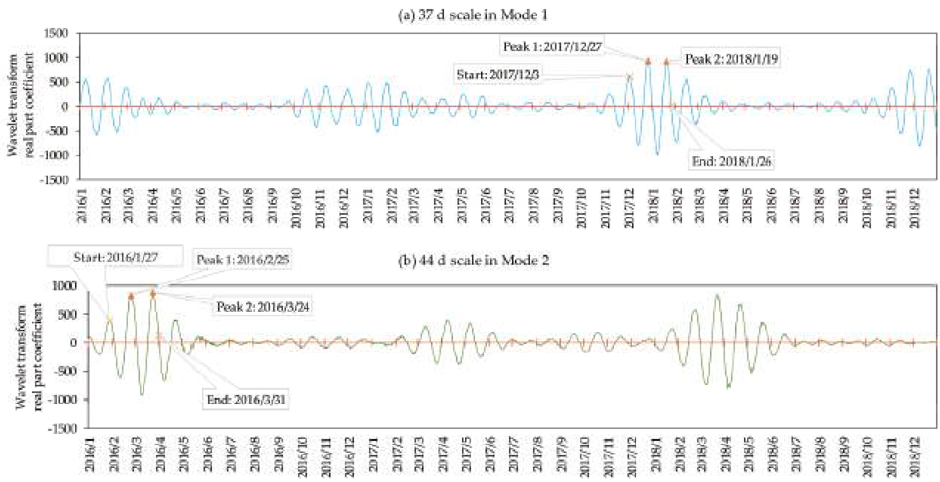


Figure 11. Wavelet transform coefficients using the main time scale (real parts).

On the basis of the above results, Shaanxi, northern China, Sichuan, and some parts of Xinjiang (whose $PM_{2.5}$ performances were poor during the first mode) should commence their governance between November and January of the following year (when $PM_{2.5}$ pollution is severe). The governance in these regions should last for two cycles after slight $PM_{2.5}$ pollution occurs for the first time, and one cycle should last for no less than 23 days. Governance in western Xinjiang should be strengthened in terms of prevention and control (in the first mode) until March. There should be at least two cycles during this period, and one cycle should last for 28 days.

3.3. Joint Governance Region

On the basis of the analysis above, we selected the cities of Xi'an and Kashgar for analysis. Both cities were in the most polluted areas in both modes. Taking the most severely polluted period as the calculation time, we used a backward trajectory of 48 h to analyze the major joint-governance cities. The backward trajectory analysis and concentration-weighted trajectory conditions are shown in Table 1.

Table 1. The backward trajectory analysis and concentration-weighted trajectory conditions.

	Location	Start Time	End Time	Calculated Time	Grid Area
1	Xi'an (34.27°N, 108.93°E)	2017.12.3	2018.1.26	55 days	28.00°N~53.00°N, 73.00°E~120.00°E
2	Kashgar (39.47°N, 75.98°E)	2016.1.27	2016.3.31	65 days	30.00°N~50.00°N, 50.00°E~89.00°E

Here, the atmospheric trajectory image and CWT values reflect the effect of grid points on the $PM_{2.5}$ levels of the analyzed city. The larger the grid value is, the more serious the impact of $PM_{2.5}$ pollution on the city. In order to better identify major pollution sources, only high-value CWT grids in China are plotted, which are shown in Figures 12 and 13. The CWT diagram of all grids is shown in Figures A3 and A4.

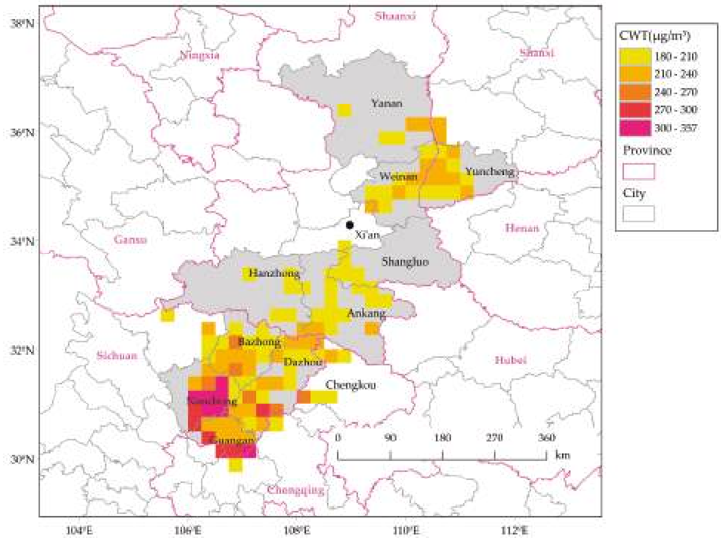


Figure 12. $PM_{2.5}$ high-value concentration-weighted trajectories (CWTs) in Xi'an.

