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Sustainable Agriculture for Climate Change Adaptation

Edited by
Kathy Lewis and Douglas Warner

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About the Special Issue Editors

Kathy Lewis (Prof.) Interests: environmental impacts of agriculture and land use; agri-environmental management; agriculture and climate change; fate and toxicity of agricultural chemicals; agricultural risk assessment and regulation. agri-environmental management; agriculture and climate change; fate and toxicity of agricultural chemicals; agricultural risk assessment and regulation.

Doug Warner (Dr.) Interests: agricultural greenhouse gas emissions and their mitigation; carbon sequestration; crop nutrition; integrated farm management and ecologically based methods of pest control; precision agriculture; farmland biodiversity and conservation

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Editorial

Editorial for the Special Issue "Sustainable Agriculture for Climate Change Adaptation"

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As we lie firmly entrenched within what many have termed the Anthropocene, the time of humans, human influence on the functioning of the planet has never been greater or in greater need of mitigation. Climate change, the accelerated warming of the planet's surface attributed to human activities, is now at the forefront of global politics. The 21st United Nations Climate Change Conference of the Parties (COP21) Paris Agreement saw a landmark agreement reached between countries belonging to the United Nations Framework Convention on Climate Change (UNFCCC). The agreement seeks to arrest climate change and maintain the global temperature rise below a 2 °C increase compared to pre-industrial levels, and to devise means and ways to adapt to its effects.

The agriculture sector not only contributes to climate change but, as a land-based industry, is also greatly affected by climate change. Agriculture has a key function in the role of the carbon and nitrogen cycles, contributing a significant proportion of methane and nitrous oxide toward global greenhouse gas (GHG) emissions, more than any other sector. The Organisation for Economic Co-operation and Development (OECD) states that 17% of GHGs arise from agricultural activities directly, with a further 7% to 14% due to changes in land use. Agriculture will be affected by climate change, particularly in some parts of the world, where the extremes of its impact will be felt severely. Flooding and droughts are predicted to increase in frequency with an associated detrimental impact on crop productivity either due to prolonged water shortages or the creation of anoxic soil conditions and crop hypoxia. Flooded soils also promote the denitrification process and an increase in the release of nitrous oxide.

The type of risk and the severity of its impact is spatially explicit, with different parts of the planet and their associated crop production systems subject to more intense effects and levels of threat, as illustrated for Iran by Alamgir et al. [1] and Bangladesh by Mirgol et al. [2]. The sub-Saharan region of Africa is becoming increasingly vulnerable to drought and temperature rises and farmers will need to adapt the types of crops they grow and their associated management practices [3–6]. Other parts of the world, including North America, may experience warmer winters, resulting in diminished vernalisation [7,8], a process required to promote flowering in certain types of crops. It is not all bad news, however. Significant potential exists to both adapt to and mitigate climate change within the agricultural sector. Any changes will need to be implemented in a sustainable manner to ensure that the solution does not cause other socio-economic or environmental problems. Each potential solution must also be tailored to individual regions and farming systems, as highlighted by Zheng et al. [9] in Australia. The introduction of Climate-Smart Agriculture and technology for use by smallholder farmers in South America, Africa and Asia [10–12] and the provision of farming subsidies to promote further engagement with these techniques is demonstrated by Arunrat et al. [13]. The growing of novel crops such as *Cannabis sativa* for energy production in Europe [14] or the utilisation of plant breeding to develop novel wheat varieties capable of reducing nitrous oxide emissions [15] are other examples.

All these factors are explored in this Special Issue. We are pleased to include a range of quality academic contributions from across the five continents, providing a truly global perspective. Multiple crops and production systems are represented, including studies that utilise valuable research completed with limited resources available.

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Article

On-Farm Evaluation of the Potential Use of Greenhouse Gas Mitigation Techniques for Rice Cultivation: A Case Study in Thailand

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Abstract: Environmental and socio-economic evaluations that imply techniques for mitigating greenhouse gas (GHG) emissions from rice cultivation are a challenging and controversial issue. This study was designed to investigate the potential use of mitigation techniques for rice cultivation. Mid-season drainage (MD), using ammonium sulfate instead of urea (AS), and site-specific nutrient management (SSNM) were chosen as mitigation techniques. Data were collected using field surveys and structured questionnaires at the same 156 farms, covering four crop years. The GHG emissions were evaluated based on the concept of the life cycle assessment of the GHG emissions of products. The farmers' assessments of mitigation techniques, with multiple criteria evaluation, were obtained by face-to-face interviews. Opinions on all mitigation techniques were requested two times covering four years with the same 156 farm owners. The multinomial logistic regression model was used to examine the factors influencing the farmers' decisions. The results show that SSNM was evaluated as the highest abatement potential (363.52 kgCO_2eq ha^{-1}), the negative value of abatement cost ($-$2565 THB ha^{-1}), and the negative value of the average abatement cost ($-$14 THB kgCO_2eq^{-1}). Among the different techniques, SSNM was perceived as the most suitable one, followed by MD and AS. Highly significant factors influencing decision making consisted of planted area, land size, farmer liability, farmer perception of yield, and GHG emissions. Subsidies or cost-sharing measures to convince farmers to adopt new techniques can enhance their practices, and more support for the development of water systems can increase their availability.

Keywords: rice field; mitigation techniques; greenhouse gas emissions; life cycle assessment; farmer acceptance; incentive measures

1. Introduction

Rice paddies are considered to be one of the most important sources of anthropogenic emissions of greenhouse gases (GHGs), particularly nitrous oxide (N_2O), methane (CH_4), and carbon dioxide (CO_2) [1] and therefore play an important role in climate change [2,3]. Notably, many studies state that N_2O emissions are associated with nitrogen (N) fertilizer application and dry land conditions [4,5], while flooded fields are a significant source of CH_4 and contribute little to N_2O emissions [6–8]. The use of agricultural machines requires the use of fossil fuels, resulting in CO_2 emissions. Projected increases in the demand for rice have raised considerable concerns about increasing greenhouse gas (GHG) emissions [9]. Thus, knowledge about trade-offs between rice yield increases and GHG emission reductions is urgently needed for the development of effective mitigation and adaptation strategies.

Considering possible strategies for mitigating GHG emissions from rice cultivation, those having no effect on rice yield would be the best techniques. Methane emissions vary markedly with water management. In particular, mid-season drainage, with the short-term removal of irrigation water, is one of the most promising strategies for reducing CH_4 emissions [10–12]. Several field measurements indicate that mid-season drainage (MD) significantly reduces CH_4 emissions and exerts a positive impact on rice yields by increasing N mineralization in the soil and increasing rice plant root development [13–17]. However, it also increases N_2O emissions by creating nearly saturated soil conditions, which promote N_2O production [18–20]. Fertilizer management has frequently been suggested as a mitigation option by substituting urea as N fertilizer with ammonium sulfate $(NH_4)_2SO_4$ (inhibits methanogens) and ammonium phosphate (promotes rice plant growth) [21]. Ammonium sulfate has a significant effect on N_2O reduction and slightly depresses CH_4 production by 10–67% [22], because sulfate-reducing bacteria can outcompete CH_4-producing bacteria under these conditions [23]. Moreover, site-specific nutrient management (SSNM) has been suggested as a method to reduce N_2O emissions by controlling the use of fertilizers with synchronization and precise farming techniques, using slow-release nutrients (including nitrification inhibitors) [24,25] and avoiding their overuse [26]. Dobermann and Cassman [27] state that an N recovery of over 70% can be achieved for many cereal crops by using intensive site-specific nutrient management, based on the principles of the 4R nutrient stewardship—the right source at the right rate, time, and place [28]. However, the sources of CH_4 and N_2O from rice fields cannot be reliably identified and discriminated in various areas.

There is an urgent need to quantify the effects and costs of mitigation strategies in rice fields, which, at present, remain difficult to enumerate, and could result as being speculative. A significant problem is that most farmers do not apply these mitigation strategies, for various reasons such as no ownership on farmland [29,30], less education or training on mitigation strategies [30,31], low income and access to credit [30–32], or less farming experience [33]. An evaluation method is therefore required that highlights decision factors and provides insight into the balance between environmental impacts, economic productivity, and social acceptance regarding mitigation strategies. Another significant problem is that the decision-making processes in terms of employing mitigation strategies are complicated by financial incentives and because agricultural activities depend on, and have a large impact on, natural resources [34]. These factors indicate the need to better understand decision making by farmers and the barriers inhibiting the adoption of mitigation and adaptation strategies.

Mitigation and adaptation are two basic, but distinctly different responses. Farmers' attitudes towards these two general responses to tackle changing climate conditions must be understood if scientists, policy makers, and others are to effectively support adaptive and mitigative actions [35,36]. Moreover, integrating mitigation and adaptation are win-win actions because they can mitigate the causes of climate change (mitigation) and adapt to changing climatic conditions (adaptation) [37]. Many studies have investigated farmer behavior and the associated socio-economic characteristics (e.g., [38–40]). Until now, mitigation costs caused by improvements in farming practices have rarely been reported, and information on the socio-economic feasibility of these mitigation techniques are still lacking, while their social acceptance and the minimization of their costs have not been discussed at any length. Therefore, the objectives of this study are: (1) to evaluate the GHG emissions of each mitigation technique for rice cultivation; (2) to clarify the farmers' assessment with multiple criteria evaluation of each mitigation technique; and (3) to examine the factors influencing the farmers' decisions to use a mitigation technique. The knowledge provided by this study can aid policy makers and other related agencies in their efforts to design and compare mitigation policies and reach mitigation goals.

2. Materials and Methods

2.1. Mitigation Technique Selection

Mitigation techniques were selected based on a literature review and on the recommendations of experts, provided in a report by the Office of Agricultural Economics [41], Ministry of Agriculture and Cooperatives, Thailand. Moreover, we expected that any mitigation techniques suggested to government agencies would be likely to be promoted and supported by the government in the near future. Based on these criteria, mid-season drainage (MD), replacement of urea with ammonium sulfate ($(NH_4)_2SO_4$) (AS), and site-specific nutrient management (SSNM) were chosen as mitigation techniques for this study.

2.2. Site Selection

Multi-stage sampling was employed for this study as follows. Firstly, at the provincial level, purposive sampling was used, focusing on farmers who have grown rice. They voluntarily participated and provided their information and opinions. Secondly, at the district and sub-district levels, cluster sampling was used to determine two clusters: irrigated areas and rain-fed areas. Moreover, farmers' average net household incomes (calculated by subtracting expenses from total revenue) for each district and sub-district were set as the criterion, based on the assumption that money is the major factor that can improve their livelihood and is the major factor likely to convince them to change their behavior. The four districts with the highest net incomes (Bang Mun Nak, Taphan Hin, Bueng Na Rang, and Pho Prathap Chang districts) and the four districts with the lowest net incomes (Sam Ngam, Wachira Barami, Wang Sai Phun, and Thap Khlo districts) in Phichit province were selected as samples.

2.3. Data Collection

Data were obtained from participatory observation, in-depth interviews, and a questionnaire survey at the same 156 farms (in irrigated and rain-fed areas of 78 farms, respectively) in four crop years (2012/2013, 2013/2014, 2014/2015 and 2015/2016) to avoid data variation. Data throughout the crop years from each crop, consisting of cultivation practices, agricultural inputs (e.g., fossil fuels, fertilizers, insecticides, herbicides, and water sources), yields, transportation costs, and benefits were collected from the farm owners. Data were also obtained from the record books for the standards for good agricultural practices (GAP) for farm owners, which was disseminated to the farmers by the Department of Agricultural Extension, Ministry of Agriculture and Cooperatives, Thailand.

2.4. Estimation of GHG Emissions

2.4.1. System Boundary and Functional Unit

The concept of the life cycle assessment of the greenhouse gas emissions of products, based on cradle-to-gate, was employed. It is because this approach is widely used for evaluating and comparing the environmental impacts of various products, and also to identify, quantify, and track the sources of GHG emissions throughout production process [42]. System boundary covers raw material production, transport of agricultural inputs (diesel fuel, gasoline fuel, chemical fertilizers, insecticides and herbicides) to the farm, land preparation, planting, harvesting, storing and post-harvest burning of crop residues (Figure 1). The transportation data were considered for two distances: the average distance from the farms to the retailer in the municipality of each sub-district and the average distance from the farms to the retailer in the community of each farm. Burning crop residues in the paddy field were included in this study because it is a common way to eliminate rice residues in Asia, including Thailand [43,44], and GHG emissions from open burning concentrated in the harvest season [45]. It is indicated that emissions from burning crop residues play an important role in the air pollution and climate change [46]. To assess the combined global warming potential (GWP), CH_4, and N_2O were calculated as CO_2 equivalents over a 100-year time scale, using a radiative forcing potential relative to CO_2 of 28 for CH_4 and 265 for N_2O [47]. The functional unit used in assessments was kg CO_2eq ha^{-1} for each technique.

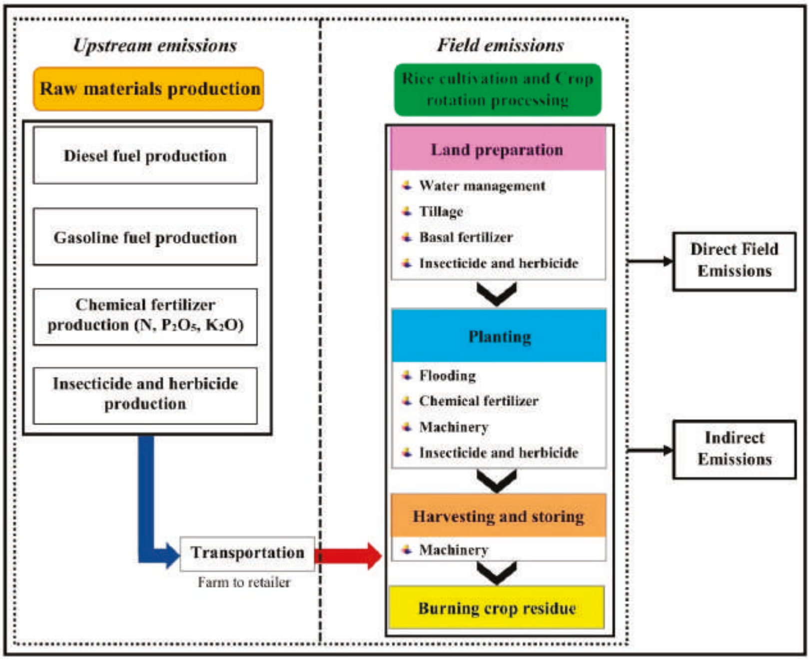

Figure 1. System boundary from cradle to farm gate of the study (adapted from Arunrat et al. [48]).

2.4.2. Calculation of GHG Emissions

The GHG emissions were calculated for each farm using four scenarios, including the business as usual (BAU) case, and the use of MD, AS, and SSNM techniques. Upstream emissions were accounted for in terms of raw material production and the transportation of agricultural inputs to the farm. Fossil fuels, chemical fertilizers, as well as insecticide and herbicide production were estimated using specific emission factors, as characterized in Ecoinvent 3.2 [49]. Emissions from the transportation of agricultural inputs to the farm were estimated based on diesel fuel consumption, using the emission factors from the National Technical Committee on Product Carbon Footprinting (Thailand) [50]. In some cases, specific emission factors for gasoline or insecticides and herbicides were not available in Ecoinvent 3.2, so country-specific emission factors for Thailand from the National Technical Committee on Product Carbon Footprinting (Thailand) [50] were used instead.

Field CH_4 emissions from rice cultivation were used as the model for the calculations, according to the 2006 Intergovernmental Panel on Climate Change (IPCC) Guidelines for National Greenhouse Gas Inventories [51]. The baseline emission factor was taken from Yan et al. [16], who adjusted region-specific emission factors for rice fields in east, southeast, and south Asian countries, and all scaling factors used were derived from the IPCC [51]. Direct and indirect N_2O emissions and CO_2 emissions from urea applications were also estimated using the methodology proposed by the IPCC [50]. The GHG emission calculations and parameters and emission factors for diesel and gasoline usage in stationary combustion were taken from the IPCC [51]. The GHG emissions from the mobile combustion of diesel fuel by farm tractors and harvesters were estimated from the emission factors of Maciel et al. [52], and GHG emissions from gasoline fuel were estimated following the EPA [53]. Figures for insecticides and herbicides were provided by the emission factors from Lal [54]. Equations, parameters, and emission factors for the calculation of GHG emissions are presented in the Supplementary Material by Arunrat et al. [48].

2.5. Economic Analysis

2.5.1. Estimation of the Costs of Each Technique

The production input of each technique consists of water (*W*), tillage (*T*), seed (*S*), labor (*L*), fertilizer (*F*), insecticide (*P*), herbicide (*H*), harvest (*V*), and land rental (*R*). The total production cost $[C(Q_i)]$ for each technique is the sum of production input costs Equation (1).

$$C(Q_i) = (C_W \times W_i) + (C_T \times T_i) + (C_s \times S_i) + (C_L \times L_i) + (C_F \times F_i) + (C_P \times P_i) + (C_H \times H_i) + (C_V \times V_i) + (C_R \times R_i) \quad (1)$$

where *i* is each technique, *C*(*Q*) is the cost of crop production, in Baht ha^{-1}, and C_W, C_T, C_S, C_L, C_F, C_P, C_H, C_V, and C_R are costs of water management, tillage, seed, labor, fertilizer, insecticide, herbicide, harvest, and land rental, in Baht^{-1} unit, respectively.

In addition, the specific details of the methods used to estimate the costs of each technique are described below.

(1) MD Technique

The cost of the MD technique was calculated by multiplying the quantity of fuel used for pumping water back into the fields, using the fuel price per unit. The cost of this technique was investigated depending on the distance from the fields and the ownership of the water source by dividing the farms into two groups: (1) those far away from water sources (natural sources or irrigation systems at >100 m or >50 m from the fields, respectively); and (2) farms with their own surface pond or artesian well.

(2) AS Technique

The use of ammonium sulfate (21-0-0) instead of urea (46-0-0) requires changes in the quantities of the fertilizers used and their costs. The relevant calculations are as follows: (1) 1 kg of urea contains 0.46 kg N; (2) it takes 2.19 kg of ammonium sulfate to replace 1 kg of urea, providing 0.46 kg of N; (3) the amount of ammonium sulfate used, multiplied by its unit price, is equal to the total cost of the ammonium sulfate used.

(3) SSNM Technique

The cost of the SSNM technique was calculated based on the following steps. Firstly, the amount of each fertilizer to be used was calculated based on the instructions provided by the Land Development Department of Thailand after soil factor analysis. For instance, in the Nong Phra sub-district, Wang Sai Phun district, the soil series is Chiang Rai, suitable for growing photosensitive rice varieties. Suggested fertilizers are 31 kg ha^{-1} of 46-0-0, 71 kg ha^{-1} of 16-20-0, and 37 kg ha^{-1} of 0-0-60, to be applied 7–10 days after sowing or 25–30 days after transplanting, and 31 kg ha^{-1} of 46-0-0, to be applied again during the early flowering phase. After the suitable amounts of all fertilizers were established, the cost of each fertilizer used was calculated by multiplying the quantity by the price per unit. Finally, the total fertilizer cost of the SSNM technique was compared to the fertilizer cost of the BAU case.

2.5.2. Average Abatement Cost (AAC)

The AAC was used to assess the economic potential for the reduction of GHG emissions in this study; AAC refers to the cost of implementing a technique to reduce GHG emissions to an anticipated level. Similar to the GHG emission estimations, AAC was estimated using four scenarios comprising the BAU case and the use of the MD, AS, and SSNM techniques. The AAC (THB kgCO$_2$eq^{-1}) of each technique was calculated by dividing the total abatement cost (THB ha^{-1}) (TAC) by the total abatement potential (kgCO$_2$eq ha^{-1}) (TAP), and each TAC and TAP were obtained by subtracting the cost under the BAU scenario. Indeed, the reduction of GHG emissions is involved with cropping system, mitigation techniques, and farmers' behavior. Therefore, ACC was then presented to the farmers of each farm during their assessments on each mitigation technique. This is because ACC can help the farmers to visualize about being environmentally friendly and reducing production costs.

2.6. Farmers' Assessment and Analysis Tools

After the last crop year (2015/2016) for data collection, the investigation of the farmers' assessment for each farm was taken place in 2017. A multiple criteria evaluation was developed to assess farmers in the qualitative evaluation of the mitigation techniques. In this study, the criteria applied in the multiple criteria evaluation for farmers' assessment on the three mitigation techniques were as defined in Table 1, adapted from Webb et al. [55]. To reduce the bias and uncertainty from the farmers' assessment, the survey was administered via a face-to-face interview in November 2016 and August 2017, with the same 156 farm owners. The farmers were introduced and explained the purposes of the survey. The farmers' assessment was investigated after calculating the AAC for each scenario and each farm, but the farmers were allowed to choose only one suitable technique to implement. A questionnaire was presented to the farmers to evaluate the rating of each mitigation technique. A four-Likert scale was adopted for the evaluation [56]. The rating scale for the farmers' assessment was: '4' = very good, '3' = good, '2' = poor, and, '1' = very poor. We used a four-point scale to interpret the farmers' response because a mid-point is considered as too ambiguous for decision making [57], which was also mentioned in Webb et al. [55]. The scores of each farmer were summed up from the scores of each criterion for the three mitigation techniques. For instance, 78 farmers gave a score of 4 (very good) to the MD technique on the criteria of effectiveness; the total score was 312 (78 $\times$ 4). Moreover, the farmers were asked about their needs for policies and incentives to support their farming.

Table 1. Definitions of the criteria for farmers' assessment (adapted from Webb et al. [55]).

Criteria	Definition
Effective	Evaluates whether or not the mitigation technique reduces GHG emissions
Flexible	Evaluates whether or not the ability of the mitigation technique to enhance opportunity for other cropping systems and places
Economically efficient	Evaluates whether or not implementing the mitigation technique reduces production cost and increases household income
Easy to implement	Evaluations whether a mitigation technique is easy to implement by farmers with technical and managerial ease
Ability to trial	Evaluates whether a mitigation technique can be easily trialed or tested before full implementation
Institutional compatibility	Evaluates whether a mitigation technique is consistent with the current management framework, laws, regulations and will be promoted and supported by the government in the near future

2.7. Estimating the Determinants of Mitigation Techniques and Socio-Economic Variables

Factors that might influence the farmers' decision to adopt or reject the mitigation techniques were examined using the multinomial logistic regression (MNL) model. The MNL model is an extension of logistic regression, which is generally effective when the dependent variable is composed of a polytomous category with multiple choices. Explanatory variables included in the MNL model were defined as two types: dichotomous and continuous variables, as detailed below (Table 2). The model was estimated using the following specification:

$$\begin{aligned} Y = \; & \beta_0 + \beta_1 AREA + \beta_2 EXP + \beta_3 OWN + \beta_4 SIZE + \beta_5 INC + \beta_6 LIB \\ & + \beta_7 LABOR + \beta_8 MEM + \beta_9 PYIELD + \beta_{10} PGHG + \beta_{11} MEA \\ & + \beta_{12} TRAIN + \beta_{13} DOUB + \beta_{14} TRI + u \end{aligned} \tag{2}$$

where *Y* is the acceptability of the mitigation technique; *AREA* is the planted area; *EXP* is the experience; *OWN* is the land owner; *SIZE* is the land size; *INC* is the farmer´s income; *LIB* is liability; *LABOR* is the amount of labor; *MEM* is the membership of the environment group; *PYIELD* is the perception of yield; *PGHG* is the perception of GHG emissions; *MEA* represents government measures; *TRAIN* represents attendance at training; *DOUB* is the double cropping system; *TRI* is the triple cropping system; and μ is the error term.

Table 2. Definition and descriptive statistics of variables used in the MNL model.

Variable	Description
Planted area	Dummy, 1 if the farm is located in a rain fed area; 0 irrigated area
Experience	Continuous, rice cultivation experience of farmer (years)
Land owner	Dummy, 1 if the farmer is a land owner; 0 otherwise
Land size	Continuous, size of plantation (ha)
Farmer income	Continuous, farmer income from in-farm and off-farm (THB year^{-1} household^{-1})
Farmer liability	Continuous, farmer liability from formal and informal financial institutions (THB household^{-1})
Number of labor	Continuous, number of laborers in the household (persons)
Membership of environment group	Dummy, 1 if the farmer is the member of an environmental group or institution; 0 otherwise
Perception on yield	Dummy, 1 if the farmer's perception is that the mitigation technique will increase the rice yield; 0 otherwise
Perception on GHG emissions	Dummy, 1 if the farmer thinks that the mitigation technique can reduce GHG emissions; 0 otherwise
Perception on measures	Dummy, 1 if the farmer's perception is that the mitigation technique will be supported by government agencies; 0 otherwise
Attendance in training	Dummy, 1 if the farmer had attended the training about the impact of climate change impact on the environment; 0 otherwise
Double cropping system	Dummy, 1 if the farmer practices as usual the double cropping system; 0 otherwise
Triple cropping system	Dummy, 1 if the farmer practices as usual the triple cropping system; 0 otherwise

3. Results and Discussion

3.1. Cost of Rice Production under BAU and Mitigation Techniques

Marked significant differences in costs between irrigated and rain-fed areas were revealed using the t-test ($p < 0.05$). The average production costs under BAU were 27,521 and 24,240 THB ha^{-1} for irrigated and rain-fed areas, respectively. Using cost structure analysis, the average variable cost was 22,375 THB ha^{-1}, consisting of an average labor cost of 11,918 THB ha^{-1} and an average material cost of 10,456 THB ha^{-1}, while the average fixed cost was 4213 THB ha^{-1}. Furthermore, a lack of laborers and water for planting were the outstanding factors increasing the production costs. The average rice yields were 5.58 and 4.58 tons ha^{-1} for irrigated and rain-fed areas, respectively. The net profit in irrigated areas was higher than that in rain-fed areas, being 34,079 and 32,960 THB ha^{-1}, respectively.

This study found that when implementing the MD technique, the average cost of rice production was 30,100 and 29,662 THB ha^{-1} for irrigated and rain-fed areas, respectively. Rain-fed areas were associated with higher average production costs than irrigated areas, about 2840 THB ha^{-1} or double the increase in costs. Comparing the cost of water source distance, farmers who owned their surface pond or artesian well, implementing MD, would face average costs 1946 THB ha^{-1} higher than those for BAU. Meanwhile, at distances of 100 and 50 m from the water sources, the costs would be 6843 and 5584 THB ha^{-1}, respectively. Consequently, this study reflects that the cost of implementing MD is reduced by 28–35% if farmers own their own surface pond or artesian well for cultivation, while the average cost will be higher with increasing distance to the water source.

To implement the AS technique, the average production costs were 28,985 and 25,998 THB ha^{-1} for irrigated and rain fed-areas, respectively. An interesting point is that organic farmers following the AS technique can reduce their costs by about 645 and 863 THB ha^{-1} for irrigated and rain-fed areas, respectively, due to their lower costs for chemical fertilizer application under the BAU case.

Therefore, if organic farmers switch from using urea to ammonium sulfate, their average costs will be reduced as well. A cost-benefit analysis showed that organic rice farming could generate higher net profits than conventional farming, of about 437 and 289 THB ha^{-1} for irrigated and rain-fed areas, respectively. Consequently, to effectively implement the AS technique, organic fertilizer should be applied in combination to further reduce costs and increase net profit while not affecting rice yields.

For SSNM, the average production costs were 26,450 and 23,354 THB ha^{-1} for irrigated and rain-fed areas, respectively. Following this technique, farmers could achieve reductions in the average production cost compared with BAU of 1068 and 885 THB ha^{-1} for irrigated and rain-fed areas, respectively. The average production costs in irrigated areas were about 182 THB ha^{-1} lower than those in rain-fed areas, as lower amounts of chemical fertilizer were applied under BAU conditions.

Comparing the cost of BAU and using mitigation techniques for both irrigated and rain-fed areas, performing SSNM can reduce the average production costs compared with BAU. However, MD and AS resulted in higher production costs than BAU. Overall, the average production costs were higher in irrigated areas than in rain-fed areas. This result reflects that the average production costs are higher when farmers own more land for growing rice, but this higher average cost tends to decrease when farmers adapt their rice cultivation behavior by adopting the option that has lower costs than BAU, without reducing the rice yields.

3.2. GHG Emissions, Abatement Potential, and AAC Under BAU and Mitigation Techniques

The results of estimates of GHG emissions, abatement potential, and AAC between BAU and the different mitigation techniques are presented in Table 3 and Figures 2 and 3. There were highly significant differences in the first and second cultivations between irrigated and rain-fed areas and for each technique. These results reflect the fact that MD is more appropriate for implementation in irrigated rather than rain-fed areas and more appropriate for the second rice cultivation than for the first cultivation. The AS technique led to a higher abatement potential for the second rice cultivation than for the first one. Meanwhile, SSNM generated a 42.6% higher abatement potential for the second rice cultivation than for the first one, with a 9.8% lower AAC for irrigated than rain-fed areas. However, among all techniques, SSNM was the most appropriate one because its AAC was lower than that for BAU, and it had a 60.2 and 58.1% higher abatement potential than MD and AS, respectively.

Table 3. Average abatement cost (AAC) using different mitigation techniques (Authors own calculation).

	GHG Emissions under BAU (kgCO_2eq ha^{-1})	GHG Emissions under Mitigation Technique (kgCO_2eq ha^{-1})	Abatement Potential (kgCO_2eq ha^{-1})	Abatement Cost (THB ha^{-1})	AAC (THB kgCO_2eq^{-1})
MD technique					
1st rice					
Irrigated	3549	3411	138	7372	53
Rain-fed	3214	3089	125	8975	71
2nd rice					
Irrigated	2767	2590	176	7960	45
Rain-fed	2185	2046	139	9663	69
AS technique					
1st rice					
Irrigated	3549	3403	146	3405	23
Rain-fed	3214	3062	151	3002	19
2nd rice					
Irrigated	2767	2618	148	3641	24
Rain-fed	2185	2022	163	3499	21
SSNM technique					
1st rice					
Irrigated	3549	3276	273	−4718	−17
Rain-fed	3214	2888	326	−3747	−11
2nd rice					
Irrigated	2767	2269	497	−6600	−13
Rain-fed	2185	1828	357	−5738	−15

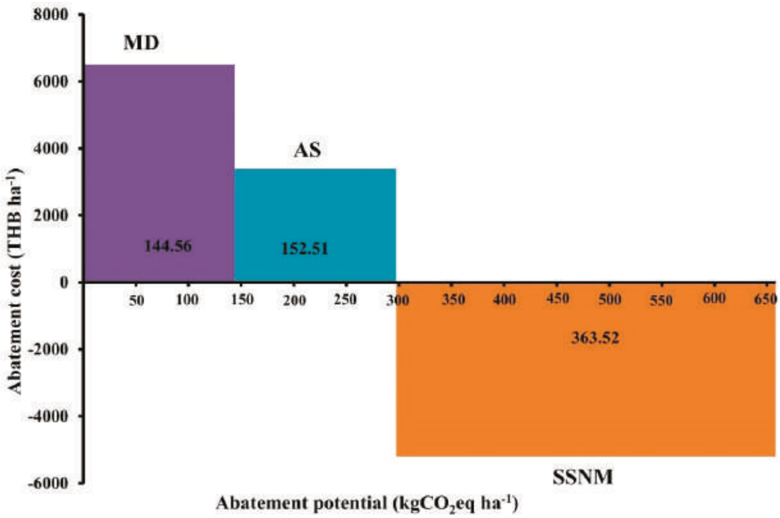

Figure 2. Comparison between abatement cost and abatement potential for each mitigation technique (Authors own calculation).

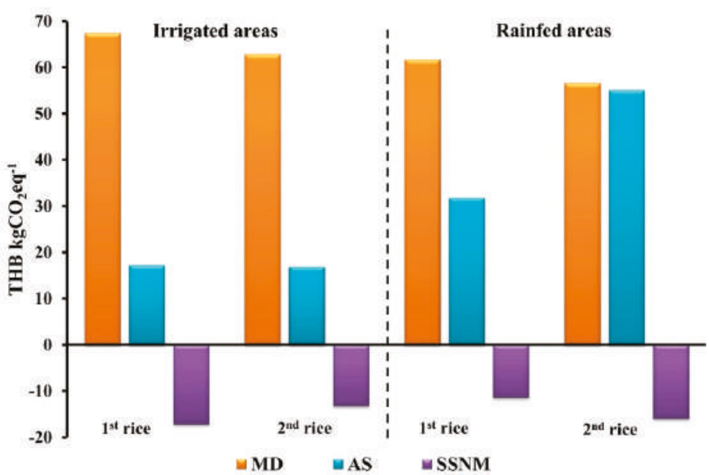

Figure 3. Average abatement cost (AAC) under BAU and using mitigation techniques (Authors own calculation).

3.3. Farmers' Assessment on Mitigation Techniques and Barriers

In the survey, farmers were requested to indicate their opinion on all mitigation techniques. Farmers' assessments across multiple criteria and the total score of each mitigation technique are provided in Table 4. As a result, the SSNM technique was the most favored one and presented the highest score, followed by MD and AS, respectively. The criteria of effectiveness, flexibility, economic efficiency, and institutional compatibility indicated the highest score regarding the SSNM technique. This is in line with Dobermann et al. [58], who reported that the higher benefit for farmers from the implementation of nutrient management strategies can increase the profitability of rice cropping, enhance socio-economic conditions, and mitigate labor shortage. Moreover, efficient nutrient management can also result in environmental benefits through a reduction of chemical fertilizers without a reduction in yield [59]. The criteria "easy to implement" and "ability to trial" were implementing the MD technique because it is easy to drain the water out of the rice field, but farmers need reliable control over irrigation water to implement this technique, otherwise rice yields are impacted. On the other hand, the AS technique obtained the lowest scores for the criteria "economic efficiency", "easy to implement", and "institutional compatibility".

Table 4. Summary of farmers' assessment with multiple criteria evaluation of each mitigation technique (Authors own calculation).

Assessment Criteria	Mitigation Techniques		
	MD	AS	SSNM
Effectiveness	542	393	588
Flexibility	317	446	565
Economic efficiency	376	201	603
Farmer implementability	496	233	468
Ability to trial	510	420	464
Institutional compatibility	495	233	570
Total score	**2736**	**1926**	**3258**

The scale used for scoring is presented in Table 4; green reflects low scores, while red reflects high scores.

The percentage of farmers ranking the mitigation techniques for each criterion, indicating the level of agreement, across the survey is provided in Table 5. The SSNM technique was the technique most favored by the farmers, with 86.5% indicating that they strongly agreed with the highest economic efficiency compared with other mitigation techniques, while only 13.5% of farmers indicated that they strongly agreed that this technique is easy to implement. Indeed, 4.5% of the farmers considered its "ability to trial" as very poor. Similarly, Chinese farmers willing to adopt low-carbon technology when the expenses of required inputs increase less after application [60]. In terms of the MD technique, 50% of the farmers strongly agreed with "effectiveness", followed by "institutional compatibility" (43.6%), "farmer implementability" (41.7%), and "ability to trial" (40.4%). However, 87.8% and 17.9% of farmers considered "flexibility" as poor and "economic efficiency" as very poor, respectively. Further, 32.1 and 10.9% of farmers evaluating the AS technique selected very good in terms of "flexibility" and "ability to trial". On the other hand, 71.2% of the farmers considered "economic efficiency" of the AS technique as very poor.

Table 5. The percentage of farmers showing a score of the level of agreement for each criteria (Authors own calculation).

Criteria/Rank	Mitigation Techniques											
	MD				AS				SSNM			
	1	2	3	4	1	2	3	4	1	2	3	4
Effectiveness	0	2.6	47.4	50.0	10.9	32.1	51.3	5.8	0	0	23.1	76.9
Flexibility	4.5	87.8	7.7	0	3.8	38.5	25.6	32.1	0	2.6	39.1	58.3
Economic efficiency	17.9	41.0	23.1	17.9	71.2	28.8	0	0	0	0	13.5	86.5
Farmer implementability	9.0	5.8	43.6	41.7	50.6	49.4	0	0	0	4.5	82.1	13.5
Ability to trial	1.3	10.9	47.4	40.4	2.6	36.5	50.0	10.9	4.5	16.7	17.9	60.9
Institutional compatibility	0	26.3	30.1	43.6	34.0	54.5	11.5	0	0	0	34.6	65.4

The scale used for scoring is presented in Table 5; green reflects low scores, while red reflects high scores.

When the farmers were asked to select one technique, 58.87% of the respondents were willing to implement SSNM, 29.29% AS, and 11.84% MD. Farmers in irrigated areas were most willing to perform SSNM, followed by AS and MD. In contrast, farmers in rain-fed areas were most willing to operate via SSNM, followed by AS, similar to those in irrigated areas, but no farmers were willing to implement

MD. As a result, we suggest that state policies should encourage SSNM in both irrigated and rain-fed areas as a practice that can result in lower fertilizer use. However, the relative willingness, beliefs, attitudes, and perceptions concerning such choices are indicators of the future likelihood to adopt a certain practice, which have also been described by McCown [61], Morton [62], and Jones et al. [63].

The reasons for the unwillingness to implement MD were water shortage, fear of increased weeds and pests, worries about nutrient losses, potential declines in rice yield, and a perception of MD being time-consuming, labor-consuming, and requiring more investment. Concerning the AS technique, farmers were worried about lower yields when not using urea, as they believe that urea contributes to greater yields, and there was a lack of knowledge about implementing the use of ammonium sulfate. Farmers unwilling to implement SSNM were concerned about yield decrease and felt that SSNM is time-consuming and complex. They also reported a lack of knowledge to support the use of soil analysis and high expenditures on soil analysis as matters of concern.

3.4. Factors Determining Farmers' Decisions

The results of the MNL model are presented in Table 6. The variables that were highly significant in the allocation of the farmers' decisions concerning each mitigation technique were as follows: (i) planted area; (ii) land size; (iii) farmer liability; (iv) farmer's perception of yield; and (v) farmer's perception of GHG emissions. Multicollinearity was checked among independent variables. The variance inflation factor (VIF) for all independent variables ranged from 1.108 to 1.265 (VIF < 5), which means that multicollinearity should not be a serious concern in this regression ($p < 0.01$).

Table 6. Estimated marginal effects of the farmers' decision to use the mitigation technique.

Variable	Mitigation Technique		
	MD	**AS**	**SSNM**
Planted area	−0.246 ** (0.0732)	−1.082 *** (0.153)	0.381 *** (0.022)
Experience	0.00384 (0.00492)	0.00376 (0.00348)	0.00743 (0.00315)
Land owner	0.00485 (0.0105)	0.0255 * (0.00503)	0.0466 * (0.0062)
Land size	−1.208 *** (0.0632)	−0.00478 (0.00255)	0.050 * (0.0260)
Farmer income	0.164 ** (0.00478)	0.403 ** (0.00455)	0.365 ** (0.00173)
Farmer liability	−0.411 * (0.00251)	−0.548 *** (0.000751)	0.332 *** (0.000177)
Number of labor	0.0301 (0.0137)	0.00428 (0.00199)	0.0676 (0.00295)
Membership of environment group	0.0446 (0.00662)	0.0507 (0.00227)	0.215 ** (0.00351)
Perception on yield	−0.0643 * (0.0338)	0.0661 (0.0255)	0.332 *** (0.00708)
Perception on GHG emissions	−0.0162 (0.0582)	−0.314 ** (0.0122)	−0.209 *** (0.00314)
Perception on measures	0.00944 (0.0132)	0.0407 (0.00671)	0.00194 (0.0118)
Attendance in training	0.0552 (0.00831)	0.0253 (0.0448)	0.0158 ** (0.00257)
Double cropping system	0.0308 (0.000744)	−0.206 ** (0.00678)	0.0321 (0.0186)
Triple cropping system	−0.0269 (0.00731)	0.0316 (0.0733)	−0.00736 (0.00228)
Constant	122461.72 ** (13562.15)	140939.82 ** (18953.05)	−159005.10 *** (10535.43)
Observations	156	156	156

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; SE in parentheses.

In the area studied, a great number of rice fields are located in rain-fed areas. The negative coefficient for rain-fed areas for MD and AS implies that these techniques are considerably less likely to be implemented in rain-fed areas compared with the irrigated areas, or not implemented at all. The reason is that when implementing MD in rain-fed areas, it is difficult to drain water into rice fields after it has been drained out, resulting in higher costs. Similarly, in terms of the AS technique, the farmers felt unaccustomed to the use of ammonium sulfate fertilizers. If adopting AS, farmers face higher costs as more ammonium sulfate fertilizer is required to maintain the same level of nutrients while possibly achieving lower yields. On the other hand, SSNM has a positive and significant influence when implemented, and it is highly likely that farmers will implement this technique.

Land size is an important factor influencing farmers' decisions in terms of various mitigation techniques. Land size had a negative and significant influence on MD, which probably means that the larger the land, the less likely the farmers are to implement MD. The same is true for AS, which can generate higher production costs in water and chemical fertilizer management. In contrast, farmers who owned more land were interested in SSNM because of its obvious cost savings. However, farmers with large areas of land were also worried about high expenses for soil characteristics analysis.

Of the significant variables, farmer liability had a positive influence favoring SSNM, while having a negative influence towards AS. Therefore, farmers with greater liabilities were interested in low-cost techniques and may reject high-cost techniques.

The effect on rice yield of each mitigation technique was the priority of the farmers. Consequently, farmers' perception of yield was one of the significant variables influencing their decision making. The results show that farmers' perception of yield had a positive and significant influence favoring SSNM. It can be inferred that farmers perceived that implementing SSNM could increase their yields, so they decided to use it.

Farmers' perception of GHG emissions had a negative and significant influence favoring SSNM and AS, meaning that farmers perceived that implementing SSNM and AS techniques would reduce GHG emissions, which was particularly the case for SSNM. Likewise, MD had a negative but non-significant influence, which might be because most farmers still do not have sufficient knowledge about the mitigation potential of each technique. It should be noted that relevant and responsible organizations should encourage and provide knowledge on GHG reduction techniques. Sources of information, including extensions, workshops, and training can enhance the adoption of a certain technology [30]. However, there are several farmers who have less chances for training, probably due to a limitation of time and budget. Therefore, participatory action research should receive more attention both from research-funding organizations and researchers to support collaborations among academicians, local authorities/leaders, and farmers [64]. This would increase the effectiveness of transferring knowledge, the sharing of knowledge and experiences, and could serve as a means to raise awareness about the positive effects of mitigation techniques.

3.5. Prioritizing Incentive Measures for the Adoption of Mitigation Techniques

Understanding farmers' decision-making behavior regarding their current practices is important and must be based on the knowledge of why farmers reject or accept different techniques [65]. Based on the results of the field survey and the in-depth interviews, three incentive measures were important from the point of the view of farmers: (1) cash incentives from governmental agencies to convince farmers to adapt their practices; (2) assistance for cost reduction—seed support and soil property analysis; and (3) support for water system development for agricultural activities—digging ponds and drilling wells near rice fields. The classification of farmers' characteristics for prioritizing supporting measures were identified as follows.

3.5.1. Planted Area

Farmers in irrigated areas rated cash incentive measures as the highest priority, while farmers in rain-fed areas were more concerned about supports for water system development.

3.5.2. Land Size

According to land tenure, farmers could be grouped as: (1) small land owners (1.3–6.5 ha); (2) medium land owners (6.6–11.6 ha); and (3) large land owners (11.7–16.8 ha). Medium land owners rated supports for water system development as the highest priority, while small and large land owners rated assistance with cost reduction as their major concern.

3.5.3. Farmer Income

Farmers could be categorized into three groups based on their income: (1) low-income farmers (52,800–128,000 THB year^{-1} household^{-1}); (2) medium-income farmers (128,001–203,200 THB year^{-1} household^{-1}); and (3) high-income farmers (203,201–278,400 THB year^{-1} household^{-1}). Farmers with medium and high incomes rated support for water system development as the first priority, followed by assistance with cost reduction and cash incentive measures. For farmers with low income, cash incentive measures were most important, because this measure had a direct impact on their income and expenses for implementing GHG mitigation techniques.

3.5.4. Farmer Liability

Regarding the levels of liability, there were three groups of farmers: low liability (58,400–538,933 THB household^{-1}), medium liability (538,934–1,019,467 THB household^{-1}), and high liability (1,019,468–1,500,000 THB household^{-1}). Low liability farmers mainly highlighted support for water system development, while medium liability farmers stressed assistance with cost reduction. High liability farmers highly valued cash incentive measures due to their direct and immediate impact on income. Farmers with low or medium liability gave higher priority to investment in their land (seeds, soil property analysis, and water sources).

3.5.5. Number of Laborers in a Household

According to the number of household members, farms were grouped into low-labor households (1–3 persons) and high-labor households (3–5 persons). Low-labor households made seed support a higher priority than high-labor households. This was because most low-labor households conducted their agricultural activities on smaller areas, so seed support and soil property analysis could greatly help to reduce their production costs. High-labor households prioritized support for water system development, because potential improvements in their water systems could allow them to increase their agricultural activities and gain more income.