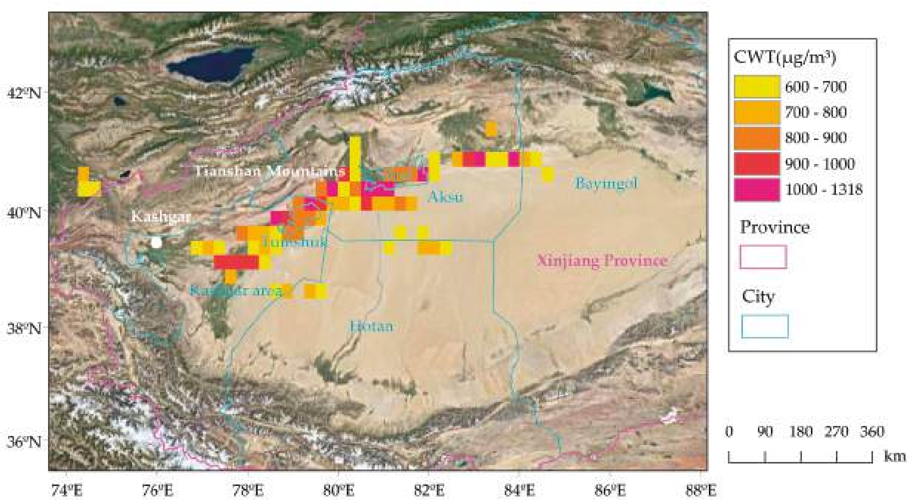


Figure 13. $PM_{2.5}$ high-value CWTs in Kashgar. The map is a Google satellite map showing the position of the Tianshan Mountains.

In Figure 12, it can be seen that Nanchong, Guangan, Bazhong, and Dazhou in the eastern Sichuan Province had the greatest impact on $PM_{2.5}$ pollution in Xi'an. During the most polluted winter, $PM_{2.5}$ in eastern Sichuan passed through Ankang, Hanzhong, and Shangluo in southern Shaanxi Province and reached Xi'an, exacerbating $PM_{2.5}$ pollution. In addition, Weinan, Yanan, and Yuncheng in the northeast were also sources of $PM_{2.5}$ pollution in Xi'an. Therefore, prevention and control strategies in Xi'an should not be limited to local governance, and joint governance should be carried out between the above cities to control pollution more effectively.

The sources of severe pollution in Kashgar are shown in Figure 13. The $PM_{2.5}$ concentration in Kashgar was most influenced by the eastern region, which had heavy pollution. The grids of these trajectories were distributed along the Tianshan Mountains, starting from Bayingol and reaching

Kashgar via Aksu, Aral, Tumshuk, and North Kashgar. Therefore, Kashgar should create prevention and control strategies for the urban agglomerations along the Tianshan Mountains.

4. Conclusions

This paper analyzed joint governance regions and key governing cycles in China through the EOF and backward trajectory analysis. The EOF decomposed $PM_{2.5}$ concentration panel data into space vectors and time coefficients. The time coefficients reflected the changing trends in pollution distribution. After transforming the time coefficients using wavelets, we could obtain the pollution periods of the main time scales and could determine key governance periods using the real parts of the wavelet coefficients. A space vector indicated the distribution of $PM_{2.5}$ pollution, which helped identify areas with serious pollution problems. Then, we selected the main cities in these areas and analyzed their sources of pollution during key governance periods to determine possible joint prevention areas. The conclusions can be summarized as follows:

- From a nationwide point of view, the overall $PM_{2.5}$ pollution in China improved from 2016 to 2018, but the improvement was limited. $PM_{2.5}$ remains a serious problem in Xinjiang and North China. This finding is different from previous studies that have claimed that China's $PM_{2.5}$ pollution is strong in the east and weak in the west. National $PM_{2.5}$ concentration panel data were decomposed using the EOF, resulting in two modes. The first mode reflected the average state of $PM_{2.5}$ pollution in China. Seriously polluted areas included northern China, western Sichuan, and parts of Xinjiang. The most polluted areas were in central Shaanxi Province. Pollution in the first mode had significant seasonal characteristics, indicating that pollution in the first and fourth quarters was serious and that the pollution degree decreased in the second and third quarters. The second mode reflected the local pollution characteristics of the Xinjiang region, indicating that there was severe pollution from February to April.
- Major prevention periods during the two EOF modes were studied using a continuous wavelet transform. This showed that the first mode had a typical oscillation, with a scale of 37 d, from November to January of the following year, and the main oscillation scale of the second mode was 44 d, from February 2016 to April 2016. In the areas where $PM_{2.5}$ pollution was in the first mode, prevention and control strategies should be carried out from November to January of the following year. After a small eruption in pollution occurs, prevention and control should be implemented for a period of no less than 23 days. After the end of the control cycle in the first mode, management and control of $PM_{2.5}$ pollution in the second mode should be strengthened for at least two cycles until March, where one cycle is 28 days.
- This paper took Xi'an and Kashgar as examples to analyze joint governance regions based on pollution trajectories. In addition to local control, $PM_{2.5}$ control strategies during winter in Xi'an should include joint control with Nanchong, Guangan, Bazhong, and Dazhou in eastern Sichuan. $PM_{2.5}$ control in winter in Xi'an should also be coordinated with Ankang, Hanzhong, and Shangluo in southern Shaanxi to alleviate the problem of pollution sources in the south. Meanwhile, Xi'an should work with Weinan, Yanan, and Yuncheng to solve the problem of pollution sources in the northwest. For Kashgar, it is necessary to establish a $PM_{2.5}$ joint governance area along the Tianshan Mountains to the east, with a focus on joint governance with the northern cities of Kashgararea, Tumshuk, Aksuarea, and Aral in the east.