3.5.6. Cropping System Pattern

Farmers using a double cropping system preferred support for water system measures, followed by cash incentives and assistance for cost reduction measures. This was because although the farmers' way of making a living in Thailand was based on rice cultivation, these farmers had limited water sources, so they selected crop rotation, which requires less water during the dry season. This could also reduce the cost of water management for agricultural activities. Among farmers using a triple cropping system, assistance for cost reduction measures was the first priority as it reduces the costs of seeds and soil property analysis.

The outstanding point was that cash incentives can be appropriate for low-income farmers or small land owners, who have fewer opportunities to increase their income and need more assistance. These farmers obviously considered subsidies are the priority. Besides, small land owners also placed emphasis on developing their land to be more appropriate for agricultural activities, as their main income relies on their land. On the other hand, high-income farmers and large land owners were aware of other alternatives to increase their income, whether from rice grain or crop rotation. Farmers with medium incomes or medium land owners were more concerned about water system development for agricultural activities than the other groups, because having enough water could lead to greater income and increased crop production efficiency [66]. For farmers with high liabilities, subsidies were of greater concern than for farmers with low or medium liabilities due to their direct and immediate effect on income.

4. Conclusions

Site-specific nutrient management (SSNM) was evaluated as the highest abatement potential (363.52 kgCO_2eq ha^{-1}), the negative value of abatement cost ($-$2565 THB ha^{-1}), and the negative value of the average abatement cost ($-$14 THB kgCO_2eq^{-1}). Based on farmers' assessment to be a mitigation technique for rice cultivation, SSNM reached the highest score for effectiveness, flexibility, economic efficiency, and institutional compatibility. This indicated that SSNM was obviously preferable and presented the highest scores for farmer acceptability, followed by the replacement of urea with ammonium sulfate ($(NH_4)_2SO_4$) and mid-season drainage. Irrigation systems, land size, farmers' liability, and perception of yield and GHG emissions were found as the main factors affecting the farmers' decision to accept the mitigation techniques. Therefore, incentive measures, such as subsidies or cost-sharing measures can convince farmers to adopt new techniques and enhance their practices. More support of water system development can increase their availability.

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Farmers' Net Income Distribution and Regional Vulnerability to Climate Change: An Empirical Study of Bangladesh

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Abstract: Widespread poverty is the most serious threat and social problem that Bangladesh faces. Regional vulnerability to climate change threatens to escalate the magnitude of poverty. It is essential that poverty projections be estimated while bearing in mind the effects of climate change. The main purpose of this paper is to perform an agrarian sub-national regional analysis of climate change vulnerability in Bangladesh under various climate change scenarios and evaluate its potential impact on poverty. This study is relevant to socio-economic research on climate change vulnerability and agriculture risk management and has the potential to contribute new insights to the complex interactions between household income and climate change risks to agricultural communities in Bangladesh and South Asia. This study uses analysis of variance, cluster analysis, decomposition of variance and log-normal distribution to estimate the parameters of income variability that can be used to ascertain vulnerability levels and help us to understand the poverty levels that climate change could potentially generate. It is found that the levels and sources of income vary greatly among regions of Bangladesh. The variance decomposition of income showed that agricultural income in Mymensingh and Rangpur is the main cause of the total income difference among all sources of income. Moreover, a large variance in agricultural income among regions is induced by the gross income from rice production. Additionally, even in the long run the gradual, constant reduction of rice yield due to climate change in Bangladesh is not a severe problem for farmers. However, extreme events such as floods, flash floods, droughts, sea level rise and greenhouse gas emissions, based on Representative concentration pathways (RCPs), could increase the poverty rates in Mymensingh, Rajshahi, Barisal and Khulna—regions that would be greatly affected by unexpected yield losses due to extreme climatic events. Therefore, research into and development of adaptation measures to climate change in regions where farmers are largely dependent on agricultural income are important.

Keywords: income distribution; cost distribution; vulnerable region; adaptation measures; Bangladesh

1. Introduction

Bangladesh has experienced severe famines [1–3]. However, heavy investments in agriculture following these famines have given rise to enhanced food production and have caused significant increases in domestic rice production [4,5]. Both the cultivation techniques and cropping patterns relating to rice production have gradually changed in terms of yield potential [6,7]. Despite huge population pressures, the country has reached self-sufficiency in rice production [8–10]. Additionally, Bangladesh's economic situation is improving; as such, it is one among a rather small group of countries that have seen remarkable progress in terms of both economic performance and development indicators [11]. However, poverty remains a critical social concern in this country [6,12,13].

Climate change will have a largely adverse impact on agricultural production in Asia [14]. For particular geographical locations and due to other environmental reasons, Bangladesh is one of the world's most disaster-prone countries [15–18]. Given climate change impacts, natural resource constraints and competing demands, agriculture and food systems continue to face considerable challenges. The livelihoods of the poor who are directly reliant on agriculture already face a profound threat due to the current climate change in Bangladesh [19,20], which could lead to increased pauperization. At the household level, climate change significantly affects food production [21] which in turn influences food prices and directly affects the poverty of low-income household [22,23]. Agricultural income and non-farm income are the most significant factors in poverty reduction among rural people [24–27]. However, Chaudhry and Wimer reported that household income plays a vital role in the social and economic development of a community and income from agriculture might result in increasing per capita income [28].

Agriculture is strongly influenced by weather and climate, which in turn have impacts on agricultural production [29]. Over the last three decades, temperature has been increasing in Bangladesh [30,31] and the average daily temperature is predicted to undergo an increase of 1.0 °C by 2030 and 1.4 °C by 2050 [32,33]. The annual rainfall is also unevenly distributed in some areas of Bangladesh. Rainfall patterns might change with increasing temperature and drought occur in some areas; however, total rainfall sometimes increases and heavy rainfall induces floods in Bangladesh. Increasing temperature also enhances extreme events, such as cyclones in coastal areas and adversely affects rice production [7,30,34–36]. Additionally, climate change is projected to affect agriculture and it is very likely that climate change will induce significant yield reduction in the future due to climate variability in Bangladesh [37–39], with a projected decline of 8–17% in rice production by 2050 [33,40]. In Bangladesh, nearly 80% of the total cropped area is dedicated to rice production, accounting for almost 90% of total grain production [39,41–46]. Agricultural production, farm income and food security are significantly affected by seasonal growing temperatures [47].

Some previous studies have projected the impacts of climate change on food production and national food security [48,49], as well as their impact on agricultural production, by collecting information under drought, rainfall, sea level rise, flood and temperature increases [39,43,50] and the impact of coastal flooding on rice [7,51,52]. However, there have been fewer studies from micro or regional points of view based on integrated household survey data or poverty measurements under yield reductions of crops due to climate change vulnerabilities. Farmers' low incomes are the main reinforcing factors in poverty traps, so this context of research is not sufficient. To consider suitable adaptation technologies and policies for farmers, impact projections in terms of regional characteristics and poverty are needed far more. To alleviate the severity of climate change's impact on farm production and poverty, adaptation strategies, such as new crop varieties, changing planting times, homestead gardening, planting trees and migration, are vital approaches [6]. Furthermore, research that projects climate change's impacts on poverty or that pinpoints especially vulnerable regions and the vulnerability of farm household income under the impact of climate change is still needed [53,54]. Using statistical analysis, the current study attempts to derive an understanding of regional characteristics in terms of income and agriculture and to assess the contributions of different components on the observed total variance of income and cost, with an eye towards determining regional vulnerability to climate change and projecting the potential effects of climate change on poverty in Bangladesh. In this study, we used high-quality plot-level agricultural production data from the nationally representative survey by the International Food Policy Research Institute (IFPRI) (Appendix A.1). We used different analytical techniques to evaluate regional characteristics and to assess the potential climate change impacts on farm production and poverty under newly developed representative concentration pathways (RCPs) and other climate scenarios. The objective of this study was to project the poverty under the impacts of climate change on crop production and to provide possible adaptive measures.

The paper is designed as follows: we draw a review of the related literature concerning climate change, vulnerability and poverty in Section 2; Section 3 is the methodology section, in which we describe the data sources, compilation procedures and the analytical approaches of the data; in Section 4, descriptive statistics and empirical results of the analysis with discussion are presented; and in Section 5, we conclude by emphasizing the future research directions and some policy guidelines.

2. Review of the Literature

The research on climate change scenarios and poverty in terms of regional characteristics is outlined concisely in this section. Climate change is a reality that is occurring and will increasingly affect the poor; moreover, it is a serious threat to poverty eradication [55]. Poor agricultural communities are always disrupted by climate change's impact on household food security and poverty [56,57]; climate change impacts could increase household poverty [55]. Poverty as a dynamic and multidimensional condition is characterized by the interaction of individual and community features, socioeconomic and political issues, environmental processes and historical circumstances. Particularly in less developed countries and regions through several direct and indirect channels, climatic variability and change can worsen poverty [58]. Lade et al. reviewed the socio-ecological relationship in rural development concepts, emphasizing the economic, biophysical and cultural aspects of poverty. This study classified the poverty alleviation strategies and developed multidimensional poverty trap models and it stated that interventions that ignore nature and culture can reinforce poverty [59].

A multi-factor impact analysis framework was developed by Yu et al. [39] and using this framework [50] Ruane et al. provided sub-regional vulnerability analyses and quantified key uncertainties in climate and crop production. Climate change impacts increase under the higher emissions scenarios and agriculture in Bangladesh is severely affected by sea level rise [50]. Over the same period, several attempts have been made regarding climate scenario development in Bangladesh, mainly using Global Climate Models (GCMs) and in some cases Regional Climate Models (RCMs) [60–62]. From these studies, the overall conclusions include increases in temperature and rainfall, different drought seasons and impacts on crop production.

The projected future yield of rice cultivars in 2030 and 2050 in different areas of Bangladesh by DSSAT crop modelling showed that Bagerhat, Dinajpur, Gaibandha, Maulvibazar, Panchagarh, Rangpur, Sirajganj and Thakurgaon districts will have high yield losses due to climate change impacts. Rainfall, temperature and CO_2 affect the yield for *aman* rice in Rangpur and Khulna divisions and for *boro* rice in Rajshahi, Barisal and the southwest region [63]. Changing patterns of rainfall and temperature in different regions of Bangladesh are significantly higher, compared to IPCC predictions. For sustainable adaptation, location-specific management of seed, crop and irrigation is needed [21]. Soil tolerance, flood tolerance and shorter varieties of rice and other crops could be used to adapt to climate change impacts [64]. Climate change is likely to have an adverse effect on rice and wheat production [5] and significant yield reductions in the future due to climate variability [38] are also directly associated with extreme weather events [19]; due to population pressures, future food production is a challenge in maintaining food security in Bangladesh [5]. Food demand changes because of urbanization, population structure, among other factors; however, food supply can change due to extreme climate change impacts on agricultural production in Bangladesh. The combined effects on rice of major climatic variables were checked by Karim et al. and they found that rice yield would decrease by 33% in both 2046–2065 and 2081–2100 for Rangpur, Barisal and the Faridpur region [65].

Total annual income of a farm household depends on farm and non-farm income. Farm income is always unstable due to the dependency of weather and even if farm income is high poverty may occur;

however, higher non-farm income could reduce the poverty [28]. Farm households in Bangladesh are the most prone to the impacts of climatic hazards. Uncertainty is high in farm income and it depends on the wide fluctuations of yields and prices. Unexpected weather can easily damage crop production, rendering farms more vulnerable [66]. In Bangladesh, farmers are fully dependent on weather for their crop production, resulting in lower farm income if extreme climatic events occur. Unexpected yield reductions cause fluctuating farm income and increase food insecurity and poverty. Agriculture is the main source of income of farmers in Bangladesh [8,21] and it might cause per capita income to increase, which in turn could further reduce poverty. The participation of government programs and off-farm income is significantly important in reducing poverty [24].

There has been much research on climate change impacts, adaptations and projections in agriculture. The IPCC's fifth assessment report showed that food production in Asia will vary and decline in many regions under the impact of climate change [37]. Rajendra et al. focused on climate change impacts on farming in northern Thailand, where the vulnerability of farm households persists under the negative impact of climate change [54]. Yamei et al. assessed the adverse effects of future climate on rice yields and provided potential adaptive measures [67]. Nazarenko et al. examined the climate response under a representative concentration pathway (RCP) for the 21st century [68], while there are fewer comprehensive scenarios for the whole country regarding farm income and poverty projections.

In addition, in-depth empirical research on farm income distribution and regional vulnerability to climate change has been lacking. Furthermore, most of the previous studies of climate change impacts on agricultural production have been for specific regions. However, a comprehensive study of climate change impacts comparing the regions of Bangladesh could be enormously significant. One of the motivations of the study is to summarize the farmers' net income scenarios for all of the regions of Bangladesh, assessing the contributions of different components on the observed total variance in income and costs and possible poverty under climate change impacts on agricultural production. Moreover, understanding farmers' local economic situations and coping strategies with climate change impacts could have immense significance for regional point of view. Based on actual farm income, this study evaluates the projected farm income under the scenario that extreme climatic events occur. It then determines the projected poverty to identify vulnerable regions and to suggest appropriate coping and poverty alleviation strategies.

3. Methodology

3.1. Survey Data

In its empirical analysis, this study uses cross-sectional data drawn from nine administrative regions across Bangladesh. These data were derived from the International Food Policy Research Institute (IFPRI), which adopted a multi-stage stratified random sampling method to collect primary data: first a selection of primary sampling units (325 villages) and then a selection of farm households (20 farms) from each primary sampling unit. Randomly selected villages with probability proportional to size (PPS) sampling using the number of households from the Bangladesh population census data in 2001. Randomly selected 20 farm households in each village from the aforementioned national census list. IFPRI researchers designed the Bangladesh Integrated Household Survey (BIHS) (Appendix A.1), the most comprehensive, nationally representative household survey conducted to date. Plot-wise crop production data were collected via semi-structured questionnaire by the IFPRI from 6503 sample farmers across Bangladesh vis-à-vis cultivated crops; the survey period was from 1 December 2010, to 30 November 2011. The original data were collected in a typical agricultural year according to rice production statistics; there was no severe crop loss in the 2010 or 2011 rice years in Bangladesh [69].

3.2. Data Compilation

This study models the poverty rate change under climate change vulnerability in different regions of Bangladesh. Based on the purpose of this study, to analyze the data we applied descriptive, inferential, statistical and multivariate techniques. Plot-wise raw data were compiled in line with the study objectives. We compiled data pertaining to many income sources for each separate household into some important sectors. In addition, for agricultural activities, we also compiled all types of input cost data into some important cost items and output values for each crop. We then compiled and combined them into one data set of households for all 6503 farms. Bangladesh consists of 30 agro-ecological zones (AEZs) that overlap with each other [69,70]. For the convenience of this research, some homogenous agro-ecological zones were combined into the nine administrative regions with their geographical locations. In this manner, we tried to develop nine mutually exclusive regions for our research. To overcome the resulting challenge in consistency under the same impact of climate change in each region [50], we categorized all the sample farmers per the nine administrative zones of Bangladesh, calling each a division (nine different colors indicating the individual divisions) (Figure 1): Barisal (700 sample farmers), Chittagong (300), Comilla (660), Dhaka (1380), Khulna (1020), Mymensingh (600), Rajshahi (580), Rangpur (543) and Sylhet (720).

Figure 1. Map of the objective regions of Bangladesh.

We estimated the costs and incomes associated with 17 major crops produced by farmers in Bangladesh (each is considered an important crop); other crops (such as pulses, oil seeds, spices except for chili and onion, vegetables, leafy vegetables, etc.) and all types of fruits (such as banana, mango, pineapple, jackfruit, papaya, guava, litchi, orange, etc.) were added to another group, "all other crops." The 18 groups are *aus* (Appendix **??**), rice local, *aus* rice LIV, *aus* rice HYV, *aman* rice local, *aman* rice LIV, *aman* rice HYV, *aman* rice Hybrid, T *aus* rice HYV, *boro* rice HYV, *boro* rice Hybrid, wheat local, wheat HYV, maize, jute, potato, chili, onion and all other crops.

To estimate per-capita income for farm household members in all nine administrative regions of Bangladesh, this study considers all income sources, including income from agriculture. The basic unit of analysis is each farm, while farming is the only significant source of income among other sources, such as employment, small business and so on, for the family in a one-year period. Net income for the farm household from agriculture was calculated by deducting total input costs from gross income:

$$\pi = \sum_i P_i Y_i - \sum_i \sum_j P_{ij} X_{ij} \quad (1)$$

where π is net income, P_i is price of crop i, Y_i is production of crop i, P_{ij} is price of input j for crop i and X_{ij} is input j for crop i.

This analysis used only the accounting costs to estimate net income from agriculture (Appendix B.1); these costs include the so-called explicit costs actually incurred by the farms and in surveys, farmers reported their own cost data. For this reason, this study regards supply of one's own land and family labor as part of agricultural income. The farm gate price of each crop for each household was used to estimate gross income derived from agricultural crops, livestock and poultry and fish production; additionally, actual input prices were used to estimate the production costs cited by each farmer and in-kind payments by crops are deducted for estimating gross income. For farmers with no information about farm gate prices or input prices for their respective crops, we used the average prices from the region. This study crosschecked the farm gate prices and input prices with data pertaining to the average national retail price data of select commodities in Bangladesh [71] during the aforementioned study period. Farmers used farm gate prices to sell their crops and for this reason, there was some divergence between national retail prices and the farmers' prices. To estimate per-capita income for each member of the farm, this study assumes that all negative returns tend towards zero so that we can calculate shares of income sources.

Income data were collected for each household and these data were used to calculate overall household income. Income was broadly classified into seven major sectors, as follows:

(i) Agricultural crop income: income from all crop types produced by farmers throughout the year;
(ii) Income from fish/shrimp farming;
(iii) Income from livestock and poultry enterprises;
(iv) Nonagricultural enterprise income: income from nurseries, food processing, fishing, nonagricultural day labor, retail, wholesale, construction, manufacturing, wooden furniture and other businesses;
(v) Remittances: remittances from within or outside Bangladesh, with the persons who sent the remittances excluded from their respective households;
(vi) Employment: both formal and informal employment, income from self-employed and/or owned businesses that are not agricultural, income received from relatives and friends not presently living with the household and so on; and
(vii) Other income: income received from land rent or property rent, income from life and nonlife insurance, profit from shares, gratuities, or retirement benefits, income from lotteries or prizes, interest received from banks, charity assistance, other cash receipts and/or other in-kind receipts.

These seven sectors of household income were used to determine the actual income and income sector shares, both of which reflect income distributions significantly.

3.3. Analytical Approach

This study used four types of statistical analysis.

3.3.1. Analysis of Variance (ANOVA)

After dividing farm households into the nine aforementioned regions, we conducted single-factor analysis of variance (ANOVA) to examine differences among the farm households of the nine regions in Bangladesh in terms of mean per-capita income.

3.3.2. Cluster Analysis

The cluster analysis (CA) technique was used to determine the main and dominant income sources in Bangladesh's various regions. Environmental (i.e., topographical) divergence is a common phenomenon in Bangladesh and it diversifies farm production, although farm households within a certain region do tend to be similar. Ward's hierarchical method and the partitioning method can be used to determine the most appropriate clusters regarding the main income sources in each region. A dendrogram—a graphical representation of the hierarchy of nested cluster explanations—is a manifestation of Ward's method and it provides clues for finding the preferable number of clusters regarding income sources.

3.3.3. Decomposition of Variances

To understand the interregional differences and to assess the contributions of different components to the observed total variance of input cost and income, different crop production data are used [72–75]. These data include per hectare crop yields, prices and all costs at the farm level and we decompose the variances in net cost and net income into different factors using the following relations.

$$\mathrm{V}(X \pm Y) = \mathrm{V}(X) + \mathrm{V}(Y) \pm 2\mathrm{Cov}(X, Y) \tag{2}$$

where X and Y are stochastic variables, such as the costs of inputs or incomes from different sectors; V $(\cdot)$ is variance and Cov $(\cdot)$ is covariance.

3.3.4. Projections: Log-Normal Distributions

There are different types of probability distributions studied in probability theory. Lognormal distribution is one of the most important one and was established long ago [76–78]. Lognormal distribution is a type of a continuous distribution. It is a probability distribution in which the logarithm of the random variable is distributed normally. This distribution is closely related to the normal distribution. Lognormal distribution is very commonly used in the social sciences, economics and finance [79].

Arata [80] pointed out that the income distribution among individuals is very important and is one of the main themes in economics. Income distribution is widely understood to be well described by a log-normal distribution.

Lognormal distribution has two parameters: mean (μ) and standard deviation (σ). If x is distributed log-normally with parameters μ and σ, then log(x) is distributed normally with mean μ and standard deviation σ. The log-normal distribution is applicable when the quantity of interest must be positive since log(x) exists only when x is positive. A positive random variable X is log-normally distributed if the logarithm of X is normally distributed.

$$ln(X) \sim N\left(\mu,\ \sigma^2\right) \tag{3}$$

Let Φ and φ be, respectively, the cumulative probability distribution function and the probability density function of the N (0, 1) distribution.

The probability density function of the log-normal distribution is;

$$f(x|\mu,\sigma) = \frac{1}{x\sigma\sqrt{2\pi}} exp\left\{\frac{-(lnx-\mu)^2}{2\sigma^2}\right\};\ x > 0 \tag{4}$$

If we substitute a poverty line into x and integrate the probability density function up to x, we can obtain a poverty rate. The poverty line, which is estimated by world Bank, is inserted into the equation [12,67].

We estimate the incomes of all sample families on the assumption of climate change impacts and draw the distribution of the estimated incomes, assuming that the distribution follows log normal distribution. To draw log normal distribution, we must find the mean and standard deviation of $ln(x)$ (Appendix B.2). From the actual per-capita income of household members in the study areas, we obtain the actual distribution of per-capita income using the lognormal distribution. Next, we project the crop yield loss from the assumption of the literature reviews and we estimate the projected per-capita income. From projected per-capita income using lognormal distribution, we obtain the estimated distribution of per-capita income. By simulating these two distributions, we find the poverty rate graph.

4. Results and Discussion

4.1. Comparison of Income Levels Among Regions

Agricultural income is a key driver in reducing poverty in Bangladesh, where it accounted for 90% of all poverty alleviation between 2005 and 2010 [81]. In terms of employment, Bangladesh's economy is primarily dependent on agriculture. Approximately 85% of the population is directly or indirectly attached to the agriculture sector [38,69].

Agriculture continues to be the main source of income in the sample households in all regions (Table 1) and this result is consistent with Hossain and Silva (2013) [5]. However, in all regions, nonagricultural profit and employment are important income sources and these results are consistent with Bangladesh Economic Review [45]. The amount of remittances varies by region: that in Sylhet is not the highest nationally but the people there do consider remittances to be the main income source in the region. The agricultural income is higher in Rajshahi than in other regions and the per capita income of this region per the study sample is US$ 423.6 (Table 2). Diversification of agricultural crops results in this region having highest income from agriculture.

Table 1. Each income sector's share in total household income (%), by region.

	B	CH	CO	D	K	M	RJ	RN	S	BD
Agril. crops	12.71	8.14	5.50	13.55	19.43	20.15	18.72	21.41	9.03	14.32
Main crops	6.08	2.89	2.34	8.25	10.81	11.44	11.72	14.84	6.15	8.36
Other crops	6.63	5.25	3.16	5.30	8.62	8.71	7.00	6.58	2.87	5.96
Fish	9.23	1.54	0.57	2.18	7.93	6.06	2.87	1.14	3.16	3.96
Livestock	2.19	1.17	1.48	3.60	6.15	5.12	4.43	3.10	1.80	3.47
Non-ag. profit	20.76	19.25	14.13	21.22	18.09	17.66	19.61	14.88	20.05	18.80
Remittance	11.04	24.99	41.48	15.68	7.64	9.11	4.48	7.58	17.77	15.22
Employment	38.91	44.35	30.80	41.10	38.52	39.04	38.83	50.54	44.02	40.10
Other income	5.16	0.55	6.04	2.66	2.23	2.86	11.06	1.35	4.18	4.12
Total	100	100	100	100	100	100	100	100	100	100

B = Barisal, CH = Chittagong, CO = Comilla, D = Dhaka, K = Khulna, M = Mymensingh, RJ = Rajshahi, RN = Rangpur, S = Sylhet, BD = Bangladesh, Main crops = *Aus*, *Aman* and *Boro* rice and other crops = Wheat, maize, jute, potato, chili, onion and so on.

Table 2. Mean, median and standard deviation of per-capita income (US$/yr), by region.

	B	CH	CO	D	K	M	RJ	RN	S	BD
Mean	308.93	336.75	378.35	362.17	369.84	307.63	423.63	308.76	301.63	327.55
Median	289.93	217.83	246.25	242.87	254.11	215.04	283.14	226.99	204.82	232.94
SD	314.75	418.11	314.22	403.66	382.81	278.08	372.71	246.61	301.02	348.64
PR	0.51	0.48	0.46	0.46	0.42	0.51	0.33	0.47	0.49	0.46

B = Barisal, CH = Chittagong, CO = Comilla, D = Dhaka, K = Khulna, M = Mymensingh, RJ = Rajshahi, RN = Rangpur, S = Sylhet, SD = Standard deviation and PR = Poverty rate.

Table 1 shows significant differences in main income sources among farmers in various regions in Bangladesh. Employment is the predominant income source in most regions, followed by nonagricultural profits and agriculture. The share of agriculture in total income varies by region. Among Bangladeshi farming households, the employment share is 40.10%, although the overall share of agriculture in total income is 14.32%. Rangpur has the highest share of agricultural income in total annual income (21.41%), followed by the Mymensingh region (20.15%). Comilla's share of remittances in total annual income was highest (41.48% of total income); in comparison, the share generated by agricultural crops in Comilla was only 5.50%. Currently, overseas workers are more often from the Comilla region than other regions in Bangladesh, with a significant proportion of them sending remittances, becoming a vital source of income in the Comilla region. Rice and other crops were the main sources of income among the sampled farm households in the study areas (Appendix C). Incomes from maize and potato appear to be growing but their respective shares remain small. There are regional land conditions and climate differences among Bangladesh's regions, so wheat, maize, onion and potato production is not familiar to all farmers. Consequently, farmers in all areas of Bangladesh tend to focus on rice cultivation.

Table 2 shows descriptive statistics of income status by region. Poverty rates were estimated by applying the poverty line and the purchasing power parity from the World Bank [22] to log-normal income distributions. The findings presented in Table 2 indicate differences in mean, median and standard deviation of net incomes among the nine regions in Bangladesh; using these findings, one can pinpoint relatively rich and poor regions.

In terms of mean net income, incomes of sampled farm households in Rajshahi are the highest, while those of Barisal, Mymensingh, Rangpur and Sylhet are lower. As some farmers had negative or zero per-capita income, the standard deviation is relatively large in certain regions. The highest standard deviation value is found in Chittagong (US$ 418.1), reflecting a large income gap among the farmers there.

The highest poverty rate (i.e., 0.51) was found in Mymensingh and Barisal (Table 2), while the lowest (i.e., 0.33) was in Rajshahi; overall, the country's upper poverty rate is 0.46. The rates in Chittagong and Sylhet were also relatively low (i.e., 0.49). The officially estimated upper poverty rate and national average poverty rate are both in the vicinity of 0.35 [12,82], which makes sense because the original data were collected from rural, farming-engaged people and excluded affluent or single urban people.

Among regions where the poverty rates were high, Barisal, Mymensingh and Sylhet had the lower mean incomes. In contrast, Chittagong had the highest standard deviation, compared to the other regions. In the regions of Barisal, Mymensingh and Sylhet, it appeared that the mean income level was low; however, in the other regions, the mean income was large. These results show that these low-income regions are vulnerable regions and should be the targets of farmers' support policies.

From results of Table 2, this study found that there are differences in mean, median and standard deviation of net incomes among the nine regions in Bangladesh and for validation of this difference, we perform ANOVA and report the results in Table 3. Analysis of variance (ANOVA) is a statistical test designed to examine means across more than two groups by comparing variances, based upon the variability in each sample and in the combined samples. We analyzed the variance within and between the sample farmers to determine the significance of any differences in per capita income of farm household members among the regions of Bangladesh. The results of the overall F test in the ANOVA summary shows the results regarding the variability of means between groups and within groups. As indicated, the overall F test is significant (i.e., p-value < 0.05), indicating that means between groups are not equal and it is statistically concluded that there have been significant differences among the regions in terms of mean per-capita income.

Table 3. ANOVA mean differences across regions.

Source of Variation	SS	df	MS	F	p-Value	F Crit
Between groups	6.31×10^{10}	9	7.01×10^{9}	4.757462	2.39×10^{-6}	1.880604
Within groups	1.91×10^{13}	12,996	1.47×10^{9}			
Total	1.92×10^{13}	13,005				

The first column in ANOVA provides us with the sum of squares between and within the groups and for the total sample farmers. The total sum of squares represents the complete variance on the dependent variable for the total sample. The second column represents the degrees of freedom, ($n - 1$). The total degrees of freedom represent 13,006 − 1 = 13,005; degrees of freedom between groups equals the number of groups minus one (10 − 1 = 9). The within groups degrees of freedom equals 13,005 − 9 = 12,996. The third (mean square) column contains the estimates of variability between and within the groups. The mean square estimate is equal to the sum of the squares divided by the degrees of freedom. The between groups mean square is 7.01×10^9; the within-groups mean square is 1.47×10^9. The fourth column, the F ratio, is calculated by dividing the mean square between groups by the mean square within the groups. The F ratio should be one if the null hypothesis is true, while both mean square estimates are equal. However, as shown in Table 3, larger F values (4.757462) imply that the means of the per capita income groups are greatly different from each other, compared to the variation in the individual sample farmers in each group. The next column is the significance level (p-value) and it indicates that the value of F ratio is sufficiently large to reject the null hypothesis. The significance level is 2.39×10^{-6}, which is less than 0.05. Therefore, the mean per capita incomes of sample households among the regions of the country were significantly different in the study year.

4.2. Regional Characteristics on Income Source

This section intends to classify regions of Bangladesh to determine the regional characteristics of income sources in each administrative region. Sectoral income shares from Table 1 are analyzed by cluster analysis and are shown in Figure 2. Here, a dendrogram depicts the income source relationships among the regions. The horizontal axis of the dendrogram (in Figure 2) represents the distance or dissimilarity between clusters and the vertical axis represents the objects (regions) of clusters. From the cluster analysis, this study attempted to find the similarity and clustering with the dendrogram, which visually displays a certain cluster shape. Regions that are close to each other (have small dissimilarities) are linked near the right side of the plot. In Figure 2, we note that Khulna and Mymensingh are very similar compared to the regions that link up near the left side, which are very different. For example, Comilla appears to be quite different from any of the other regions. The number of clusters formed at a particular cluster cutoff value can be quickly determined from this plot by drawing a vertical line at this value and counting the number of lines that the vertical line intersects. In this study, we can see that, if we draw a vertical line at the value of 18.0, four clusters will result. One cluster contains four regions, one contains three regions and two clusters each contain only one region, as shown in Figure 2, in which Barisal, Mymensingh, Khulna and Rajshahi are more alike than resembling Rangpur. In addition, Chittagong, Dhaka and Sylhet are more alike than resembling Comilla.

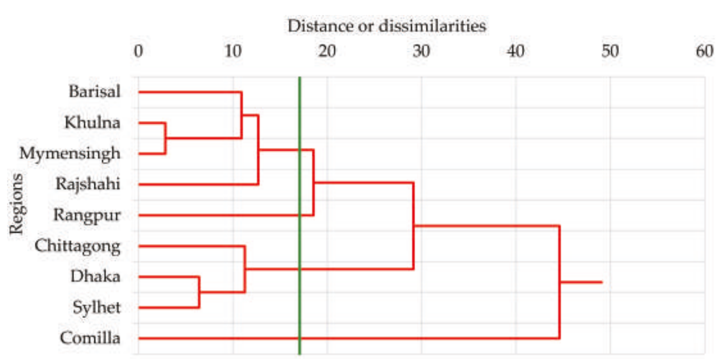

Figure 2. Dendrogram showing clusters for main income sources, by region.

Table 4 summarizes regional characteristics of income sources. Clusters 1 and 2 are largely dependent on agriculture. Clusters 3 and 4 are not largely dependent on agriculture. This result indicates the importance of agricultural research for clusters 1 and 2.

Table 4. Cluster characteristics of main income sources, by region.

Cluster	Region	Main Income Source	Distinction
1	Barisal, Mymensingh, Khulna, Rajshahi	Agricultural. crops, non-agricultural profit, employment	
2	Rangpur		Dominant Employment
3	Chittagong, Dhaka, Sylhet	Non-agricultural profit, remittance, employment	
4	Comilla		Dominant Remittance

Using the dendrogram in Figure 3 (agricultural crop share in total agricultural income analyzed by cluster analysis), four clusters were determined (Table 5) as the clusters suitable for representing agricultural crop income sources among the regions. We followed the same procedure for this dendrogram (Figure 3) that we followed in Figure 2.

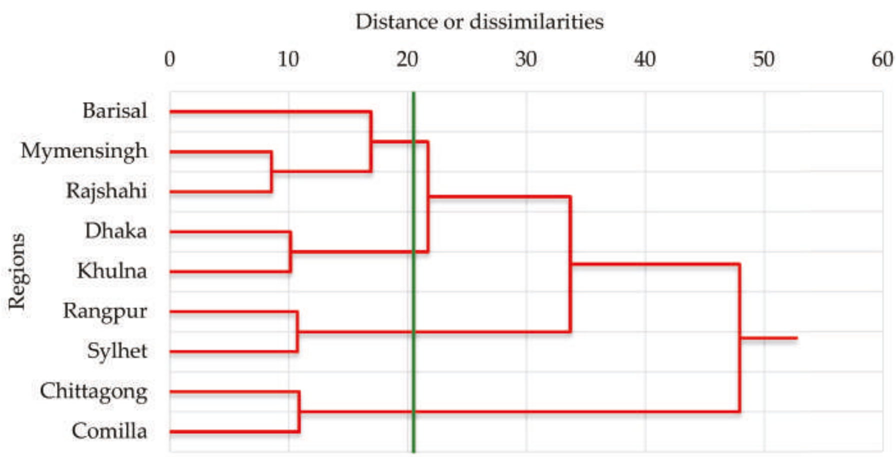

Figure 3. Dendrogram showing clusters for agricultural income sources, by region.

Table 5. Cluster characteristics of agricultural income sources, by region.

Cluster	Region	Main Income Source	Distinction
1	Barisal, Mymensingh, Rajshahi	Rice, other crops	
2	Rangpur, Sylhet		Dominant rice
3	Chittagong, Comilla		Dominant other crops
4	Dhaka, Khulna	Rice, jute, chili, onion, other crops	

The selected clusters show significant differences among the regions. Rice and other crops were identified as the main agricultural income sources of clusters 1–3, whereas rice, jute, chili, onion and other crops were those of cluster 4. The selected clusters produced the significant differences among the regions. In addition, rice predominated in cluster 2, while other crops predominated in cluster 3. These findings imply, for example, that rice is the main agricultural income source in Rangpur and Sylhet, while other crops are those in Chittagong and Comilla.

4.3. Reasons for Broad Income Distribution within a Region

To grasp the diversity of income for sampled farm households, the income can be decomposed into seven broad components, such as Agriculture, Fish, Livestock and poultry, Nonagricultural enterprise profit, Remittance, Other income and Employment income, in each region. We applied decomposition of variances and the results are shown in Table 6. The decomposition of variances is useful in evaluating how much each source of income contributes to total income variation of farm households. The decomposed variance share was derived from annual per capita income from the seven aforementioned broad income source sectors. Across Bangladesh, differences in remittances, other income and employment are important factors that all contribute the largest share of variation in total income. If a family can find good employment both inside and outside its region, it can become relatively wealthy, although income share from employment does not significantly more contribute in all regions (Table 6).

Table 6. Share of broad income components (%) in total income variation, by region.

	B	CH	CO	D	K	M	RJ	RN	S	BD
V(b)	6.57	1.67	1.94	4.19	8.18	13.87	3.18	20.59	2.49	4.79
V(c)	20.03	0.19	0.03	1.57	35.73	8.17	1.11	0.23	1.98	6.42
V(d)	1.08	0.18	0.17	0.87	1.78	4.58	2.81	0.98	1.05	1.54
V(e)	17.39	13.64	6.33	16.50	13.47	11.90	5.09	7.84	19.73	11.63
V(f)	8.70	40.78	54.36	10.94	10.22	12.99	1.61	30.23	29.95	17.78
V(g)	4.84	0.05	14.76	1.16	0.61	2.38	69.70	0.37	2.82	21.63
V(h)	19.44	27.29	11.61	44.54	17.17	25.26	7.16	38.32	21.01	22.05
2*Cov(e,h)	21.95	15.22	10.81	20.22	12.85	14.22	7.32		20.96	14.16
2*Cov(b,c)								1.43		
2*Cov(c,h)							2.03			
2*Cov(f,g)		0.99								
2*Cov(c,e)						6.63				
Total	100	100	100	100	100	100	100	100	100	100

B = Barisal, CH = Chittagong, CO = Comilla, D = Dhaka, K = Khulna, M = Mymensingh, RJ = Rajshahi, RN = Rangpur, S = Sylhet and BD = Bangladesh; b = Agriculture, c = Fish, d = Livestock and poultry, e = Nonagricultural enterprise profit, f = Remittance, g = Other income and h = Employment income.

We found in Table 6 that agriculture is one of the main contributors to income differences in Mymensingh and Rangpur regions. Figure 4 shows total income distribution by income sources for the whole country, of which 22% of income inequality of total income is explained by inequality of employment income, while 13.87% and 20.59% of income inequality of total income explained by agriculture in Mynemnsingh and Rangpur respectively (Figures 5 and 6). Furthermore, this result indicates that remittance is the most important sector inducing income disparity in Comilla, compared to employment in Dhaka and Rangpur. In addition, other income sources are significant sources of income to confirm the total income disparity in Rajshahi. This finding likely explains that the income inequality of total income makes the larger contribution of inequality in agricultural income for crop farm households in Bangladesh.

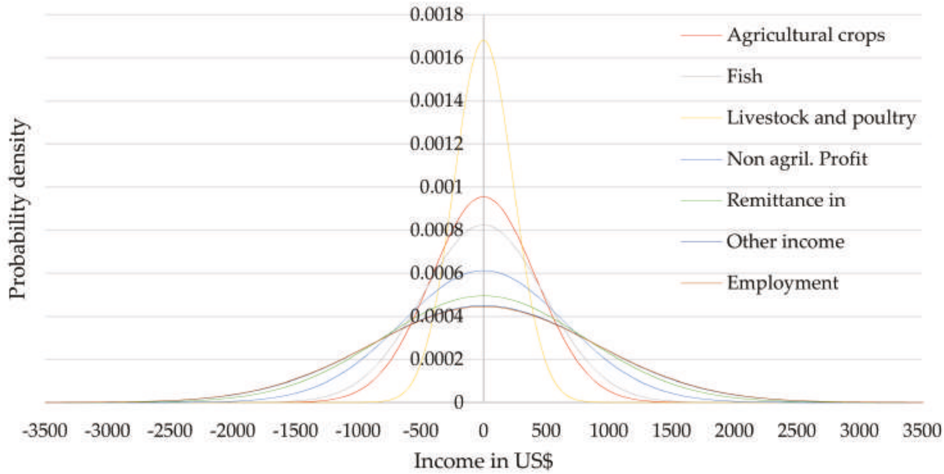

Figure 4. Distribution of total income for farm households in Bangladesh by income sources.

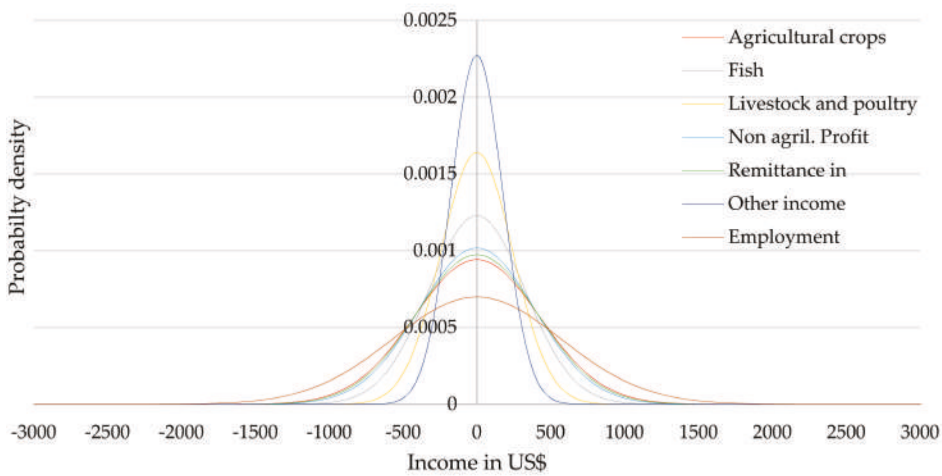

Figure 5. Distribution of total income (US$) for farm households in Mymensingh by income sources.

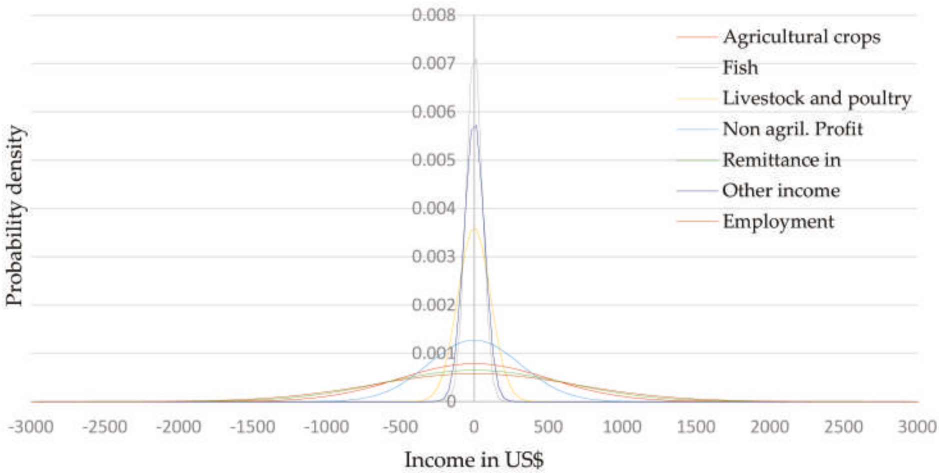

Figure 6. Distribution of total income (US$) for farm households in Rangpur by income sources.

4.4. Factors in Agricultural Income Differences

The main factors of agricultural income differences are shown in Table 7 obtained by the decomposed variance method. We estimate the variance component shares of crops for all farms across nine regions. From Table 6, we identify that agriculture is one of the main reasons for income differences in Mymensingh, Rangpur, Barisal, Khulna and Rajshahi. The empirical estimates of Table 7 indicate that the main variation in agricultural income comes from *aman* HYV (g) and *boro* HYV (j) rice. However, the results also display the contributions of other crop income to total agricultural income variation.

Table 7. Shares of crop income (%) in total agricultural income variation, by region.

	B	CH	CO	D	K	M	RJ	RN	S	BD
V(b)	0.35	0.07	0.03	0.15	0.10	0.00	0.01	0.00	0.36	0.11
V(c)	0.08	0.04	0.03	0.00	0.00	0.06	0.06	0.01	0.04	0.04
V(d)	0.64	0.43	0.01	0.02	1.54	0.06	0.13	0.13	1.06	0.53
V(e)	5.23	0.00	0.36	0.36	0.53	0.50	0.50	0.15	2.06	1.02
V(f)	0.47	0.02	0.16	0.02	0.07	0.06	0.01	0.15	0.00	0.10
V(g)	8.95	7.67	1.12	1.63	10.15	3.84	7.64	12.95	7.88	8.50
V(h)	0.02	0.00	0.00	0.00	0.09	0.09	0.05	0.11	0.00	0.06
V(i)	0.70	0.00	0.06	0.01	0.06	0.00	0.00	0.36	0.16	0.14
V(j)	6.36	4.32	8.13	34.03	17.72	20.89	17.72	14.03	48.26	25.30
V(k)	2.49	2.13	1.26	5.71	3.88	0.69	3.56	3.40	17.82	5.03
V(l)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
V(m)	0.00	0.00	0.01	0.04	0.15	0.00	0.23	0.18	0.00	0.11
V(n)	0.00	0.00	0.27	0.07	0.10	0.00	0.53	0.65	0.00	0.28
V(o)	0.26	0.00	4.28	4.74	2.46	0.04	0.91	0.93	0.14	2.38
V(p)	0.49	0.04	20.77	0.35	0.03	0.08	1.78	6.48	0.16	2.68
V(q)	1.65	0.90	0.81	11.56	12.40	0.98	0.17	0.49	0.08	6.00
V(r)	0.00	0.00	0.00	6.51	0.54	0.00	0.63	0.02	0.00	1.91
V(s)	67.37	75.85	43.55	29.35	44.77	62.62	16.16	24.67	21.98	44.00
2*Cov(o,r)				5.43	0.85		0.81			1.79
2*Cov(g,j)		5.75				9.73	11.64	13.34		
2*Cov(g,k)		2.79			0.37		4.55	7.94		
2*Cov(g,p)						0.02	3.58	11.66		
2*Cov(o,p)			18.45			0.34	6.19	2.33		
2*Cov(g,s)							9.54			
2*Cov(j,s)							13.61			
2*Cov(d,j)	4.95		0.72		4.20					
Total	100	100	100	100	100	100	100	100	100	100

B = Barisal, CH = Chittagong, CO = Comilla, D = Dhaka, K = Khulna, M = Mymensingh, RJ = Rajshahi, RN = Rangpur, S = Sylhet, BD = Bangladesh; b = *Aus* rice local, c = *Aus* rice LIV, d = *Aus* rice HYV, e = *Aman* rice Local, f = *Aman* rice LIV, g = *Aman* rice HYV, h = *Aman* rice Hybrid, i = T *Aus* rice HYV, j = *Boro* rice HYV, k = *Boro* rice Hybrid, l = Wheat Local, m = Wheat HYV, n = Maize, o = Jute, p = Potato, q = Chili, r = Onion, s = All other crops.

Rice is the leading crop in Bangladesh, accounting for more than 90% of total cereal production covering 75% of Bangladesh's total cropped area [45,69]. For Mymensingh and Rangpur, variances in both *aman* HYV and *boro* HYV rice are high. For other regions, variances in *boro* HYV are high.

All other crops(s) are among the main causes (44% variance share) of income differences for all of Bangladesh since all types of pulses, oil seeds, spices, vegetable, leafy vegetables and fruits are included in the group of "all other crops." Moreover, all other crops(s) explain the larger contribution to total agricultural income variation because, in some regions, vegetables and fruits, among others, excluding rice, are important agricultural income sources.

The distribution of crop income among total agricultural income for the whole country is shown in Figure 7, which follows in Figures 8 and 9 for Mymensingh and Rangpur, respectively, with selected crops mainly produced by farmers in these regions. We found that *boro* rice has the widest variation in both the region and the highest inequality of total agricultural income, explained by the inequality of *boro* HYV income.

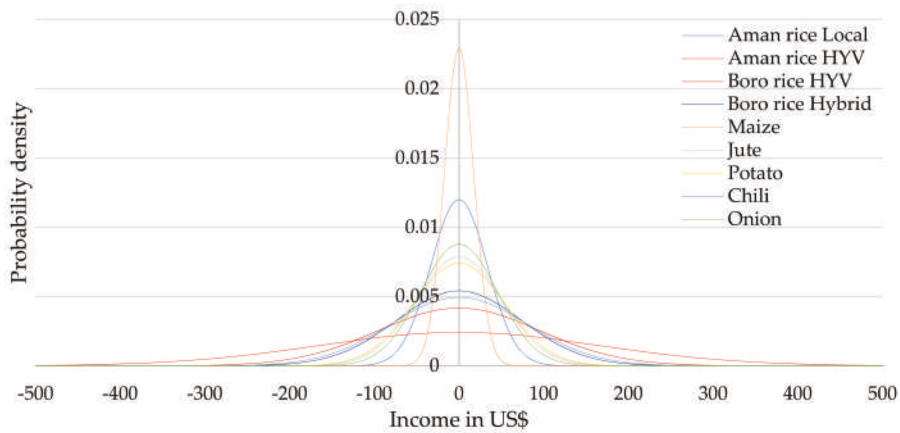

Figure 7. Distribution of agricultural income for farm households in Bangladesh by crop income.

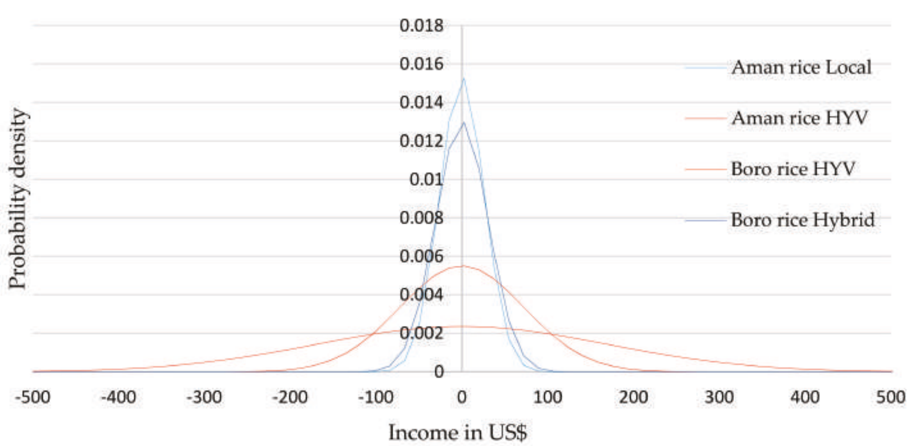

Figure 8. Distribution of agricultural income for farm households in Mymensingh by crop income.

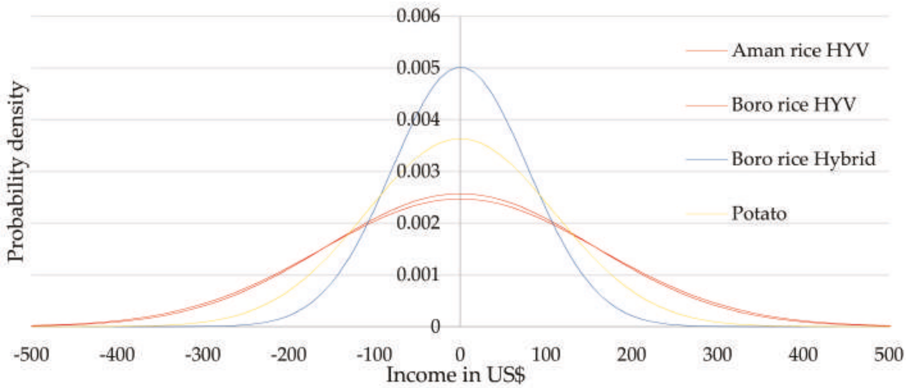

Figure 9. Distribution of agricultural income (US$) for farm households in Rangpur by crop income.

4.5. Factors Contributing to Variations in Income from Aman HYV and Boro HYV Rice Production

According to the results of Table 7, it is important to determine the factor causing the net income differences in *aman* HYV production. From decomposed variance of gross income and gross cost, we find in Table 8 that gross income is the main factor in net income difference, indicating that, although farmers in same region cultivated *aman* HYV rice, their gross incomes were different.

Table 8. Decomposed variances share (%) of GI and GC for *aman* HYV rice, by region.

	B	CH	CO	D	K	M	RJ	RN	S	BD
V(GI)	75.31	74.34	98.38	53.87	76.53	57.17	66.88	74.25	45.49	69.45
V(GC)	80.97	33.57	35.80	91.18	36.13	49.23	55.56	30.27	55.10	45.67
−2*Cov(GI, GC)	−56.27	−7.91	−34.18	−45.06	−12.66	−6.39	−22.44	−4.52	−0.59	−15.11
Total	100	100	100	100	100	100	100	100	100	100

B = Barisal, CH = Chittagong, CO = Comilla, D = Dhaka, K = Khulna, M = Mymensingh, RJ = Rajshahi, RN = Rangpur, S = Sylhet and BD = Bangladesh; GI = Gross income; and GC = Gross cost.

These gross income differences mainly induce the net income disparities in Comilla, Khulna, Chittagong and Rangpur, while gross cost induces the income disparities in Dhaka and Barisal for *aman* HYV rice. Additionally, gross cost also contributes to the total net income disparity of *aman* HYV rice production. To determine the variance in gross cost for *aman* HYV rice production, we estimate the variance component shares of all costs contributing to gross cost and present them in Table 9.

The results show the factors responsible for large variations in cost from *aman* HYV rice production. As shown in Table 9, variances in seed (c) shows in third row, chemical fertilizer (g) in row seven and hired labor costs (k) in row eleven, are high across all regions. In Dhaka, the highest 80% of inequality of gross cost for *aman* HYV rice production is explained by the inequality of hired labor cost (k), while in Barisal, the highest 25% inequality of gross cost is explained by inequality of seed cost. These costs were the main factors inducing the income differences in *aman* HYV rice production. This result indicates the importance of farming knowledge and easy input access to rice cultivation.

Table 9. Decomposed variances share (%) of costs for *aman* HYV rice production, by region.

	B	CH	CO	D	K	M	RJ	RN	S	BD
V(b)	3.64	3.73	3.79	0.97	3.66	5.50	3.72	8.79	4.32	3.24
V(c)	25.01	1.87	24.54	1.47	3.55	5.56	3.12	6.78	3.81	5.15
V(d)	0.53	1.79	1.04	1.32	8.33	2.04	4.15	6.70	0.67	3.69
V(e)	0.07	0.18	0.19	0.08	0.41	0.64	0.77	0.64	0.23	0.33
V(f)	0.54	0.48	0.28	0.07	0.65	0.10	0.65	0.54	0.14	0.35
V(g)	5.32	9.73	6.27	1.54	12.74	6.72	7.57	7.05	3.38	6.42
V(h)	0.98	0.06	0.01	0.04	0.30	2.76	0.05	0.57	1.42	0.50
V(i)	9.49	2.29	1.88	0.35	4.25	1.29	1.31	2.70	1.62	2.10
V(j)	3.47	0.58	1.62	0.10	0.44	0.70	0.15	0.26	3.04	0.69
V(k)	15.16	39.90	45.37	80.58	37.61	70.65	40.88	58.04	74.50	59.53
2*Cov(f,g)	1.72	2.37	1.33	0.33	2.14	0.77	3.05	1.26		1.41
2*Cov(i,f)	2.07		0.59	0.13			1.17	1.03	0.41	0.54
2*Cov(i,g)	11.50		3.88	0.77	5.69	3.26	4.29	4.69	1.94	3.32
2*Cov(k,g)	5.46	20.32		8.55	19.47		18.35			12.74
2*Cov(c,j)	15.04							0.95	4.52	
2*Cov(k,f)		3.79		2.04			4.82			
2*Cov(k,i)		1.90	9.21	1.67	0.75		5.94			
2*Cov(c,k)		11.0								
Total	100	100	100	100	100	100	100	100	100	100

B = Barisal; CH = Chittagong; CO = Comilla; D = Dhaka; K = Khulna; M = Mymensingh; RJ = Rajshahi; RN = Rangpur; S = Sylhet; and BD = Bangladesh; b = Rental cost of land; c = Seed cost; d = Irrigation cost; e = Manure/compost cost; f = Pesticide cost; g = Chemical fertilizer cost; h = Draft animal cost for land preparation; i = Rental cost for tools and machinery; j = Threshing cost; and k = Hired labor cost.

In Table 7, we note that *boro* HYV also had an influence on agricultural income. It is essential to determine the factors affecting the net income variation for *boro* HYV rice cultivation. Table 10 summarizes the decomposed variance of gross income and gross cost from *boro* HYV rice production and shows that gross income is the main factor in net income differences for *boro* HYV rice production, except for in Chittagong and Sylhet. However, gross cost also contributes to the total net income disparity of *boro* HYV rice production.

Next, we want to know which costs are the main factors in income differences in *boro* HYV rice production. To know the variance in gross costs for *boro* HYV rice production, we estimate the variance component shares of all cost expenditures contributing to gross cost and present them in Table 11. We found that the variances in seed (c) shows in third row, irrigation (d) in row four, chemical fertilizer (g) in row seven and hired labor cost (k) in row eleven, are high in all regions, indicating that adaptation strategies, such as low input costs, have priorities for the large gross income variances of *boro* rice cultivation.

Table 10. Decomposed variance share (%) of gross income and cost of *boro* HYV rice, by region.

	B	CH	CO	D	K	M	RJ	RN	S	BD
V(GI)	101.34	46.75	264.6	62.73	79.59	70.15	69.81	80.61	67.68	91.68
V(GC)	43.86	79.49	97.26	41.17	40.46	47.38	60.96	28.25	84.98	54.04
−2*Cov (GI, GC)	−45.20	−26.24	−261.9	−3.90	−20.05	−17.53	−30.77	−8.86	−52.66	−45.72
Total	100	100	100	100	100	100	100	100	100	100

B = Barisal, CH = Chittagong, CO = Comilla, D = Dhaka, K = Khulna, M = Mymensingh, RJ = Rajshahi, RN = Rangpur, S = Sylhet and BD = Bangladesh; GI = Gross income and GC = Gross cost.

These input costs were made the net income differences in this rice production for sample farmers. Based on the findings in Table 11, it is also important to note that, in Chittagong region, the variance in hired labor cost (k) is highest (69.84%) while it is lowest in Comilla region (27.25%). This result implies that 69.84% of inequality of gross cost is elucidated by the inequality of hired labor cost in Chittagong region. As shown in the fourth row, irrigation cost (d) contributes a significant share of the variation of gross cost; the highest 22.93% of inequality of gross cost is explained by the inequality of irrigation cost in Dhaka, compared to the lowest in Chittagong. This result implies that reduction of input cost variances will ensure the low net income differences for this rice production. Farm households are not entirely self-sufficient regard the labor supply for their farming. In peak times of agricultural production, such as transplanting, weeding and harvesting, hired labor demand occurs. However, the labor supply is low in Chittagong due to hill tract areas of Bangladesh [69], resulting in the higher costs of labor.

Table 11. Decomposed variance share (%) of costs for *boro* HYV rice production, by region.

	B	CH	CO	D	K	M	RJ	RN	S	BD
V(b)	2.87	0.66	0.50	1.88	2.66	4.11	1.32	5.32	2.63	2.27
V(c)	4.10	0.71	2.21	3.67	4.78	2.72	1.73	4.34	2.20	3.61
V(d)	8.89	2.70	4.06	22.93	22.39	22.42	10.70	16.00	7.57	18.01
V(e)	0.24	0.05	1.10	0.31	0.76	0.88	0.33	2.56	0.12	0.80
V(f)	0.89	0.09	0.18	0.16	0.48	0.33	0.31	0.60	0.07	0.33
V(g)	7.71	3.31	1.98	6.71	14.76	12.82	4.71	13.54	3.23	8.21
V(h)	0.04	0.03	0.00	0.05	0.79	10.08	0.13	0.38	2.04	1.16
V(i)	2.42	0.89	1.01	0.93	1.47	1.09	0.47	1.68	1.12	1.23
V(j)	0.98	0.20	0.15	1.08	0.75	2.24	0.24	0.39	0.18	0.78
V(k)	38.05	69.84	27.25	42.04	38.45	31.49	51.04	38.17	65.10	51.51
2*Cov(f,g)	3.91	0.73	0.66	0.90	2.15		1.49	3.46	0.50	1.55
2*Cov(d,g)	4.98		1.18				4.35			
2*Cov(f,i)	1.07	1.15	2.62	0.39	0.52		0.52	0.97	0.26	0.61
2*Cov(g,i)	4.68	2.70	1.99	2.87	5.47	3.76	2.14	5.69	1.99	3.43
2*Cov(g,k)	11.72	14.45	6.27	11.25			10.64		11.72	
2*Cov(i,k)	7.46		6.84	4.83	4.58	8.05	3.89			5.90
2*Cov(e,i)		2.50	9.58					1.25	0.22	0.60
2*Cov(f,k)			5.34				5.99			
2*Cov(e,g)			1.50					4.90	0.44	
2*Cov(e,f)			7.04					0.76	0.63	
2*Cov(d,k)			8.70							
2*Cov(e,k)			9.85							
Total	100	100	100	100	100	100	100	100	100	100

B = Barisal, CH = Chittagong, CO = Comilla, D = Dhaka, K = Khulna, M = Mymensingh, RJ = Rajshahi, RN = Rangpur, S = Sylhet and BD = Bangladesh; b = Rental cost of land, c = Seed cost, d = Irrigation cost, e = Manure/compost cost, f = Pesticide cost, g = Chemical fertilizer cost, h = Draft animal cost for land preparation, i = Rental cost for tools and machinery, j = Threshing cost and k = Hired labor cost.

4.6. Future Projections

Production levels in agriculture, fishery and livestock raising are projected to change due to climate change [39,83]. We therefore sought to project the impact of rice yield change on the state of poverty in Bangladesh. If rice is a commercial crop, a price hike due to any damage from climate change could increase Bangladeshi farmers' living standards. However, rice remains a subsistence crop among most Bangladeshi farmers; therefore, we assume that rice yield reduction will lead to a rice consumption reduction.

The effects of climate change on rice yields, as has been estimated and shown by International Food Policy Research Institute [37], are such that, without adaptation to climate change impacts, *aman* HYV and *boro* HYV rice yields will decline by 3.5% and 10.2%, respectively, in Bangladesh. According to the Geophysical Fluid Dynamics Laboratory (GFDL) scenarios, if temperature changes by 4.0 °C, then 17% decline in overall rice will occur in Bangladesh [84].

According to this projection, we assumed that, due to climate change effects on *boro* HYV and *aman* HYV, rice yields will be reduced by 10% and 4%, respectively, as well as a 17% reduction in overall rice among the sample households. We applied log-normal distribution to project the poverty rate due to income reduction by yield loss on the effects of climate change.

Figure 10 shows the annual per-capita income (actual and projected) in US$ of the sample households across Bangladesh. In general, one can see from this figure that the sample population density (i.e., probability density) mostly lies within the low annual per-capita income range, which is less than the poverty line. Additionally, the probability density of the low-income range increases in the projected income distribution when one considers rice yield loss due to climate change.

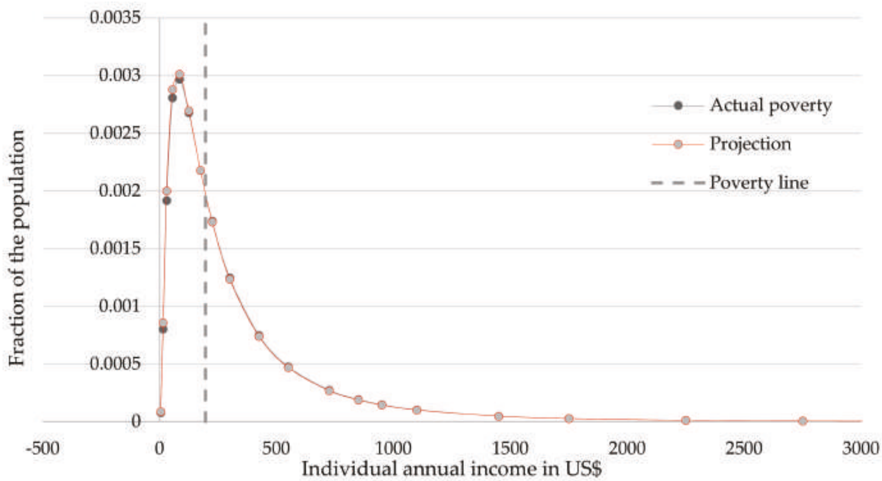

Figure 10. Annual per-capita income (US$) distribution of Bangladesh (17% loss of rice).

From the decomposed variance share of income sources in Table 9, we found that agriculture was the main reason for income differences in Mymensingh and Rangpur. Now, we can examine the effects of climate change on rice production (10% and 17% losses) in these two regions by log-normal distribution.

We analyzed and found that constant reduction of rice yield (10% loss) by climate change in Bangladesh is not such a severe problem for farmers. Because the change in net per-capita income is very small, there is not a dramatic change of poverty rate. However, if unexpected extreme events, such as floods, flash floods, droughts and sea level rise, occur in specific areas of Bangladesh, they create a more vulnerable situation for the farmers' livelihood. In addition, the probability density of low-income range increases (Figures 11 and 12) in both Mymensingh and Rangpur districts, where rice income decreases due to climate change.

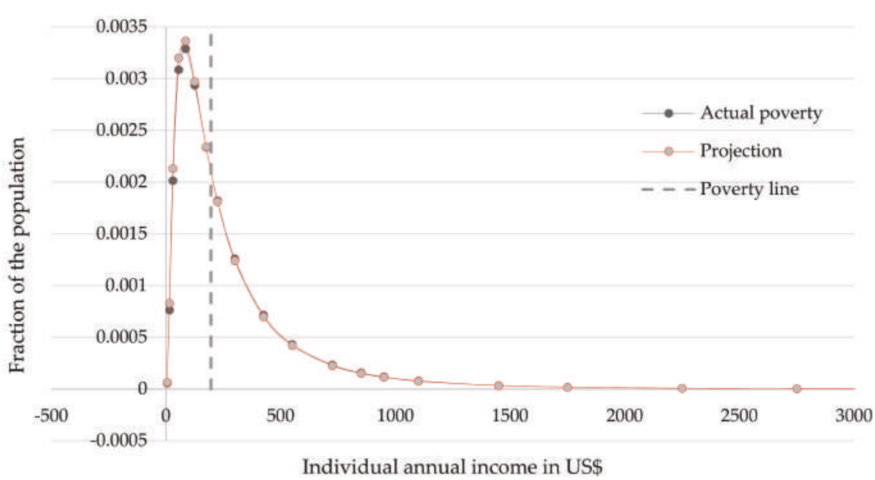

Figure 11. Annual per-capita income (US$) distribution of Mymensingh (17% loss of rice).

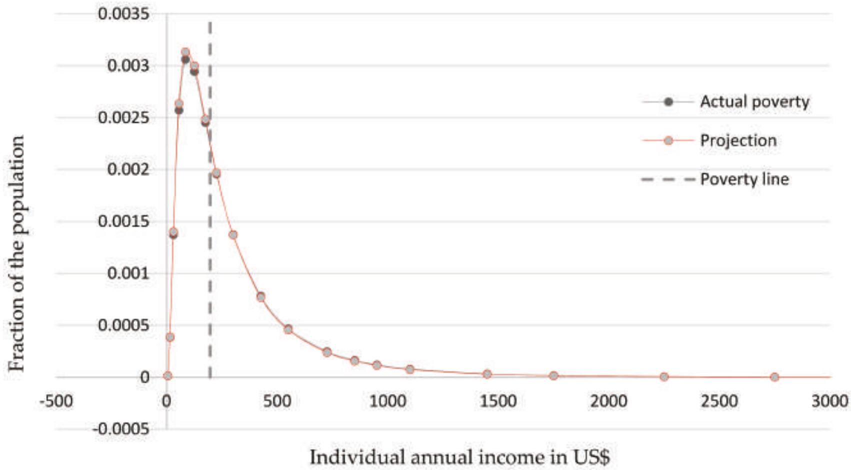

Figure 12. Annual per-capita income (US$) distribution of Rangpur (17% loss of rice).

We also applied the same analysis in Figures 10–12 to all of the regions and Table 12 shows the results of the poverty rate after income changes due to assumed yield losses of *aman* HYV, *boro* HYV rice and overall rice.

Table 12. Change in poverty rate following a loss of rice yield due to climate change.

		B	CH	CO	D	K	M	RJ	RN	S	BD
	Actual	0.507	0.484	0.446	0.455	0.415	0.496	0.323	0.462	0.484	0.454
10% loss	Projected	0.508	0.491	0.447	0.458	0.417	0.502	0.330	0.466	0.487	0.457
	Change	0.001	0.007	0.001	0.003	0.002	0.006	0.007	0.004	0.003	0.003
	Increase (%)	0.197	1.446	0.224	0.659	0.482	1.210	2.167	0.866	0.620	0.661
17% loss	Projected	0.513	0.494	0.449	0.460	0.422	0.511	0.335	0.473	0.490	0.461
	Change	0.006	0.010	0.003	0.005	0.007	0.015	0.012	0.011	0.006	0.007
	Increase (%)	1.183	2.066	0.673	1.099	1.687	3.024	3.715	2.381	1.240	1.542

B = Barisal, CH = Chittagong, CO = Comilla, D = Dhaka, K = Khulna, M = Mymensingh, RJ = Rajshahi, RN = Rangpur, S = Sylhet and BD = Bangladesh.

The estimated results suggest that rice yield loss would reduce the annual per-capita income of the sample farm households and increase the poverty rate in various regions across Bangladesh. It was found that the highest poverty rate increase (3.024%) would occur in Mymensingh, Rajshahi (3.715%) and Rangpur (2.381%). Rajshahi and Rangpur are in northwestern Bangladesh and are prone to drought; climate change would affect rice production specifically in the summer, when *boro* rice is being produced. Mymensingh is affected by floods, flash floods and heavy rainfall each year, owing to the effects of climate change on *aman* and *boro* harvests.

Climate Change Impact Scenario

Extreme events, such as floods, droughts and changes in seasonal rainfall patterns, negatively impact crop yields in vulnerable areas [85–87]. In Bangladesh, the rural poverty rate would be exacerbated [88] as a result of the impacts of extreme events on the yield of rice crop and increases in food prices and the cost of living [89,90]. The impacts of climate change on poverty would be heterogeneous among countries [91]. Due to the impact of climate change, rice production would decrease and some rice exporting countries, such as Indonesia, the Philippines and Thailand, would benefit from global food price rises and reduced poverty, while Bangladesh would experience a net increase in poverty of approximately 15% by 2030 [89,91].

Climate change refers to changes in climate attributed directly as temperature, precipitation, CO_2 concentrations and solar radiation or indirectly as river floods, flash floods and sea level rise that alter the composition of the global atmosphere, as well as to natural climate variability observed over comparable time periods [33,50].

Temperature Increase

Temperature is an important factor for *boro* rice production and the maximum temperature is always more vulnerable with a negative impact on rice yields. In Bangladesh, seasonal temperature suddenly fluctuates, causing drastically declines in the yield of *boro* rice. *Boro* rice yields decrease by a maximum of 18.7% due to an increase in minimum temperature of 2.0 °C–4.0 °C and by 36.0% for 2.0 °C–4.0 °C maximum temperature increases in different location of Bangladesh in 2008 [92]. According to the Intergovernmental Panel on Climate Change (IPCC), SRES emissions scenarios and climate models being considered, global mean surface temperature is projected to rise in the range of 1.8 to 4.0 °C by 2100 [93]. Following the previous assessment, the IPCC concludes in their fifth assessment report (AR5) that it will be difficult to adapt with large-scale warming of approximately 4°C or more, which will increase the likelihood of severe, pervasive and irreversible impacts [91,94,95].

According to the previous projection of temperature fluctuations in Bangladesh, we assume that, due to the maximum and minimum temperature fluctuations, in the future, the overall rice production will decrease by approximately 17% of the sample farmers and results are shown in Table 12. The table shows that maximum 3.7% poverty will increase in Rajshahi and second highest (3.0%) in Mymensingh region and this implies that it is important to adaptation strategies for Rajshahi and Mymensingh for high temperature.

Rainfall Decreases (Drought)

Inadequate rainfall leads to greater drought frequency and intensity, while increased evaporation increases the chance of complete crop failure [96,97]. Drought is the most widespread and damaging of all environmental stresses [35,98]. In South and Southeast Asia, including some states of India, severe drought affects rain-fed rice and yield, with losses as high as 40% and the total area affected measuring 23 million hectares, amounting to $800 million [99]. Bangladesh experienced severe drought in different years and locations in the districts of the northwestern border [100]. Erratic rainfall and drought reduce crop production by 30% and 40%, respectively [84]. *Boro* rice production will decrease due to rainfall in winter [92]. This study noted that, with 5-mm and 10-mm rainfall reductions in the future, *boro* rice will decrease by a maximum of 16.6% and 24.2%, respectively, in the winter. Drought caused 25% to 30% crop reduction in the northwestern part of Bangladesh based on from 2008 [101]. Due to the high rainfall variability and dryness, the northwestern region is the most drought-prone area in Bangladesh [102,103]. Rajshahi, Chapai-Nawabganj, Naogaon, Natore, Bogra, Joypurhat, Dinajpur and Kustia districts are drought prone areas in Bangladesh because of their moisture-retention capacity and infiltration rate characteristics [104].

According to the previous projection of drought, we assume that, if rainfall decreases and drought occur in the future, the overall rice production will decrease by approximately 20% of the sample farmers in northwestern districts of Bangladesh. By using log-normal distribution, we project the poverty rate due to income reduction by yield loss because of drought.

Table 13 shows the results of the poverty rate (Figure 13) after income changes due to assumed yield losses of overall rice by drought in the northwestern region in Bangladesh, while the Dinajpur (10.175% poverty increase), Rajshahi (5.670% poverty increase) and Naogaon (11.245% poverty increase) districts are most vulnerable to poverty. Dependency on agriculture with high variability of annual rainfall has made the northwestern regions highly susceptible to droughts and high poverty rates, compared to other parts of the country. Conservation of water could play an important role in reducing the impact of drought and alleviating poverty in this area [103].

Table 13. Poverty rate in drought-prone districts on rainfall decrease.

	BG	CN	DI	KU	NG	NT	RJ	JT
Actual	0.242	0.354	0.285	0.447	0.249	0.448	0.388	0.268
Projected	0.263	0.361	0.314	0.452	0.277	0.452	0.410	0.282
Change	0.021	0.007	0.029	0.005	0.028	0.004	0.022	0.014
Increase (%)	8.678	1.977	10.175	1.119	11.245	0.893	5.670	5.224

BG = Bogra, CN = Chapai-Nawabganj, DI = Dinajpur, KU = Kustia, NG = Naogaon NT = Natore, RJ = Rajshahi and JT = Joypurhatr.

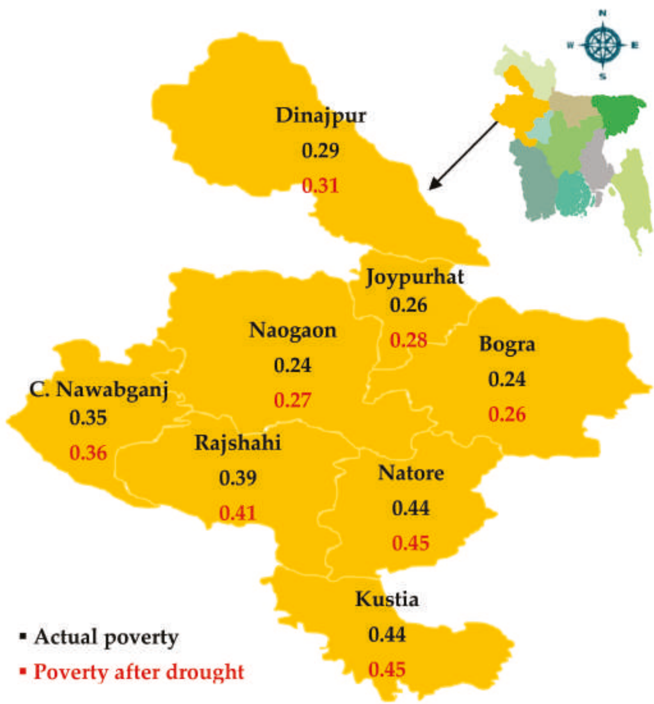

Figure 13. Changing poverty rates caused by drought in northwestern regions.

Flood

From the GBM basins, the monsoonal discharge of water causes seasonal floods and affects most of the areas of Bangladesh, with extent varying by year [50]. Floods occur almost every year and in 1998, floods covered almost 70% of total land area in Bangladesh, causing the maximum damage by floods in Bangladesh [105]. According to the IPCC's fourth assessment report, the intensity and frequency of floods and cyclones will increase in the near future [33]. Moreover, the IPCC's fifth assessment report (AR5) predicts that greater risks of flooding will increase on the regional scale [91,94–99]. In addition, extreme flood events will reduce crop production by 80% in Bangladesh [37,84].

Mymensingh, Sylhet, Dhaka, Comilla, some parts of Rangpur and Khulna regions are the mainly river-flooded areas in Bangladesh [50]. We assume that, if extreme floods, as in 1998 (the magnitude of the 1998 flood was the maximum in Bangladesh), occur, farm production will decrease by 80% in the flood-prone regions of Bangladesh. By log-normal distribution we project the poverty rate due to income reduction by yield loss due to the effects of extreme floods. The results are shown in Table 14.

Table 14. Poverty rate due to yield loss by flood in Bangladesh.

	CO	D	K	M	RN	S
Actual	0.446	0.455	0.415	0.496	0.462	0.484
Projected	0.465	0.502	0.479	0.554	0.529	0.519
Change	0.019	0.047	0.064	0.058	0.067	0.035
Increase (%)	4.260	10.330	15.422	11.694	14.502	7.231

CO = Comilla, D = Dhaka, K = Khulna, M = Mymensingh, RN = Rangpur and S = Sylhet.

The estimated results in Table 14 suggest that rice yield loss would reduce the annual per-capita income of the sample farm households and increase the poverty rate in various regions across Bangladesh (Figure 14). It was found that the highest poverty rate increases would occur in Rangpur (14.502%) and Khulna (15.422%). This result implies that coping strategies to highly flood affected areas of crops loss should have priority.

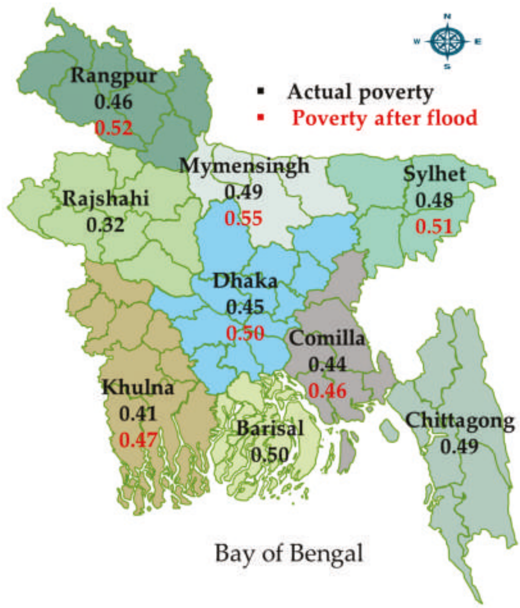

Figure 14. Changing poverty rates caused by floods in different regions.

Flash Floods

The northeastern parts of Bangladesh—mostly Sunamganj, Kishorganj, Netrokona, Sylhet, Habiganj and Maulvibazar—are prone to flash floods during the months of April to November and these areas are covered by many haors, where water remains stagnant [106]. Farmers of these districts produced *boro* rice in almost 80% of their land, while only approximately 10% of the area is covered by transplanted *aman* production [107]. In 2017, flash floods affected these areas and damaged almost 90% (maximum) of *boro* rice [108]. According to this scenario, we assumed that if in the future this extreme event occurs in haor areas, *boro* rice yields will be reduced by a maximum of 90% of the sample households. We applied log-normal distribution to project the poverty rate due to income reduction by yield loss due to the effects of flash floods on *boro* rice yields by a maximum of 90%.

Table 15 shows the results of the poverty rate after incomes changed due to assumed yield loss of *boro* rice in flash flood regions in Bangladesh, while Kishorganj district is most vulnerable to poverty

(19.214% increase) if flash floods occur (Figure 15). The projected results are treated as flash flood to be changed the poverty in northern-eastern parts of Bangladesh and this region are vulnerable on flash flood. Therefore, ex-ante coping strategies are important to the damages of flash flood.

Table 15. Poverty rate in flash flood region in Bangladesh.

	HB	KI	MV	NT	SU	SY	TH
Actual	0.354	0.458	0.624	0.585	0.511	0.427	0.354
Projected	0.381	0.546	0.637	0.628	0.550	0.452	0.381
Change	0.027	0.088	0.013	0.043	0.039	0.025	0.027
Increase (%)	7.627	19.214	2.083	7.350	7.632	5.855	7.627

HB = Habiganj, KI = Kishorganj, MV = Maulvibazar, NT = Netrokona SU = Sunamganj, SY = Sylhet and TH = Total Haor.

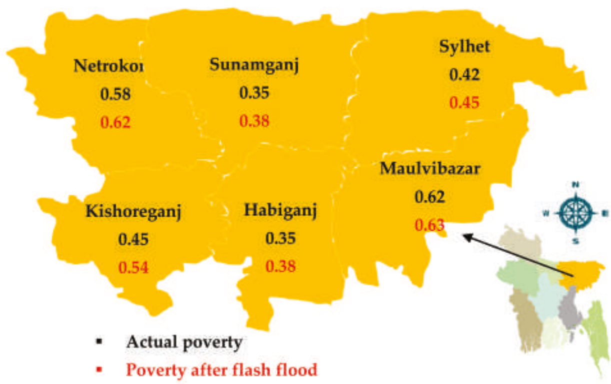

Figure 15. Changing poverty rate caused by flash floods in northeastern regions.

Sea Level Rise

Approximately 80% of the land of Bangladesh is flatlands, while 20% is 1 m or less above sea level, which is the coastal area (southern 19 districts beside the Bay of Bengal) and particularly vulnerable to sea level rise [109]. The coastal area covers approximately 20% of the country (including 19 districts beside the Bay of Bengal), which is approximately 30% of the net cultivable area and 25.7% of the population of Bangladesh [110,111]. Sea level rise will directly result in increased coastal flooding, which will increase in the event of storm surges. IPCC's fourth assessment report [33] reports that a 1-m sea level rise will displace approximately 14,800,000 people by inundating a 29,846-sq. km. coastal area [112]. Nicholls and Leatherman in 1995 [113] predicted that a 1-m sea level rise would result in a 16% of national rice production loss in Bangladesh [114].

In terms of number of people affected with respect to sea level rise, Bangladesh has been rated as the third most vulnerable country in the world. By 2050, approximately 33 million people would be suffering from surging, assuming a sea level rise of 27 cm. A full 18% of the total land area in Bangladesh would submerge with a 1-m rise in sea level [115]. Based on the IPCC fifth annual report (AR5), across all representative concentration pathways (RCPs), global mean temperature (°C) is projected to rise by 0.3 to 4.8 °C by the late-21st century and global mean sea level (m) is projected to increase by 0.26 to 0.82 m [91]. The Global Circulation Model (GCM) predicts an average temperature increase of 1.0 °C by 2030, 1.4 °C by 2050 and 2.4 °C by 2100; the study revealed that the sea level will rise by 14 cm, 32 cm and 62 cm, respectively. A rise in temperature would cause significant decreases in production of 28 % and 68 % for rice and wheat, respectively [84].

According to this scenario, we assumed that, due to sea level rise in the southern part of Bangladesh, *boro* rice yields will be reduced by 30% of the sample households. We applied log-normal distribution to project the poverty rate due to income reduction with yield loss based on the effects of sea level rise.

Table 16 shows the results of the poverty rate after income changes due to assumed yield loss of rice in coastal regions due to sea level rise, while Khulna district is the most vulnerable to poverty and poverty will increase by 6.752% (Figure 16). Changing continuous sea level rise in the coastal region result in no significant loss reduction for rice.

Table 16. Poverty rate in sea level rise regions in Bangladesh.

	SK	KH	BT	PR	JL	BG	BS	PT	BL	LK	NK	FN	CT	CX
Actual	0.599	0.295	0.363	0.388	0.640	0.532	0.419	0.628	0.491	0.529	0.438	0.481	0.505	0.462
Projected	0.609	0.315	0.370	0.390	0.650	0.545	0.431	0.636	0.493	0.533	0.440	0.487	0.515	0.464
Change	0.010	0.020	0.007	0.002	0.011	0.013	0.013	0.008	0.002	0.004	0.002	0.007	0.010	0.002
Increase (%)	1.688	6.752	1.924	0.527	1.674	2.388	3.081	1.255	0.491	0.770	0.410	1.361	1.901	0.367

SK = Satkhira, KH = Khulna, BT = Bagerhat, PR = Pirozpur, JL = Jhalakati, BG = Barguna, BS = Barisal, PT = Patuakhali, BL = Bhola, LK = Lakshmipur, NK = Noakhali, FN = Feni, CT = Chittagong and CX = Cox's Bazaar.

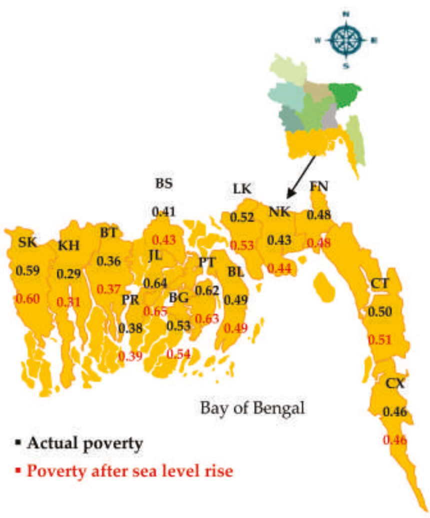

Figure 16. Changing poverty rate caused by sea level rise in southern regions.

Representative Concentration Pathways (RCPs)

In assessing future climate change, the fifth assessment report (AR5) of the IPCC selected four RCPs, –RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5 [91], with RCP 4.5 and RCP 8.5 covering both medium and extreme scenarios. These four RCPs describe four probable climate futures depending on how much greenhouse gasses are emitted over the next 85 years.

According to the IPCC's fifth annual report (AR5), across all representative concentration pathways (RCPs), global mean temperature (°C) is projected to rise by 0.3 to 4.8 °C by the late-21st century [68]. Increasing temperatures will increase the number of growing days over time. Heat stress is a major issue for crop production and reduces yields.

Climate change will certainly continue in coming decades and affect agricultural production. Yamei Li et al. worked on simulating total climate change impacts on rice production under RCP scenarios and projected that average rice yields during the 2020s, 2050s and 2080s would decrease by 12.3%, 17.2% and 24.5% under RCP 4.5 and by 14.7%, 27.5% and 47.1% under RCP 8.5, respectively [67].

According to this scenario, we assumed that, due to total climate change impacts, rice yields would be reduced by a maximum of 47% based on RCP 8.5 among the sample households. We applied log-normal distribution to project the poverty rate due to income reduction by yield loss. Table 17 shows that, under RCP 4.5 and RCP 8.5, the poverty rate will increase in all of the regions because of rice income reductions.

Additional increases in average poverty occur in Rajshahi, Mymensingh, Rangpur, Khulna and Sylhet region under both RCP 4.5 and RCP 8.5 with variations in the total climate change impacts on rice production. The yield of rice is predicted to decrease more under RCP 8.5 than RCP 4.5, resulting in per-capita income decreases. Under RCP 8.5, this study predicts a maximum increase in poverty of 10.526% in Rajshahi and the lowest of 3.139% in Comilla (Table 17). It is possible that our predicted rice yield declines by RCP scenario and relatively drought prone areas, such as Rajshahi, will be more vulnerable (Figure 17). The results from our drought scenarios are comparable to the results for RCP 8.5 and it is consistent that Rajshahi region is more vulnerable under climate change impacts. In both scenarios, our predicted yield decline and resulting per-capita income decline increase poverty. Climate change forces a decline in rice yield [116], suggesting that the predicted decreases in heat stress yield can be mostly attributed to an increased drought tolerant variety.

Table 17. Changes in poverty rates following a loss of rice yield due to RCPS.

		B	CH	CO	D	K	M	RJ	RN	S	BD
25% loss of rice under RCP 4.5	Actual	0.507	0.484	0.446	0.455	0.415	0.496	0.323	0.462	0.484	0.454
	Projected	0.516	0.490	0.455	0.462	0.424	0.510	0.345	0.471	0.497	0.463
	Change	0.009	0.006	0.009	0.007	0.009	0.014	0.022	0.009	0.013	0.009
	Increase (%)	1.775	1.240	2.018	1.538	2.169	2.823	6.811	1.948	2.686	1.982
47% loss of rice under RCP 8.5	Projected	0.524	0.500	0.460	0.470	0.438	0.526	0.357	0.488	0.507	0.474
	Change	0.017	0.016	0.014	0.015	0.023	0.030	0.034	0.026	0.023	0.020
	Increase (%)	3.353	3.306	3.139	3.297	5.542	6.048	10.526	5.628	4.752	4.405

B = Barisal, CH = Chittagong, CO = Comilla, D = Dhaka, K = Khulna, M = Mymensingh, RJ = Rajshahi, RN = Rangpur, S = Sylhet and BD = Bangladesh.

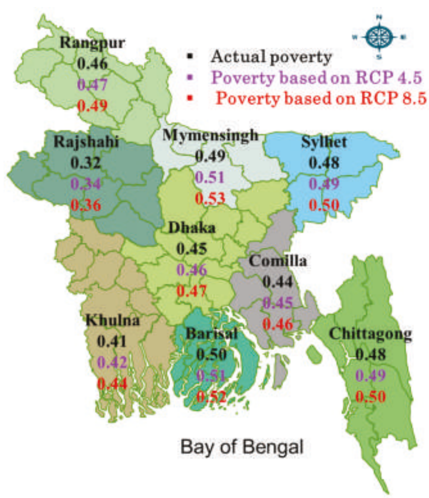

Figure 17. Changing poverty rate caused by total climate change impact based on RCP 4.5 and 8.5.

5. Conclusions

This paper has focused on the agrarian sub-national regional analysis of climate change vulnerability in Bangladesh under various climate change scenarios and its potential impact on poverty. It has drawn some significant evidence of regional vulnerability to climate change from regional characteristics, per-capita income, total income disparity, cost of production and poverty, based on statistical analysis of farm survey data. Our findings indicated that some regions are vulnerable to climate change impact on agricultural production among the administrative regions of Bangladesh, where coping strategies and techniques are important.

Bangladeshi farmers are producing crops, although there is much uncertainty due to associated risks of climate change. The results of our study show that, from the income shares of income source sectors, farmers in Mymensingh and Rangpur are largely dependent on agriculture. Of these regions, Mymensingh is one of the regions with the highest poverty rates. The income share in income sources revealed that income category shares across the various regions of Bangladesh are far from uniform. Income share comparisons and cluster analysis classified the regions into three groups as follows. (1) In some regions, namely Rajshahi, Khulna and Dhaka, income from agriculture is important and these regions receive relatively high income. (2) In other regions, namely Mymensingh, Rangpur and Barisal, agriculture income is important but the regions receive relatively low income. (3) The other regions, which are Comilla, Chittagong and Sylhet, are not strongly dependent on agriculture and Comilla region strongly relies on income from remittances. The principal targets of agricultural research for poverty reduction are considered to be in group (2).