The method proposed in this paper can be used to analyze the joint governance regions and periods of $PM_{2.5}$ pollution in key cities across the entire country, and it can also be used in smaller areas, such as provinces or cities. The method is simple, feasible, and has universality. However, due to the many factors affecting the concentration of $PM_{2.5}$ and the limited space of this paper, the important influencing factors of $PM_{2.5}$ pollution prevention and control were not analyzed, which should be the focus of further research.

Author Contributions: Conceptualization, C.L.; methodology, Y.L.; software, K.W.; validation, W.Z.; formal analysis, Z.L.; investigation, Y.L.; resources, C.H.; data curation, J.Z.; writing—original draft preparation, Y.L.; writing—review and editing, J.F.; visualization, C.L.; supervision, Z.L.; project administration, W.Z.; funding acquisition, W.Z. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

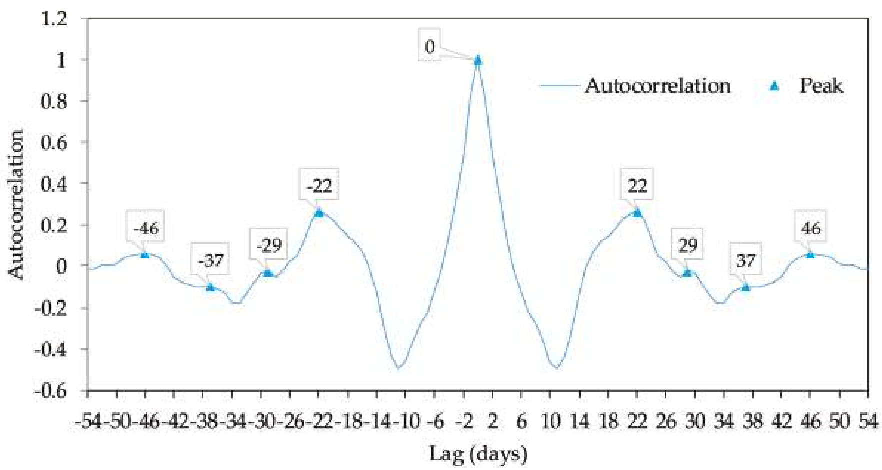

Figure A1. Autocorrelation of time coefficients in the first mode. The positive and negative lags are restricted to N – 1, where N is the length of the time coefficient. Every autocorrelation peak is marked as a triangle with an abscissa.

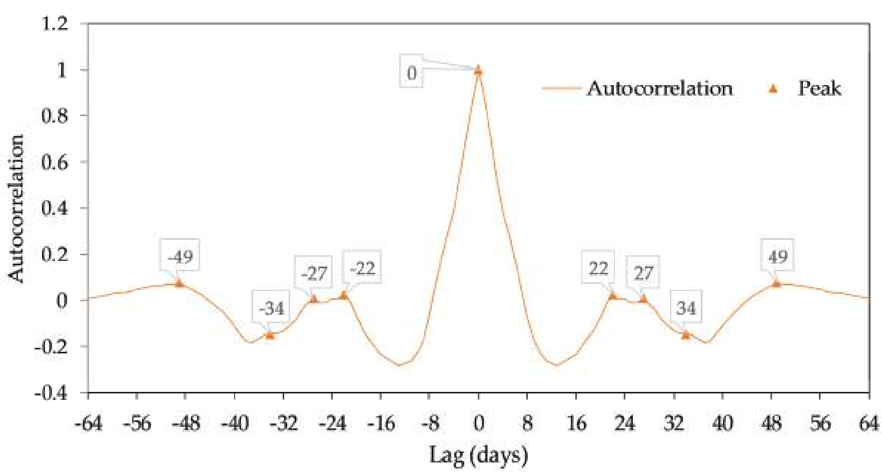

Figure A2. Autocorrelations of time coefficients in the first mode. The positive and negative lags are restricted to N – 1, where N is the length of the time coefficient. Every autocorrelation peak is marked as a triangle with an abscissa.