Variance decomposition of income showed that agricultural income in Mymensingh and Rangpur is the main cause of income differences. Moreover, large variances in agricultural income in the regions are induced by gross incomes from rice production, indicating that rice yield can have large impacts on income levels. Therefore, research and development and technical support for farmers to realize high and stable rice yields in these regions are important.

This paper used modelling to predict crop yield changes by different aspects of climate change under droughts, floods, flash floods, sea level rise and RCP scenarios. We account for some uncertainty in crop yields and the resulting reduction in per-capita income of farm households. The proposed lognormal distribution projected the poverty rate and examined the vulnerable regions. The key is to understand the future projections of poverty rates on assumptions of *boro* HYV and *aman* HYV rice yield decreases on each farm due the climate change impacts and climate volatility subjecting the poor to poverty rate increases in different regions. Current climate change impacts are not the same in different regions; in particular, different extreme climatic events in specific regions often result in irreversible losses. One of the examples of the interventions of climatic events is that dependency on agriculture with high variability in annual rainfall has render the northwestern parts highly vulnerable to droughts and has increased the high poverty rates, compared to other parts of the country. Extreme floods can increase the poverty rates in Rangpur, Mymensingh and Khulna regions. Kishorganj district is the most vulnerable on poverty (8.8% increase) if sudden flash floods occur in the northeastern part of the country. Due to sea level rise, coastal areas will face poverty.

Strategies and techniques to cope with climate change for regions where small-scale farmers are largely dependent on agriculture are important challenges. Among the negative consequences of climate change impacts, subsistence farmers are suffering more from vulnerabilities such as extreme poverty or hunger. However, adaptation techniques in agriculture are a vital tool to avoid the adverse impacts of climate change [117]. Given the complex nature of droughts, floods, flash floods and sea level rise as phenomena, the development of drought-tolerant, short-maturing and salt-tolerant varieties is critically important.

More generally, our results are focused on farm income and poverty, including regional vulnerability due to climate change impacts on agricultural production. In recent years, climate change impacts have played a vital role in increasing the poverty rate and income variability among farm households in Bangladesh. Extreme environmental hazards are faced by farmers in this country and their net farm production decreases drastically, increasing the poverty rate while changes in weather conditions are a less severe problem for farmers due to their involvement in other income activities. We actually performed this study focusing on revealing the comprehensive impact of climate change on farm production and the crops are that the most important for per capita income differences across the country and that enhance the poverty rate, using the covariance and lognormal distribution methods.

This study has attempted to bridge the gap between academic research and professional practices in the context of potential climate change impacts on crop production and poverty. Because of the relatively large sample size, compilation and manipulation of the data were challenging. With the assessment of poverty and regional vulnerability due to climate changes, it is hoped that the study in general will assist in guiding authorities in terms of interventions aimed at climate change risk reduction in Bangladesh. Therefore, we believe that this research will help to reveal the mechanisms behind the per capita income differences and projected poverty rates of farm households based on different climate change impact scenarios across Bangladesh. Future work might also be more micro level for policy making to test root-level poverty and to further evaluate the impact of climate change on different crops and it should include the model for poverty determinants to confirm the relationships studied and their adaptations.

Author Contributions: M.S.A. conceived the research, compilation and analyze the data, drafted, edited and revised the manuscript; J.F. modified the methodology of the research, checked, edited and revised the manuscript; S.K. designed, compilation and analyze the data, edited and revised the manuscript; M.R.B. checked the statistical tools and maps of the objective regions; and M.A.S. helps to compilation of data and first draft of the manuscript.

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

Appendix A

Appendix A.1

In this study, we used the primary data from Bangladesh Integrated Household Survey (BIHS 2011–2012) by IFPRI, https://dataverse.harvard.edu/dataset.xhtml?persistentId=hdl:1902.1/21266.

Appendix A.2

"*aus*" is former rainy season, "*aman*" is rainy season and "*boro*" is dry season irrigated rice.

Appendix B

Appendix B.1

$$\begin{aligned} Net\ accounting\ cost_i = \; & \sum_i \sum_j P_{ij} X_{ij} \\ & = c_{i,\ Rental\ cost\ of\ land} + c_{i,\ seed\ cost} + c_{i,\ irrigation\ cost} \\ & + c_{i,\ manure\ or\ compost\ cost} + c_{i,\ pesticides\ cost} + c_{i,\ fertilizer\ cost} \\ & + c_{i,\ draft\ animal\ cost} + c_{i,\ machinery\ cost} + c_{i,threshing\ cost} + c_{i,\ hired\ labor\ cost} \end{aligned} \tag{A1}$$

$$Production\ value_i = \sum_i P_i Y_i \tag{A2}$$

$$\begin{aligned} Gross\ income_i & = \sum_i P_i Y_i - Inkind\ payment_i \\ & = \sum_i P_i Y_i - (C_{i,\ irrigation\ cost\ paid\ by\ crop} + C_{i,\ labor\ cost\ paid\ by\ crop}) \end{aligned} \tag{A3}$$

$$Net\ income(\pi)_i = Gross\ income_i - Net\ accounting\ cost_i \tag{A4}$$

Appendix B.2

We estimate per-capita incomes (US$) of all sample families on assumption of climate change impacts and draw the distribution of the estimated incomes assuming that the distribution follows log normal distribution. To draw log normal distribution, we have to find mean and standard deviation of *ln*(*x*). Firstly, we divide the per capita income in different class and make the average (*x*) of each class and we find the frequency of household (*n*) in each per-capita income class. Then we find the log of average per-capita class, log (*x*); and multiplied by the frequency of household in each class, *n* * log (*x*). Next average,

$$u = \frac{\sum n\{\log(x)\}}{\sum n} \tag{A5}$$

Then we estimate, $\log(x) - u$, $\{\log(x) - u\}^2$ and $n\{\log(x) - \mu\}^2$

Next standard deviation,

$$\sigma = \sqrt{\frac{\sum n\ \{\log(x) - u\}^2}{\sum n}} \tag{A6}$$

Returns the lognormal distribution of *x*, where ln (*x*) is normally distributed with parameters Mean and Standard deviation. Use this function to analyze data that has been logarithmically transformed.

$$\begin{aligned} f_X(x) &= \tfrac{1}{dx}Pr(X \leq x) = \tfrac{1}{dx}Pr(lnX \leq lnx) = \tfrac{1}{dx}\Phi\left(\tfrac{lnx-\mu}{\sigma}\right) = \varphi\left(\tfrac{lnx-\mu}{\sigma}\right)\tfrac{1}{dx}\left(\tfrac{lnx-\mu}{\sigma}\right) \\ &= \varphi\left(\tfrac{lnx-\mu}{\sigma}\right)\tfrac{1}{\sigma x} = \tfrac{1}{x}.\tfrac{1}{\sigma\sqrt{2\pi}}exp\left(-\tfrac{(lnx-\mu)^2}{2\sigma^2}\right) \end{aligned} \tag{A7}$$

Syntax: LOGNORM.DIST(*x*, mean, standard deviation and cumulative)

Appendix C

Table A1. Household income (US$/yr.) from different sources, by region.

	B	CH	CO	D	K	M	RJ	RN	S	BD
Agril. crops	159.35	124.17	82.83	194.67	273.63	225.23	322.78	246.71	131.77	200.28
Main crops	76.23	44.11	35.22	118.52	152.25	127.87	202.10	170.95	89.86	116.89
Other crops	83.13	80.06	47.61	76.16	121.39	97.36	120.69	75.76	41.92	83.39
Fish	115.70	23.47	8.54	31.34	111.73	67.72	49.43	13.14	46.17	55.45
Livestock	27.43	17.81	22.35	51.76	86.61	57.25	76.48	35.67	26.20	48.60
Non-Ag. profit	260.29	293.63	212.95	304.83	254.71	197.39	338.22	171.49	292.70	262.92
Remittance	138.41	381.12	624.89	225.28	107.64	101.84	77.30	87.37	259.51	212.90
Employment	487.70	676.42	464.06	590.46	542.42	436.33	669.77	582.29	642.59	560.94
Other income	64.65	8.41	90.96	38.22	31.36	32.01	190.70	15.53	60.98	57.61
Total	1253.53	1525.04	1506.60	1436.53	1408.12	1117.77	1724.70	1152.23	1459.92	1398.71

B = Barisal, CH = Chittagong, CO = Comilla, D = Dhaka, K = Khulna, M = Mymensingh, RJ = Rajshahi, RN = Rangpur, S = Sylhet, BD = Bangladesh, Main crops = *Aus*, *Aman* and *Boro* rice and other crops = Wheat, Maize, Jute, Potato, Chili, Onion etc.

Table A2. Each agricultural crop's share in total net agricultural income (%), by region.

Crops	B	CH	CO	D	K	M	RJ	RN	S	BD
Rice	45.51	33.66	32.99	37.39	43.52	55.62	51.27	57.72	67.05	47.22
Aus	6.37	2.89	1.51	0.64	3.03	0.84	1.11	1.39	5.19	2.24
Aman	24.36	17.83	6.42	5.22	15.55	15.37	17.27	22.12	18.45	14.96
Boro	14.78	12.95	25.06	31.54	24.95	39.42	32.89	34.21	43.41	30.02
Wheat	0.00	0.00	0.19	0.22	0.70	0.07	1.32	0.96	0.00	0.48
Maize	0.00	0.00	0.84	0.30	0.26	0.00	1.40	2.01	0.00	0.56
Jute	0.61	0.00	3.03	10.53	5.85	0.44	2.80	2.96	0.11	4.37
Potato	0.66	0.37	5.49	0.53	0.18	0.36	4.04	4.68	1.00	1.62
Chili	1.82	2.17	2.69	6.85	5.72	1.54	0.67	1.20	0.53	3.40
Onion	0.00	0.00	0.01	5.79	1.01	0.00	1.81	0.32	0.00	1.70
Other crops	51.39	63.80	54.77	38.38	42.76	41.96	36.67	30.16	31.31	40.65
Total	100	100	100	100	100	100	100	100	100	100

B = Barisal, CH = Chittagong, CO = Comilla, D = Dhaka, K = Khulna, M = Mymensingh, RJ = Rajshahi, RN = Rangpur, S = Sylhet and BD = Bangladesh.

Table A3. Costs and income (US$/ha) associated with aman and boro HYV rice production, by region.

	Aman HYV										*Boro* HYV									
	B	**CH**	**CO**	**D**	**K**	**M**	**RJ**	**RN**	**S**	**BD**	**B**	**CH**	**CO**	**D**	**K**	**M**	**RJ**	**RN**	**S**	**BD**
b	53.77	74.83	76.13	53.84	30.12	45.34	46.93	38.08	57.28	47.08	64.59	82.41	75.69	50.94	32.39	45.13	49.55	42.71	54.49	49.14
c	64.29	38.14	72.11	79.90	64.27	33.96	45.27	30.77	45.13	47.80	60.51	46.47	70.82	71.22	66.36	42.49	73.53	40.41	43.01	58.24
d	1.33	4.58	8.04	34.37	11.12	27.00	37.48	12.43	5.65	19.52	63.70	60.16	135.28	165.63	114.87	122.83	116.16	93.95	61.48	113.42
e	1.19	1.54	2.87	1.55	1.73	2.81	7.00	2.45	3.84	3.22	2.40	5.36	9.24	4.22	10.59	8.17	8.65	25.41	1.92	7.98
f	5.98	11.33	8.48	6.22	3.34	9.16	9.36	9.31	4.81	7.49	14.01	14.25	13.96	7.34	9.24	13.41	11.12	13.73	3.65	9.72
g	26.33	45.58	60.39	50.65	40.65	63.05	49.46	50.75	27.61	47.88	59.67	92.28	92.46	90.84	97.05	106.66	73.24	107.18	45.80	84.34
h	9.08	0.61	0.43	0.67	2.57	3.96	1.61	1.84	6.60	3.22	1.55	1.58	0.30	1.02	2.82	5.72	2.55	2.06	5.54	3.05
i	26.59	43.06	37.71	33.86	25.06	25.65	22.36	26.46	31.04	27.43	42.48	46.83	36.75	33.65	28.94	26.73	21.83	30.41	25.77	29.51
j	17.58	17.31	9.34	6.11	9.51	8.45	4.04	3.36	5.89	7.64	15.92	29.29	14.55	16.23	19.54	10.05	5.96	9.59	4.27	11.99
k	85.80	155.19	133.77	171.81	113.27	115.80	134.27	106.25	107.67	120.55	152.40	305.40	237.84	242.40	151.19	157.81	190.60	125.47	227.20	192.16
TC	291.93	392.18	409.27	438.98	301.63	335.18	357.78	281.70	295.53	331.82	477.24	684.02	686.89	683.49	533.00	539.01	553.19	490.92	473.14	559.55
TP kg/ha	3573	3655	1913	3131	2515	2776	3650	3500	2572	3023	4659	4821	5136	6181	5122	4950	6025	5733	4218	5304
GI	734.65	710.58	387.39	614.66	477.69	577.30	661.75	669.42	476.78	585.58	841.58	964.00	999.64	1169.99	1009.64	1082.65	1115.88	1115.55	749.11	1023.34
GI-TC	442.72	318.40	−21.88	175.69	176.07	242.12	303.96	387.72	181.25	253.75	364.35	279.98	312.75	486.49	476.65	543.65	562.69	624.64	275.96	463.80

B = Barisal, CH = Chittagong, CO = Comilla, D = Dhaka, K = Khulna, M = Mymensingh, RJ = Rajshahi, RN = Rangpur, S = Sylhet and BD = Bangladesh; b = Rental cost of land, c = Seed cost, d = Irrigation cost, e = Manure/compost cost, f = Pesticide cost, g = Chemical fertilizer cost, h = Draft animal cost for land preparation, i = Rental cost for tools and machinery, j = Threshing cost, k = Hired labor cost, TC = Total cost, TP = Total production and GI = Gross income.

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Article

The Value of Tactical Adaptation to El Niño–Southern Oscillation for East Australian Wheat

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Abstract: El Niño–Southern Oscillation strongly influences rainfall and temperature patterns in Eastern Australia, with major impacts on frost, heat, and drought stresses, and potential consequences for wheat production. Wheat phenology is a key factor to adapt to the risk of frost, heat, and drought stresses in the Australian wheatbelt. This study explores broad and specific options to adapt wheat cropping systems to El Niño–Southern Oscillation, and more specifically, to the Southern Oscillation Index (SOI) phases ahead of the season (i.e., April forecast) in Eastern Australia, when wheat producers make their most crucial management decisions. Crop model simulations were performed for commercially-grown wheat varieties, as well as for virtual genotypes representing possible combinations of phenology alleles that are currently present in the Australian wheat germplasm pool. Different adaptation strategies were tested at the site level, across Eastern Australia, for a wide range of sowing dates and nitrogen applications over long-term historical weather records (1900–2016). The results highlight that a fixed adaptation system, with genotype maturities, sowing time, and nitrogen application adapted to each location would greatly increase wheat productivity compared to sowing a mid-maturity genotype, mid-season, using current practices for nitrogen applications. Tactical adaptation of both genotype and management to the different SOI phases and to different levels of initial Plant Available Water ('PAW & SOI adaptation') resulted in further yield improvement. Site long-term increases in yield and gross margin were up to 1.15 $t \cdot ha^{-1}$ and AU$ 223.0 ha^{-1} for fixed adaptation (0.78 $t \cdot ha^{-1}$ and AU$ 153 ha^{-1} on average across the whole region), and up to an extra 0.26 $t \cdot ha^{-1}$ and AU$ 63.9 ha^{-1} for tactical adaptation. For the whole eastern region, these results correspond to an annual AU$ 440 M increase for the fixed adaptation, and an extra AU$ 188 M for the PAW & SOI tactical adaptation. The benefits of PAW & SOI tactical adaptation could be useful for growers to adjust farm management practices according to pre-sowing seasonal conditions and the seasonal climate forecast.

Keywords: ENSO; Southern Oscillation Index; SOI; El Niño; La Niña; soil water; environment type; climate adaptation; management practices; crop model; APSIM

1. Introduction

In Australia, the wheat industry is challenged by complex genotype x environment x management (GxExM) interactions [1,2], due in part to the high spatial and temporal variability of the Australian climate (e.g., [3]). In the eastern part of the continent, annual variations in temperature and rainfall that are influenced by El Niño–Southern Oscillation (ENSO) [1,4,5] affect frost, heat, and drought stress patterns [5–7], and ultimately, wheat production [1,3,5]. Drought and warmer temperatures, but also greater frost risk due to the clear night sky, are generally associated with the onset of El Niño episodes [5,8,9], and limit grain yield [10–13]. Stronger ENSO climate oscillations are expected in the near future, as climate forecasts project more frequent extreme El-Niño and La-Niña conditions [14,15].

As the major driver of inter-annual climate variability in Eastern Australian [4,5,16], ENSO is a quasiperiodic climate pattern that occurs across the tropical Pacific Ocean every 3–8 years. It is caused by variations in the surface temperature of the tropical eastern Pacific Ocean, and the air surface pressure in the tropical western Pacific [17]. The Southern Oscillation Index (SOI), as measured by surface pressure anomaly difference between Tahiti and Darwin, has been used to investigate ENSO effects on crops. Five SOI phases have been defined through grouping all sequential two-month pairs of the SOI into five clusters, using principal component analysis and a cluster analysis [18]. Hammer et al. [1] found that using the 5-phase SOI classification (based on SOI values for the current and previous month) could significantly increase wheat profits (up to 20%) and decrease failure risk (up to 35% less risk) in Goondiwindi, South-Eastern Queensland, Australia, through adapting wheat cultivars and nitrogen fertiliser.

Strategies for yield improvement include breeding new cultivars and adapting management practices to the target population of environments [19]. Climate forecasting offers new opportunities in terms of agricultural planning and operation [4]. In the Australian broad-acre dryland wheat production area, most major decisions occur prior to sowing. Producers can potentially react to early indicators of upcoming rainfall and temperature. Early estimation of SOI phases can thus help farmers adjust management practices such as which cultivar to sow, when to sow, and what nitrogen fertilisation to apply [5,20,21].

In Eastern Australia, wheat crops rely heavily on soil-stored plant available water (PAW) [6,22]. An appropriate combination of sowing data, variety maturity, and pre-sowing PAW is crucial to allow flowering and grain filling to occur with minimal stress, in particular frost, heat, and drought stress, and thus, to maximise yield potential [6,7,23–25]. In this context, crop modelling can assist farmers to adapt their practices to specific SOI phases through adequate choice of maturity type and sowing date, in order to get extra benefit and increased profit [26].

The aims of this paper were to determine the values of (i) fixed adaptation (no distinction between the years) and (ii) adaptations to specific pre-sowing plant available water (PAW) and/or SOI phase. In this study, adaptation strategies were defined in terms of sowing, maturity type, and nitrogen fertilisation, to target the greatest long-term productivity at each site. The APSIM crop model [27], together with a phenology model [28], frost impact module [12] and heat impact module [10], were used to predict flowering time and yield of wheat, and search for the best long-term adaptation strategies.

2. Materials and Methods

2.1. Climatic Data

Fifteen weather stations representing local pedo-climatic conditions from the East Australian wheatbelt [7,22] were selected (see Chenu et al., 2013 [22] for more details) to compare adaptation options to Southern Oscillation Index (SOI) phases (Figure 1, Table 1).

The SOI, which corresponds to differences in sea level pressure between Tahiti and Darwin, has been classified in five phases [18]: 'consistently negative' (I), 'consistently positive' (II), 'rapidly falling' (III), 'rapidly rising' (IV) and 'consistently near zero' (V). These phases were grouped into three classes: consistently negative and rapidly falling (SOI phases I & III), consistently positive and rapidly rising (SOI phases II & IV), and consistently near zero (SOI phase V), as suggested by Potgieter et al. [3]. Weather records from 1900 to 2016 (117 years) were extracted from the Australian weather database (SILO Patched Point Dataset [29]; http://www.longpaddock.qld.gov.au/silo/). The SOI phase classification was sourced from Seasonal Climate Outlook in the Long Paddock (http://www.longpaddock.qld.gov.au/). In this study, the SOI phases were classified using SOI values from March–April to look at the effects for a pre-season indicator. From 1900 to 2016, 36 years had been classified as SOI phases I & III, 45 years as SOI phases II & IV and 34 years as SOI phase IV.

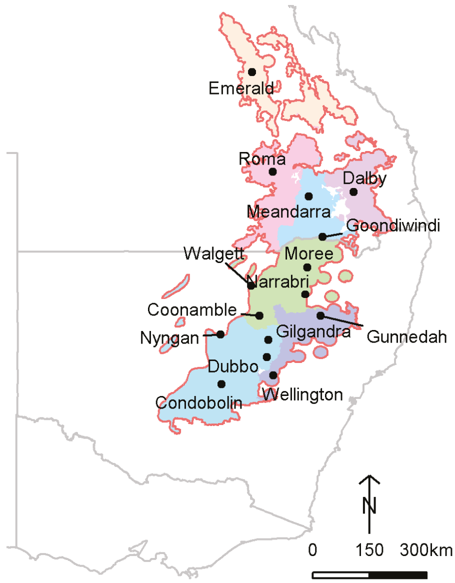


Figure 1. Map of the seven regions of the East Australian wheatbelt, with 15 sites chosen to represent those regions. Details on the locations can be found in Chenu et al., 2013 [22].

Table 1. Regions, locations, soil nitrogen at sowing and nitrogen fertilisation (in the baseline simulations), minimum pant available water (PAW) at sowing chosen to represent the East Australian wheatbelt. Initial and applied nitrogen (N) is indicated by 'x-y-z-a': x, initial N present in the soil at sowing; y, N applied at sowing as urea; z and a, N applied as nitrate at the stages 'beginning of stem elongation' and 'mid-stem elongation', respectively.

Region	Location	Lat.	Long.	Nitrogen (kg ha^{-1})	Minimum PAW at Sowing (mm)
Central Queensland	Emerald	−23.53	148.16	30-50-0-0	80
Eastern Darling Downs	Dalby	−27.18	151.26	30-130-0-0	80
Eastern NSW	Gunnedah	−30.98	150.25	50-70-60 *-0	80
	Wellington	−32.80	148.80	50-50-50 †-0	50
Northern NSW	Moree	−29.48	149.84	30-80-0-0	80
	Walgett	−30.04	148.12	30-80-0-0	80
	Narrabri	−30.32	149.78	30-130-0-0	80
	Coonamble	−30.98	148.38	50-70-60 †-0	50
Southern West Queensland	Roma	−26.57	148.79	30-50-0-0	80
Western Darling Downs	Meandarra	−27.32	149.88	30-80-0-0	80
	Goondiwindi	−28.55	150.31	30-80-0-0	80
Western NSW	Nyngan	−31.55	147.2	50-60-60 †-0	80
	Gilgandra	−31.71	148.66	50-50-50 †-0	50
	Dubbo	−32.24	148.61	50-50-50 †-0	50
	Condobolin	−33.07	147.23	50-60-60 †-0	80

* >80 mm of rainfall from sowing to the stage "end of tillering–beginning of stem elongation". † >100 mm of rainfall from sowing to the stage "end of tillering–beginning of stem elongation".

Monthly temperature and cumulated rainfall were calculated as the average for each month from 1900 to 2016. Daily minimum and maximum temperatures were used to determine occurrences of frost and heat events.

2.2. Crop Simulations and Gross Margins

Wheat yield (dry weight without moisture content) was simulated for the 15 sites (Figure 1, Table 1) from 1900 to 2016. The simulations were performed with the APSIM 7.5 model [27,30], which has been widely tested for wheat across Eastern Australia (e.g., Chenu et al., 2011; Holzworth et al., 2014; Christopher et al., 2016 [6,27,31]; http://www.apsim.info/APSIM.Validation/Main.aspx), and a wheat-phenology gene-based module [28], a heat impact module [10], and a frost impact module with a frost-stress threshold of −2 °C [12].

For each site and year, the simulations were begun with a summer fallow starting from 1 November with a soil containing 20% of its potential available soil water capacity (PAWC). Wheat crops were sown at two-day intervals within a fixed sowing window from the 1 April to 30 June for all 15 sites, when the soil held enough plant available water (PAW) at sowing (Table 1). Soil nitrogen and surface organic matter were reset at sowing. The base nitrogen fertilisation was chosen to reflect local farming practices, and therefore, varied with site and seasonal rainfall, as defined in Chenu et al., 2013 [22] (Table 1). Plants were grown at a density of 100 plants per m^2. Seasons with not enough soil water on 1 April (i.e., when management options were chosen for the tactical adaptation scenarios, see below) were excluded from the analysis.

Different management strategies were tested with a range of sowing dates (sowing every two days from 1 April to 30 June) and nitrogen applications. An extra 0 to 140 $kg \cdot ha^{-1}$ (at 20 $kg \cdot ha^{-1}$ interval) of nitrogen was applied to the base simulations. Nitrogen fertilisation was applied at the same stage(s) as in the base simulations (i.e., local farming practices) with the same proportions, i.e., at sowing and/or 'beginning of stem elongation' depending on the seasonal opportunities.

Simulations were performed for 208 genotypes including commercial varieties and virtual genotypes that could potentially be bred based on the flowering alleles present in the Australian germplasm pool (see Zheng et al., 2013 for details [28]). Virtual genotypes were created including all combinations of *VRN-A1*, *VRN-B1*, *VRN-D1,* and *PPD-D1* genes (two alleles for each gene), and the full range of values of additional thermal time requirement from floral to flowering (from 425 to 1025 °Cd [28]). Genotypes with the same phenology (from different allelic combinations) were disregarded, so that a total of 156 genotypes unique for their phenology were considered. Overall, the selected genotypes had APSIM parameters ranging from 0 to 1.2 for the photoperiod sensitivity (0.6 for the reference genotype Janz), 0.9 to 1.7 for the vernalisation sensitivity (0.9 for Janz), and 425 to 1025 °Cd for the additional thermal time requirement from floral to flowering (675 °Cd for Janz).

Odd and even years were first simulated separately as some crops matured after 1 November (date of the simulation initialisation). Odd- and even-year simulations were then merged together. Overall, 800 thousand simulations were run through the CSIRO HTCondor service using ClusterRun platform with the runs being completed in less than 4 h [32].

The gross margin was estimated for each simulation based on wheat and nitrogen prices. Other costs of wheat production were ignored, as only variations in gross margin were considered in this study (i.e., only the fertilisation costs varied among the tested management options). The wheat and nitrogen (as urea) prices were sourced from Australian Commodity Statistics [33], and calculated as median values from 2003 to 2012 (i.e., AU$ 269 and AU$ 547 per tonne for wheat and urea, respectively). Variation in grain quality was not considered in this study as the APSIM-wheat model is currently not able to accurately simulate changes in wheat protein content. Increase in gross margin at each site was multiplied with the planting area of the considered region (averaged data from 1975 to 2000, 2004 and 2006; source: Australian Bureau of Statistics), and all regional values were summed to obtain the total increase in gross margin for the Eastern region. Hence, gross margin estimations did not account for changes in fertilizer prices, changes in planting area, changes in wheat prices related to the harvested grain quality, nor changes in wheat prices related to fluctuations in the domestic and/or global market.

2.3. Fixed and Tactical Adaptation Options

Different scenarios exploring the GxExM interactions were evaluated to test their values for different pre-sowing levels of soil water and/or for the three different SOI classes at each studied site. The acceptable range of soil PAW (from minimum required PAW at sowing (Table 1) to the PAWC) calculated at 1 April was divided into three groups (0–33%, 33–67%, 67–100%) to represent Low, Median and High pre-sowing water levels. The 156 genotypes unique for their phenology were considered, as well as sowing dates from 1 April to 30 June and different nitrogen fertilisation options (see previous section).

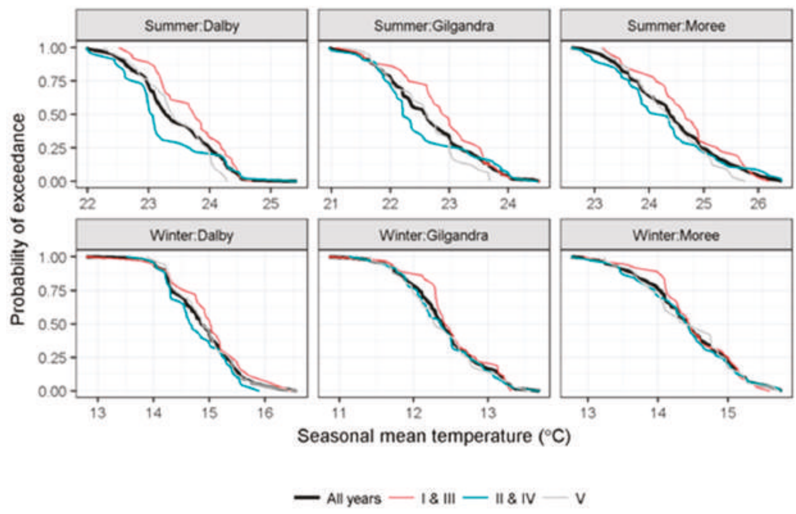
To provide a reference against conventional practice, a baseline scenario was defined. In this scenario, the reference cultivar Janz was simulated from 1900 to 2016 for a sowing at 21 May using standard farmer practices for fertilisation (Table 1) [22]. A strategic 'fixed scenario' that considers the best management and best genotype for all years (in terms of highest average yield) at each location ('Fixed adaptation') was used as benchmark for best long-term practices (1900–2016). To investigate the potential tactical advantages of adapting, whereby a grower would modify planting decisions based on the SOI phases and/or soil PAW prior to sowing, scenarios with optimised genotypes and management practices specific to SOI classes and/or PAW groups were defined (at each location) through maximizing the average yield for crops grown within each SOI class and/or PAW group. For each location, the tactical adaptation scenarios consisted in either (1) the 'PAW' scenario, which considered the best overall genotype and management within situations from each PAW group, (2) the 'SOI' scenario, which considered the best overall genotype and management within situations from each SOI class, or (3) the 'PAW & SOI' scenario where both genotype and management were optimised for each combination of PAW group × SOI class. For the different scenarios, yield differences and changes in gross margin compared to the baseline and fixed adaptation scenarios were calculated for each year.

3. Results and Discussion

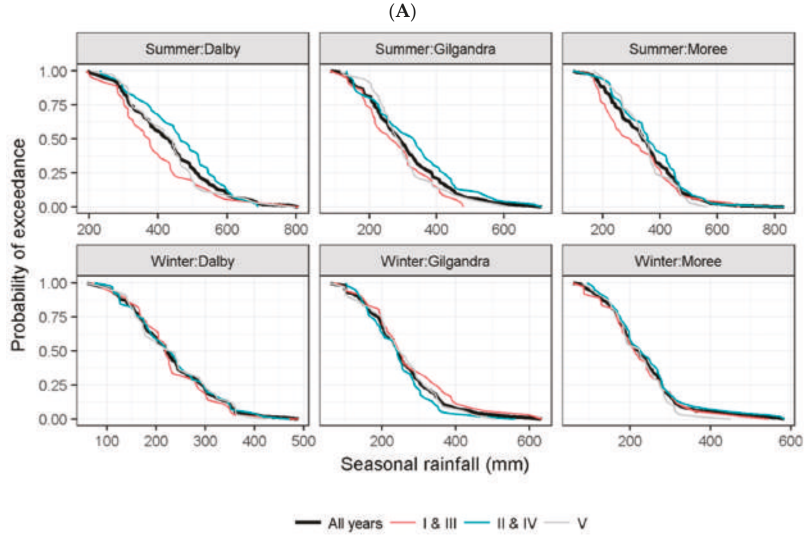
3.1. SOI Impacts on Seasonal Temperature and Rainfall

In the Eastern wheatbelt, SOI phases from the end of summer (calculated in March–April) were typically associated with temperature and cumulated rainfall recorded during the 'summer' fallow preceding the wheat crop (November to April). Higher temperatures were recorded for years with consistently negative SOI (phase I), and to a lesser extent, for years with rapidly falling SOI (III), while lower temperatures occurred in years with consistently positive SOI (II), and to a lesser extent, in years with rapidly increasing SOI (IV) (data not shown, Figure 2A and Figures S1–S3). For instance, the temperature in years from SOI phase I was up to 1.5 °C higher than the 'all years' data in February and March in Emerald, Roma and Gunnedah (data not shown). By contrast, summer rainfall tended to be lowest for SOI phases I & III, and highest for SOI phases II & IV (Figure 2B and Figure S7). As wheat crops in the Eastern wheatbelt heavily rely on soil-stored plant available water (PAW) [6,22], this implies that differences observed in summer rainfall for the different SOI phases are likely to impact crop water-stress pattern and yield, and also the type of genotype and management best suited for specific adaptation.

The impacts of SOI phases (calculated in March–April) for the upcoming 'winter' season (May to October) were weaker than climate variations observed during the previous 'summer' (Figure 2 and Figures S1–S8). In 'winter', differences in temperatures were forecasted for most sites with a tendency for greater differences in the northern sites (e.g., Emerald, Roma, and Meandarra), with highest temperatures for SOI phases I & III, and lowest for SOI phases II & IV (Figure 2B and Figures S4–S6). In any case, monthly temperatures of any SOI phases differed by less than 0.5 °C compared to 'all years' (data not shown, Figure 2A and Figures S4–S6). The impact of SOI phases on rainfall was only visible for a few sites, and mainly for higher rainfall in SOI phase IV years (data not shown, Figure 2B and Figure S8). As found in previous studies (e.g., [34]), ENSO had a substantial impact in northern sites, while a relatively weak impact in southern sites (data not presented for sites south of Condobolin).



(**A**)



(**B**)

Figure 2. Cumulative probability distributions (probability of exceedance) of 'summer' and 'winter' average temperature (**A**) and cumulated rainfall (**B**) for the three SOI classes, singly (SOI phases I & III, SOI phases II & IV, and SOI phase V) and combined ('all years') for 1900–2016 at three sites in the Eastern wheatbelt. The three SOI classes correspond to SOI consistently negative and rapidly failing (phases I & III), SOI consistently positive and rapidly rising (phases II & IV), and SOI consistently near zero (phase V). SOI phases were determined in March–April, prior to sowing. The 'summer' data were recorded from the previous November to April, while 'winter' data are for the up-coming May to October period. See Figures S1–S8 for average, minimum and maximum temperature, and cumulated rainfall at other sites for both the 'summer' and 'winter' periods.

3.2. ENSO Impacts the Frequency of Occurrence of Frost and Heat Events around Flowering

Extreme temperatures can greatly decrease yield by affecting reproductive organs or impacting grain filling [11,12]. Australian wheat farmers manage their crops to minimise the risk of frost, heat, and drought by targeting the flowering time into an optimum window [7,25]. The last frost day with a 10% risk of frost tended to be earlier in SOI phases II & IV, and delayed in SOI phases I & III mostly in the eastern sites (Figure S9). By contrast, the first heat day with a 30% risk of heat tended to be earlier in SOI phases I & III, and delayed in SOI phases II & IV. Hence, in terms of temperature, the low-risk flowering window tended to last longer for SOI phases II & IV, while it tended to be reduced for SOI phases I & III. Using the three ENSO phases (i.e., El Niño, La Niña and Neutral), Alexander and Hayman [35] found similar trends for distribution and tails of last frost day in 15 sites across the Australian wheatbelt.

3.3. Variations in Yield across SOI Phases

For the reference cultivar and management (i.e., baseline simulations: Janz sown 21 May with farmer fertilisation practices), long-term average yield ranged from 0.93 to 2.71 t·ha^{-1} across sites and averaged 2.06 t·ha^{-1} among the 15 studied sites (Figure 3; 'all years'). Greatest yields were achieved in SOI phases II & IV, with long-term average yield ranging from 0.98 to 2.70 t·ha^{-1} across locations and averaging 2.10 t·ha^{-1} for Eastern Australia. By contrast, long-term average yield in the SOI phases I & III were commonly lower, ranging from 0.90 to 2.70 t·ha^{-1} across locations, and averaging 2.00 t·ha^{-1} for Eastern Australia. Strong links between wheat yield with ENSO were also found in the Eastern wheatbelt in other studies [18,36]. While the early study of Rimmington et al. [37] suggested little impact of ENSO types on wheat yields in Southern and Western Australia, more recent studies found wheat yields to be affected by ENSO in Southern and South-eastern Australia [38,39].

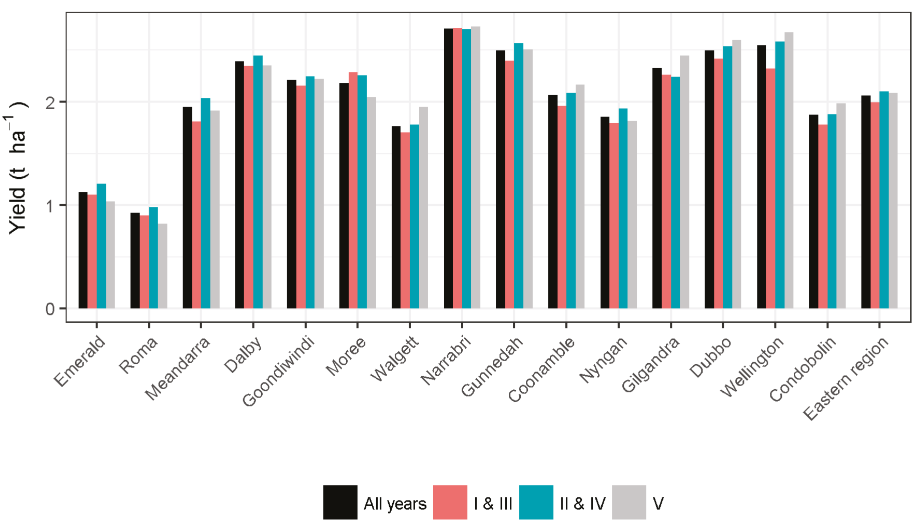


Figure 3. Simulated average yield in the baseline scenario for all years (1900–2016) and for years from each of the three SOI classes at 15 sites across the Eastern wheatbelt and for the whole Eastern wheatbelt region. Baseline simulations corresponded to a standard farmer practice (a medium-season cultivar Janz was sown at semi-optimum sowing date (21 May) with current fertilisation practice). The three SOI classes correspond to SOI consistently negative and rapidly failing (SOI phases I & III), SOI consistently positive and rapidly rising (SOI phases II & IV), and SOI consistently near zero (SOI phase V). SOI phases were determined in March–April, prior to sowing.

3.4. Optimising Genotype and Management across All Years Results in Consistent Yield Improvement and Higher Gross Margins

A large number of adaptation strategies were simulated, combining a wide range of genotypes (with all potential phenology range for Australian wheat) and diverse management practices (a broad range of sowing dates and nitrogen fertilisation options). These strategies were first applied to optimise average yield for a site across all years ('fixed adaptation') by selecting the top yielding genotype × management combination (Figure 4, Figure 5 and Figure S10).

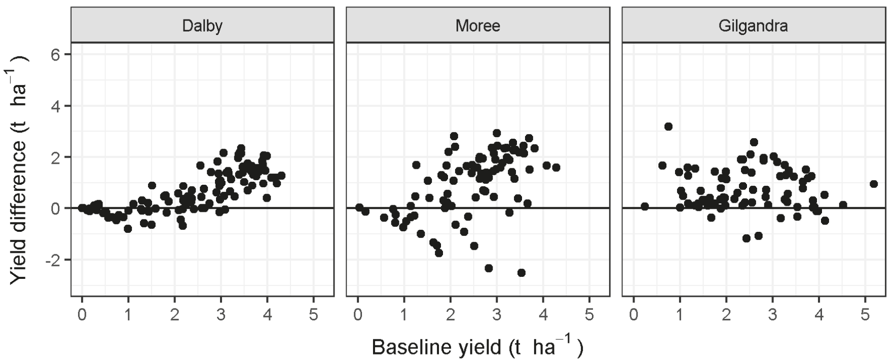


Figure 4. Yield advantage of fixed adaptation over the baseline scenario. The yield difference is calculated for each year. The baseline corresponds to simulated yield for a medium-season cultivar Janz sown at semi-optimum sowing date (21 May) with current fertilisation practice. See Figure S10 for other sites.

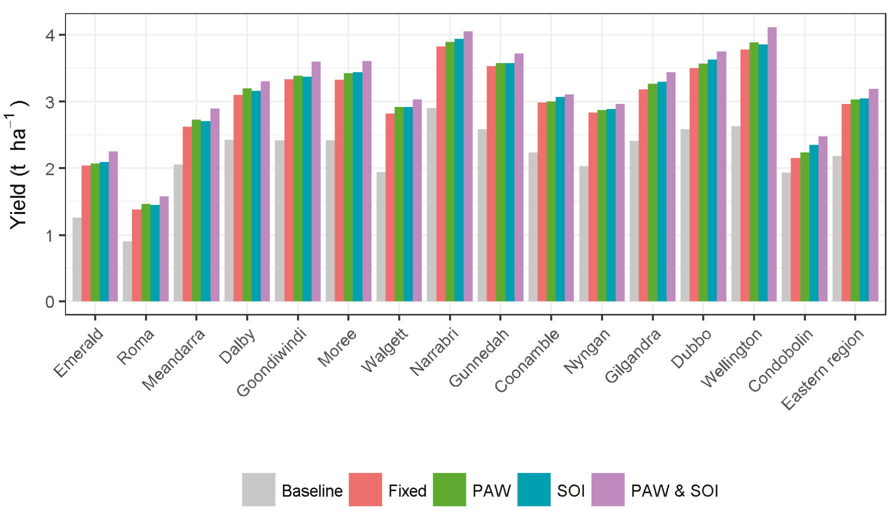


Figure 5. Simulated mean yields for the baseline, fixed adaption, and all the studied tactical adaptation scenarios related to pre-sown soil water and SOI forecast. The baseline corresponds to simulated yield for a medium-season cultivar Janz sown at semi-optimum sowing date (21 May) with no extra nitrogen input. The fixed adaptation scenario corresponds to optimised genotype and management across all years for each site. The three tactical adaptation scenarios include specific adaptation to soil PAW (plant available water) groups, SOI classes, and PAW & SOI groups. These adaptations correspond to optimised genotype and management for each PAW group and/or SOI class. SOI phases were determined in March–April, prior to sowing.

Compared to the baseline, the fixed adaptation scenario increased yields in the majority of years in all sites, although yield losses were also observed for a few years in all sites (Figure 4 and Figure S10). Regional yield (average across all sites) thus increased from 2.06 (baseline) to 2.96 t·ha^{-1} (fixed adaptation) (Figure 5). At the site level, long-term average yield ranged from 1.38 to 3.82 t·ha^{-1} for fixed adaptation compared to 0.91 to 2.90 t·ha^{-1} for the baseline, meaning a yield increase from 0.22 to 1.15 t·ha^{-1} (0.78 t·ha^{-1} on average for the whole region; Figure 3). Compared to the baseline, the fixed adaptation strategy corresponded to an earlier sowing with more nitrogen application of, in general, a shorter-maturing genotype in the northern part of the region, and a longer-maturing genotype in the southern part of the region (data not shown).

In terms of gross margin, site long-term increases from the baseline to fixed adaptation scenario ranged from AU$ 40.5 to 223.0 ha^{-1}, which corresponds to a regional increase of AU$ 153.00 ha^{-1} on average for the whole region. Across Eastern Australia, fixed adaptation resulted in an AU$ 440.00 M increase in gross margin compared to the standard current practice considered here.

3.5. Benefits of Tactical Compared to Fixed Adaptation Vary with the Location, the Soil Pre-Sowing Conditions and the SOI Forecast

To explore the potential of tactical adaptation over fixed adaptation, the genotype and management were optimised for pre-sowing PAW- and/or SOI-specific conditions, and then compared to the fixed adaptation scenario. For most sites (Figure 5), slight increases in long-term average yield were simulated when adapting the genotype and management to either pre-sown PAW or SOI solely. Substantial improvements occurred when optimising average yield for both the genotype and the management for each SOI class and PAW group together (PAW & SOI), rather than sole optimisation of either the PAW group or SOI class. It can nevertheless be noted that fewer of the 117 seasons were classified in each of the nine PAW & SOI groups than in each of three PAW groups or the three SOI classes, meaning that the optimised yield is prone to more uncertainty due to the likely reduction in environmental variations within groups of years considered.

However, tactical adaptation scenarios only allowed yield to increase for some of the years compared to the fixed adaptation (Figure 6 and Figures S11–S13). Actually, when adapting the PAW group only (‘PAW adaptation’), losses in yield compared to the fixed adaptation occurred relatively frequently, with losses that were typically small, but which could be as substantial as 2 t·ha^{-1} in some locations (Figure 6 and Figure S11). Similar trends and extents were observed for adaption to SOI classes. Adapting to both PAW and SOI tended to increase the frequency of yield gains, especially in poor seasons (i.e., when yield was medium to low in the fixed adaptation scenario), mainly due to better tuning of the crop phenology (maturity type $\times$ sowing time) to the considered environmental conditions. However, yield losses compared to the fixed adaptation still occurred frequently in locations such as Wellington, while they were relatively rare in locations like Coonamble and Moree (Figure S13). Note that the unbalanced number of years among PAW groups, SOI classes, and PAW $\times$ SOI groups might cause bias in the adaptation values and risks.