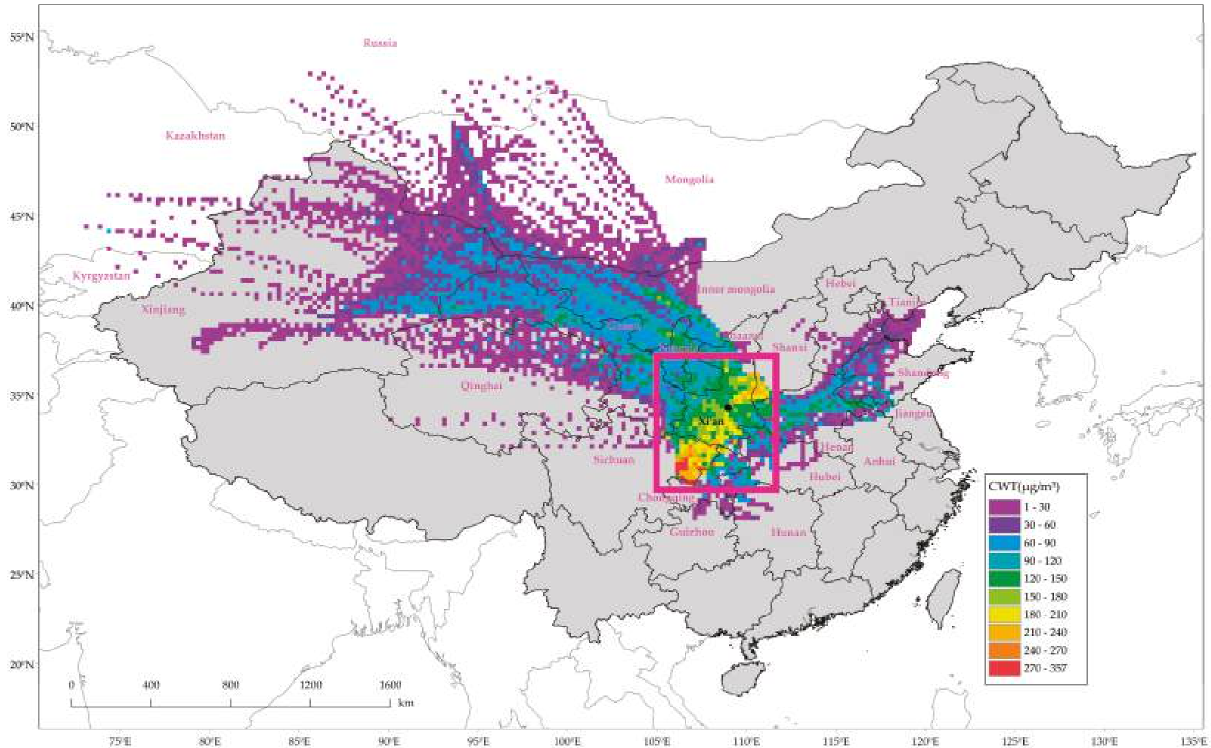

Figure A3. CWTs of all grids in the first mode. The area of analysis of this article is within the red rectangle.

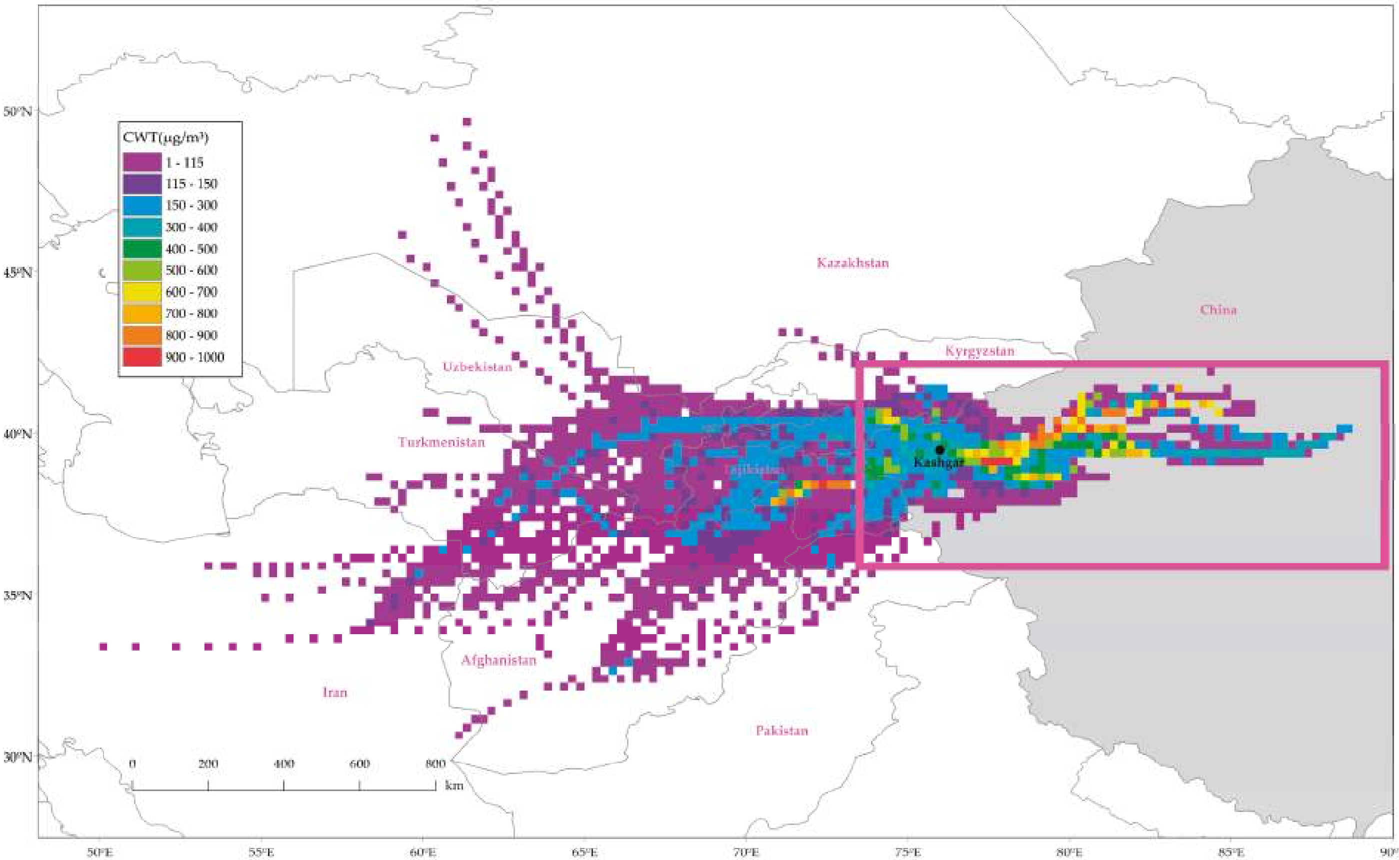

Figure A4. CWTs of all grids in the second mode. The area of analysis of this article is within the purple rectangle.