Overall, when considering the optimised genotypes and management for each PAW group (‘PAW’), long-term average yield and gross margin increased at each site from 0.012 to 0.13 t·ha^{-1}, and from AU$ 2.63 to 41.9 ha^{-1}, respectively, compared to the fixed adaptation scenario (Figure 7). When considering genotype and management practices optimised for each SOI class (‘SOI’), long-term average yield and gross margin at each site increased from 0.037 to 0.17 t·ha^{-1}, and from AU$ 5.00 to 41.50 ha^{-1}, respectively. Finally, when considering optimised management and cultivar for each combination of PAW group and SOI class (‘PAW & SOI’), average yield and gross margin at each site increased from 0.15 to 0.46 t·ha^{-1}, and from AU$ 34.2.00 to 108 ha^{-1}, respectively, compared to the fixed adaptation. Hammer et al. (1996) studied the adapted values of SOI phases through changing cultivars and nitrogen fertilisation at Goondiwindi, and also found a substantial, although more limited, increase in gross margin ($26 ha^{-1}) compared with results in this study ($48 ha^{-1}, Figure 7B) [1].

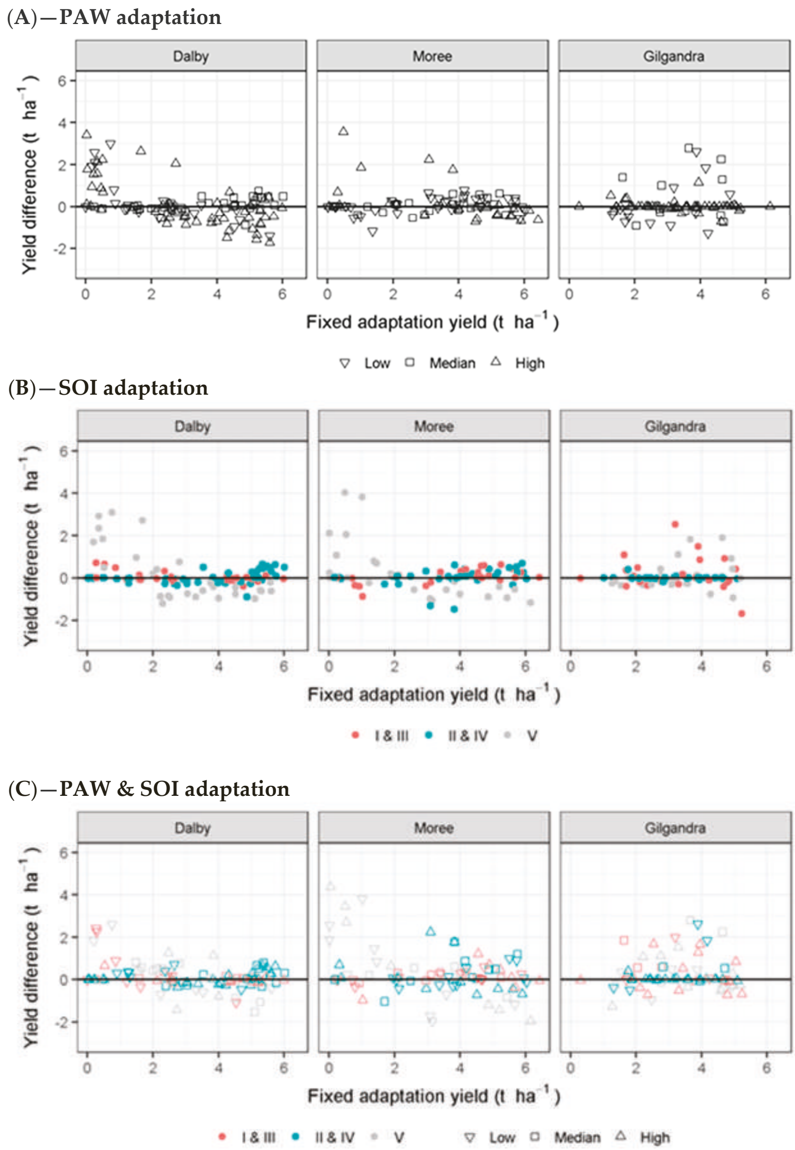
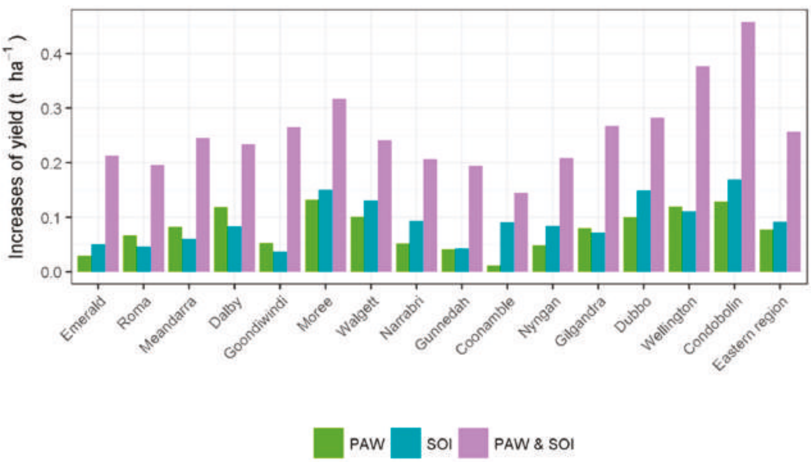


Figure 6. Yield advantage of tactical adaptation scenarios for (**A**) pre-sowing soil PAW (low, median and high), (**B**) SOI classes (I & III, II & IV and V), and (**C**) both PAW & SOI groups over fixed adaptation. The yield difference is calculated for each year. The fixed adaptation scenario corresponds to optimised genotype and management across all years. The three tactical adaptation scenarios correspond to optimised genotype and management for each PAW (plant available water) group and/or SOI class. SOI phases were determined in March–April, prior to sowing. See Figures S11–S13 for other sites.

(**A**)



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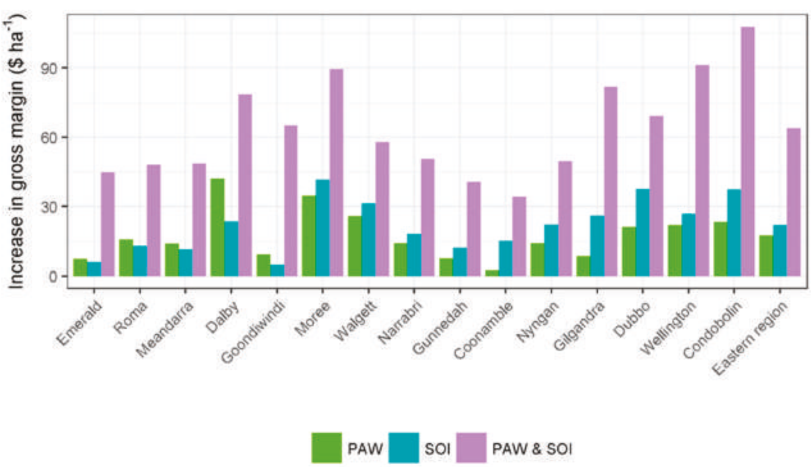

Figure 7. Increase in simulated yield (**A**) and gross margin (**B**) for tactical adaptation options compared to the fixed adaptation in each studied site and the whole Eastern wheatbelt. Increases in yield were averaged for all years from 1900 to 2016. The three tactical adaptation options correspond to optimise long-term yield for either (i) low/medium/high pre-sowing plant available water (PAW), (ii) each class of Southern Oscillation Index (SOI), or (iii) each combination of PAW group and SOI class.

At the regional scale, long-term mean increased in yield and gross margin of PAW & SOI tactical adaptation versus fixed adaptation were 0.26 t·ha^{-1} and AU$ 63.90 ha^{-1}, respectively. The cumulated regional increase in gross margin was AU$ 188 M for the Eastern wheatbelt. Note that the increase gross margin in this paper considered fixed nitrogen price, and accounted for neither changing wheat price related to the harvested grain quality, nor to the domestic and/or global market.

3.6. Should Eastern Australian Wheat Producers Adapt Their Decisions Based on SOI Phases?

In Australia, SOI phases impact the climate and crops mostly in the eastern part of the wheatbelt. In this region, wheat management occurs almost exclusively at sowing. While specific adaptation could be more accurate later in the season, i.e., when climate trends in regard to El Niño/La Niña are clearer, early forecast of the SOI phases is required to allow farmers to prepare seeds and plan suitable management. The potential gains of specific adaptation to such pre-sowing forecasts of SOI phases combined with knowledge on initial soil water appeared to be substantial (Figures 5 and 7). While the gains are variable depending on the location, the extra costs for seed companies and farmers to store large stocks of seeds required for specific adaptation may have to be considered, especially at the farm scale. Unpredictable rainfall in the autumn before sowing may also constrain sowing opportunities [1]. That said, the potential gains of specific adaptation appear to be well above what could be expected from most breeding innovations, at least in the short term [40].

Other methods exist to forecast short-term or seasonal climate. For instance, the Australian Bureau of Meteorology produced twice-weekly weather forecasts for a period of 270 days, with a dynamic model called POAMA (http://poama.bom.gov.au/info/poama-2.html) [41–43]. Such seasonal forecasts have been used to look at management strategies of crops [44–46]. To improve these forecasts, which use on a grid of about 250 km, the Bureau of Meteorology is now proposing seasonal forecasts (ACCESS-S) based on ACCESS (Australian Community Climate and Earth System Simulator; http://www.bom.gov.au/australia/charts/about/about_access.shtml) using a 60 km grid. Other indices than SOI or ENSO phases could also be used for specific adaptation, such as the Inter-decadal Pacific Oscillation (IPO) phases [47] or drought environmental types [20,22,48,49] if climate forecasts are sufficiently reliable. For instance, crop models have been used to assess the value of broad and specific adaptations to select sorghum varieties and managements for different types of drought environments [20].

4. Conclusions

In this study, we assessed the value of fixed adaptation (no distinction between the years) and tactical adaptations based on pre-sowing plant available water (PAW) and/or SOI forecasts to increase productivity at given sites. Overall, with our current knowledge, it appears that yield gains can be made from improving cultivar and management strategy both regardless of climate forecast (fixed adaptation), and as a tactical adaptation to pre-sowing soil water conditions and climate forecasts. The benefits of PAW and SOI tactical adaptation could be useful for farmers to adjust farm management practices according to the season, and may be improved with new forecasting climate methods such as the newly developed ACCESS-S model.

Supplementary Materials: The following are available online at http://www.mdpi.com/2225-1154/6/3/77/s1. Figure S1: Cumulative probability distributions of 'summer' average temperature for the three SOI classes, singly and combined ('all years'), Figure S2: Cumulative probability distributions of 'summer' maximum temperature for the three SOI classes, singly and combined ('all years'), Figure S3: Cumulative probability distributions of 'summer' minimum temperature for the three SOI classes, singly and combined ('all years'), Figure S4: Cumulative probability distributions of 'winter' average temperature for the three SOI classes, singly and combined ('all years'), Figure S5: Cumulative probability distributions of 'winter' maximum temperature for the three SOI classes, singly and combined ('all years'), Figure S6: Cumulative probability distributions of 'winter' minimum temperature for the three SOI classes, singly and combined ('all years'), Figure S7: Cumulative probability distributions of 'summer' total rainfall for the three SOI classes, singly and combined ('all years'), Figure S8: Cumulative probability distributions (probability of exceedance) of 'winter' total rainfall for the three SOI classes, singly and combined ('all years'), Figure S9: Probability of last frost day and first heat day for the three SOI classes, singly and combined ('all years'), Figure S10: Simulated yield advantage of fixed adaptation over the baseline scenario, Figure S11: Simulated yield advantage of PAW tactical adaptation scenario over fixed adaptation scenario, Figure S12: Simulated yield advantage of SOI tactical adaptation scenario over fixed adaptation scenario, Figure S13: Simulated yield advantage of PAW & SOI tactical adaptation scenario over fixed adaptation scenario.

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Possible Scenarios of Winter Wheat Yield Reduction of Dryland Qazvin Province, Iran, Based on Prediction of Temperature and Precipitation Till the End of the Century

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Abstract: The climate of the Earth is changing. The Earth's temperature is projected to maintain its upward trend in the next few decades. Temperature and precipitation are two very important factors affecting crop yields, especially in arid and semi-arid regions. There is a need for future climate predictions to protect vulnerable sectors like agriculture in drylands. In this study, the downscaling of two important climatic variables—temperature and precipitation—was done by the CanESM2 and HadCM3 models under five different scenarios for the semi-arid province of Qazvin, located in Iran. The most efficient scenario was selected to predict the dryland winter wheat yield of the province for the three periods: 2010–2039, 2040–2069, and 2070–2099. The results showed that the models are able to satisfactorily predict the daily mean temperature and annual precipitation for the three mentioned periods. Generally, the daily mean temperature and annual precipitation tended to decrease in these periods when compared to the current reference values. However, the scenarios rcp2.6 and B2, respectively, predicted that the precipitation will fall less or even increase in the period 2070–2099. The scenario rcp2.6 seemed to be the most efficient to predict the dryland winter wheat yield of the province for the next few decades. The grain yield is projected to drop considerably over the three periods, especially in the last period, mainly due to the reduction in precipitation in March. This leads us to devise some adaptive strategies to prevent the detrimental impacts of climate change on the dryland winter wheat yield of the province.

Keywords: CanESM2; HadCM3; precipitation; temperature; winter wheat yield

1. Introduction

The temperature of the Earth is increasing more rapidly than during the previous decades, leading to extensive climate change [1]. The Earth's temperature is projected to maintain its upward trend slightly in the next few decades [1]. A significant rise in the concentration of greenhouse gases such as CO_2, CH_4, N_2O, and water vapor, mainly caused by human activities, has intensified this trend [2]. The concentration of greenhouse gases, volume of ozone, aerosols, and sunspots seem to be the most noticeable reason for temperature variations and climate change in the recent century [3].

More than two billion people live in drylands, constituting nearly 40% of the world's population [4]. Cereals are the major crops cultivated in drylands [5]. Crop production in drylands mainly depends on precipitation during the growing season [6]. Moreover, the rise in temperature has led to exacerbating droughts and a considerable loss in crop yields in arid and semi-arid regions [7].

It is necessary to manage drylands in a sustainable way, by which food security is achieved [8]. To do so, there must be some possible measurements and predictions to protect vulnerable sectors such as agriculture and water resources in drylands [9].

General Circulation Models (GCMs) are the most developed tools for the simulation of general responses to the accumulation of greenhouse gases [10]. Studies have shown that the results of GCMs cannot be exploited directly because they are not accurate enough in describing sub-grid data [10]. Therefore, Statistical Downscaling Models (SDSMs) are one of the tools that have been developed to deal with this problem [11]. SDSMs are the most frequently used models in agricultural research, where some independent variables are measured and collected to predict dependent variables [12]. Tatsumi et al. [13] applied the Hadley Centre Coupled Model (version 3; HadCM3) and Coupled Global Climate Model 3 (CGCM3) to forecast the daily minimum, maximum, and average temperature of Shikoku city in Japan, using downscaling techniques. Their results indicated that the temperature is likely to increase in the Shikoku region, Japan, within the period 2071–2099. In a similar study, Ribalaygua et al. [14] used downscaling techniques to simulate the daily minimum and maximum temperature and daily precipitation in a region located in Spain. Their results showed that maximum and minimum temperatures will rise, while precipitation will decrease in the 21st century. Johns et al. [15], by applying the HadCM3 model, predicted that some regions of Central America and Southern Europe might be moister in the future, whereas Australia may experience a type of drier climate.

In recent years, researchers have studied the potential impacts of climate change on plant growth by using different types of simulation models [16,17]. Russell et al. [18] reported that most of the alterations in wheat yield in the United States are related to climate change. Temperature and precipitation, as two important climatic variables for the evaluation of future grain yield, have been investigated by many researchers. For instance, [16] indicated that the changes in temperature and precipitation within the last 30 years in Mexico had positively impacted on the winter wheat yield. In another study, Landau et al. [19], by applying a multiple-regression model, indicated that the temperature increase led to an improvement in the winter wheat crop characteristics, while the precipitation increase could have negative impacts.

The downscaling of GCMs parameters and studying the possible changes in wheat yield due to climatic effects have been distinctly investigated [14,20]. Lhomme et al. [21], for example, studied the potential effect of climate change on durum wheat yield in Tunisia using the downscaled values of some scenarios. Moreover, the efficiency of the IPCC scenarios has rarely been evaluated and compared [22]. In the present study, the downscaling of two important climatic parameters—temperature and precipitation—was done by the Canadian Earth System Model (CanESM2) and HadCM3 models for the province of Qazvin, located in Iran, where the climate is semi-arid and the dryland farming of winter wheat dominates. Then, the most efficient scenario was chosen to predict the dryland winter wheat yield of the province for the next few decades through a multiple-regression model. The efficiency of the fourth and fifth IPCC scenarios in predicting the temperature and precipitation of the region was also compared.

2. Materials and Methods

2.1. Geography, Climate, and Dryland Farming of the Province

The province of Qazvin has an area of 15,821 km^2, located between 48–45 to 50–50 East of the Greenwich Meridian of longitude and 35–37 to 36–45 North latitude of the Equator. Its average altitude is 1278 m above sea level. It has a semi-arid climate with the annual mean precipitation, daily mean temperature, and relative humidity of 301 mm, 14.2 °C, and 51%, respectively. The province is affected by Siberian and Mediterranean winds, which are considerably important factors in controlling the climate of the province. The geographical situation of the studied area is shown in Figure 1.

The total winter wheat yield of the province is 445 million kg, 364 million kg (82%) of which belongs to irrigated farming and 80.7 million kg (18%) to dryland farming. The total cultivated area for winter wheat is nearly 202,497 ha, 95792 ha and 106,704 ha of which are under irrigated and dryland farming, respectively. The average dryland winter wheat yield of the province is estimated to be 1541 kg ha^{-1}.

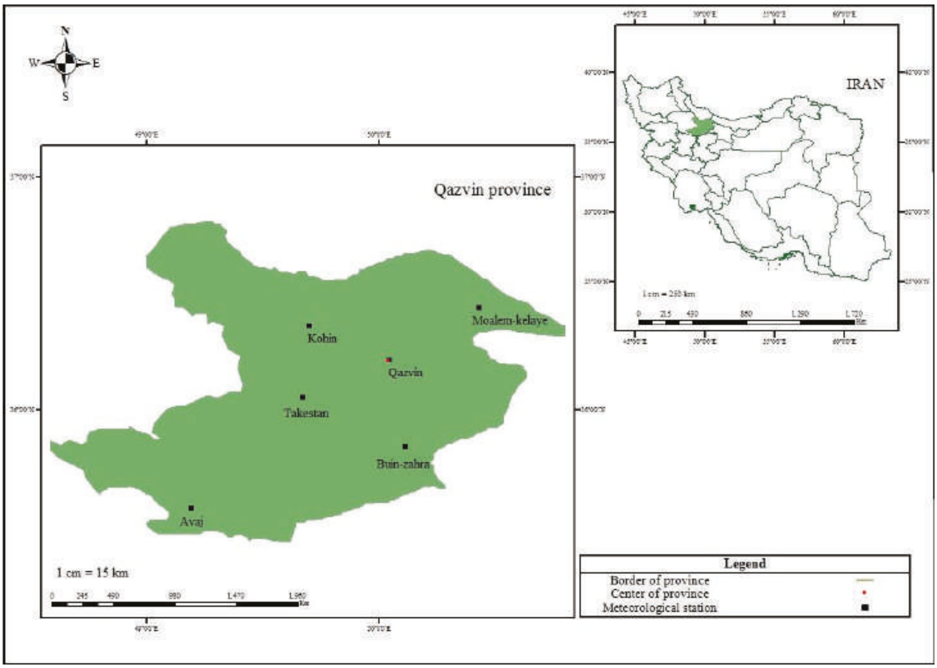

Figure 1. Map of the studied area.

2.2. Methodology

The daily mean temperature and precipitation data for 32 years (1985–2017) were collected from the six meteorological stations in the province (Figure 1). Thereafter, the daily mean temperature and precipitation of all days of all years were calculated separately by the Thiessen polygons method using the software ArcGIS version 10 via Equations (1) and (2):

$$P_a = \frac{\sum p_i A_i}{\sum A_i} \quad (1)$$

$$T_a = \frac{\sum t_i A_i}{\sum A_i} \quad (2)$$

where P_a and T_a are the daily mean precipitation and temperature of the province, respectively; p_i and t_i are the daily mean precipitation and temperature in the station i, respectively; and A_i is the area of the province.

The HadCM3 and CanESM2 models were used to compare the scenarios. HadCM3 has a spatial resolution of 2.5° × 3.75° (latitude by longitude) and the representation produces a grid box resolution of 96 × 73 grid cells. This produces a surface spatial resolution of about 417 km × 278 km, reducing to 295 km × 278 km at 45 degrees North and South. In CanESM2, the long-term time series of standardized daily values are extracted into a one column text file per grid cell. The 128 × 64 grid cells cover global domain according to a T42 Gaussian grid. This grid is uniform along the longitude with a horizontal resolution of 2.81° and is nearly uniform along the latitude of roughly 2.81°. The calibration of the stations (points) against the grid-cells (pixels) was done by the downscaling of the SDSM linear regression model. Data from the years 2006–2015 and 2016–2017 were used for the calibration and validation of both models, respectively. Figures 2 and 3 show the observed versus the simulated values of the temperature and precipitation for the years 2006–2015. Meanwhile, since 26 synoptic variables are considered as predictor variables in these models, having a unique equation was not logically possible because of the accumulated error. To solve this problem, only the predictor variables, being more correlative with the daily mean precipitation and temperature than others, were chosen. Then, the correlation between the variables was detected by Pearson's correlation test ($p < 0.01$) and the most important variables were selected according to the statistical significance between them and the dependent variables ($p < 0.01$). To analyze the climatic data across the study, it was necessary to apply a Statistical Downscaling Model (SDSM). To do so, SDSM version 5.2 was used. SDSM is a decision support tool for assessing local climate change impacts using a powerful statistical downscaling technique. It has the potential to rapidly develop downscaled climatic data [11]. To make statistical connections between the predictor and predicted variables, some regression equations were acquired to predict the climatic variables for the next few periods under the impact of climate change. After acquiring the regression equations and measuring their accuracy, the scenarios were produced through both models for the periods 2010–2039, 2040–2069, and 2070–2099. The properties of these scenarios are indicated in Table 1.

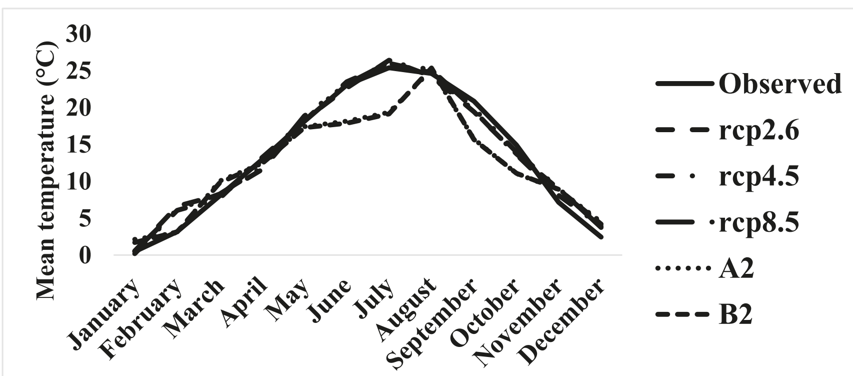

Figure 2. Results of the comparison between the observed and simulated monthly mean temperature values (2006–2015).

Table 1. Properties of the used standard Intergovernmental Panel on Climate Change [10] scenarios.

Models	Scenarios	Properties
CanESM2	rcp2.6	Radiative forcing peaks at 3 W m^{-2} and stabilizes to 2.6 W m^{-2} by the end of 2100; CO_2 concentration is estimated to be 490 ppm by 2100.
	rcp4.5	Radiative forcing is estimated to be 4.5 W m^{-2} by 2100; CO_2 concentration is estimated to be 650 ppm by 2100
	rcp8.5	Radiative forcing is estimated to be 8.5 W m^{-2} by 2100; CO_2 concentration is estimated to be 1370 ppm by 2100
HadCM3	A2	Describes a very heterogeneous world with high population growth, slow economic development, and slow technological change.
	B2	Describes a world with intermediate population and economic growth, emphasizing local solutions to economic, social, and environmental sustainability.

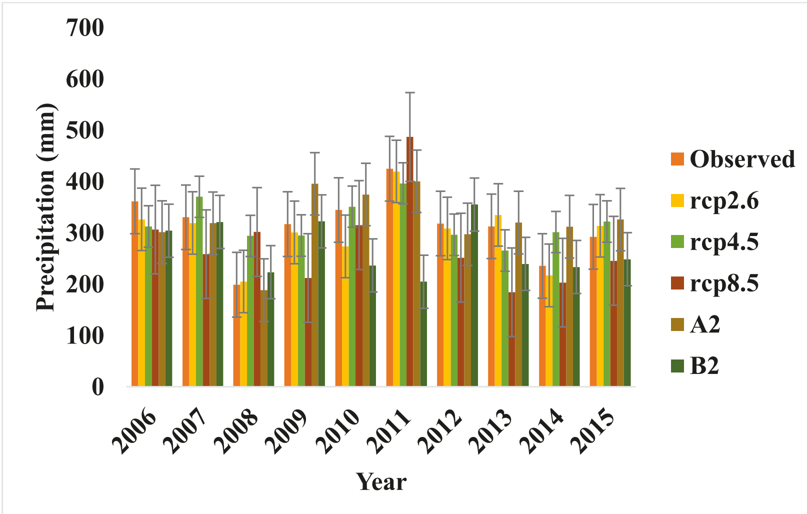

Figure 3. Results of the comparison between the observed precipitation values (2006–2015) and the simulated precipitation values. I = ± SD: standard deviation, the overlapping bars show no significant differences.

The efficiency of the scenarios was compared and the most efficient scenario was recognized through the statistical indicators of Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Nash-Sutcliffe coefficient (NS), Coefficient of Determination (R^2), and Analysis of Variance (at $p < 0.01$) as follows:

$$Z_i = \frac{P_i - \overline{P}}{\sigma_P} \text{or } Z_i = \frac{O_i - \overline{O}}{\sigma_O} \tag{3}$$

$$MAE = \sum_{i=1}^{n} \left| \frac{P_i - O_i}{n} \right| \tag{4}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (P_i - O_i)^2}{n}} \tag{5}$$

$$NS = 1 - \left(\frac{\sum_{i=1}^{n} (O_i - P_i)^2}{\sum_{i=1}^{n} (O_i - \overline{O})^2} \right) \tag{6}$$

$$R^2 = \left[\frac{\frac{1}{n} \sum_{i=1}^{n} (Pi - \overline{P})(Oi - \overline{O})}{\sigma_P \times \sigma_O} \right] \tag{7}$$

where Z_i is the standardized daily mean precipitation or temperature values; O_i and P_i are the observed and simulated daily mean precipitation or temperature values, respectively; $\overline{O}$ is the average of the observed daily mean precipitation or temperature values; $\overline{P}$ is the average of the simulated daily mean precipitation or temperature values; σ_O is the variance of the observed daily mean precipitation or temperature values; σ_P is the variance of the simulated daily mean precipitation and temperature values; and n is the number of data.

Isaaks and Serivastava [23] suggested the MAE and RMSE as statistical indicators able to compare the accuracy of variables. Once the MAE and RMSE values are closer to zero in a scenario, the scenario would be more efficient for predicting climatic variables [24]. When they are exactly 0, it means that there is no error in the predicting task [24]. The Nash-Sutcliffe coefficient (NS) shows to what extent the regression line between the simulated data and measured data can be similar to the regression line

1:1. Its domain is from the negative infinity to 1, and NS = 1 reveals either a complete similarity or a perfect efficiency of a scenario [25]. Meanwhile, R^2 gives information on the correlation between the observed and predicted data and its domain is from 0 to 1 [26]. When R^2 becomes closer to 1, there will be a significant correlation between the data groups [26]. Significant differences between the observed data and values of the predictor scenarios can be distinguished by the analysis of variance [27]. Lack of any significant difference reveals a similarity between the predicted and observed data. In addition, to obtain more appropriate results for the prediction of precipitation, the occurrence of precipitation approach was used. This is a dichotomous method by which the accuracy of whether the occurrence or non-occurrence of precipitation is evaluated. If there is no occurrence of precipitation, then the answer is 'NO', while the answer 'Yes' is a sign of precipitation occurrence [28]. There are four statuses when the observed data are compared with scenario predictions, where a couple of predictions could be true and the remaining predictions could be false. The scenario with a higher percentage of true predictions was selected as the most efficient scenario for predicting the precipitation.

Finally, to predict the dryland winter wheat yield of the province for the next decades and to make a connection between the climatic and yield data for the period 2005–2014, a linear regression model was used. Furthermore, Pearson's correlation test (at $p < 0.01$) between the simulated and observed data, RMSE, and R-square were used to check the regression's validity. All statistical analyses were performed by the software SPSS version 21 (IBM Inc., Chicago, IL, USA).

3. Results

3.1. Temperature Predictions

All three CanESM2 scenarios predicted that the daily mean temperatures would generally increase in the periods 2010–2039, 2040–2069, and 2070–2099 (Table 2). However, the scale of these increases differed by the different scenarios. The scenario rcp2.6 projected that the daily mean temperature of the periods 2010–2039, 2040–2069, and 2070–2099 would be 13.6, 13.9, and 13.9 °C, respectively, which are 0.9, 1.2, and 1.1 °C higher when compared to the observed daily mean temperature. The other scenario rcp4.5 also predicted an increasing trend in the daily mean temperature in the three prospective periods and showed that the mean daily temperature would be 13.4, 14.2, and 14.4 °C in the periods 2010–2039, 2040–2069, and 2070–2099, respectively, each being 0.7, 1.4, and 1.6 °C higher when compared to the observed one. The scenario rcp8.5 predicted the highest temperature trends in comparison with the other two scenarios. It predicted that the mean daily temperature would rise by 13.8, 14.8, and 15.5 °C in the periods 2010–2039, 2040–2069, and 2070–2099, with changes of 1.0, 2.0, and 2.7 °C, respectively, in analogy with the observed value.

Both scenarios (A2 and B2) of HadCM3 generally predicted an increasing daily mean temperature trend for the three future periods in comparison with the observed one, except for scenario B2, which projected a very slightly decreasing trend only for the period 2070–2099 (Table 3). The scenario A2 forecasted that the mean daily temperature would rise to 12.7, 12.8, and 12.8 °C in the periods 2010–2039, 2040–2069, and 2070–2099, being 0.0, 0.1, and 0.2 °C higher, respectively, when compared to the value of the observed period. The mean daily temperatures were projected by the scenario B2 to increase to 12.6 and 12.7 °C in the periods 2010–2039, 2040–2069, respectively. In contrast, it predicted that the mean daily temperature would decrease to 12.6 °C in the period 2070–2099. Accordingly, the predicted temperature changes by scenario B2 are 0.02, 0.05, and −0.04 °C in the periods 2010–2039, 2040–2069, and 2070–2099, respectively, when compared to the observed period.

Table 2. Results of the daily mean temperature predictions of the CanESM2 scenarios for the periods 2010–2039, 2040–2069, and 2070–2099.

Scenarios	Periods	Daily Mean Temperature (°C)
Observed period	1985–2005 (obs)	12.7
rcp2.6	2010–2039 (P1)	13.6
	2040–2069 (P2)	13.9
	2070–2099 (P3)	13.9
	°C change P1 vs. obs	0.9
	°C change P2 vs. obs	1.2
	°C change P3 vs. obs	1.1
rcp4.5	2010–2039 (P1)	13.4
	2040–2069 (P2)	14.2
	2070–2099 (P3)	14.4
	°C change P1 vs. obs	0.7
	°C change P2 vs. obs	1.4
	°C change P3 vs. obs	1.6
rcp8.5	2010–2039 (P1)	13.8
	2040–2069 (P2)	14.8
	2070–2099 (P3)	15.5
	°C change P1 vs. obs	1
	°C change P2 vs. obs	2
	°C change P3 vs. obs	2.7

Table 3. Results of the daily mean temperature predictions of the HadCM3 scenarios for the periods 2010–2039, 2040–2069, and 2070–2099.

Scenarios	Periods	Mean Temperature (°C)
Observed period	1985–2005 (obs)	12.7
A2	2010–2039 (P1)	12.7
	2040–2069 (P2)	12.8
	2070–2099 (P3)	12.8
	°C change P1 vs. obs	0
	°C change P2 vs. obs	0.1
	°C change P3 vs. obs	0.2
B2	2010–2039 (P1)	12.6
	2040–2069 (P2)	12.7
	2070–2099 (P3)	12.6
	°C change P1 vs. obs	0.02
	°C change P2 vs. obs	0.05
	°C change P3 vs. obs	−0.04

3.2. Precipitation Predictions

Overall, the three scenarios of CanESM2 projected a diminishing trend in the annual precipitation for the future periods 2010–2039, 2040–2069, and 2070–2099, when compared to the observed period (Table 4). However, the scenario rcp2.6 projected a less decreasing trend in the annual precipitation for the period 2070–2099. The scenario rcp2.6 predicted that the annual precipitation would drop to 287 and 277 mm in the periods 2010–2039 and 2040–2069, respectively, and decrease to 296 mm in the period 2070–2099. The projected annual precipitation by the scenario rcp4.5 would be 258, 264, and 293 mm in the periods 2010–2039, 2040–2069, and 2070–2099, respectively. The other scenario rcp8.5 forecasted that the annual precipitation would be 283, 278, and 278 mm for the periods 2010–2039, 2040–2069, and 2070–2099, respectively.

Scenario A2 of HadCM3 predicted a decreasing trend in the annual precipitation for the periods 2010–2039, 2040–2069, and 2070–2099, in analogy with the observed period (Table 5). The annual precipitation projected by scenario A2 would be 340, 292, and 276 mm for the periods 2010–2039, 2040–2069, and 2070–2099, respectively. Scenario B2 also forecasted that the annual precipitation for the periods 2010–2039 and 2040–2069 would be 310 and 321 mm, respectively, when compared to the observed period, which conveys a reducing trend. In contrast, it projected an increased annual precipitation of 875 mm for the period 2070–2099, which will be noticeably higher than the observed amount.

Table 4. Results of the annual precipitation predictions of the CanESM2 scenarios for the periods 2010–2039, 2040–2069, and 2070–2099.

Scenarios	Periods	Precipitation (mm)
Observed period	1985–2005 (obs)	346
rcp2.6	2010–2039 (P1)	287
	2040–2069 (P2)	277
	2070–2099 (P3)	296
	% change P1 vs. obs	−18
	% change P2 vs. obs	−21
	% change P3 vs. obs	−15
rcp4.5	2010–2039 (P1)	258
	2040–2069 (P2)	264
	2070–2099 (P3)	293
	% change P1 vs. obs	−29
	% change P2 vs. obs	−26
	% change P3 vs. obs	−16
rcp8.5	2010–2039 (P1)	283
	2040–2069 (P2)	278
	2070–2099 (P3)	278
	% change P1 vs. obs	−20
	% change P2 vs. obs	−21
	% change P3 vs. obs	−21

Table 5. Results of the annual precipitation predictions of the HadCM3 scenarios for the periods 2010–2039, 2040–2069, and 2070–2099.

Scenarios	Periods	Precipitation (mm)
Observed period	1985–2005 (obs)	346
A2	2010–2039 (P1)	340
	2040–2069 (P2)	292
	2070–2099 (P3)	276
	% change P1 vs. obs	−1
	% change P2 vs. obs	−16
	% change P3 vs. obs	−22
B2	2010–2039 (P1)	310
	2040–2069 (P2)	321
	2070–2099 (P3)	875
	% change P1 vs. obs	−10
	% change P2 vs. obs	−7
	% change P3 vs. obs	86

3.3. Comparison of the Scenarios

The variance analysis results showed a higher efficiency for the RCP scenarios than the A and B scenarios in predicting the daily mean temperature of the region (Table 6), because there was no statistically significant difference between the temperature values simulated by the RCPs and the observed values (at $p < 0.01$), while the temperature values simulated by A and B significantly differed from the observed ones (at $p < 0.01$). Among the three scenarios of the model CanESM2, rcp2.6 was selected as the most efficient scenario for predicting the daily mean temperature, as it had the highest Nash-Sutcliffe coefficient and R^2 value and the lowest MAE and RMSE values when compared to scenarios rcp4.5 and rcp8.5.

The results of variance analysis indicated that all scenarios were efficient enough to predict the annual precipitation of the region (Table 7), since no statistically significant difference was found between the simulated and observed values (at $p < 0.01$). The scenario rcp2.6 displayed the lowest values for both MAE and RMSE. Moreover, it showed the highest Nash-Sutcliffe coefficient and R^2 value. Thus, it was selected as the best scenario for predicting the annual precipitation. In addition, the scenarios of CanESM2 simulated closer annual precipitation values to the observed values than the HadCM3 scenarios (Table 8). The CanESM2 scenarios resulted in higher values of true predictions and lower values of false prediction than the scenarios of HadCM3. The indicators provided in Table 8 also, in general, confirmed the excellence of scenario rcp2.6 for predicting the annual precipitation.

Together, these indicators showed a relatively higher efficiency for the CanESM2 scenarios than the HadCM3 scenarios in predicting the daily mean temperature and annual precipitation of the region.

Table 6. Results of the efficiency evaluation of the used scenarios for the daily mean temperature predictions.

Models	Scenarios	MAE	RMSE	Nash-Sutcliffe	R^2	Analysis of Variance
CanESM2	rcp2.6	0.348	0.445	0.808	0.8177	0.772 ^{ns}
	rcp4.5	0.355	0.45	0.801	0.8047	
	rcp8.5	0.362	0.461	0.795	0.8174	
HadCM3	A2	0.0529	0.0658	0.707	0.7346	0.000 **
	B2	0.0523	0.0654	0.706	0.7380	

ns: no-significant; **: significant at $p < 0.01$.

Table 7. Results of the efficiency evaluation of the used scenarios for the annual precipitation predictions.

Models	Scenarios	MAE	RMSE	Nash-Sutcliffe	Analysis of Variance
CanESM2	rcp2.6	0.434	1.297	−2.139	0.279 ^{ns}
	rcp4.5	0.442	1.298	−3.154	
	rcp8.5	0.45	1.351	−8.576	
HadCM3	A2	0.444	1.33	−7.243	0.453 ^{ns}
	B2	0.442	1.299	−3.222	

ns: no-significant.

Table 8. Occurrence of precipitation under the used scenarios.

Occurrences	CanESM2			HadCM3	
	rcp8.5	rcp4.5	rcp2.6	B2	A2
Hit (hit event)	390	395	366	406	425
CN (correct Negative)	1832	1827	1856	1816	1797
Miss (miss event)	1246	1225	1250	1191	1159
FA (false alarm events)	184	205	180	239	271
% true prediction ($\frac{Hit+CN}{n}$)	44.79	44.35	44.25	43.72	43.37
% false prediction ($\frac{Miss+FN}{n}$)	55.2	55.64	55.75	56.27	56.62

3.4. Yield Predictions

The results of the regression analysis and Pearson's correlation test showed that the precipitation in March was the most effective factor for the dryland winter wheat yield of the region (Table 9). The prediction results indicated that the yield would noticeably reduce to 1176, 984, and 890 kg ha^{-1} in the periods 2010–2039, 2040–2069, and 2070–2099, respectively (Table 10). The reduction percentage in the above-mentioned periods is predicted to be −22, −34, and −41%, respectively. These reductions in the yield are consistent with the reductions in the mean precipitation in March during the three prospective periods (Figure 4). The reduction in the yield in the periods 2040–2069 and 2070–2099 will be more severe than that of the period 2010–2039, which is in line with a more severe reduction in the precipitation in March than in the former periods.

Table 9. Regression and correlation results of the yield and precipitation data.

Crop	Regression Model	R	R^2	RMSE (%)	Significance Level	Predictor Model
winter wheat	Forward	0.78	0.62	18.82	0.012 *	Y = 20.883X + 625.846

*: significant at $p < 0.05$ where Y is dryland winter wheat yield; X is the precipitation in March; and the constant numbers are Y-intercepts.

Table 10. Results of the dryland winter wheat yield predictions for the periods 2010–2039, 2040–2069, and 2070–2099.

Crop	Cropping Year	Grain Yield (kg ha^{-1})
Winter wheat	2010–2011 (obs)	1512
	2010–2039 (P1)	1176
	2040–2069 (P2)	984
	2070–2099 (P3)	890
	% change P1 vs. obs	−22
	% change P2 vs. obs	−34
	% change P3 vs. obs	−41

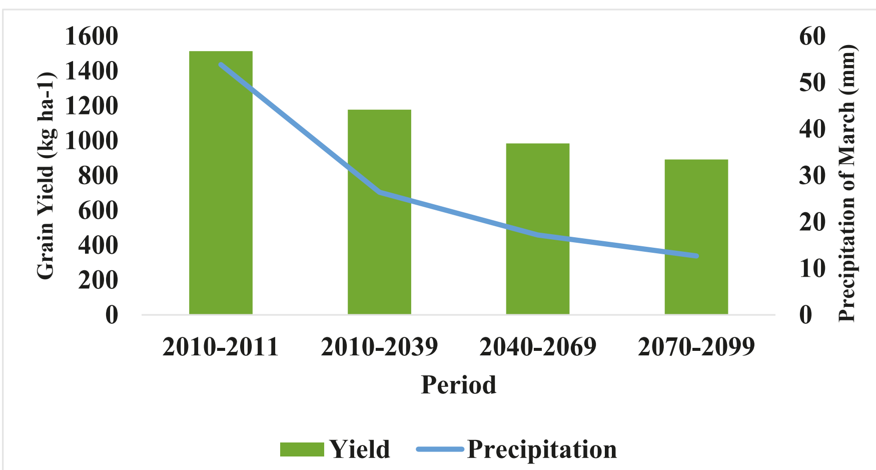

Figure 4. Relationship between the yield reduction and rcp2.6-induced precipitation of March in the three future periods.

4. Discussion

4.1. Temperature Predictions

GCMs have widely been used for predicting future temperature trends. Van Vuuren et al. [29] showed that the mean temperature was likely to increase in the future in many parts of the world. For instance, Basheer et al. [30] claimed that the climate over the Dinder River Basin would be warmer in the upcoming decades. Majhi and Pattnayak [31] also revealed that there would be a gradual temperature increase in Nabarangpur district at the end of the 21st century. Our results also indicated that the temperature would generally increase in the three investigated periods; however, the magnitude of these increases are dependent on the scenarios applied. The CanESM2 scenarios postulated a higher variability in the predicted temperature values than the HadCM3 scenarios. In addition, the temperature changes predicted by CanESM2 were noticeably higher than those predicted by HadCM3. Such different trends have also been observed by [22], who compared some GCMs such as HadCM3 and CanESM2. These diverse trends could have been due to the different scenarios used, as was the case for the study of [32]. Among the CanESM2 scenarios, rcp8.5 and rcp4.5 predicted the highest temperature values, respectively, whilst rcp2.6 projected the lowest ones. These results are in line with the findings of [22]. The greatest temperature values predicted by scenarios rcp8.5 and rcp4.5 seem plausible due to the underlying physical laws to simulate the ongoing increases in the radiative forcing and CO_2 concentrations by the end of the 21st century. In contrast, rcp2.6 simulated a lower radiative forcing towards the end of the 21st century as well as lower CO_2 concentrations.

4.2. Precipitation Predictions

All scenarios, except B2, revealed that there would be a reduction in the annual precipitation in all investigated periods. Scenarios rcp4.5 and rcp8.5 projected the maximum and the minimum reductions in the annual precipitation, respectively, which was a very similar result to what [33] concluded. Scenario B2 projected substantial increases in the annual precipitation for the period 2070–2099. Moreover, scenario rcp2.6 projected a less decreased annual precipitation for the aforementioned period. One study has shown that there is a possibility for a reduction in the rivers' ice thickness in winter and a slight increase in the discharge during the break up from May to June in Siberia [34]. This phenomenon can be caused by extreme warming around Siberia in the period 2070–2099. To confirm this notion, Shiklomanov et al. [35] predicted an increased mean temperature trend for Siberia by the late 21st century. The province of Qazvin is extremely affected by Siberian winds. Therefore, the increased and less decreased annual precipitation projections for the period 2070–2099 by scenarios B2 and rcp2.6 might be logical. Nevertheless, the properties of the scenarios used could be among other reasons for the different precipitation results achieved. Scenarios rcp2.6 and B2 more optimistically simulated the future projections when compared to the other scenarios used. For instance, rcp2.6 predicted a radiative forcing of 3 W m^{-2} and a CO_2 concentration of 490 ppm; and B2 described a world with intermediate population and economic growth, emphasizing local solutions to economic, social, and environmental sustainability. Thus, a more optimistic simulation of the annual precipitation of the region could have been another possible reason for the increased and less decreased precipitation values predicted. Vallam and Qin [22], using a statistical downscaling technique, also showed that scenarios rcp2.6 and B2 could predict either increased or at least lesser decreased rainfall percentage for Frankfurt (Germany), Singapore, and Miami (USA) in the 2080s when compared to the other scenarios used. However, the CanESM2-derived RCP scenarios led to great variabilities in predicting future meteorological variables, especially rainfall in arid regions [22]. This might be another plausible reason for the increase (14%) in the annual precipitation predicted by rcp2.6.

4.3. Yield Predictions

Studies have shown that there is a significant correlation between winter wheat yield and the climatic variables [16]. Thus, the most efficient scenario (rcp2.6) in predicting both temperature and precipitation was applied to predict the dryland winter wheat yield of the province. The results of the Pearson's correlation test indicated that the precipitation in March was the most effective factor on yield ($r = 0.78$, $p < 0.01$). A study on the effects of precipitation on dryland cereals yield in three provinces of Iran was performed, where the climate is semi-arid [36]. The results of the study showed that the yield of dryland winter wheat was significantly correlated to precipitation, especially the precipitation in April. In the province of Qazvin, dryland winter wheat is at the tillering stage in March (personal communication with the farmers). It seems that the lower precipitation in March could lead to a lower number of head-bearing tillers and lack of the opportunity for their survival, finally resulting in lower grain yields. Karimi [37] investigated the effects of precipitation during the tillering of dryland winter wheat in Iran and reported a significant impact on the final grain yield. Even though agricultural factors such as soil, fertilizers, and other climatic variables like radiation could also be effective, Lobell [16] indicated that precipitation had a more considerable influence on dryland farming. Meanwhile, the value of R^2 between the observed and simulated data was 0.62, meaning that the yield was 62% dependent on the annual precipitation and the other 38% was dependent on other unspecified factors. The percentage of RMSE was about 18% between the observed and simulated data, which was an acceptable value that showed the adequate accuracy of the predictions [38]. Moreover, the observed reductions in the precipitation in March during the three future periods could have been due to shifts in the seasons due to warmer temperatures of the areas by which the studied region is affected. As mentioned earlier, the temperature of Siberia has been projected to rise by the late 21st century [35]. Since the province of Qazvin is extremely affected by Siberian winds, it is plausible that these winds will alter the seasons of this province.

5. Conclusions

In this study, the downscaling of two important climatic variables—temperature and precipitation—was done by the CanESM2 and HadCM3 models for the province of Qazvin, located in Iran. The used scenarios were able to predict the daily mean temperature and annual precipitation for the three different future periods 2010–2039, 2040–2069, and 2070–2099. The CanESM2 scenarios seemed to be more efficient than the HadCM3 scenarios in simulating the future temperature and precipitation trends of the region. Generally, the region's daily mean temperature tended to increase and the annual precipitation tended to decrease in the three prospective periods investigated. However, scenarios rcp2.6 and B2, respectively, predicted that the precipitation would decrease less or even increase in the third period (2070–2099). Scenario rcp2.6 was assumed to be the most efficient to predict the dryland winter wheat yield of the province for the upcoming decades. The grain yield was projected to considerably decrease in the three periods, especially in the last period. The yield reductions are assumed to mainly be due to the decrease in precipitation in March during the investigated periods. Some adaptive strategies to prevent the detrimental impacts of climate change on the province dryland wheat yield include the cultivation of resistant winter wheat varieties to drought as well as earlier sowing dates. The authors would like to recommend the comparative use of the applied CanESM2 and HadCM3 scenarios to predict climatic variables of other semi-arid regions.

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Perspective

New Breeding Techniques for Greenhouse Gas (GHG) Mitigation: Plants May Express Nitrous Oxide Reductase

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Abstract: Nitrous oxide (N_2O) is a potent greenhouse gas (GHG). Although it comprises only 0.03% of total GHGs produced, N_2O makes a marked contribution to global warming. Much of the N_2O in the atmosphere issues from incomplete bacterial denitrification processes acting on high levels of nitrogen (N) in the soil due to fertilizer usage. Using less fertilizer is the obvious solution for denitrification mitigation, but there is a significant drawback (especially where not enough N is available for the crop via N deposition, irrigation water, mineral soil N, or mineralization of organic matter): some crops require high-N fertilizer to produce the yields necessary to help feed the world's increasing population. Alternatives for denitrification have considerable caveats. The long-standing promise of genetic modification for N fixation may be expanded now to enhance dissimilatory denitrification via genetic engineering. Biotechnology may solve what is thought to be a pivotal environmental challenge of the 21st century, reducing GHGs. Current approaches towards N_2O mitigation are examined here, revealing an innovative solution for producing staple crops that can 'crack' N_2O. The transfer of the bacterial nitrous oxide reductase gene (*nosZ*) into plants may herald the development of plants that express the nitrous oxide reductase enzyme (N_2OR). This tactic would parallel the precedents of using the molecular toolkit innately offered by the soil microflora to reduce the environmental footprint of agriculture.

Keywords: radiative warming; atmospheric phytoremediation; N_2O; nitrous oxide reductase; N_2OR; *nosZ*; fertilizer; crop breeding; transgenic; GHG

1. Introduction—Nitrous Oxide Continues to Bloom Unabated

Atmospheric nitrogen (N) deposition is a pressing matter for climate change scientists concerned with the increasing danger that nitrous oxide (N_2O), a noxious greenhouse gas (GHG), poses. Reactive nitrogen (Nr)—ammonia (NH_3), nitrogen oxides (NO_x), nitrates (NO_3^-), and N_2O—enters the biosphere from its original form of atmospheric N as at least three derivatives: gas, dry deposit, and precipitation (wet deposition) [1,2]. The sources of N_2O are largely anthropogenic [3]. Many crops must receive N-based fertilizer to reach yield targets, which is supplied by inorganic fertilizers and animal manure [4]. In an effort to boost the yield in crop staples like wheat, corn, and soybeans, farmers apply N fertilizers at rates and times that are not always properly synchronized with crop demand [5]. While crops thrive when fertilized, experimental analysis has demonstrated that up to

40% of fertilizer N can be lost via leaching [6,7]. Other routes of N loss include soil erosion, NH_3 volatilization and oxidation, and bacterial/fungal denitrification [8], although N losses through NH_3 volatilization are higher than those via N leaching [9]. Around 62% of total global N_2O issues from natural and agricultural soils, and the bulk of this production, mainly results from the processes of bacterial nitrification and denitrification [10].

Nr compounds enter the atmosphere through biological processes, but the invention of the Haber-Bosch process in 1908 was a critical moment for the sudden increase in Nr and GHG production globally [11]. This process of artificial N-fixation allowed for the large-scale reduction of N_2 to NH_3, producing massive amounts of synthetic N-based fertilizers that supported dramatic increases in high-yield farming [12]. This process now accounts for 80% of anthropogenic N-fixation (the remaining 20% resulting from combustion [13], with anthropogenic N-fixation in turn accounting for 60% of global N-fixation [14]). Haber-Bosch remains the industry standard synthetic N fertilizer today and as a result, has contributed to the ~2% increase in atmospheric levels of N_2O [15,16]. This effect is also magnified by the global emissions of N_2O produced by fossil fuel combustion [17] and the natural ability of legumes to fix N through symbiotic relationships with soil bacteria [18].

N_2O is the third most prevalent GHG, behind carbon dioxide (CO_2) and methane (CH_4) [19]. The concentration of this gas in the atmosphere has been steadily increasing since the early 1900s (Figure 1), and it is 265 times more radiative than CO_2 [19]. N_2O also has an atmospheric lifetime of 121 years; by comparison, CH_4 has an atmospheric lifetime of only 12 years, but CO_2 also has a long half-life and can take anywhere from 20–200 years to be absorbed by the ocean [19], compounding the 'greenhouse gas' effect. Since chlorofluorocarbons (CFCs) were banned in 1989, N_2O has become the leading cause of ozone layer depletion [20].

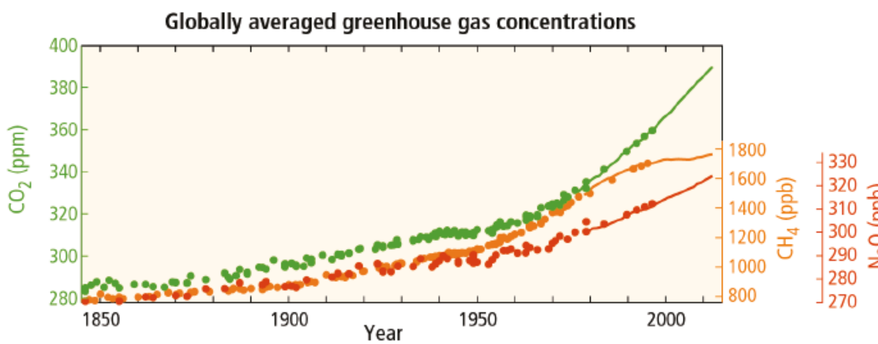

Figure 1. GHG levels since 1850. The green line represents the increase in CO_2 concentration since 1850; the orange line represents the increase in CH_4 concentration since 1850; lastly, the red line represents the increase in N_2O since 1850 [19].

N_2O emission results from the coupled oxidation and reduction of N performed by heterotrophic [21] (and some autotrophic) soil proteobacteria: (1) the nitrification pathway is catalyzed by autotrophs (*Nitrosomonas* spp. and other genera [22]) and also heterotrophs, and involves the oxidation of NH_3/ammonium(NH_4^+) to nitrite (NO_2^-) [23] and nitric oxide (NO) [24]), which is followed by the oxidation of NO_2^- to NO_3^- by *Nitrobacter* spp. [25]; and (2) the denitrification pathway, whereby NO_3^- is reduced to N_2O and ultimately inert N_2 gas [26]. As many as a third of soil bacterial species [27] lack the *nosZ* gene that reduces N_2O to inert N_2 [28], which leads to a sizeable amount of incomplete denitrification reactions and the subsequent buildup of N_2O since it is an obligate intermediate [29]. This N_2O diffuses out of the soil and into the atmosphere, contributing to the greenhouse effect, contaminating water, and leading to serious human health implications [30,31].

2. Combating GHGs: Current N_2O Mitigation Strategies and Limitations

Demands for crop-borne food must be met, and so researchers must address the hazards of N-based fertilizers [32]. There are multiple N_2O mitigation strategies either currently in commercial use or in development (summarized in Table 1).

Table 1. Summary of current N_2O mitigation strategies.

Strategy	Mechanism of Action	Pros	Cons
(1) Conservation tillage and crop rotation [33]	Tillage, rotation of N-fixing crops, cover cropping [33]	Prevent NH_3 volatilization and eventual N_2O emissions [34,35]	Unreliable N_2O mitigation [36,37]. Yield reduction [38]. Not effective at scrubbing N_2O from the air
(2) Best management practices (BMPs) [39]	Correct source, placement, time, and rate of fertilization [40]. Proper irrigation (fertigation) [41]	Proven to reduce N_2O emissions [41] and other N losses [42]	Technical constraints [43]
(3) EENFs [44]	Multiple types: stable, short-release (SRFs), and constant-release (CRFs); rely on enrichment of chemical inhibitors or coated N-compounds that are released into the soil over a period of time [45]; urease inhibitors (UIs) [46]	Proven to reduce N_2O emissions [47,48]	Inconsistent yields from year to year [48]. More expensive than standard N fertilizers [49]. Long lifetime of N-compounds in soil can lead to NH_3 volatilization [50,51]. Not effective at scrubbing N_2O from the air
(4) Synthetic N_2O mitigators	SNIs suppress activity of nitrifying bacteria in the soil [52]. SDIs operate by unknown mechanism [44,53,54]	SNIs and SDIs reduce N_2O emissions [52,54]	Effectiveness depends on environmental conditions, prefer low temperature and sandy soils [55]. Not effective at scrubbing N_2O from the air
(5) Biological N_2O mitigators	BNIs suppress activity of nitrifying bacteria in the soil by releasing compounds that inhibit NH_3-oxidizing pathways [56]. BDIs inhibit nitrate reductase to inhibit N_2O production [57]	BNIs demonstrated to reduce N_2O emission [56]; BDIs inhibit denitrification and can conceivably mitigate N_2O emissions [57]	BNI-exuding plants must be grown in rotation with other crops [58]. Little work done on BDI-exuding plants [57]. Not effective at scrubbing N_2O from the air
(6) Microbial bioremediation	Proper water table management to facilitate growth of rhizobia [59]; inoculation of plant roots with genetically modified N_2O-cracking rhizobia [60,61]	Enables plants to degrade contaminants in the soil; N_2O-cracking rhizobia demonstrated to reduce N_2O emissions [60,61]	Most effective on crops that naturally cultivate a rhizosphere of N_2O-reducing [62] microorganisms, i.e., soybean [63]. Not effective at scrubbing N_2O from the air
(7) Rhizosecretion	Transformation of amenable crops to express recombinant bacterial proteins that reduce N_2O [64]	Plants that secrete N_2O-cracking enzyme could target N_2O in soil [64]	Plant transformation is a time-consuming process [65]. Bacterial proteins may not function efficiently in heterologous hosts [66]. Not effective at scrubbing N_2O from the air
(8) Atmospheric phytoremediation	Transformation of amenable crops with genes expressing recombinant bacterial proteins that reduce N_2O [67]	Arm crops and other plant species to mop up N_2O in the atmosphere [67], including N_2O emitted by other non-agricultural sources	Plant transformation is a time-consuming process [65]. Bacterial genes may not function in a heterologous system [66]. Not yet experimentally validated via gas analysis

BDI, biological denitrification inhibitor; BNI, biological nitrification inhibitor; EENFs, enhanced efficiency nitrogen fertilizers; SDI, synthetic denitrification inhibitor; SNI, synthetic nitrification inhibitor.

(1) **Conservation tillage and crop rotation**. Mechanical incorporation (tillage) of N-based fertilizer into the soil may also be effective [68], but this is affected by many other parameters, such as the method of N application (i.e., broadcast vs surface urea ammonium nitrate). These techniques also result in a reduced yield [38]. Conservation tillage increases N_2O emissions compared with no-till and conventional tillage techniques using broadcast application, while tillage in general does not reduce N_2O emissions produced from surface urea ammonium nitrate-treated fields [69]. Other studies have shown that conservation tillage *reduces* N_2O emissions [70], underscoring the lack of reliability of this N management technique [36,37]. Crop rotation with N-acquisitive plant species can also reduce N_2O emissions following the application of high N-fertilizer treatment [33]; cover cropping can also control N_2O emissions, but the results are often variable and in some cases can increase N_2O emissions [71];

(2) **Best management practices (BMP) [39]**. Such nitrogen use efficiency techniques are myriad and involve simple steps such as proper fertilizer placement, timing of fertilizer application, the right type of N-compound, and so on. Others involve the proper incorporation of N-compounds into the soil so that they may be taken up by the plant more effectively and will be less likely to volatilize [72]. Fertigation, a technique involving careful irrigation of fields following the application of N fertilizer, is effective at mitigating N_2O emissions [41]. Such knowledge-based N management practices have been shown to be effective at both increasing crop yield and reducing immediate N_2O emissions [73], but some approaches may also increase N_2O production in the long term [55]. Their effectiveness also depends heavily on proper practices put in place by the farmers themselves, which requires proper training [43];

(3) **Fertilizer management using enhanced efficiency nitrogen fertilizers (EENFs)**. These fertilizer cocktails are concocted in such a way that they prevent the volatilization of NH_3 and inhibit nitrification/denitrification [46]. EENFs generally fall into one of three categories: (a) stabilized fertilizers, which contain nitrification and/or urease inhibitors; (b) slow-release fertilizers (SRFs), whereby the N source in the fertilizer is released over time from encapsulated granules, although the release rates can be variable; and (c) controlled-release fertilizers (CRFs), where the release rate is constant [45]. Urease inhibitors (UIs) are also a common EENF component. N-(*n*-butyl) thiophosphoric triamide (NBPT), phenylphosphorodiamidate (PPD), and hydroquinone are used worldwide and act by inhibiting the bacterial hydrolysis of urea into NH_3 in fertilizer [46,74,75]. UIs are typically used in conjunction with nitrification inhibitor (NIs) for maximum effectiveness [76,77], but NBPT alone can reduce N_2O emissions from N-treated soil [78]. There is controversy regarding the effectiveness of EENFs; while reductions in N_2O emissions from the soil have been recorded [47,48], recent studies have shown that crop yields are only marginally higher when EENFs are used in place of standard N fertilizers [79]. Those studies that demonstrated reduced N_2O emissions also reported inconsistent results from year to year [50]. Questionable effectiveness notwithstanding, EENFs are more expensive than conventional N-containing fertilizers and require special handling and storage [49,80], which are all features that make these fertilizers less attractive to farmers;

(4) **Synthetic N_2O mitigators**. Synthetic nitrification inhibitors (SNIs) and UIs are both used in EENFs and can be applied to crops in conjunction with standard N fertilizer. NIs inhibit the activity of *Nitrosomonas* to block the nitrification of N in fertilizer (the oxidation of NH_3 to hydroxylamine via ammonia monooxygenase (AMO)) [23,52]. The efficacy of the inhibitors is also dependent on environmental conditions, as they are unstable; 3,4-dimethylpyrazole phosphate (DMPP), for example, exhibited reduced activity in hot, dry conditions [81]. The use of these inhibitors can also lead to less than desirable results: DMPP and 3-methylpyrazole 1,2,4-triazole (3MP + TZ) have been shown to increase N_2O emissions in vegetable crop systems, as the inhibitors promote the buildup of N in the fraction of the soil most available to bacteria during the breakdown of vegetative matter. Synthetic denitrification inhibitors (SDIs) suppress denitrification via unknown mechanisms [82], although some are known to inhibit the activity of fungal copper reductase [83].

SDIs nitrapyrin [84], toluidine [54], and acetylene [44] all effectively mitigate N_2O emission, albeit with toxic side-effects [55], and they do not technically inhibit nitric oxide reductase;

(5) **Biological N_2O mitigators**. This category is comprised of compounds produced by plants that inhibit enzymes in either the bacterial nitrification or denitrification pathway. The exploitation of such inhibiting root exudates is another intriguing approach towards N_2O mitigation [82]. Biological nitrification inhibitors (BNIs) are compounds that block the activity of NO_2^- producing enzymes. The roots of the tropical grass *Brachiaria humidicola* exude brachialactone, a compound that can mitigate N_2O emission from soil [85]. Attempts at developing BNI-producing cultivated wheat by crossing *Triticum aestivum* with BNI-producer *Leymus racemosus*, a wild wheat, have imparted some BNI activity, but also made the lines susceptible to rust infection [86]. The use of BNIs as an effective N_2O mitigator is also severely limited by the fact that the enactor of nitrification is a plant itself and cannot be applied to growing crops, although growing *B. humidicola* in rotation with maize saw a four-fold increase in yield [87]. Biological denitrification inhibitors (BDIs) are a relatively new discovery. Currently, the only example of such an inhibitor is the procyanidin produced by the invasive Fallopia spp. (Asian knotweed). This compound has been demonstrated to be an allosteric inhibitor of *Pseudomonas brassicacearum* nitrate reductase and while it does reduce denitrification in the soil, it has not yet been proven to mitigate N_2O levels [57];

(6) **Microbial bioremediation [88]**. The success of N fertilizer management techniques and proper irrigation is largely due to the creation of a microsphere conducive to denitrifying bacteria flourishing [89]. Proper water table management techniques can promote the growth of N_2O-cracking bacteria in the soil and reduce N_2O emissions from the managed soil regions [59]. Another type of microbial bioremediation takes advantage of the ability of certain bacterial species to inhabit the root nodules of leguminous crops. Field peas [62], broad beans [90], and soybean [63] house bacteria (or rhizobia) that fix N and, unfortunately, also produce N_2O gas. While maintaining the rhizosphere, N_2O emissions can be mitigated by inoculating the roots of leguminous plants with rhizobia modified to express higher levels of a bacterial N_2O-cracking enzyme [60]. Genetically engineered strains of *Bradyrhizobium japonicum* have been used to inoculate the roots of soybean and reduced N_2O emissions [61]. Needless to say, this method is far more effective on crops that naturally cultivate a rhizosphere of N_2O-reducing microorganisms. It is also another technique that cannot target atmospheric N_2O;

(7) **Rhizosecretion**. This is a biotechnology-based approach, involving the transformation of amenable crop plants with genes expressing recombinant bacterial proteins that reduce N_2O by secreting N_2O-cracking enzymes [64,91]. Plants can be engineered to express proteins under the control of promoters that induce hairy root formation in plants. This rooting response results from the presence of the *rolABCD* genes from *Agrobacterium rhizogenes*, the bacterium that induces hairy root disease [92]. The rhizosecretion expression system harnesses the ability of *A. rhizogenes* to both target gene expression to the roots and to increase root biomass, subsequently increasing the amount of recombinant protein secreted into the soil [91]. Tobacco plants expressing a bacterial N_2O-cracking enzyme tagged for secretion under the control of the *A. rhizogenes rolD* promoter have been successful in demonstrating reducing activity [64,93]. Gas analysis was not performed to confirm that these plants mitigated N_2O emission. Ultimately, this approach arrives at a similar problem as other 'rhizoremediative' techniques: the N_2O-reducing ability of such a transgenic plant would be limited to the rhizosphere. This system would not have access to the bulk of N_2O gas, much of which comes from other sources;

(8) **Atmospheric phytoremediation using genetically engineered plants**. The potential of transgenic plants for environmental phytoremediation is well-documented: several fungal and bacterial oxidoreductases have been functionally expressed in plants as phytoremediation strategies including pentaerythritol tetranitrate reductase [94], mercuric reductase [95], and arsenate reductase [96]. This type of plant-based decontamination strategy provides advantages,

such as stable cultivation and control of the remediant organism and atmospheric exposure of the gas-cracking enzyme [97].

Atmospheric phytoremediation may ameliorate problems created by the other N_2O mitigation strategies described. The concept here is to develop crops with the ability to "crack" N_2O in both the soil and the atmosphere by incorporating the bacterial *nosZ* gene into their genomes. This gene encodes the nitrous oxide reductase enzyme (N_2OR), an oxidoreductase that catalyzes the removal of N_2O from the atmosphere, a process performed naturally by both denitrifying and non-denitrifying bacteria in the soil [98]. While conventional N_2O mitigation strategies aim to control N_2O production at earlier stages in the nitrification/denitrification pathway, this approach will target the atmospheric sum of N_2O emitted by all sources (Figure 2).

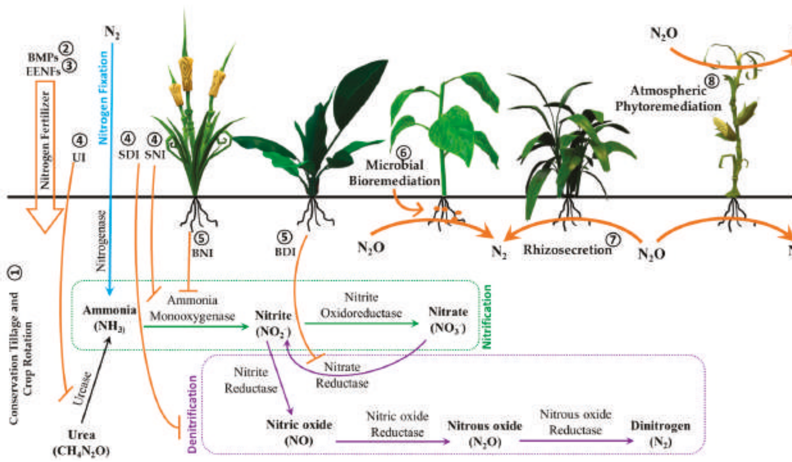

Figure 2. Nitrification-denitrification pathway and overview of current N_2O mitigation strategies. Orange arrows and lines show eight N_2O mitigation strategies described in Table 1. Green arrows show nitrification and purple arrows represent denitrification reactions. BDI, biological denitrification inhibitor; BMPs, best management practices; BNI, biological nitrification inhibitor; EENFs, enhanced efficiency nitrogen fertilizers; SDI, synthetic denitrification inhibitor; SNI, synthetic nitrification inhibitor; UI, urease inhibitor. **O** Encircled numbers refer to Table 1 strategies.

3. Nitrous Oxide Reductase—An Orphaned Soil Protein?

The *nosZ* gene can be categorized as either 'clade I' or 'clade II' based on sequence and *nos* operon organization, including the lack of an accessory *nosR* gene in the clade II members [99]. Clade II *nosZ* genes are also known as 'atypical' *nos* genes since they are found in non-denitrifying bacterial species. The N_2OR enzyme that the clade II gene encodes catalyzes the same reaction performed by the clade I-encoded enzyme, but has a higher affinity for N_2O [100], an important factor to consider when conceptualizing the development of an *nosZ*-expressing plant.

N_2OR is a multi-copper protein encoded by the *nosZ* gene (which is accompanied by an operon cluster of additional genes (*nosRDFYL*) [101]) and is the only enzyme that can catalyze the conversion of N_2O into N_2. The first active N_2OR was characterized from the soil bacterium *Pseudomonas stutzeri* and similar enzyme structures were resolved in bacterial species *Marinobacter hydrocarbonoclasticus* (formerly *Pseudomonas nautica*) (Figure 3), *Achromobacter cyclocastes*, and *Paracoccus denitrificans*. N_2OR is a head-to-tail homodimer and each monomer contains two domains: an electron transferring domain (binuclear Cu_A centre) and a catalytic domain (tetranuclear Cu_Z centre) [102]. There is some variability between the species regarding Cu_Z bridging and cupric coordination in the catalytic centre, suggesting that N_2OR substrate binding is species-specific. Regardless, the catalytic mechanism of N_2O reduction in N_2OR is still unclear [103].

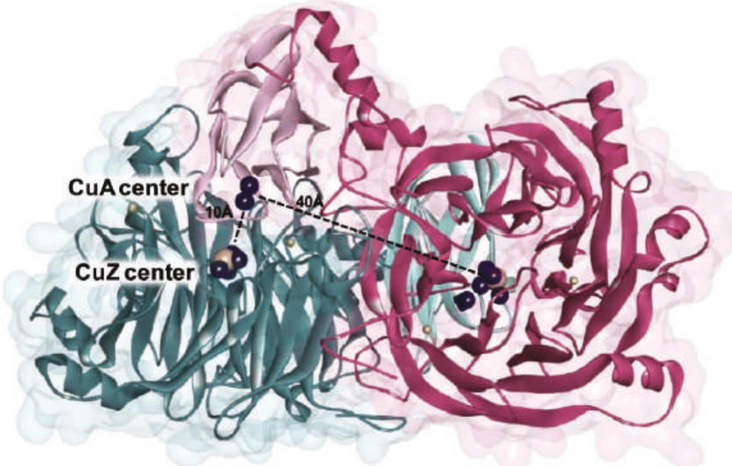

Figure 3. Structure of *Marinobacter hydrocarbonoclasticus* nitrous oxide reductase (N_2OR) homodimer. N_2OR is organized as a head-to-tail homodimer. Monomers are coloured differently so that they can be distinguished. In both monomers, the N-terminal domain is dark-coloured. The N-terminal domain forms a seven-bladed β-propeller fold that coordinates the catalytic tetranuclear active site Cu_Z through seven histidine residues at its hub. The C-terminal domain forms a cupredoxin fold and binds the dinuclear mixed-valent Cu_A centre [104].

The proven ability of N_2OR to "crack" the N_2O molecule raises the question of why the protein has not yet been incorporated into a commercially available transgenic cropping choice for environmentally motivated producers and small-plot farmers. Work has been done on this gene and its potential role in plant biotechnology since it was originally isolated in 1998 from the anaerobic soil bacterium *A. cyclocastes* [105,106], but it has yet to be converted into a commercially valuable tool. In this sense, N_2OR may be considered an "orphaned" protein, neglected among a veritable molecular toolkit of genes in the soil microflora [107,108]. Such forays into integrating soil and air sciences are demonstrative of the possibilities of what the soil microbiome offers biotechnologists [27]; it has already been discussed regarding the N-management possibilities offered by the microbiome and the current practice of 'bioprospecting' is also revealing a plethora of beneficial bacterial products, which is only accelerating thanks to whole-system approaches involving computational analyses [109].

Web of Science reports that between 1900 and 1991, there are no records binned under the combined topics "nitrous oxide reductase" and "microb*". The scientific literature blossomed from its first occurrence of 1992 to the present day, witnessing at least 175 publications dealing with the science of this important enzyme in our total environment. The scientific community waited until 1996 to start discussing denitrification in a plant context, according to these same search terms. With the search terms "nitrous oxide reductase" and "plant", the scientific record shows that soil microbiologists have taken a growing interest in the movement of N into the atmosphere (Figure 4). It is encouraging to note that in the same time period, the linkage between N_2OR and climate began its nascent phase.

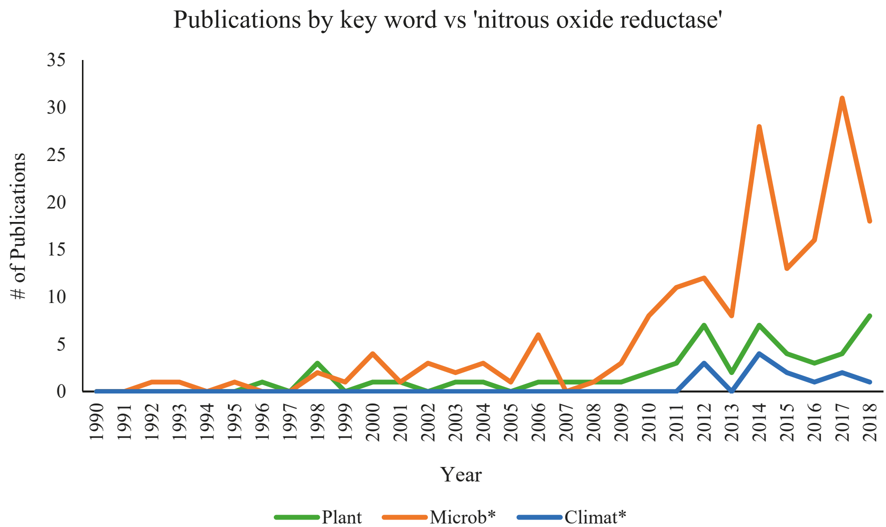

Figure 4. Nitrous oxide reductase-related publications released since 1990 on Web of Science (Clarivate Analytics). Publications by key word vs "nitrous oxide reductase" from 1990 to 2018. The orange line indicates "nitrous oxide reductase" + "microb*"; green: "nitrous oxide reductase" + "plant"; blue: "nitrous oxide reductase" + "climat*".

4. Catch Me If You Can: Can Plants Catalytically Convert N_2O *in planta*?

Rather than a 'cat and robin redbreast' conundrum, we are confronted with an opportunity to deploy protein engineering to ensure that more N_2OR molecules are attracted to the substrate binding site of the copper enzyme. Protein engineering offers ways to sidestep the challenges of expressing a complex bacterial protein in a plant [110]. There are potential issues with a recombinant metalloprotein like N_2OR, such as whether the ABC transporter can assemble within a plant cell, or the plant can incorporate copper into the electron transferring and catalytic domains [111,112]. It is possible to re-engineer N_2OR and produce a functional product [66], so there is precedent for designing an artificial metalloenzyme through rational protein design. This approach may be key to engineering a plant-compatible N_2OR protein.

A principle challenge associated with imparting N_2OR functionality to plants is that transforming the *nosZ* sequence alone may not be effective [113]; in *P. stutzeri*, the transcription of *nosZ* was dependent on the *nosDFY* genes being expressed, as they encode components of a putative ABC transporter system for the biogenesis of the Cu_Z centre [114]. Therefore, catalytically active N_2OR may not be produced when only *nosZ* is expressed in a heterologous host [28]. Nevertheless, a model N_2O-expressing plant has been engineered [64,93]. The clade I *nosZ* gene from soil bacterium *Pseudomonas stutzeri* was successfully expressed in a heterologous system—in this case, the tobacco plant (*Nicotiana tabacum*). In those proof-of-concept experiments the *nosZ*-expressing tobacco plants reduced 826 µg N_2O/min/gram of leaf tissue [115]. Assuming the tobacco yield to be 0.50 tonne/ha [116], the calculated N_2O-cracking ability of the *nosZ*-expressing tobacco could be as high as 600 kg of N_2O/ha/day [115], or 60 tonnes/ha/year (100 day growing season). This value surpasses the calculated N_2O flux of 0.05–1.98 kg N_2O/ha/year [117]. In other words, if every tobacco plant in the world produced N_2OR, this industrial crop (6.6 million tonnes were produced worldwide in 2016 [118]) could conceivably crack 785 Tg of N_2O (1 Tg = 1 million metric tonnes) during an average growing season of 100 days, far surpassing the estimated ~30 Tg of N_2O emitted per year [119]. Such catalytic capacity would give the 'Stop Smoking' campaigns a whole new flavour.

Although these transgenic plants produced a functional N_2OR enzyme, no gas analysis was performed to quantifiably ensure that these plants could reduce N_2O to N_2 using a recombinant N_2OR. In the future, it is imperative that such analyses be performed to properly judge the efficacy of such a gene-stacking trait system for atmospheric phytoremediation.

An associated issue rests with *P. stutzeri* being an anaerobic species that produces enzymes that function optimally in a low-oxygen environment. While expressing *nosZ* in plants to reduce N_2O appears to be an elegant solution, the N_2OR enzyme was not evolutionarily engineered to be functional in the presence of oxygen. Most soil bacteria that produce N_2OR do so in an anaerobic environment [102].

In the past five years, studies have identified several prokaryotic species that may express an oxygen-compatible N_2OR. Aerobic N_2O reducers may be undertaking an important role in mitigating the amounts of N_2O emitted to the atmosphere in events of oxic-to-anoxic transitions, but these systems have not yet been validated in plants. Here, we discuss two candidates for an oxygen-compatible *nosZ* expression system: clade II-*nosZ* member *Gemmatimonas aurantiaca gen nov.*, spp. *nov.* strain T-27, a polyphosphate-accumulating soil aerobe that is strongly represented in many oxygen-rich soil samples [120]; and *Azospira oryzae*, another clade II N-fixing bacterium originally isolated from the roots of rice (*Oryza sativa*) [121]. N_2O reduction by the *G. aurantiaca* strain T-27 was observed in both the absence and presence of oxygen [120]. The inability of this organism to consume N_2O in the complete absence of oxygen and the observed oxygen-induced activation of *nosZ* expression compels one to consider *in planta* overexpression, whereby the diurnal fluctuation of photosynthetic oxygen production may offer an egress for N_2O accumulation. The *A. oryzae* strains I09 and I13 also show more rapid N_2OR recovery rates and tolerance against oxygen inhibition than *P. stutzeri* [121] and so may be appropriate candidates for crop plant transformation and N_2OR expression.

If the ideal *nosZ* sequence were to be identified and transformed into commercially important crop plants, the benefits would be numerous and profound: seed-borne GHG technology foresees the transgenic cassette passed on from generation to generation, meaning that constant application of the beneficial catalyst would not be required (as with NI application and rhizoremediation); the expression of *nosZ* in the aerial tissues of the plants allows the reducing enzyme to confront N_2O much more easily than when the enzyme is expressed in the soil.

5. Novel Breeding Task: "Gas Cracking" Plants

The challenge of expressing heterologous bacterial proteins in plants necessitates codon optimization due to differences in GC content and codon bias with eukaryotes [122]. Altering the codon bias (or applying 'directed evolution' [123]) of a bacterial gene to be expressed in plants has been highly successful: *P. stutzeri nosZ* in tobacco [115], 5-enolpyruvylshikimate-3-phosphate (EPSP) synthase from *Agrobacterium tumefaciens* in Roundup Ready crops [124], and *Bacillus thuringiensis Cry* genes in maize [125] and rice [126]. Indeed, the global advance promulgating engineered crops is pillared on today's artificial intelligence-guided plant codon optimization rules offered by both large and small boutique DNA houses. However, there has been success expressing native bacterial sequences in plants, i.e., in the case of cotton expressing the native sequence of the *P. stutzeri* gene *ptxd* (*PHOSPHONATE DEHYDROGENASE*) [127,128]. One can dare to fathom how a universally-functional *nosZ* expression system could conceivably redirect some aspects of GHG mitigation research. Such a plant transformation cassette could theoretically be applied to any plant—wheat, rice, soybean, peat moss [129]—recruiting these species for the purpose of denitrification mitigation.

Even with an effective *nosZ* expression system, there are additional challenges in developing *nosZ*-expressing plant lines. There are relatively few powerful monocot-optimized expression systems available [130] (although *Bt* corn, LibertyLink wheat, and Roundup Ready wheat can attest to the effectiveness of the 35S promoter system in monocots), and there is difficulty in transforming monocots [65]. With the advent of new plant transformation technologies like the soil bacterium

Ochrobactrum haywardense [131] and the *BABYBOOM/WUSCHEL2* system [132], the production of genetically modified crops with stacked or pyramided GHG genes may be expedited in the near future.

6. Conclusions—Challenges to the Future Success of *nosZ*

We must address what may be the greatest challenge of all for the modern molecular plant breeder: convincing the general public that transgenic crops may be beneficial for all the plant-planet's denizens, as modified crops that enter the food stream may appear unpopular in some boroughs. Regardless, there is a clear, urgent need to control soil N_2O losses due to the detrimental effects of this potent GHG in the atmosphere. Climate-smart crops should be given a crack at directly addressing this issue and tackling climate change. Such GHG-reducing plant lines, endowed with the ability to catalytically "crack" N_2O in the air, could be vital in the battle to shift public perception towards the acceptance of "GMOs" in agricultural research.

Involvement of N_2O in climate change and global warming has been the subject of increasing investigations due to its potential heat-trapping properties [3]. N_2O emission from soil is primarily the result of an incomplete enzymatic reaction which is mediated by the bacterial enzyme, N_2OR [98]. Therefore, in the late 1990s [105,106], the development of N_2OR-positive transgenic plants was proposed as an environmental phytoremediation strategy with promise to remove N_2O from soil and the atmosphere (Figure 2). However, producing a foreign protein in a plant cell is often a serious challenge. For example, different codon usage [133] and cellular properties between eukaryotic and prokaryotic cells are considered as unknown aspects of this strategy. At least two key questions need to be addressed in future studies to probe the probability for success of this green gene de-toxic tactic for accelerating the destruction of nitrous oxide via canopy catalysis: (1) Which candidate is the best source-organism to donate *nosZ* sequence for plant transformation? Activity of bacterial N_2OR is associated with the anaerobic conditions in soil [101], whereas the plant cell is mostly an aerobic environment. Photosynthesis and respiration cause different levels of oxygen content in plant cells in a diurnal cycle which is not consistent with the enzymatic activity of N_2OR in anaerobic soil bacteria. Therefore, selecting obligate or facultative aerobic bacteria containing active N_2OR enzymes as 'the source code' would be pivotal; (2) Which plant cell compartment is the best destination for targeting N_2OR accumulation? The native enzyme N_2OR in bacteria is directed to the periplasm, where Cu chaperones provide enough Cu for the assembly of metal centres [134]. The absence of periplasmic space in plant cells reinforces the notion that subcellular localization of N_2OR may influence its enzymatic activity *in planta*. Moreover, the important role of Cu in the functional assembly of N_2OR posits whether the transformation of bacterial *nosDFY*, along with *nosZ*, is essential for a functional enzyme. Urgent exploration of how the cellular pool of metal nutrients and proteins (pseudo chaperones) in eukaryotic cells may suffice to activate N_2OR *in planta* may compel the use of such climate-smart plants.

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climate

Article

The Nexus of Weather Extremes to Agriculture Production Indexes and the Future Risk in Ghana

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Abstract: The agricultural industry employs a large workforce in Ghana and remains the primary source of food security and income. The consequences of extreme weather in this sector can be catastrophic. A consistent picture of meteorological risk and adaptation patterns can lead to useful information, which can help local farmers make informed decisions to advance their livelihoods. We modelled historical data using extreme value theory and structural equation modelling. Subsequently, we studied extreme weather variability and its relationship to composite indicators of agricultural production and the long-term trend of weather risk. Minimum and maximum annual temperatures have negligible heterogeneity in their trends, while the annual maximum rainfall is homogenous in trend. Severe rainfall affects cereals and cocoa production, resulting in reduced yields. Cereals and cocoa grow well when there is even distribution of rainfall. The return levels for the next 20–100 years are gradually increasing with the long-term prediction of extreme weather. Also, heavy rains affect cereals and cocoa production negatively. All indicators of agriculture had a positive relationship with maximum extreme weather.

Keywords: extreme weather; agriculture production; return level; extreme value theory; weather; risk

1. Introduction

Many developing countries particularly those in the tropical regions are sensitive to changing the climate, especially where temperatures are already threatening agricultural production [1–3]. They have restricted access to a human and physical asset that can mitigate its effects [4]. These difficulties are often manifold by the lack of connection to new technologies and established markets [2,4]. Ghana is an example of a country facing these challenges. The irrigated land for agricultural use covers only 1% of farmland, and the majority of the farmers are entirely dependent upon seasonal rainfall [5–7].

This concern about the changing climate is due to its negative impact on the living conditions of humankind. Developing nations, particularly Ghana, is increasingly concerned about the changing climate because they are more vulnerable compared to developed nations. Climate change is a significant issue of risk to sustainable growth in Africa. As such, the efforts of African countries to realise the Millennium Development Goals can be considered as an offer if the adverse effects of climate change are taken seriously by Africa nations. Generally, African states contribute very little to climate change yet they bear the major brunt of it. Also, the Africa continent is more vulnerable to the effects of this changing climate as a result of its excessive reliance on rainfed agriculture, and extreme poverty [8]. The critical long-term effects of climate variation include: change in precipitation leading to reduced agricultural production, reduced food security, deterioration of water security, and reduction of fish stocks due to high temperature and displacement. Also, sea-level upsurge due to climate variation affects coastal areas greatly. The adverse effects of climate change in the form of a reduction in agricultural output ultimately lead to a delay in the development of African countries where a more substantial part of national income comes from agriculture. Also, the agricultural sector functions as a basis of livelihood for most people in Africa [8].

To tackle climate change, Ghana signed the United Nations Framework Convention on Climate Change (UNFCCC) at the Earth Summit in Rio de Janeiro in June 1992, following the adoption of the Convention on 9 May 1992 [9]. In Ghana, three critical physical effects of climate change identified include temperature change, precipitation change, and sea level rise [7]. According to a report [10], there is a shift in the rainfall regime in Ghana towards a longer dry season and vanishing wet season. Despite the signing of the Convention by Ghana, the country continues to face the adverse effects of climate change in the area of health, agricultural, already depletion of coastal areas, and low water levels. For example the country's only hydroelectric dam (which produces 80% of the national electricity supply) due to lower rainfall [11]. The consequence of climate change on the Ghanaian economy is due to the lack of environmental adaptation strategies and the socio-economic costs of adapting those strategies to mitigate the effects of climate change.

Climate change affects the transport system in the areas that are heavily dependent on weather conditions [12,13]. According to Reference [14], climate change adversely affects the critical elements of food production such as soil, water, and biodiversity. As a result, Ghana's economic dependence on areas (as energy, agriculture and forestry) which are particularly susceptible to the changing climate makes it more prone to the adverse effects of weather. In this vein, it is essential to carry out studies on the changing climate and its volatility in Ghana.

Specifically, this article examines the following.

➢ Examining the trends in extreme maximum rainfall and extreme high/low temperature
➢ Assessing the variability and weather risk of extreme maximum/minimum
➢ Analysis of the relationship of extreme weather to agriculture production indexes

- Effect of exceptionally high rainfall on agriculture production indexes
- Effect of extremely high temperature on agriculture production indexes
- Impact of low temperature on agriculture production indexes

Rare weather conditions like severe rainfall, extreme temperature (and heat waves), or strong winds, may have significant effects on sectors such as agriculture and health, which may result in severe risk to human life [15]. Further, risks of extreme heat and drought depend not only on the severity of the event but also on the sensitivity and vulnerability of the exposure system [16].

The existing studies only show regional climate parameters and how the joints of their scales occur. We contend that the environmental parameters if could serve as a tool for eliminating human disasters if their extreme conditions are well understood and managed correctly [17]. Focusing on the regional research, particularly climate system, the influence of climate change and uncertainty in weather conditions could alter and transform societal and institutional behaviours [18,19].

Substantial studies concede extreme value theory as a method that estimates rare event whiles generalised extreme value distribution (GEVD) is capable in determining the probability of events occurrence that fall outside of an observed data range. Given this, GEVD has attracted attention in diverse areas of research such as climatology data analysis [20–23]. Issues relating to Extreme Value Theory gradually implemented in practical covariate approach of non-stationary conditions [15,20,24–28]. An investigation by [29–31] on daily rainfall at various observation sites in West Africa revealed an increasing trend of yearly maximum rainfall. Research has shown variations in extreme rainfall [30]. Thus extreme rain is related to a decline in annual precipitation intensity. In weather forecasting, efforts are made to predict the impact of weather conditions on food security [32]. Such reviews can help planners provide adequate protection and adaptation solutions that contribute to the resilience of the population and the reduction of socio-economic disasters. In the world over, 33% of observed crop production modifiability emanates from a change in climate thereby, a cause of variations of crop yield in Africa [33–35]. The intra-inter yearly rainfall and temperature show considerable effects on crops production and therefore ensures food safety [36].