References

1. Li, J.; Zhu, Y.; Kelly, J.T.; Jang, C.J.; Wang, S.; Hanna, A.; Xing, J.; Lin, C.-J.; Long, S.; Yu, L. Health benefit assessment of PM2.5 reduction in Pearl River Delta region of China using a model-monitor data fusion approach. *J. Environ. Manage.* **2019**, *233*, 489–498. [CrossRef] [PubMed]
2. Zhao, P.; Zhang, X.; Xu, X.; Zhao, X. Long-term visibility trends and characteristics in the region of Beijing, Tianjin, and Hebei, China. *Atmos. Res.* **2011**, *101*, 711–718. [CrossRef]
3. Wang, H.-J.; Chen, H.-P. Understanding the recent trend of haze pollution in eastern China: Roles of climate change. *Atmos. Chem. Phys.* **2016**, *16*, 4205–4211. [CrossRef]
4. Xie, Y.; Dai, H.; Zhang, Y.; Wu, Y.; Hanaoka, T.; Masui, T. Comparison of health and economic impacts of PM2.5 and ozone pollution in China. *Environ. Int.* **2019**, *130*, 104881. [CrossRef] [PubMed]
5. Wang, Y.; Yao, L.; Wang, L.; Liu, Z.; Ji, D.; Tang, G.; Zhang, J.; Sun, Y.; Hu, B.; Xin, J. Mechanism for the formation of the January 2013 heavy haze pollution episode over central and eastern China. *Sci. China Earth Sci.* **2014**, *57*, 14–25. [CrossRef]
6. The Chinese State Council Atmosphere Pollution Prevention and Control Action Plan. Available online: http://www.gov.cn/zwgk/2013-09/12/content_2486773.htm (accessed on 2 February 2020).
7. Li, D.; Zhao, Y.; Wu, R.; Dong, J. Spatiotemporal Features and Socioeconomic Drivers of PM2.5 Concentrations in China. *Sustainability* **2019**, *11*, 1201. [CrossRef]
8. Chen, X.; Li, F.; Zhang, J.; Zhou, W.; Wang, X.; Fu, H. Spatiotemporal mapping and multiple driving forces identifying of PM2.5 variation and its joint management strategies across China. *J. Clean. Prod.* **2020**, *250*, 119534. [CrossRef]
9. Jin, Q.; Fang, X.; Wen, B.; Shan, A. Spatio-temporal variations of PM2.5 emission in China from 2005 to 2014. *Chemosphere* **2017**, *183*, 429–436. [CrossRef]
10. Wang, J.; Zhang, M.; Bai, X.; Tan, H.; Li, S.; Liu, J.; Zhang, R.; Wolters, M.A.; Qin, X.; Zhang, M. Large-scale transport of PM2.5 in the lower troposphere during winter cold surges in China. *Sci. Rep.* **2017**, *7*, 13238. [CrossRef]
11. Wu, X.; Ding, Y.; Zhou, S.; Tan, Y. Temporal characteristic and source analysis of PM2.5 in the most polluted city agglomeration of China. *Atmos. Pollut. Res.* **2018**, *9*, 1221–1230. [CrossRef]
12. Fang, C. Important progress and future direction of studies on China's urban agglomerations. *J. Geogr. Sci.* **2015**, *25*, 1003–1024. [CrossRef]
13. Chen, J.; Zhou, C.; Wang, S.; Hu, J. Identifying the socioeconomic determinants of population exposure to particulate matter (PM2.5) in China using geographically weighted regression modeling. *Environ. Pollut.* **2018**, *241*, 494–503. [CrossRef] [PubMed]
14. Wang, J.; Wang, S.; Li, S. Examining the spatially varying effects of factors on PM2.5 concentrations in Chinese cities using geographically weighted regression modeling. *Environ. Pollut.* **2019**, *248*, 792–803. [CrossRef] [PubMed]
15. Zhang, N.-N.; Ma, F.; Qin, C.-B.; Li, Y.-F. Spatiotemporal trends in PM2.5 levels from 2013 to 2017 and regional demarcations for joint prevention and control of atmospheric pollution in China. *Chemosphere* **2018**, *210*, 1176–1184. [CrossRef] [PubMed]
16. Zhao, H.; Wang, T.; Jiang, F.; Xie, M. Investigation into the source of air pollutants to hong kong by using backward trajectory method during the trace-p campaign. *J. Trop. Meteorol.* **2009**, *25*, 181–186.
17. Liao, T.; Wang, S.; Ai, J.; Gui, K.; Duan, B.; Zhao, Q.; Zhang, X.; Jiang, W.; Sun, Y. Heavy pollution episodes, transport pathways and potential sources of PM2.5 during the winter of 2013 in Chengdu (China). *Sci. Total Environ.* **2017**, *584–585*, 1056–1065. [CrossRef]
18. Zhang, Z.Y.; Wong, M.S.; Lee, K.H. Estimation of potential source regions of PM2.5 in Beijing using backward trajectories. *Atmos. Pollut. Res.* **2015**, *6*, 173–177. [CrossRef]
19. Kong, L.; Tan, Q.; Feng, M.; Qu, Y.; An, J.; Liu, X.; Cheng, N.; Deng, Y.; Zhai, R.; Wang, Z. Investigating the characteristics and source analyses of PM2.5 seasonal variations in Chengdu, Southwest China. *Chemosphere* **2020**, *243*, 125267. [CrossRef]
20. Zeng, Y.; Cao, Y.; Qiao, X.; Seyler, B.C.; Tang, Y. Air pollution reduction in China: Recent success but great challenge for the future. *Sci. Total Environ.* **2019**, *663*, 329–337. [CrossRef]
21. Mi, K.; Zhuang, R.; Zhang, Z.; Gao, J.; Pei, Q. Spatiotemporal characteristics of PM2.5 and its associated gas pollutants, a case in China. *Sustain. Cities Soc.* **2019**, *45*, 287–295. [CrossRef]

22. Zhou, X.-L.; Wang, Q.; Shang, J.-G.; Liu, C.-S. *Time Series Analysis for Pm2.5 and Pm10 in Beijing Based on Wavelet Transform Method*; Khatib, J.M., Ed.; World Scientific Publ Co Pte Ltd.: Singapore, 2016; ISBN 978-981-4723-00-8.
23. Fan, F.; Liu, R. Exploration of spatial and temporal characteristics of PM2.5 concentration in Guangzhou, China using wavelet analysis and modified land use regression model. *Geo-spatial Inf. Sci.* **2018**, *21*, 311–321. [CrossRef]
24. Chen, X.; Yin, L.; Fan, Y.; Song, L.; Ji, T.; Liu, Y.; Tian, J.; Zheng, W. Temporal evolution characteristics of PM2.5 concentration based on continuous wavelet transform. *Sci. Total Environ.* **2020**, *699*, 134244. [CrossRef] [PubMed]
25. Huang, P.; Zhang, J.; Tang, Y.; Liu, L. Spatial and Temporal Distribution of PM2.5 Pollution in Xi'an City, China. *Int. Environ. Res. Public Health* **2015**, *12*, 6608–6625. [CrossRef] [PubMed]
26. Liang, Y.; Fang, L.; Pan, H.; Zhang, K.; Kan, H.; Brook, J.R.; Sun, Q. PM2.5 in Beijing - temporal pattern and its association with influenza. *Environ. Health* **2014**, *13*, 102. [CrossRef]
27. Feng, X.; Li, Q.; Zhu, Y.; Hou, J.; Jin, L.; Wang, J. Artificial neural networks forecasting of PM2.5 pollution using air mass trajectory based geographic model and wavelet transformation. *Atmos. Environ.* **2015**, *107*, 118–128. [CrossRef]
28. Mahajan, S.; Liu, H.-M.; Tsai, T.-C.; Chen, L.-J. Improving the Accuracy and Efficiency of PM2.5 Forecast Service Using Cluster-Based Hybrid Neural Network Model. *IEEE Access* **2018**, *6*, 19193–19204. [CrossRef]
29. Prakash, A.; Kumar, U.; Kumar, K.; Jain, V.K. A Wavelet-based Neural Network Model to Predict Ambient Air Pollutants' Concentration. *Environ. Model. Assess.* **2011**, *16*, 503–517. [CrossRef]
30. Gan, C.-M.; Wu, Y.; Madhavan, B.L.; Gross, B.; Moshary, F. Application of active optical sensors to probe the vertical structure of the urban boundary layer and assess anomalies in air quality model PM2.5 forecasts. *Atmos. Environ.* **2011**, *45*, 6613–6621. [CrossRef]
31. Zhang, H.; Zhang, S.; Wang, P.; Qin, Y.; Wang, H. Forecasting of particulate matter time series using wavelet analysis and wavelet-ARMA/ARIMA model in Taiyuan, China. *J. Air Waste Manage. Assoc.* **2017**, *67*, 776–788. [CrossRef]
32. Mao, T.; Wan, W.; Yue, X.; Sun, L.; Zhao, B.; Guo, J. An empirical orthogonal function model of total electron content over China. *Radio Sci.* **2008**, *43*, 1–12. [CrossRef]
33. Duan, X.; Gu, Z.; Li, Y.; Xu, H. The spatiotemporal patterns of rainfall erosivity in Yunnan Province, southwest China: An analysis of empirical orthogonal functions. *Global Planetary Chang.* **2016**, *144*, 82–93. [CrossRef]
34. Li, Q.; Chen, P.; Sun, L.; Ma, X. A global weighted mean temperature model based on empirical orthogonal function analysis. *Adv. Space Res.* **2018**, *61*, 1398–1411. [CrossRef]
35. Li, L.; Gottschalk, L.; Krasovskaia, I.; Xiong, L. Conditioned empirical orthogonal functions for interpolation of runoff time series along rivers: Application to reconstruction of missing monthly records. *J. Hydrol.* **2018**, *556*, 262–278. [CrossRef]
36. Kim, S.E.; Seo, I.W.; Choi, S.Y. Assessment of water quality variation of a monitoring network using exploratory factor analysis and empirical orthogonal function. *Environ. Modelling Soft.* **2017**, *94*, 21–35.
37. Chen, P.; Liu, L.; Yao, Y.; Yao, W. A global empirical orthogonal function model of plasmaspheric electron content. *Adv. Space Res.* **2020**, *65*, 138–151. [CrossRef]
38. Xu, G.; Ren, X.; Xiong, K.; Li, L.; Bi, X.; Wu, Q. Analysis of the driving factors of PM2.5 concentration in the air: A case study of the Yangtze River Delta, China. *Ecological Indicators* **2020**, *110*, 105889. [CrossRef]
39. Lai, S.; Zou, S.; Cao, J.; Lee, S.; Ho, K. Characterizing ionic species in PM2.5 and PM10 in four Pearl River Delta cities, South China. *J. Environ. Sci.* **2007**, *19*, 939–947. [CrossRef]
40. Gao, H.; Yang, W.; Yang, Y.; Yuan, G. Analysis of the Air Quality and the Effect of Governance Policies in China's Pearl River Delta, 2015–2018. *Atmosphere* **2019**, *10*, 412. [CrossRef]
41. Yan, D.; Lei, Y.; Shi, Y.; Zhu, Q.; Li, L.; Zhang, Z. Evolution of the spatiotemporal pattern of PM2.5 concentrations in China – A case study from the Beijing-Tianjin-Hebei region. *Atmos. Environ.* **2018**, *183*, 225–233. [CrossRef]
42. PM25. Available online: http://www.pm25.in/ (accessed on 2 February 2020).
43. National Urban Air Quality Real-Time Release Platform. Available online: http://106.37.208.233:20035/ (accessed on 2 February 2020).