Similar studies demonstrate that rainfall and temperature adversely affect crop yield. It calls for authorities in Africa to enforce sustainable food security policies [37,38]. In a period of severe soil moisture, flowering development stagnates [39]. Research has shown that drought is inimical to the growth of cocoa. Therefore, there is a causality between rainfall and cocoa yield [40]. Analogously, the sustenance of a bumper harvest is positively related to rainfall distribution than the total amount of rainfall received annually [41]. However, Reference [42] argues on the positive and negative causality of crops production in Ghana.

The yearly rainfall in cocoa growing areas in Ghana is more than 2000 mm. Also, two rainfall seasons are recorded from April to July and September to November, where July to August faces relative dry weather with high humidity condition. There is a dry weather condition between a second month and the eleventh month of the annual calendar [40,43]. Variations in climate pose a threat to the health of animals, and unfavourable heat affects them reproductively [44,45].

The 21st century saw a decline in yields ranging from 2.5% and 10% as temperature rises in some agronomic species [46]. The results of the evaluation of the effect temperature on crop yield at various levels indicate a decrease in yield. For example, the decline in barley production is due to the low temperatures during the vegetative stages and represents about 42% of low yield. The different seasons with low temperatures and high rainfall are unusable conditions for the potato, resulting in reduced yields [47].

Ascertained by [48–50], climate change due to the uncertainty of precipitation has a significant impact on agriculture production. On this account, this study introduces a different dimension into the analysis of weather effects on agriculture by looking at the extremes conditions of temperature and rainfall hence; we aim to fill this gap in the literature.

Given the increasing occurrences of climate change, there is a need for researchers to consider extreme conditions that often occur due to climate variability and its related events. Relying on climate variation in a whole without considering the specifics thus, minimum and maximum extremes have resulted in a situation where policies are formulated but not directed at specific extreme effects. This study looks at weather variability concerning maximum and minimum extreme conditions to enhance the formulation of targeted policies to help curb their impact on agriculture production. Further, we have investigated the relationship between extreme weather events and agriculture production indexes and assessed agricultural risk using extreme value theory (EVT) and structural equation modelling, which are different from previous studies.

2. Materials and Methods

2.1. Climate Change and Variability in Ghana

The regional scenarios of seasonal precipitation and temperature changes in 32 regions globally analysed by (IPCC, 2014) show the current variations in climate and the range of variations in 30-year period predicted by GCM, focused in 2025, 2055, and 2085. This background information is critical in explaining the probable effects of climate variation on livestock and crop production.

The IPCC approximate that the past period saw temperatures increased by an average of 0.6 °C. The preceding 25 years, there was no observation of atmospheric temperatures from 1995–2006, 11 out of 12 was the warmest years [51]. Countries are beginning to experience consequences related to global warmings, such as the long-term drought within the Sahel zone in Africa and the expansion of the malaria transmission belt of tropical Africa [52]. Universally, the figure noted for weather-associated natural adversities is fast increasing. From the 1960s, accounts of natural risks have tripled. During 2007, fifteen (14) out of fourteen (15), "emergency appeals" for emergency public-spirited assistance were in the areas of storms, droughts and floods, five times more than in the prior year [53]. Ghana's, climate variation is experiencing increasing unpredictable rainfall and temperatures in all regions [54].

Also, global warming is predicted to show variations in rainfall patterns, acidification, and moisture [55]. In this context, the global effect of climate variation on global life-assistance systems remains uncertain. Some parts experience extreme precipitation resulting in flooding; for example, the Mediterranean areas are experiencing a decline that could result in drought conditions [55]. By some reports [55], the anticipation of global average temperatures will rise between 1.4–5.8 °C by close of the century, as sea levels, increase as melting glaciers melt. Observations recently, however, indicate that many predictions concerning climate change are near the higher limit of the IPCC estimates. Sea levels, for example, have exceeded the IPCC estimates of up to 30 cm [56].

Based on a study by Reference [57], is establish that an estimated 35% of the entire land in Ghana is affected by increasing desertification. The unexpected variability of precipitation patterns is observed for years in Ghana as affirmed by Reference [58]. With the historical data, precipitation was mostly high in the 1960s, but fell to low levels by the end of 1970s and then rose again in 1980s. This fall in precipitation patterns is still prevalent currently, as Reference [59], with 20 years of data, observed this; temperatures are rising throughout Ghana and is precipitation decreasing and becoming gradually unpredictable. The effects of changing climate are anticipated to be severe in Ghana, even though there are rises and fall in both yearly temperatures and precipitation. Conceding to the World Bank's projection, the temperature trend from 2010–2050 shows warming in almost the highest-temperature parts of Ghana, including the North and the Upper Regions.

Nevertheless, the region with the lowest temperature is the Brong Ahafo region. These are base on different climate scenarios [58]. For example, looking at the scenario, it was recognised that the temperatures of the three northern regions would increase by 2.1–2.4 °C by 2050. On the contrary, the predicted increase in Ashanti, West, East, Volta, and Central regions ranges from 1.7–2.0 °C and those of Brong Ahafo 1.3–1.6 °C.

We also reviewed the latest temperature and precipitation forecasts from the Intergovernmental Panel on Climate Change (IPCC) [60] to simulate the impact of climate change on agricultural production in Ghana. These projections are on Phase Five of the Coupled Model Inter-comparison Project (CMIP5), which brings together the results of 39 different global models. We used projections for West Africa until 2035. According to the first scenario, the most optimistic, the temperature should increase by 0.7 degrees and precipitation by 8%. These increases represent the expected minimum increase in temperature and the maximum expected increase in precipitation. The second scenario concerns the median increase in temperature (0.9 degrees) and precipitation (1%). The third scenario, the least optimistic, concerns the maximum expected increase in temperature (1.5 degrees) and the maximum decrease in precipitation (4%). A meta-analysis of crop yield response to climate change, using local average temperature as an indicator of change, concluded that global warming at 2 °C could lead to an increase in wheat, rice, and maize yields, with yields subsequently decreasing with increased warming. The AR4 also showed that crop-level adaptations had a markedly positive effect on all crops, regions, and warming levels [61].

According to Reference [62], Tables 1 and 2 show some of the climate changes in Ghana and the corresponding time periods.

Table 1. The projections of precipitation in Ghana.

Location	Climate Type	Forecast Changes
Accra	Coastal Savanna Zone	From 52% decreases to 44% increases in wet season rainfall by the year 2080.
Kumasi	Deciduous Forest Zone	From 48% decreases to 45% increases in wet season rainfall by the year 2080. Based on their A2 scenario, which generally shows the largest greenhouse gas (GHG) impact, predicts the weakest increase in wet season rainfall, 1.13%.
Tarkwa	Rain Forest Zone	From 45% decreases to 31% increases in wet season rainfall.
Techiman	Forest-Savanna Transition Zone	From 46% decreases to 36% increases in wet season rainfall. The A2 scenario, which generally shows the largest GHG impact, predicts the largest decrease in wet season rainfall, −2.94%.
Tamale	Guinea Savanna Zone	From 36% decreases to 32% increases in wet season rainfall consistent trend toward decreased rainfall.
Walembelle	Northern Guinea Savanna Zone	From 25% decreases to 24% increases in wet season rainfall
Bawku	Sudan Savanna Zone	Range from 28% decreases to 30% increases in wet season rainfall.

Source: Extracted from [8,43].

Table 2. Temperature projections in various climate stations in Ghana.

Location	Climate Type	Temperature Projections	
		Wet Season	Dry Season
Accra	Coastal Savanna Zone	1.68 ± 0.38 °C by 2050 2.54 ± 0.75 °C by 2080	1.74 ± 0.60 °C by 2050 2.71 ± 0.91 °C by 2080
Kumasi	Deciduous Forest Zone	1.71 ± 0.39 °C by 2050 2.60 ± 0.77 °C by 2080	1.81 ± 0.68 °C by 2050 2.83 ± 1.04 °C by 2080.
Tarkwa	Rain Forest Zone	1.69 ± 0.37 °C by 2050 2.56 ± 0.75 °C by 2080	1.76 ± 0.67 °C by 2050 2.76 ± 1.01 °C by 2080.
Techiman	Forest-Savanna Transition Zone	1.77 ± 0.43 °C by 2050 2.71 ± 0.85 °C by 2080	1.95 ± 0.79 °C by 2050 3.05 ± 1.20 °C by 2080.
Tamale	Guinea Savanna Zone	1.84 ± 0.46 °C by 2050 2.83 ± 0.91 °C by 2080	2.05 ± 0.75 °C by 2050 3.18 ± 1.18 °C by 2080.
Walembelle	Northern Guinea Savanna Zone	1.92 ± 0.52 °C by 2050 2.96 ± 0.98 °C by 2080	2.10 ± 0.71 °C by 2050 3.27 ± 1.11 °C by 2080.
Bawku	Sudan Savanna Zone	1.92 ± 0.53 °C by 2050 2.97 ± 0.98 °C by 2080	2.11 ± 0.68 °C by 2050 3.25 ± 1.08 °C by 2080

Source: Extracted from [8,43].

2.2. Seasonal Changes of Precipitation and Temperature

The climate of Ghana is tropical, with a dry season in winter and a rainy season during the summer due to an African monsoon. The duration of the rains varies according to the ecological zones. As shown in Figure 1, the rainy season is usually from May to September to the north, from April to October in the centre, and from April to November to the south. However, on the east coast, the rainy season is shorter than the rains from April to June, with no rainfall in July and August, and it picks up slightly in September and October. The south is the coolest part of Ghana, where it has more than

1500 mm (per year), and even more the small west coast, where it reaches 2000 mm (80 inches) per year. The north is the driest in Ghana, where rainfall is about 1000 mm (40 inches) per year and the east coast, including the city of Accra, where it falls below 800 mm (31.5 in).

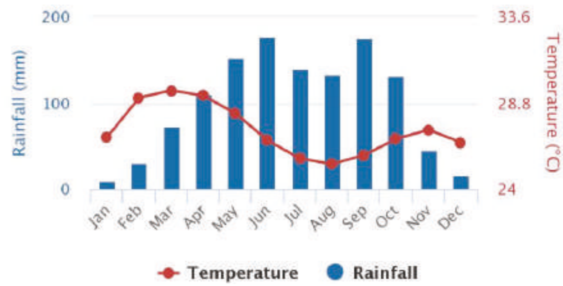

Figure 1. The Monthly trend of temperature and rainfall in Ghana.

2.3. The trend of Climate Change in Ghana

Ghana is located in West Africa, bordered to the north by Burkina Faso, east to Togo, west to Ivory Coast, and south to the Gulf of Guinea. It is located between 4.50 degrees north and 11.50 degrees north and longitude 3.50° west and 1.30° east. The country has an area of 239,460 Km^2 and a surface area of 8520 Km^2 as seen in Figure 2. The country has a population of around 24 million since 2010, with an annual growth rate of about 2.5% [63]. Young people dominate this population. The main exports are cocoa, gold, wood, diamonds, bauxite, manganese, and hydroelectricity. Until recently, the country also began to export crude oil. In 1991/92, the poverty level in Ghana reached 51.7 per cent, and this figure has steadily declined in recent years to 39.5 per cent in 1998/99, 28.5 per cent in 2005/06, and 24.2 per cent in 2012/2013. The country enjoys a high temperature while the average annual temperature is between 24 °C and 30 °C. Despite the average annual temperature, temperatures may be 18 °C and 40 °C in the southern and northern parts of Ghana. Rainfall in Ghana is generally declining from south to north. A more prosperous region in Ghana is the far southwest, with an annual rainfall of about 2000 mm. However, the annual rainfall in northern Ghana is less than 1100 mm. The country has two major systems of rain: the double-twin system and the single maximum regime. For the maximum binary system, the maximum periods are from April to July and from September to November in southern Ghana. While the only maximum system is from May to October in northern Ghana, the prolonged drought lasts from November to May. Over the years, temperatures have risen in all ecological regions of Ghana, while rainfall levels have generally declined and standards have steadily increased [9].

Despite dramatic improvements in technology and crop yields, food production continues to depend heavily on the climate because solar radiation, temperature and rainfall are the critical factors of increase in crop production. The climate is affected by the diseases of plant and the spread of pests, including the supply and demand for irrigation water. For instance, in recent decades, the ongoing drought in the Sahel has caused a continued deterioration in food production [64] in Ghana. The effect of the changing climate on crops was in 1990, where the crop has suffered or decreased. Also, due to drought, climate indicators such as rainfall and average mean temperature are associated with crop change [57]. Table 3 below presented climate change variations experienced.

Figure 2. Location Map of Ghana.

Table 3. Climatic variations experienced in Ghana.

Time Period	Climatic Variations
January–July 1976	Scorching weather conditions
1983–1984	Drought: A yearlong of bushfires
October–December 1989	Scorching weather conditions
1991	Lots of rains throughout the year
1995	About 40 days of intensive rains
2004	Noticeable are frigid winds during March–April (Easter) and November–January was very cold weather
2005	Cold periods resulting in animal deaths
August 2006	One week of intensive rains, and
2007	Lots of rains in August and September.

Source: Extracted from [62].

2.4. The Generalized Extreme Value Distribution (GEVD)

The GEVD is part of the family of continuous distribution functions that allows a continuous range of shapes and consists of classes of distribution functions such as Gumbel, Fréchet, and Weibull. Considering the Fisher-Tippett Gnedenko theorem, the GEVD is a limit-form distribution function, which maximises the maxima of the sequence of random variable considered as independent and identical distributed (i.i.d). It, therefore, models the maximum of a finite sequence of random variables. The combined model of maxima is by Equation (1):

$$G_{\gamma,\mu,\sigma} = \exp\left\{-\left(1+\gamma\left(\frac{x-\mu}{\sigma}\right)^{-\frac{1}{\gamma}}\right)\right\} \text{ with, } \gamma \neq 0,\ \sigma > 0 \text{ and } \gamma\left(\frac{x-\mu}{\sigma}\right) > 0 \quad (1)$$
$$\sigma > 0$$

The derivative of Equation (1), give a probability density function in Equation (2) as:

$$g_{\gamma,\mu,\sigma} = \frac{1}{\sigma}\left(1+\gamma\left(\frac{x-\mu}{\sigma}\right)\right)^{-1-\frac{1}{\gamma}} \exp\left\{-\left(1+\gamma\left(\frac{x-\mu}{\sigma}\right)\right)^{-\frac{1}{\gamma}}\right\},\ \gamma \neq 0 \tag{2}$$

where μ and σ are the location and scale parameters, respectively [20].

The GEVD shape parameter γ also termed as the extreme value index. The decay rate of GEVD seen as γ^{-1}. If $\gamma > 0$ for a class of distributions, G fits distributions as; the heavy-tailed Fréchet distribution, Cauchy, Student's t, Pareto class, and mixture other distributions. G fit into the short-tailed Weibel distribution, uniform, and beta distribution if $\gamma < 0$. G fits the right-tailed Gumbel distributions (normal, exponential, gamma, and lognormal) if $\gamma = 0$ [65–67].

2.5. Maximum Likelihood Estimation for GEVD

The assumption that $X_1, \ldots, X_m$ follows an (i.i.d) and also from generalised extreme value distribution with parameter when $\gamma \neq 0$ the log-likelihood function given as:

$$\text{Provided that } 1+\gamma\left(\frac{x_{(i)}-\mu}{\sigma}\right) > 0 \text{ for } i = 1, 2, \ldots, m \tag{3}$$

$$l(\mu,\sigma,\gamma) = -m\ln\sigma - (1+1/\gamma)\sum_{i=1}^{m}\ln\left[1+\gamma\left(\frac{x_{(i)}-\mu}{\sigma}\right)\right] - \sum_{i=1}^{m}\left[1+\gamma\left(\frac{x_{(i)}-\mu}{\sigma}\right)\right]^{-1/\gamma} \tag{4}$$

Parameters combination that deviates from the above conditions (Equation (3)), i.e., in a configuration where at least one of the observed data exceeds the endpoint of the distribution (Equation (4)), the likelihood is zero, and the log-likelihood is equal to $-\infty$. This case $\gamma = 0$ requires separate treatment with GEVD's Gumbel restriction leading to logarithmic log-likelihood as in Equation (5);

$$l(\mu,\sigma) = -m\ln\sigma - \sum_{i=1}^{m}\left(\frac{x_{(i)}-\mu}{\sigma}\right) - \sum_{i=1}^{m}\exp\left\{-\left(\frac{x_{(i)}-\mu}{\sigma}\right)\right\} \tag{5}$$

Equations (2) and (3) are differentiated and maximised concerning the parameter vector (μ,σ,γ), Solving for (μ,σ,γ), results to the maximum likelihood estimates for the whole GEVD model [20,28,68,69]. Maximum likelihood estimation offers the advantage of estimation of the three parameters together and applicable to the series of maxima per block [70].

Model Checking for GEVD

The model fit of GEVD measure after estimating the parameters by utilising residual plots function as defined by Equation (6),

$$res = \begin{cases} \left(1+\frac{\gamma}{\sigma}(x-\mu)\right)^{-1/\gamma} & if\ \gamma = 0 \\ \exp\left[-\exp\left(-\frac{x-\mu}{\sigma}\right)\right] & if\ \gamma \neq 0 \end{cases} \tag{6}$$

Ascertain by Reference [20] conversion of data to unit exponential distributed residuals is on the null assumption that GEVD fits the data.

2.6. Return Period or Level Estimates

The frequency of extreme quantiles incidence estimated with a fixed value of return level. The return level is the mean number of events taking place within a unit period, e.g., one year [71]. Return levels are essential for prediction purposes and estimated from stationary models. The expected return time is the number of time (years) one is expected to wait on average before the observation of another extreme event of at least the same intensity. If a threshold exceedance of a given probability of an observed extreme incidence in any given time (year) is p, then the mean return period T is such that $T = 1/p$.

2.7. Test for Stationarity and Seasonality

The stationarity of the data conducted by the augmented Dickey-Fuller (ADF) stationarity test on the assumption that there is no trend [72]. The quality of convergence of the weather extremes is access using the Kolmogorov–Smirnov (K-S) and Anderson–Darling goodness-of-fit tests. The K-S test, relying on the empirical study of the cumulative distribution function, is used to determine whether the sample is from the hypothesised continuous distribution. The K-S approach is less sensitive for normal distribution [72]. The Anderson-Darling test, an enhancement of the K-S test, compares the fit to the expected cumulative distribution function of the observed cumulative distribution function. This test gives more substantial weight to the tail of the distribution than the K-S test [72].

The assumption is that the data is from a population which is independent identically distribution (i.i.d). The alternative hypothesis is a two-tail test on the assumption that the data follow a monotonic trend. Thus, the following test statistics by Mann-Kendall determine by Equation (7):

$$S = \sum_{k}^{n-1} \sum_{j=k+1}^{n} sgn\left(x_j - x_k\right) \tag{7}$$

with sgn the signum function.

3. Methodology

This paper analyses past Composite Indexes in Agriculture ranges from 1961–2016: crops production, cocoa production, livestock production, cereal production, and food production in Ghana. The data also consider records of maximum rainfall, maximum temperature, and minimum temperature value as weather indicators from January 1965 till July 2016. We sourced the data from the Ghana Meteorological Agency for climate data, and agriculture production indexes from the Food and Agriculture Organization also in Ghana. Rainfall and temperature are assumed to be the primary determinants of weather in Ghana as seen in Figure 1. The first task was to check for stationarity of the weather variables using Augmented Dickey-Fuller (ADF) unit root test and then the Mann-Kendall Trend Test of seasonality. It was necessary to apply methods that explicitly allow for testing non-stationarity in the distribution parameters of climate variables [20].

Next step was to model from the dataset of the weather indicators employing the Block Maximum Method for the weather extremes under Generalized Extreme Value Distribution (GEVD). There were two approaches to the modelling of Block minima data for the minimum temperature. Either the GEVD for minima fitted to this data or the data negated and the GEVD for maxima fitted [20]. The latter approach was adopted since the Extremes Toolkit does not include a routine to estimate the GEVD for minima directly. The block maxima method is a parametric approach to Extreme Value Theory. It entails fitting the GEVD to a specific group of maximum values chosen in a given sample of data. It focuses on the statistical behaviour of the largest or smallest value in a sequence of independent random variables. Assume that the sequence is grouped into blocks of size N (with a reasonably large number) and that only the maximum score M_i $(i = 1, 2, 3, \ldots, n)$ of each block extracted. Each M_i $(i = 1, 2, 3, \ldots, n)$ of the weather indicators is then used to estimate the relationship between the composite indexes of agriculture production.

The mean return period defines the amount of time (e.g., years) that is expected to pass on average before a new extreme with the same or increased intensity. Given the likelihood that events past a certain threshold will follow an extreme of a particular security at any given time (year) is defined as p, then the mean return period T can be calculated as $T = 1/p$.

Food production index includes food crops that are considered edible, and that contain nutrients with the exclusion of coffee and tea because they have no nutritive value although edible (FAO). Figure 3 shows the primary crop food calendar.

Finally, we investigated the relationship between extreme weather events and agriculture production using SEM software to evaluate the potential impacts of weather extremes on Agriculture production. We used SEM regression for the paths equation modelling analysis with the partial least squares (SEM) estimation technique [73]. SEM is a modelling approach with a flexible procedure, which can handle data with missing values, strongly correlated variables, and small samples. SEM-regression works with both continuous and discrete observed variables as indicators. The SEM estimates loading and path parameters between variables and maximises the variance explained for the outcome variables [73].

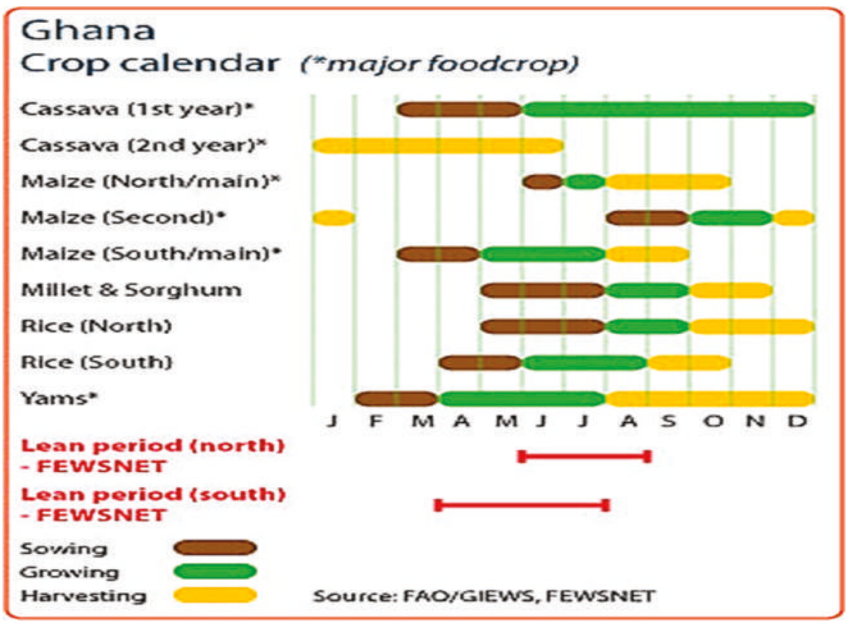

Figure 3. Major food crops calendar in Ghana.

4. Results and Discussion

4.1. Stationarity Test for the Weather Indicators

The ADF test is captured in Table 4 indicating the significance of the *p*-value statistics. The premise of non-stationary at 1%, 5%, and 10% rejected, and therefore we conclude the stationarity of the weather indicators.

It is reported by scholars that, Mann-Kendall Trend Test of stationarity is reliable and efficient. In line with this, analysing environmental data demands the exposure of movements of events on separate points [74]. Based on this, the test outcome illustrates high or low trends in weather conditions of a particular jurisdiction.

Table 4. Stationarity and Seasonality test.

Augmented Dickey-Fuller Stationarity Test					
Test Variable	**Test's Critical Values**			**Test Statistics**	***p*-Value**
	1%	**5%**	**10%**		
Annual maxi. Rainfall	−3.958	−3.410	−3.127	−16.350	0.0000
Annual maxi. Temperature	−10.007	−3.431	−2.862	−2.567	0.0000
Annual mini. Temperature	−12.482	−3.431	−2.862	−2.567	0.0000

Seasonal Mann-Kendall Trend Test						
Series	**Statistics**		***p*-value**		**tau**	**Slope 95% CI**
	z (trend)	**z (Het)**	**p (trend)**	**p (Het)**		
Maxi. Rainfall	0.434	22.376	0.664	0.0216	0.0019	0.0044 [−0.0194,0.0308]
Maxi. Temperature	21.842	4.779	<0.001	0.9410	0.1320	0.0318 [0.0286,0.0346]
Mini. Temperature	25.123	23.894	<0.001	0.1320	0.1520	0.0231 [0.0212,0.0250]

95% confidence interval in parenthesis.

In Table 4, the estimated annual trend is 0.0044 mm/year, a yearly increase in the maximum annual rainfall. The *p*-value based on the Kendall seasonal trend test is $p = 0.6640$, which shows no importance. The 95% confidence interval on both sides for the trend (−0.014,0.0307), the chi-square test for heterogeneity (Het) gave a *p*-value of 0.0216. Therefore, there is a difference in the level of a trend in the different seasons of the maximum annual rainfall. As shown in Table 4, the estimated annual trend is 0.0318 degrees Celsius (°C)/year, which is a yearly increase in the yearly maximum temperature. The *p*-value corresponds to the Kendall seasonal test for the $p < 0.001$ trends, indicating that it is statistically significant. The 5% level of significance on both sides for the trend is (0.0286, 0.0346). The chi-square heterogeneity test (Het) provides a *p*-value of 0.9410, so there is no evidence for different sets of stresses at different times of the maximum annual temperature. The estimated annual trend is 0.0231 degrees Celsius (°C)/year, a yearly increase in the maximum annual temperature. The *p*-value of the Kendall seasonal trend test, $p < 0.001$, indicating that it is statistically significant. The 5% level of significance on both sides for the trend is (0.0212,0.0250). The chi-square test for heterogeneity (Het) gives a *p*-value of 0.1318, i.e., no indication of the different trend in different seasons of the minimum annual temperature.

4.2. GEVD Model for Extreme Maximum Rainfall

In Table 5, the estimated return periods of maximum rainfall likely to occur over the next 5, 10, 20, 50 or even 100 years fitted by GEVD. The estimated results are (μ, σ, γ) (149.03,23.98,0.0024), with standard errors (3.758, 2.718, 0.1002). The approximate 95% confidence intervals for the parameters are thus (141.67, 156.39) for μ, (18.65, 29.31) for σ, and (−0.193,0.198) for γ.

Table 5. Generalised extreme value estimates of maximum rainfall.

GEV	**Maximum Rainfall**		
	Location	**Scale**	**Shape**
Estimates	$\mu = 149.03$	$\sigma = 23.98$	$\gamma = 0.0024$
Std error	3.758	2.718	0.1002
95% CI (normal app)	(141.67,156.39)	(18.65,29.31)	(−0.193,0.198)
Estimated Return Levels	**95% Lower**	**Estimate**	**95% Upper**
5-year return level	173.14	185.06	196.98
10-year return level	186.59	203.13	219.68
20-year return level	196.99	220.50	244.03
50-year return level	206.49	243.04	279.57
100-year return level	210.72	259.95	309.05

The validity and reliability of the extrapolation of GEVD fit is assessed base on the observed data. Four graphical analyses assist with model checking [20,75]. Figure 4 shows diagnostic plots assessing the accuracy of the GEVD model fitted. Neither the quantile plot nor the density plot has any reason to doubt the validity of the fitted model: each drawn set of points is almost linear. The return level plots asymptotically converge to a determinate value due to the positive estimates, with the curve approaches a straight line. The sample variable under consideration provides an adequate representation graphically of the empirical estimates. Finally, the corresponding density estimate appears to be consistent with the density curve. As a result, all four diagnostic diagrams support the GEVD model as in Figure 4 (Top-left: empirical plot; Top-right: empirical quartile plot; Bottom-left: density plot; Bottom-right: return level plot).

The determination of the limiting distribution by maximising the GEV negative log-likelihood for annual maximum rainfall leads to the following function in Equation (8):

$$G(z) = \exp\left\{-\left[1 + 0.00243\left(\frac{z - 23.98}{149.03}\right)\right]^{\frac{-1}{0.00243}}\right\} \tag{8}$$

Equation (8) gave estimates of return levels for 5, 10, 20, 50, and 100-years and their 5% significant level as shown in Table 3. Thus, based on the data from 1965 to 2016, once in 50 years we should expect to see an extreme annual maximum rainfall hit between 206.5 and 279.6 mm. The upper bound of the model prediction for the 50-years Return level of 279.6, but 510 mm extreme rainfall recorded in 1968. Of course, this is undoubtedly extreme beyond regular extreme events, which is not expected based on the model's predictions. Results from Table 2, indicates that extreme maximum rainfall is steadily increasing significantly over the 100 years.

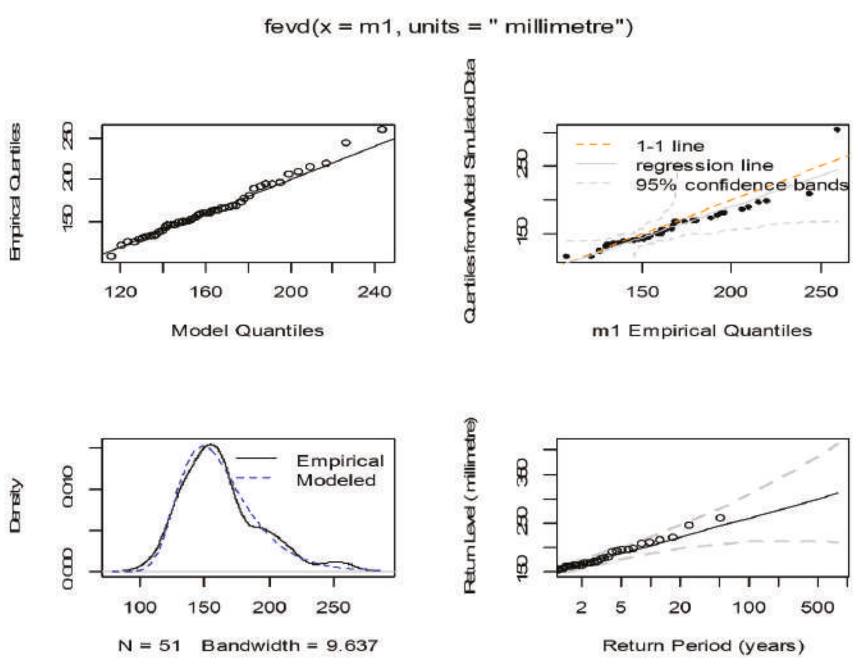

Figure 4. Diagnostic annual maximum rainfall plots.

4.3. GEVD Model for Extreme Maximum Temperature

As shown in Table 6, the estimated return level of maximum temperature likely to occur over the next 5, 10, 20, 50, or even 100 years by fitting these data to the GEVD. The maximum rainfall data yield estimates for (μ, σ, γ) of (41.933,0.892, 0.203), with standard errors (0.137,0.105,0.079). The approximate 95% confidence intervals for the parameters are thus (41.66,42.20) for μ, (0.686,1.098) for σ, and (0.0463,0.359) for γ.

Table 6. GEVD estimates of maximum temperature.

GEVD	Maximum Temperature		
	Location	**Scale**	**Shape**
Estimates	$\mu = 42.08$	$\sigma = 0.826$	$\gamma = -0.292$
Std error	0.128	0.0912	0.0942
95% CI (normal app)	(41.664,42.202)	(0.686,1.098)	(0.046,0.359)
Estimated Return Levels	**95% lower**	**Estimate**	**95% upper**
5-year return level	42.82	43.08	43.35
10-year return level	43.16	43.44	43.72
20-year return level	43.39	43.72	44.04
50-year return level	43.59	44.00	44.41
100-year return level	43.67	44.17	44.67

Analytic plots used in estimating the accuracy of the GEVD model fitted to the annual maximum temperature data shown in Figure 5 (Top-left: empirical plot; Top-right: empirical quartile plot; Bottom-left: density plot; Bottom-right: return level plot). All four diagnostic schemes provide support for fitting the GEVD to the maximum annual temperature.

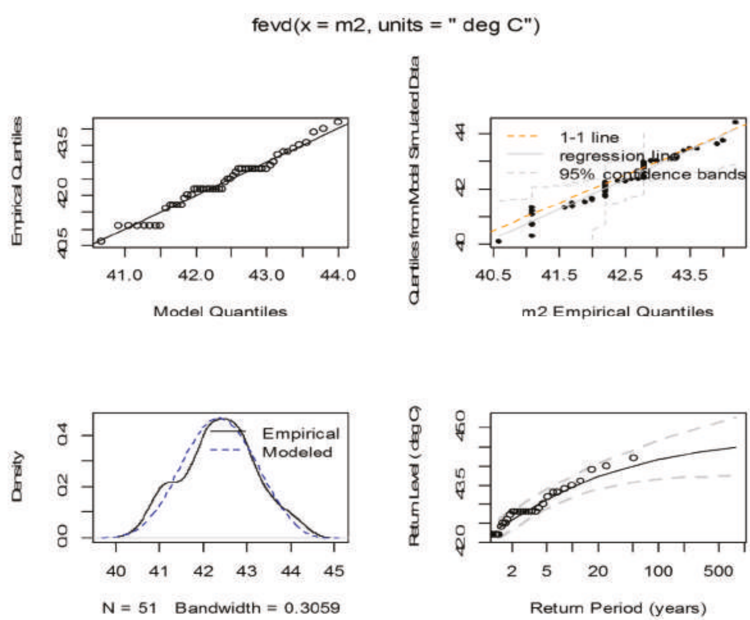

Figure 5. Diagnostic annual maximum temperature plots.

The determination of the limiting distribution by maximising the GEV negative log-likelihood for annual maximum temperature leads to the following function, Equation (2): (μ, σ, γ) of (42.081, 0.826, −0.292)

$$G(z) = \exp\left\{-\left[1 + 0.826\left(\frac{z - 0.892}{42.08}\right)\right]^{\frac{-1}{-0292}}\right\} \tag{9}$$

From Equation (9), estimates of return periods for 5, 10, 20, 50, and 100-years and their confidence intervals at 95% as shown in Table 6. Thus, based on the data from 1965 to 2016, once in 100 years we should expect to see an extreme annual maximum temperature hit between 43.6 °C and 44.4 °C maximum temperature. The upper bound of the model prediction for the 100-years return is 44.4 °C, but 65 °C extreme annual temperature recorded in 1989. Of course, this is also undoubtedly extreme beyond regular extreme events, which is not expected based on the model's predictions. It is revealed by Table 6, that extreme maximum temperature consistently increasing marginally over the 100 years.

4.4. GEVD Model for Extreme Minimum Temperature

In Table 7 below, the estimated return periods of minimum rainfall likely to occur over the next 5, 10, 20, 50 or even 100 years fitted to the GEVD. The maximum rainfall variable yields estimates for (μ, σ, γ) of $(6.408, 5.261, -0.632)$, with standard errors (0.817, 0.758, 0.148) respectively. Approximate 95% confidence intervals for the parameters are thus (4.806, 8.011) for μ, (3.774, 6.747) for σ, and (−0.922, −0.342) for γ.

Table 7. GEV estimates of Minimum Temperature.

GEV	**Minimum Temperature**		
	Location	**Scale**	**Shape**
Estimates	μ = 6.408	σ = 5.261	γ = −0.632
Std error	0.817	0.758	0.148
95% CI(normal app)	(4.806,8.011)	(3.774,6.747)	(−0.922,−0.342)
Estimated Return Levels	**95% lower**	**Estimate**	**95% upper**
5-year return level	10.355	11.506	12.657
10-year return level	11.882	12.723	13.564
20-year return level	12.761	13.456	14.151
50-year return level	13.233	14.022	14.812
100-year return level	13.333	14.274	15.216

Equation (10) is the determination of the limiting distribution by maximising the GEV negative log-likelihood for annual minimum temperature leads to the following function:

$$G(z) = \exp\left\{-\left[1 - 0.632\left(\frac{z - 5.261}{6.408}\right)\right]^{\frac{-1}{(-0.632)}}\right\} \tag{10}$$

Supposing the relative stability of the GEVD process producing estimates for annual minimum temperature in degree Celsius (°C), the model estimates that the 5-year return level is 11.5 °C with 95% confidence interval (10.4, 12.7). For ten years it is a 12.7 °C extreme minimum temperature with 95% confidence interval (11.9, 13.6), and for 50 years it is 14.0 °C extreme minimum temperature with 95% confidence interval (13.2, 14.8). Thus, based on the data from 1968 to 2016, once in 100 years we should expect to see an extreme annual minimum temperature hit between 13.3 °C and 15.2 °C. For the period under annual extreme minimum temperature, there was no extreme beyond normal extreme events. In Table 7, the extreme minimum temperature is consistently increasing over the 100 years' duration. In Figure 6 (Top-left: empirical plot; Top-right: empirical quartile plot; Bottom-left: density plot; Bottom-right: return level plot), all four diagnostic schemes provide support for fitting the GEVD to the minimum annual temperature.

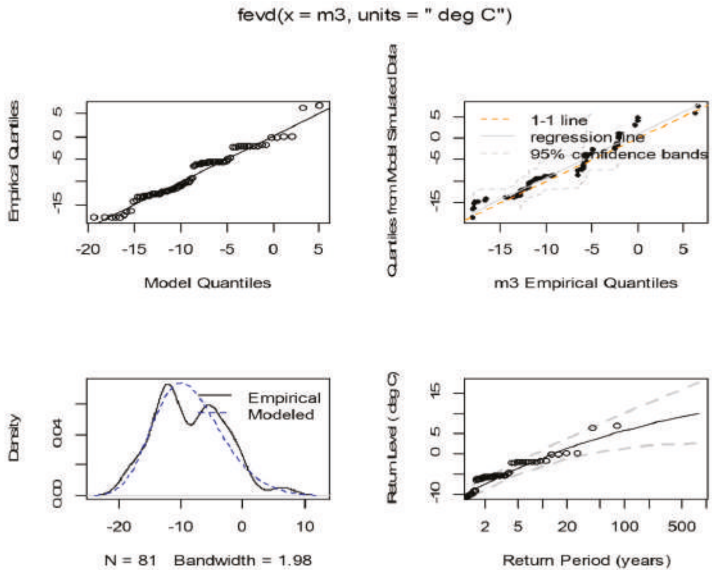

Figure 6. Diagnostic annual minimum temperature plots.

4.5. Return Level

Given 50-year return level for each of the indicators of extreme weather (for the year 2076), the return levels of extreme maximum rainfall in Ghana is higher than 150 mm reaching a warning line of extremely torrential rain, as defined by the Meteorological Service of Ghana. Similarly, the 50 years return level for maximum temperature exceeds 40 °C reaching a warning line of unusual temperature as defined by the Meteorological Service of Ghana. Also, the 50 years return level for extreme minimum temperature is lower than 20 °C reaching a warning line of frigid cold, as defined by the Meteorological Service of Ghana.

4.6. Structural Equation Modeling (SEM)-Regression Analysis

The term "structural equation modelling" (SEM) conveys two significant phases of the process: (a) causal effects under the research epitomised by a lot of structural equations (i.e., regression), and (b) these structural relationships can be presented to enable more specific concepts of theory studying. The assumed model (Figure 7) can then be statistically tested in a simultaneous analysis of the entire variables system to determine its compatibility with the data. If the suitability is appropriate, the model argues for the acceptance of assumed interactions between the variables; if inappropriate, the likelihood of such relationships fails to accept [76]. We chose PLS-SEM in present work for the following reasons: It is suitable for studies of theory construction [77,78]. It is appropriate to assess the sophisticated models of the cause-effect interaction [79,80]. The PLS-SEM assume a non-boundary approach, with fewer restrictions regarding sample size and data distribution [77].

SEM-regression estimation procedure was used to examine the hypothesised relationships as shown in Figure 4 between weather indicators and agriculture production. The results of SEM analysis showed a significant correlation between extreme weather and Agriculture production.

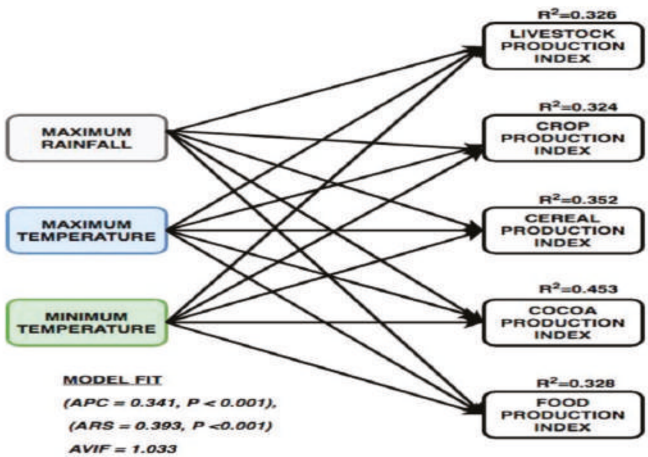

Figure 7. The Conceptual frame of the relationship of extreme weather on agriculture production indexes.

4.6.1. The relationship between Maximum Rainfall and Composite Agriculture Indexes

The analysis as showed in Table 8 is that, Livestock production index ($\beta = -0.1840$, $p = 0.144$), crop production ($\beta = -0.189$, $p < 0.133$), Cereal production ($\beta = -0.266$, $p < 0.031$), Cocoa ($\beta = -0.461$, $p < 0.001$), and food production index ($\beta = -0.190$, $p < 0.131$). Each is influenced by the effect of extreme maximum rainfall negatively on all composite agriculture indexes with no significant effect on crop production, food production, and livestock indexes. There has been a significant effect on cereal production and cocoa production indexes.

Table 8. Standardised Regression Weights and significance of correlations.

Predictor	Outcome	Path Coefficient	*p*-Values
Maximum Rainfall	Livestock Production Index	−0.184	0.144
	Crop production index	−0.189	0.133
	Cereal Production index	−0.266 *	0.031
	Cocoa production	−0.461 ***	<0.001
	Food Production Index	−0.190	0.131
Maximum Temperature	Livestock Production Index	0.305 *	0.015
	Crop production index	0.263 *	0.037
	Cereal Production index	0.276 *	0.025
	Cocoa production	0.424 *	0.023
	Food Production Index	0.268 *	0.033
Minimum Temperature	Livestock Production Index	0.457 ***	<0.001
	Crop production index	0.482 ***	<0.001
	Cereal Production index	0.415 ***	<0.001
	Cocoa production	−0.211 *	0.038
	Food Production Index	0.484 ***	<0.001

Significance of coefficient: *** $p < 0.001$ and * $p < 0.050$.

The results as shown in Table 8, shows each index is influenced by the effect of extreme maximum rainfall negatively, with no significant impact on crop production, food production, and livestock indexes. There has been a considerable effect on cereal production and cocoa production indexes. Maximum extreme rainfall hurts the performance of cereals.

Consequently, a unit increase in maximum extreme rainfall leads to a decrease in cereal production by 0.266 units. Maximum extreme rain leads to filtration of essential nutrients necessary for grain growth. Under such condition, any nutrient whether organic or inorganic leached beyond the reach of the roots, will result in reduced yields.

For cereals to bear maximum yields, rainfall, especially during tasseling for maize, is needed in moderation, inter-sparse with sunlight for maximum yields. Torrential rains do not favour most crops production and most especially cereals. Several studies have shown the importance of rainfall variability in crop production in various spatial scales [33,38].

Excessive rain has an adverse impact on agriculture. These effects run via different mechanisms. Heavy rains and floods have resulted in crop damage and the creation of poor conditions for harvesting, storage and transport of agricultural products. It is not astonishing that maximum rainfall has a negative association with all the variables under consideration, but only cereal and cocoa production indexes are statistically significant. Rainfall affects more variations in cocoa yields from year to year than with any other climatic factor. Trees are prone to a soil water shortage. The rain should be abundant and well distributed throughout the year. The annual precipitation between 1500 mm to 2000 mm is generally preferred. Droughts with rainfall below 100 mm per month should not exceed three months. The flooding of farmland leads to the leaching of nutrients needed for the growth of cocoa trees. If the phenomenon occurs over a period, this often leads to the death of cocoa trees or poor yields are observed [81]. It affects the flowering of cocoa trees and leads to flower aborting in some instances.

4.6.2. The Relationship between Maximum Temperature and Composite Agriculture Indexes

As shown in Table 8, Livestock production index (β = 0.305, p = 0.015), crop production (β = −0.263, p = 0.037), Cereal production (β = 0.276, p = 0.025), Cocoa (β = 0.424, p = 0.023), and food production index (β = 0.268, p < 0.033). Each is influenced significantly by the effect of extreme maximum temperature positively on all agriculture production indexes.

As shown in Table 8, each outcome is influenced significantly by the effect of extreme maximum temperature positively on all agriculture production indexes. The result indicates that a unit change in the maximum temperature will result in about 0.305 change in livestock production index. The nature of Ghana's livestock production immune it from the effects of extreme temperature conditions. Most animals are subject to a free or semi-intensive management system where animals are about to move freely.