44. Hsu, Y.-M.; Wang, X.; Chow, J.C.; Watson, J.G.; Percy, K.E. Collocated comparisons of continuous and filter-based PM2.5 measurements at Fort McMurray, Alberta, Canada. *J. Air Waste Manag. Associ.* **2016**, *66*, 329–339.
45. How Inverse Distance Weighted Interpolation Works. Available online: https://pro.arcgis.com/en/pro-app/help/analysis/geostatistical-analyst/how-inverse-distance-weighted-interpolation-works.htm (accessed on 18 February 2020).
46. Su, L.; Yuan, Z.; Fung, J.C.H.; Lau, A.K.H. A comparison of HYSPLIT backward trajectories generated from two GDAS datasets. *Sci. Total Environ.* **2015**, *506–507*, 527–537. [CrossRef] [PubMed]
47. North, G.; Bell, T.; Cahalan, R.; Moeng, F. Sampling Errors in the Estimation of Empirical Orthogonal Functions. *Monthly Weather Rev.* **1982**, *110*, 699–706. [CrossRef]
48. Grinsted, A.; Moore, J.; Jevrejeva, S. Application of Cross Wavelet Transform and Wavelet Coherence to Geophysical Time Series. *Nonlinear Processes Geophys.* **2004**, *11*, 561–566. [CrossRef]
49. Torrence, C.; Compo, G.P. A Practical Guide to Wavelet Analysis. *Bulletin Am. Meteorol. Soc.* **1998**, *79*, 61–78. [CrossRef]
50. Teolis, A. *Computational Signal Processing with Wavelets*; Birkhäuser: Boston, NY, USA, 1985.
51. He, P.; Li, P.; Sun, H. Feature Extraction of Acoustic Signals Based on Complex Morlet Wavelet. *Procedia Eng.* **2011**, *15*, 464–468. [CrossRef]
52. Draxler, R.R. The Use of Global and Mesoscale Meteorological Model Data to Predict the Transport and Dispersion of Tracer Plumes over Washington, D.C. *Wea. Forecasting* **2006**, *21*, 383–394. [CrossRef]
53. Stein, A.F.; Draxler, R.R.; Rolph, G.D.; Stunder, B.J.B.; Cohen, M.D.; Ngan, F. NOAA's HYSPLIT Atmospheric Transport and Dispersion Modeling System. *Bull. Amer. Meteor. Soc.* **2015**, *96*, 2059–2077. [CrossRef]
54. Song, Z.; Bai, X. *An Overview of RSMC Beijing Modeling System for Trajectories, Dispersion and Deposition*; IEEE International Symposium on Geoscience and Remote Sensing: Denver, CO, USA, 2006; pp. 3361–3364.
55. Draxler, R.R.; Gillette, D.A.; Kirkpatrick, J.S.; Heller, J. Estimating PM10 air concentrations from dust storms in Iraq, Kuwait and Saudi Arabia. *Atmos. Environ.* **2001**, *35*, 4315–4330. [CrossRef]
56. Wang, J.; Wang, S.; Jiang, J.; Ding, A.; Zheng, M.; Zhao, B.; Wong, D.C.; Zhou, W.; Zheng, G.; Wang, L.; et al. Impact of aerosol–meteorology interactions on fine particle pollution during China's severe haze episode in January 2013. *Environ. Res. Lett.* **2014**, *9*, 094002. [CrossRef]
57. Wang, Y.Q.; Zhang, X.Y.; Draxler, R.R. TrajStat: GIS-based software that uses various trajectory statistical analysis methods to identify potential sources from long-term air pollution measurement data. *Environ. Modelling Softw.* **2009**, *24*, 938–939.
58. Hsu, Y.-K.; Holsen, T.M.; Hopke, P.K. Comparison of hybrid receptor models to locate PCB sources in Chicago. *Atmos. Environ.* **2003**, *37*, 545–562. [CrossRef]
59. Han, Y.-J.; Holsen, T.M.; Hopke, P.K.; Yi, S.-M. Comparison between Back-Trajectory Based Modeling and Lagrangian Backward Dispersion Modeling for Locating Sources of Reactive Gaseous Mercury. *Environ. Sci. Technol.* **2005**, *39*, 1715–1723. [CrossRef] [PubMed]
60. Wang, Y.Q.; Zhang, X.Y.; Arimoto, R. The contribution from distant dust sources to the atmospheric particulate matter loadings at XiAn, China during spring. *Sci. Total Environ.* **2006**, *368*, 875–883. [CrossRef] [PubMed]
61. Petre, S.; Randolph, L.M. *Spectral Analysis of Signals*; Prentice Hall: Upper Saddle River, NJ, USA, 2005.
62. MathWorks China Find Periodicity Using Autocorrelation. Available online: https://ww2.mathworks.cn/help/signal/ug/find-periodicity-using-autocorrelation.html?lang=en (accessed on 20 February 2020).

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