Also, most cattle raised in Ghana are more adaptable to the state of the coast. As a result, maximum temperatures in Ghana does not affect them negatively since most of the animal rearing areas are almost in the coastal savannah region where the temperatures are not as high as the actual Sahel regions.

Breeding animals are sensitive to climate change and are severely affected by heat stress with an adverse effect on reproductive function [44,82]. According to Reference [83], high temperature and radiant heat load affect the reproductive rhythm through the hypothalamohypophyseal-ovarian axis. The primary factor in regulating ovarian activity is GnRH of thalamus and gonadotropin, i.e., FSH and LH of the anterior pituitary wall.

Research by [84,85] showed that the LH pulse amplitude and frequency of heat stressed cattle decreased. However, this is not the case in Ghana as shown in the results. Extreme temperatures that result in detrimental conditions not recorded in Ghana. High extreme temperatures hurt the crop production index, cereals production index, cocoa production, and food production index.

The maize pollen viability declines at temperatures above 35 °C [86–88]. Temperature increases in the 21st century may lead to yield losses of between 2.5% and 10% in some agronomic species [46]. Other assessments of crop yield due to temperature have produced different outcomes. Studies conducted by [89,90] showed estimates of yield between 3.8% and 5% decreases According to [90], crop growth for maize, soybeans and cotton will increase gradually with temperatures ranging from 29 °C to 32 °C and then sharply decrease as temperatures rise above this limit. It is however not surprising that maximum temperature in Ghana does not have adverse effects on yields. Maximum temperatures in Ghana is from 29 °C to 32 °C recorded in a dry season where no cultivation is taking place.

The period for production is the rainy season where temperatures hardly get close to 29 °C to 32 °C. Cocoa especially requires much heat, but direct sunshine damages it. As a result, some level of protection is necessary, especially when trees are young. Cocoa trees respond well to moderately high temperatures with a maximum yearly mean of 30 °C to 32 °C [91]. It is however not surprising that maximum temperature associate positively with cocoa production in Ghana where the maximum temperature falls within the acceptable range for cocoa.

4.6.3. The Relationship between Minimum Temperature and Composite Agriculture Indexes

As shown in Table 8, livestock ($\beta = 0.457$, $p < 0.001$), crop ($\beta = 0.482$, $p < 0.001$), Cereal ($\beta = 0.415$, $p < 0.001$), Cocoa ($\beta = -0.211$, $p = 0.038$), and food ($\beta = 0.439$, $p < 0.001$). Each is influenced significantly by the effect of extreme minimum temperature adversely on cocoa and positively on food, livestock, cereal, and crop production indexes.

As shown in Table 8, each outcome is influenced significantly by the effect of extreme minimum temperature adversely on cocoa production index and positively on (food, livestock, cereal, and crop) production index. Except for the cocoa sector, which is associated negatively with minimum extreme temperature the remaining areas are associated positively with low temperature. Average monthly temperatures below 23 °C are considered to suppress flowering.

The range in the average monthly temperature of the mainstream of cocoa-growing regions is found to be from 15 °C to 32 °C and considered to be the optimum for cocoa growth. The absolute minimum for any reasonable period is taken to be 10 °C, below which frost injury is likely [82]. Temperatures below the absolute minimum have a devastating impact on cocoa yields, as the results show.

Low arable yields caused by unfavourable weather conditions during certain stages of the growing season. The effects of unfavourable weather situations have shown reduced arable yields in recent decades. During the vegetative stage, low temperatures cause a reduction in barley yields. Low temperatures account for about 42% of the decrease in yield. Estimates show low temperatures in April, high rainfall in May and a heat wave in July followed by a cold and rainy August created unfavourable growth conditions for potatoes resulting in a decrease in yields [47].

Low yields of corn associated with a combination of low amounts of irradiation during the growing season (64% of low yields) and cold and wet spring (79% of low yields) cause delayed planting and slow biomass growth. Delayed frost has often worsened this situation (36% of low returns). Also, low yields contributed to the stress of drought and heat in flowering (21 per cent of low yields) and the recording of water during harvesting (29% of low yields) [47]. The type of low temperatures that often result in yield reduction is not the type often recorded in Ghana. Shallow temperatures experienced during the growing seasons in Ghana, hence its positive association with all the parameters except cocoa.

Regression estimates showed in Figure 7, extreme weather could explain almost 35.2% of the variance seen in cereal production ($R^2 = 0.352$), 45.3% of the variance seen in cocoa production ($R^2 = 0.453$), 32.6% of the variance seen in livestock production ($R^2 = 0.326$), 32.4% of the variance seen in crop production ($R^2 = 0.324$), and 32.9% of the variance seen in food production index ($R^2 = 0.328$). The whole model demonstrated an acceptable fit to the data for (APC = 0.341, $p < 0.001$), (ARS = 0.393, $p < 0.001$) and AVIF = 1.033

4.6.4. Paths Equations

As seen below, Equations (11)–(15) are the path equations for prediction of the agriculture production indexes and weather extremes.

Let X_1 = Extreme Maximum Rainfall, X_2 = Extreme Maximum Temperature

X_3 = Extreme Minimum Temperature

Thus, obtained are the following regression models for indexes prediction

$$Livestock\ production\ index = -0.184\ MaxRain + 0.305\ MaxTemp + \ 0.457\ MinTemp \quad (11)$$

$$Crop\ production\ index = -0.189\ MaxRain + 0.206\ MaxTemp + \ 0.482\ MinTemp \quad (12)$$

$$Cereal\ production\ index = -0.266\ MaxRain \ + 0.276\ MaxTemp \ + \ 0.455\ MinTemp \quad (13)$$

$$Cocoa\ production\ index = -0.461\ MaxRain + 0.257\ MaxTemp - 0.211 MinTemp \quad (14)$$

$$Food\ production\ index = -0.190\ MaxRain + 0.268\ MaxTemp + 0.484\ MinTemp \quad (15)$$

5. Conclusions

In this present study, we created and examined a model that could contribute to understanding the linkage, and predictability of severe weather and agriculture production in Ghana. The model and structure outlined, tested the nature of extreme maximum rainfall, extreme maximum temperature, extreme minimum temperature and the relationship that exist on agriculture production.

The annual maximum rainfall showed a decreasing trend. However, the yearly maximum temperature and minimum temperature exhibited a significant increase. As observed, there appears no significant trend heterogeneity for each month of the yearly minimum and maximum temperatures, while the annual maximum rainfall shows homogeneity for precipitation in each month. The results show that Extreme Value Theory (EVT) is a reliable tool for climate extreme scenarios construction, where maximum likelihood method supported the evaluation of distribution parameters for weather extreme. Generalised extreme value model is found to be the most suitable model with fulfilling all statistical selection criteria. The return level for the model is constructed to predict the weather extremes for a long run in future. There is generally an increase in weather extreme as it consistently increasing from time to time for the next 100 years.

Evidence from results indicated extreme maximum rainfall adversely affects cereal and cocoa production. Cereals and cocoa thrive well when the rainfall is well distributed and not concentrated in some months and leaving other months virtually without rains.

Maximum extreme temperatures contribute positively to all the indicators under consideration. Minimum extreme temperatures also except cocoa production have a positive impact on the remaining parameters. In the case of cocoa minimum extreme temperatures result in black pod diseases which causes yield reduction. The effect of the temperature and rainfall that is maximum or minimum on food production index depends on their impact on other cereals, livestock and crop productions. Where their respective measures are positive, it results in a positive outcome for food production index. To help improve the food production index of the country there is the need to consider investing in other production sectors. Based on the results the following recommendations are proposed for consideration by policymakers.

The planting time for cereals should be considered going forward, to avoid the detrimental effects of maximum extreme rainfalls. By so doing the yields of cereals will not be affected since they will avoid the period of torrential rains, which affects yields. The diversification of cereals production will help guide against the effect of maximum extreme rainfall on the cereals sector. Some cereals can withstand the impact of maximum extreme rains; diversification into those areas will help reduce the impact of maximum extreme rains if not eliminated.

Minimum extreme temperatures are reported to have detrimental effects on cereals. We recommend the developing of resistant varieties that can withstand the minimum extreme temperatures, which are negatively affecting cereals production. In the case of developing a resistant variety for cocoa, it will help deal with the situation. Since cocoa it is a perennial crop, it will be impossible to use planting period to help deal with the effects of maximum extreme rainfalls. Developing a resistant cocoa variety that will be able to withstand both extreme conditions will be a key in mitigating extreme effects on cocoa yields.

Other research focuses on the more complex problem of catastrophic agricultural risk. To some degree, the catastrophic agricultural risk is the result of extreme weather events. However, the catastrophic agricultural risk is not the same as extreme weather risk. Factors such as environment, agricultural investment, and farmer management should be of interest. To this extent, the distribution of potential damages and losses after a particular type of extreme weather condition should be of interest.

Improving the resilience of Ghanaian agriculture sector is essential. To help do this, farmers and stakeholders in the food production chain should consider the options for adaptation. Adaptation is highly context-specific; this is important for crop, region and climatic zone to use specific adaptation strategies to help minimise the effect of weather extremes on agriculture. The ability of the agricultural sector to deal with climate events will assume a downward trend as the globe warms, and is likely to exceed or fall at specific temperatures and rainfalls. Therefore, farmers need to get used to measures for effective, sustainable, and resilient crop and animal production. Thereby enhancing farmers understanding of growing seasons, improved crop rotation systems, adaptive water management techniques, and higher quality weather forecasts.

For further study, researchers can make a long-term prediction for another weather parameter which indirectly affects the agriculture sector like, production industry on which human life is dependent.

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climate

Review

Geographic Information and Communication Technologies for Supporting Smallholder Agriculture and Climate Resilience

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Abstract: Multiple factors constrain smallholder agriculture and farmers' adaptive capacities under changing climates, including access to information to support context appropriate farm decision-making. Current approaches to geographic information dissemination to smallholders, such as the rural extension model, are limited, yet advancements in internet and communication technologies (ICTs) could help augment these processes through the provision of agricultural geographic information (AGI) directly to farmers. We analysed recent ICT initiatives for communicating climate and agriculture-related information to smallholders for improved livelihoods and climate change adaptation. Through the critical analysis of initiatives, we identified opportunities for the success of future AGI developments. We systematically examined 27 AGI initiatives reported in academic and grey literature (e.g., organisational databases). Important factors identified for the success of initiatives include affordability, language(s), community partnerships, user collaboration, high quality and locally-relevant information through low-tech platforms, organisational trust, clear business models, and adaptability. We propose initiatives should be better-targeted to deliver AGI to regions in most need of climate adaptation assistance, including SE Asia, the Pacific, and the Caribbean. Further assessment of the most effective technological approaches is needed. Initiatives should be independently assessed for evaluation of their uptake and success, and local communities should be better-incorporated into the development of AGI initiatives.

Keywords: climate change adaptation; livelihoods; geographic information; agriculture; resilience

1. Introduction

The agricultural industry is supported by 500 million smallholder farms, responsible for approximately 56% of global agricultural production [1,2]. Smallholder farmers are increasingly resource-poor and confronted by challenges associated with climate change, natural disasters, resource availability and access, and food insecurity [1,3]. Global climatic changes are influencing crop growth and yield, water balances, input availability, and agricultural system management components [4], with ensuing impacts on farming practices [5–7]. Smallholders are faced with both long-term climate stressors and short-term shocks [8]. Geographic variability in climate impacts coupled with low levels of coping and adaptive capacity results in high levels of vulnerability for marginalised farmers [9–11].

Vulnerability varies geographically (often at very local levels). This arises from the complexity of smallholder livelihoods, with multiple on-farm/off-farm activities [12], variation in asset levels and market orientation [13], local (within-farm) variability in productivity [14], gendered roles and access to resources [15], and differential capacity to manage risk [16], affecting smallholder capacity to respond and adapt to climatic challenges.

Incorporating geographic components (i.e., locational properties) into information for climate adaptation is valuable for enhancing environmental decision-making in high risk sectors, such as agriculture. Rapid advancements in geographic information technologies (e.g., geographic information systems (GIS)) and the availability of geospatial data allow for sophisticated capture, analysis, storage, dissemination and access of information across space and time. Concurrently, advancements in information communication technologies (ICTs) (e.g., short message service (SMS); smartphones; Web 2.0), have further increased the usability of geographic information derived from a diversity of sources [17].

Note, while popularity in use of the term geospatial has grown (e.g., geospatial web [18]; geospatial semantics [19]), ambiguity remains over the difference between geospatial and geographic information. Geographic describes information with a reference to Earth's surface and near-surface [20], and geospatial data has been defined as location properties (any descriptive information about the location or area of, and relationships among geographic features) related to any terrestrial feature/ phenomena [21]. We adopt the term geographic information/data, despite much of the material reviewed employing the term geospatial. We consider geographic information to be any information to which location on the Earth is a relevant feature, including both explicit and implicit [22] locational data.

Geographic information used within the agriculture sector—here termed agricultural geographic information (AGI)—is increasingly available to smallholders, yet uptake is limited. Despite a range of geographic information types, such as remote sensing, household surveys, or climate/market reports, accessibility and/or availability is often not in useful/usable formats. Traditionally, information provision to smallholders in developing countries is provided via agricultural extension organisations through farmer field schools, innovation networks and farming associations [23]. However, resource constraints and the diverse needs of smallholders limit the flow of top-down information [24]. For example, resource constraints of agricultural extension staff have been identified as a challenge under climate change in the South Pacific [25] and the lack of transparency and connectivity a constraint to information delivery in India [26].

To this end, we suggest a different or complementary model to supply smallholders with information is necessary, whereby smallholders can harness AGI to make better-informed and cost-saving decisions [27]. Using ICTs to communicate with farmers directly offers a potential for AGI to enhance sustainable agriculture [28], particularly through resources provision for increasing climate resilience at multiple landscape scales [29]. For example, access to geographic information regarding which drought-resistant crops to plant, including when and how, may increase smallholders' capacities to prepare for and withstand such long term climate stresses. Or, localised and context-specific weather forecasts delivered directly to farmers' mobile phones may allow timely decisions and mitigating actions to be taken that reduce the impacts of storms on farming livelihoods. The World Bank, African Development Bank, and African union claim that the greatest opportunities for economic growth and poverty alleviation (in Africa) are provided by ICTs in the agriculture industry [30]. Yet, the evidence base for ICT and use of AGI to support adaptive capacity of smallholders is poorly documented [31]. Baumüller [32] argues that the potential use of ICTs, such as mobile services for smallholder agriculture remains largely unfulfilled. Consequently, here we review recent trends and approaches to utilising geographic information and ICTs for agriculture, and in particular, initiatives for communicating climate and other agriculture-related information to smallholder farmers for improved livelihood security, climate change adaptation and landscape resilience. Our aim is not only to contribute to rectifying the dearth of systematically documented and analysed uses of ICTs in smallholder agriculture, but also to uncover valuable lessons for the design and application of future

AGI initiatives. We achieve this through a systematic review of multi-source literature to address the following research questions:

i. What are the key challenges that AGI initiatives aim to address?
ii. What technological approaches have been adopted to provide AGI to smallholder farmers?
iii. Who are the target users of AGI initiatives and how have initiatives been adopted?
iv. What are the factors promoting or limiting the success of AGI initiatives?

We acknowledge that earlier review works exist on related topics with similar aims and methods to those we present here. The Food and Agriculture Organisation of the United Nations (FAO) [33] reviewed a decade of ICT advancements with applications to agriculture and rural development presenting important findings, such as the significant influence of elements like quality partnerships and the digital divide on project success. But this report was largely descriptive and based on a narrow selection of projects and therefore lacks the analytical depth and rigour associated with our systematic review of AGI initiatives. The World Bank [34] also produced a report on ICT in agriculture, but a similar critique to above could be applied. Baumüller [32] systematically analysed the impact of various mobile services for smallholder agriculture, offering useful lessons for future service developments and an assessment of current shortcomings, including a lack of useful empirical evidence and limitations to current methodologies for evaluating project impact. Our work differs in that it is not constrained to examining only mobile services, but includes a broader range of ICTs used in AGI initiatives, and specifically considers delivery of information of a geographic nature. Duncombe [35] also analysed mobile phone use for agriculture in developing countries, and again, our work examines a more technologically-diverse breadth of AGI initiatives. Further, our work includes the review of AGI initiatives found and described in multiple sources, as opposed to reviews based on only practice-based literature (e.g., [34]) or academic research articles (e.g., [35]).

We first provide a brief background to geographic information and farmer information needs in agriculture, followed by a detailed methodology, presentation of results and discussion in relation to the stated research questions, with particular emphasis on lessons learned from examining a broad range of AGI initiatives. We conclude by identifying critical knowledge gaps and future opportunities.

2. Geographic Information in Agriculture

AGI encompasses a wide range of information types and can be provided through a similarly wide range of technologies. This includes any agricultural information provided through ICTs that has a geographic component, such as location-specific information delivered via SMS, telephone or the Internet, as well as geographic information produced through more sophisticated technological approaches, such as GIS mapping and spatial modelling. GIS technologies provide flexible spatially-explicit tools that support decision making for environmental and natural resource management [36]. Combined with remote sensing technologies, mapping, modelling and monitoring environmental change aids climate change adaptation and mitigation initiatives across the agriculture sector [37,38]. These technologies have contributed to advances in precision agriculture and improved crop management in commercial broad acre agriculture [39–41], yet AGI utilisation by smallholders remains limited. Reflecting on successes from other sectors, geographic information has been used to respond to natural disasters and increase community resilience across a range of environments [42,43], and resilience building in the agricultural sector, particularly in smallholder communities, has similar use potential. Such an aspiration aligns well with the concept of climate smart agriculture (CSA)—to increase food and livelihood security, and farming and landscape resilience [8,44,45]—but explicitly identifies smallholders' needs for improved information access to enable better decision making for sustainable agriculture.

2.1. Information Needs of Smallholders

Smallholder farmers require diverse information to support their livelihoods, with development in the agriculture sector dependent on success in generating, sharing, and applying knowledge [1,46]. Information can be obtained from scientists, educators, advisors, policy makers, and informal networks and smallholders themselves [31]. Information needs differ between farmers based on multiple factors, including socio-economic circumstance, literacy levels, access to resources, size of landholding, and agroclimatic conditions [28]. These factors, in conjunction with a range of socio-political conditions, such as governance structures, cultural norms and gender roles, influence how different individuals obtain and seek (applicable) information (e.g., [47]).

2.1.1. Information Availability

Availability of appropriate climate change adaptation information for smallholders often varies by geography and culture. For example, public media and personal experience form dominant information sources amongst Vietnamese farmers [48]. Conversely, in India, farmers rely on external experts such as non-governmental agricultural research for advice, despite their long histories of traditional knowledge [49]. Less formal agricultural knowledge transfer takes place through face-to-face interactions and verbal communication via mobile phones in rural communities [49]. Television, radio, agriculture offices/departments, neighbours and progressive farmers provide the most useful information sources, at least in part due to exposure and availability [50]. Further, the availability of precise and timely weather-based agro-advisory messages are useful in making informed and cost-saving decisions regarding cultivation conditions [27].

2.1.2. Information Accessibility

Information is commonly delivered to farmers through agriculture extension and advisory services [23]. Primarily top-down approaches, these transfer technologies, skills and knowledge to rural farmers and families to enhance crop/livestock production systems, household food security, and livelihoods, through increasing incomes, nutrition, education, and strengthening natural resource management [3]. However, several deficiencies of extension systems restrict their effectiveness, including limited staff, rigid organisation, poor capacity, a top-down linear culture, weak links to the research sector, and limited reach to farmers [28]. In India, for example, there are many [often duplicate] extension systems, yet the majority of farmers still suffer from inadequate information access [28]. Compounding these issues, women in rural communities bear considerable proportions of farming workloads, but have limited roles in receiving information and making decisions (see [27]). Women are often poorer with less land ownership and have difficulty accessing agricultural information from sources aside from other farmers [51]. Munyna [52] argues that women being ill-informed about technologies, markets, and other agriculture information is detrimental to agricultural development.

2.1.3. Information Applicability

Scale of agricultural systems can influence who has access to [relevant] information. For example, national information produced at the government level may not be effective for improving farming practices at more localised scales. At the local scale, farmer field schools are a variation of extension services. Small groups of farmers routinely gather to observe and evaluate potential suitability of agricultural interventions for their farms [53]. This approach also builds social capital, but often exhibits fiscal limitations [54]. Researchers have argued for an increased emphasis on local rather than global initiatives in developing countries with improved relevance and applicability of information (see [55]). This includes the exchange of knowledge in appropriate formats that respect the oral traditions of many indigenous cultures [56].

3. Methodology

To identify AGI initiatives for analysis, literature was assessed from (i) peer-reviewed academic journals, and (ii) projects listed elsewhere or in grey literature, such as through government/non-government organisation, and other key development organisations and/or private sector agency databases. Assessing academic literature involved multiple keyword searches of the Web of Science Core Collection database, which focused on the topic areas of information, climate, and agriculture practices (in that hierarchical order) (Figure 1). Articles were constrained to include only current or recent literature (published after the year 2000; the time period considered to represent the growth of relevant geographic information, the internet, and other ICTs; when mobile technology penetration rates began to expand in developing countries [32]), those published in English language, and only items with full-text versions available. We acknowledge relevant literature will also exist in other languages, such as French, Spanish, Mandarin, or Hindi, among others, and hence incapacity to analyse non-English sources is a limitation of this study [57]. Articles which met all criteria (n = 156) were read and either entered into a spreadsheet for summarisation and analysis, or discarded if deemed not relevant. Assessment of relevance was made in relation to the research questions presented in Section 1. An article may have met all search criteria by using geographic information technologies to examine some aspect of improving agricultural practices in the context of climate change, but if the article did not describe initiatives specifically for communicating such information with farmers it was deemed not applicable to our research questions and thus was excluded. This process was performed initially by one author, and afterwards verified by another. Articles were also discarded if they only provided duplication (e.g., multiple articles describing the same initiative).

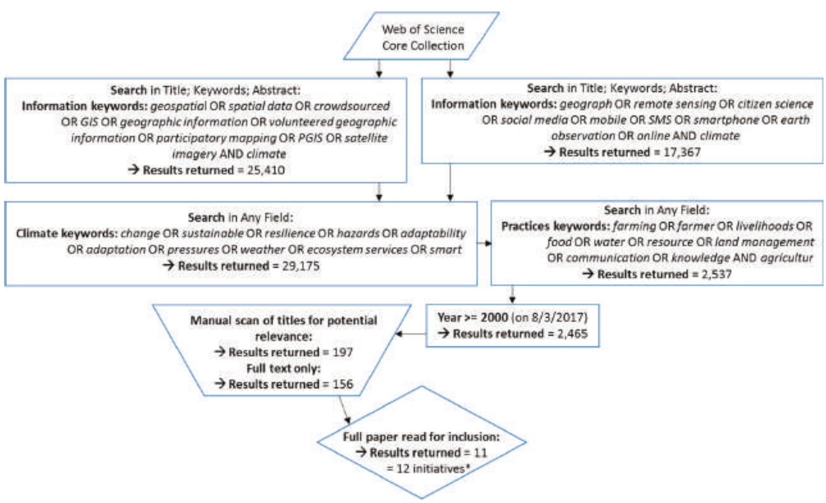

Figure 1. Flow diagram for the academic literature search resulting in 11 relevant papers (12 agricultural geographic information (AGI) initiatives) for analysis (see Table 1 for sources). * One paper described multiple initiatives.

Assessing grey literature involved identifying databases, sources, agencies, and other websites that may contain information on relevant community, agriculture and climate-related AGI initiatives. Where a database had a large number of initiatives, filtering based on keywords (in line with those presented in Figure 1) produced a subset which was manually reviewed for inclusion in a database used for summarisation and analysis. Grey literature assessment was inherently less systematic and could not be automated, and we note the limitation to findings for inclusion in this paper, as once a perceived cross-section of different types of initiatives was obtained the search was ceased. This resulted in

15 AGI initiatives identified. In total, 27 individual AGI initiatives were identified through the above scholarly and grey literature search methods (See Table 1). All initiatives were summarised and analysed in a spreadsheet according to key information relevant for answering the predefined research questions. This included descriptive information (such as initiative name, source, and year), target location and users, initiative aims and approach to achieving aims, climate-related challenges being addressed (short and long term), geographic technologies adopted, the participatory nature of each initiative, adoption and usage information, and details of if/how the initiative was evaluated and by whom.

Table 1. All AGI initiatives identified for this review, including description, target locations and source.

Initiative	Description	Targeted Country or Region	Source
Agriculture Monitoring System	Agriculture monitoring system and technologies for collecting, analysing, and disseminating information. Includes satellite remote sensing, GIS, and mobile GPS. Provides a knowledge base for government, NGOs, rural communities and other stakeholders that will aid sustainable land use and agriculture.	Afghanistan	[58]
Airtel Kilimo	Mobile phone and SMS advisory service. Dissemination of information related to crops, weather and market prices for improved farmer livelihood security.	Kenya	[59]
Avaaj Otalo	Top-down mobile phone advisory service. Delivery of weather, crop, fertiliser and other agriculture information to farmers. Addresses shortcomings of the extension system.	India	[60]
Climate Wizard Tool	Web-based system for climate change data analysis and mapping. Provides practical information for local and regional agriculture managers. Facilitates advanced statistical analyses for more technical users.	Global	[61]
CROPROTECT	Internet and smartphone application utilising GIS and Google Earth. Knowledge exchange system for farmers to acquire and share information relating to pest, weed and disease management.	United Kingdom	[62]
Digital Green	Participatory videos (local languages) used to involve local communities in sharing scientific agriculture information and local knowledge to improve livelihoods through better and more adaptive farming practices.	India, Ghana, Ethiopia	[53,63]
Farmer Decision Support System (FDSS)	Advisory information for registered farmers via SMS to assist farming decisions e.g., when and how to plant, harvest, fertilise and manage crops. 7-day weather forecasts also provided.	Philippines	[64]
Farmforce	SMS and smartphone application to link farmers with other actors in the agro-value chain to reduce transaction costs, aid compliance with food standards, and increase information exchange.	Asia, Africa, Latin America	[65]
Geospatial Information for Rice Crop Monitoring (GIRCM)	Agriculture information derived from image classification and rice crop area estimation to enhance food security. Still in proposal stage.	Afghanistan	[66]
Indian Farmers Fertiliser Cooperative (IFFCO) Kisan Agriculture App	Smartphone application to provide crop information in various formats for enhanced decision making. Aimed at farmers who are receptive to new technologies and business approaches.	India	[67]
Information Technology and Indigenous Knowledge with Intelligence (ITIKI)	Early warning system that integrates information from sensor networks and local knowledge on droughts. Communication using SMS, mobile phone calls, website posts, digital billboards and radio broadcasts to disseminate forecast information to farmers.	Kenya, Sub-Saharan Africa	[68]
iska	GPS-located weather forecasts (various time intervals) distributed via SMS to farmers to improve decision making and reduce weather-related crop losses.	West Africa	[69,70]

Table 1. *Cont.*

Initiative	Description	Targeted Country or Region	Source
Jayalaxmi Agro Tech	Crop-specific smartphone applications for access to agriculture, horticulture and animal husbandry information (English and regional languages).	India	[71]
LandCaRe DSS	Spatial simulation modelling to produce information for stakeholders and farmers involved in decision making related to land management and long-term impacts of climate change at regional and farm scales.	Germany	[72]
Mobile geospatial information for African farmers (MGIAF)	Mobile phone alerts regarding purchasing of drought-tolerant crops for farmers in remote regions. GIS maps for extension officers and community development workers for information dissemination to farmers.	Kenya	[73]
Mobile market information service (MMIS)	SMS request service for rural farmers to receive information on market information (e.g., product prices) to improve selling practices and decision making.	Papua New Guinea	[74]
Mobile soil information for African farmers (MSIAF)	Web-mapping platform for providing soil information to farmers and government workers. Accessed via the internet or mobile phone.	Kenya	[73]
(M)obile Solutions	Mobile phone voice and SMS messages (Hindi or a local language) sent to farmers. Contain information relating to weather, pests, seed varieties, climate change and climate-smart technologies. Provides recommended actions. Option for farmers to provide feedback to inform future messaging.	India	[27]
Participatory Mapping Disaster Risk Reduction Local Knowledge (PMDRRLK)	Participatory approaches and co-produced mapping to improve local resilience to climate change related hazards and increase the use of local environmental knowledge.	Switzerland	[75]
Plantwise Knowledge Bank	Online and smartphone-based knowledge bank with pest identification tools and factsheets on plant health to aid community farming.	Global	[62]
Radio Monsoon	National meteorological information and local knowledge for weather forecasts disseminated to fishermen via social media and the internet, landline and mobile phones, and loudspeakers positioned in fishing communities.	India	[76]
SmartScape	Internet and GIS tool to allow users to experiment with policy options, predict cropping system changes, and compare cropping scenarios. Produces information to be shared with stakeholders, such as policymakers, community agriculture groups, or non-government organisations.	United States of America	[77]
Sowing Application	Smartphone application and SMS used to advise registered farmers best times for sowing seeds based on soil health indicators and rainfall and weather information. Alerts issued for extreme weather conditions that may damage crops or impact farmers.	India	[78]
Tigo Kilimo	Mobile phone dissemination of information on weather, crops and markets for enhanced decision making to improve food security, livelihoods and household income for farmers.	Tanzania	[51]
Watershed Management Information System (WATMIS)	Web-based information and decision support system integrating soil, vegetation, climate and other environment information to assist agriculturalists, resource managers and the rural extension community in managing water scarcity.	India	[79]
World AgroMeteorological Information Service (WAMIS)	Web-server for disseminating agrometeorological products and information bulletins. Provides knowledge and training to large numbers of agriculture stakeholders cost effectively via the internet.	Global	[80]
Wireless Sensor Network—Decision Support System (WSN-DSS)	Wireless sensor network and web-based decision support system for irrigation scheduling. Supports farmers in restructuring agricultural land to address issues of food security and inefficient farming.	Tunisia	[81]

4. Results

4.1. AGI Initiatives

Target users of the AGI initiatives and the key challenges they seek to address are reflected in the distribution of where implementation occurred (see Table 1 for name and summary description of each initiative). Initiatives were concentrated in the global south, particularly south Asia, and east/west Africa. India and Kenya were highlighted as individual countries with the highest numbers of initiatives reviewed. Initiatives largely targeted smallholder farmers and rural communities (n = 18). Some AGI initiatives specifically targeted women farmers (Tigo Kilimo), farmers with low education levels (Tigo Kilimo), fishing households (Radio Monsoon), and progressive farmers more receptive to new technologies and practices (IFFCO Kisan Agriculture App). These target user groups are synonymous with those of more traditional approaches to agricultural extension and advisory services [3]. Other target users included scientists (e.g., PMDRRLK), governments (Smartscape), the agriculture extension community (WATMIS), NGOs and conservation organisations (Agriculture Monitoring System; Smartscape; LandCaRe DSS), risk management agencies (PMDRRLK), and the private sector (Agriculture Monitoring System).

Almost all initiatives adopted a top-down approach (n = 23), with only a few employing bottom-up practices (Digital Green, PMDRRLK and CROPROTECT). Greater emphasis was on communicating AGI to farmers, or providing a service that farmers can receive information from, rather than working with farmers to utilise AGI to support livelihoods. Of the initiatives adopting a bottom-up approach, Digital Green identified 'champions' from a local community to film and edit videos on new farming practices and topics, such as health (outputs were in local languages and topic selections were informed by scientists). Videos were then screened regularly in the community to share learnings. The localised participatory nature of Digital Green was important for people to relate to AGI information and increased adoption of sustainable livelihood practices throughout the community. IFFCO directly targeted progressive farmers, or those more likely to trial and adopt new practices based on capacity, circumstance, and interest. This assumed that farmers who receive AGI through the app, and adopt new practices, will then influence others in the community, either directly through sharing learnings or indirectly through demonstrated success.

4.1.1. Agro-Climatic Challenges Being Addressed

Many initiatives addressed climate adaptation of farmers through increasing livelihood security (n = 19), with some initiatives specifically aiming to increase household income or food security (n = 15). Several initiatives focus on addressing both long-term and short-term climate change to combat adverse impacts on livelihoods [53] and agricultural productivity [60]. In Kenya, where rainfed agriculture supports the majority of subsistence livelihoods, ITIKI sought to address the challenge of limited rainfall monitoring through the development of an integrated communication framework for indigenous knowledge and scientific drought forecast information. In Tunisia, issues of agricultural water wastage and mal-management of resources were being addressed by WSN-DSS, supporting farmers with weather information, improved irrigation scheduling and water management. In rural Africa, MSIAF aimed to mitigate the long-term stress of drought by alerting farmers to market locations to purchase drought-tolerant beans. Initiatives addressing short-term climate shocks were largely related to weather variability, including increased frequency and intensity of meteorological natural disasters (PMDRRLK; WAMIS; iska; Digital Green), extreme conditions like hailstorms and unseasonal rains (Sowing Application), and erratic weather (Radio Monsoon; (M)obile Solutions).

4.1.2. Technological Provisioning to Smallholder Farmers

Various technologies were utilised in the AGI initiatives (Figure 2). MMIS, Tigo Kilimo, Airtel Kilimo, (M)obile Solutions, and FDSS provided simple weather, crop or market information to farmers via low-tech tools, such as SMS and mobile phones, whereby farmers could either receive automatic updates (push notifications) or request information through SMS request or calling a helpline. Varying degrees of complexity were built into these basic mobile phone-based solutions. The inclusion of multiple languages and a peer-to-peer chat function were provided in the Airtel Kilimo mobile service. iska harnessed GPS technology to provide location-specific weather information via SMS. Other AGI initiatives employed internet capabilities to develop custom platforms and smartphone applications, expanding the possible information services offered in terms of both content and format, including support of images, video, animation, interactive content and maps, and hyperlinks to additional online resources. Jayalaxmi Agro Tech offered a range of crop-specific smartphone applications that aimed to enhance food and livelihood security by providing text, audio and visual content on crop information, pricing analytics, and on-demand weather to farmers in English and local languages. Similarly, IFFCO Kisan Agriculture App and Sowing Application aided farmer decision making through the provision of crop or weather information through text, voice, photo and video content. Plantwise Knowledge Bank used smartphones to augment their community-based information exchange activities by pooling information into a central resource for farmers and stakeholders to access; this is particularly useful for remote access by individuals. While GPS was explicitly stated for few AGI initiatives (WATMIS; iska; Agriculture Monitoring System), other initiatives using smart devices likely exploited this technology to provide their locational services.

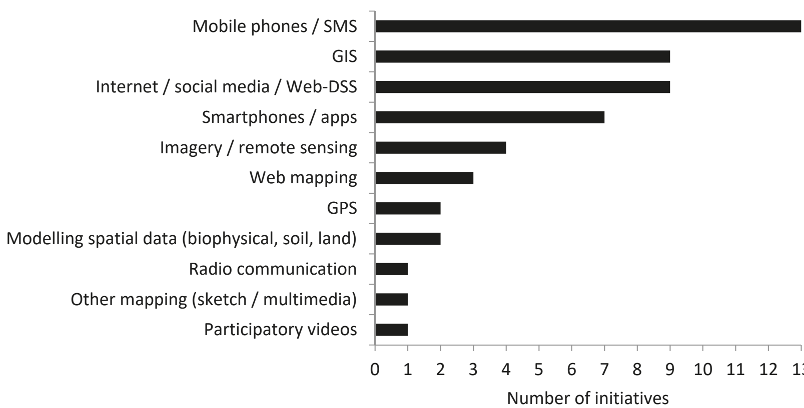

Figure 2. Technologies featured in reviewed AGI initiatives.

Some web-based platform initiatives included and disseminated more data-rich geographic information, such as fine resolution satellite imagery e.g., WATMIS and Agriculture Monitoring System. Satellite imagery and other forms of remote sensing are valuable for detailed depictions of landscape environments and remote capture of data [82]. In Afghanistan, experimentation with methods of classifying satellite imagery was undertaken to strengthen national capacity on rice crop monitoring for sustainable development and food security (GIRCM). WATMIS incorporated GIS and remote sensing data for viable and cost-effective integrated watershed and natural resource planning and management, used by agriculturalists, rural communities and extension services, and land managers. Many AGI initiatives used GIS in combination with ICTs to increase landscape resilience. For example, environmental mapping of drought extent, soils and crops were disseminated to extension workers and farmers, through mobile phones (MSIAF). Online capabilities of technologies have allowed user feedback and sharing of local knowledge for a range of applications, in particular, through social media and crowdsourcing platforms [17]. Radio Monsoon included social media through multiple AGI dissemination methods, and participatory mapping activities that harness local knowledge were used in PMDRRLK. Aside from these two initiatives, social media was absent in all other initiatives. More traditional and primitive forms of information communication, such as radio, loudspeakers and billboards in communities were utilised in some initiatives (e.g., Radio Monsoon; ITIKI).

4.1.3. Adoption of Initiatives

Our review identified limited details of AGI initiative adoption details, with a number being at the proposal, pilot or development stage (n = 10). For those with uptake statistics, assessments of adoption were complex. While the number of users or downloads (e.g., of a smartphone application) of an initiative seemed a standard measure of uptake, more nuanced patterns and differences between numbers of downloads, active users, repeat users, and those who implemented changes to their livelihood practices were also observed. Tigo Kilimo reported 400,000 registered users in two years. Of these, 61% were repeat users, with many trialling the service once but not returning. 30% of users reported continued use with concurrent use of new agricultural practices or growing new crops more likely. 39% were more likely to experience increased income than those not engaging with the service. An analogous service, Airtel Kilimo, reported similar adoption patterns, observing 6432 of their total 22,438 registered users (December 2014) as active, with approximately 50% of users implementing farming changes. IFFCO Kisan Agriculture App reported 170,000 users (October 2016), of which 10–20% were estimated to be active. Iska self-reported to have reached more than 80,000 farmers [70] and sent more than 8.5 million weather forecasts [71]. However, no data were provided on how farmers benefited from this service, or how weather forecasts improved livelihoods and were received/read. Digital Green claimed to have reached one million individuals across 13,592 villages through their participatory video approach, with 574,222 farmers adopting at least one of the best-practice video promotions. Yet, similar to iska, no data were available regarding individuals that have/have not implemented new practices, and why uptake has/has not occurred.

4.2. Factors Promoting or Limiting AGI Success

Given the results of the initiatives reviewed, four cross-cutting themes emerged which are important for promoting or limiting the success of AGI initiatives for climate change adaptation: Farmer capacity, delivery approach, technology used, and the organisation delivering the information (summarised in Table 2).

Table 2. Summary of factors promoting and limiting the success of AGI initiatives for addressing key agro-climatic challenges.

	Factors Promoting Success	Factors Limiting Success
Farmer capacity	Affordability to farmers	Participation capacity (exclusion through gender, costs, digital divide)
	Available languages	Limited languages
		Information alone often not enough for meaningful change
Approach	Partnerships with existing community groups	Methods for incorporating community knowledge into GIS
	User collaboration/sharing	Purely top-down approach—lack of interactivity
	Farmers involved in design	User registration required
Technological	High quality, locally-relevant information	Acquisition and sourcing of suitable and quality information/data
	Low tech and user friendly—ease of use	Availability and capacity of telecommunications infrastructure
	Allows participant feedback—interactivity functionality	Personal and community information security
Organisational	Organisational trust	Low user retention
	Potential for expansion—agile service	(In)ability to reach target users
	Marketing and endorsements	
	Clear business model, including funding	Funding of initiatives

4.2.1. Farmer Capacity

The most sophisticated AGI initiatives may be ineffective if target users are unable to access or utilise the information. Various socio-economic factors potentially limit accessibility for smallholder farmers, e.g., the level of disposable income required to acquire and/or access technologies like the internet, computers, smartphones, or televisions. Even relatively low-cost technologies like mobile phones may be inaccessible for many individuals, particularly in developing nations [83]. Consequently, poorer farmers are disadvantaged with increased difficulty in accessing AGI, despite often being the most in need. With reference to increasing participation in CROPROTECT, Bruce [62] described a lessening of digital divides in recent years, but poorer minorities still may lack access to ICTs. Communication technologies for enhancing knowledge access are often most beneficial for younger and more highly educated individuals [49]. Conversely, Bojovic et al. [84] demonstrated a weakening of digital divides for online participation in climate adaptation with groups that are typically excluded appearing as active participants (e.g., older or uneducated individuals). The contrasting ability of geographic information and ICTs to disproportionately benefit those who have access could be exacerbated if existing socioeconomic divisions within and across communities become greater [85].

One measure to increase farmer capacity is to incorporate local and additional languages in AGI initiatives, to ensure the usefulness of information and geographic information reach to maximise farmers benefitted. Information services provided only in English, for example, reduce the capacity of farmers who have first/only language to access the information. Producing and providing content in local languages facilitates comprehension and immediate connection with the local community (see Digital Green; [63]). However, using a local language alone reduces opportunities to expand platform use into other populations/geographical areas. Provision of information in both local/regional and national/international languages increases the probability of meeting a target user's preference [59]. Projects incorporating detailed information in multiple languages relevant to the scale of operation, including regional and local dialects (e.g., Airtel Kilimo, Jayalaxmi Agro Tech, and Digital Green) are likely to exhibit improved information dissemination and utilisation.

4.2.2. Approach

Approaches with participatory elements offer multiple potential benefits over purely top-down approaches. Where individuals can share their own information with others and/or feedback with AGI initiative developers they may feel their input is more valued and subsequently more interconnected to build community resilience [86]. Partnering with existing community groups can be a useful approach to increasing community participation. Digital Green leveraged community groups, such as women's self-help groups or farmers' groups by actively partnering with government, non-government, and private agencies with strong integration and relationships with communities, and cites these partnerships as critical to their success. Whilst having users involved in initiative development is beneficial, requiring registration for participation is seen as a limiting factor. Registering and then subscribing to content causes confusion with some users and has deterred people from using AGI services ([59]; e.g., CROPROTECT).

4.2.3. Technological

A major consideration for the successful implementation of any AGI initiative is the availability and capacity of the information and telecommunications infrastructure. This includes infrastructure for capturing and disseminating information, and for farmers to receive and use it. For example, if an initiative requires high-speed internet access to deliver high-resolution images/videos, then internet coverage is essential, as is the accessibility of affordable internet-enabled devices and data plans. Similarly, if AGI initiatives are designed to include mechanisms for user participation and feedback, then necessary ICT functionalities are required to facilitate interactivity. Many of the reviewed initiatives emphasised the importance of low-tech, user-friendly technological platforms, especially for those with low digital literacy. Additionally, the information itself is important in AGI initiatives, particularly in relation to content, quality and scale. High quality and trustworthy, locally-relevant information is most useful; sourcing and compiling such data can be technologically-challenging for the success of AGI projects [59]. Jayalaxmi Agro Tech attempted to ensure information was relevant to users by developing multiple smartphone applications specific to individual crops and livestock, whereby farmers can select an app to receive only relevant advice to their own farming practices. Attention also needs to be paid to ensuring the security and privacy of users and the data they might supply to the system, particularly in approaches that encourage public participation.

4.2.4. Organisational

Organisational factors include the organisation responsible for developing and implementing the AGI initiative and the kind of support an initiative receives. Initial funding and ongoing financial capital for maintenance, management, and information sourcing are vital for AGI initiatives. Monetary uncertainty may result in premature cessation of an initiative. Funded by a university competition prize, Radio Monsoon was received very positively by village fisherman and the local forecasters. However, the initiative ceased after two years of operation, as funding was no longer available [76]. Many of the reviewed initiatives were developed by universities and funded by external grants/agencies which resulted in uncertain or short-term initiative lifespans (<5 years) and funding unpredictability. This is problematic for climate change adaptation as climate impacts and building livelihood resilience occur over longer timeframes and multiple generations. Programs that are supported financially and in-kind by multiple sources congruently, including through local and international partnerships with the private sector, government agencies, non-government bodies, and the research sector, such as FDSS, and with a clear business model to manage these funds, appear to have greater success and longevity through decreased pressures of financial insecurity.

Reaching and maintaining users is essential for the success of any AGI initiative. Product marketing is imperative to reach users of relevance, and to raise awareness of initiative existence and accessibility. IFFCO Kisan Agriculture App utilised an existing mobile phone service with relevant potential users to target uptake. Search engine optimisation and social media sites can also provide effective and affordable marketing tools [67], but accessibility to these technologies and services is reflective of farmer socio-economic development levels. The IFFCO Kisan Agriculture App social media marketing strategy was augmented by the addition of local celebrity endorsements. GSMA [59] describe marketing and user retention challenges linked to brand identity and loyalty. Airtel Kilimo is provided to farmers through Kenyan mobile network provider Airtel, and multiple ownership, name and brand changes of Airtel have negatively impacted customer loyalty, and thus initiative uptake. Conversely, good reputation and high organisational trust can foster the success of AGI initiatives through user loyalty, sharing of positive experiences and promotion to other farmers (e.g., Tigo Kilimo).

5. Future Potential of AGI

We reflect upon the results and cross-cutting themes discussed above to recommend future avenues for ensuring successful adoption of AGI initiatives by smallholders for climate change adaptation and mitigation.

5.1. Geographical Targeting

Observational factors (Table 2) suggest that both demand- (by the need for climate adaptation solutions) and opportunity- (by the growth of populations with functional access to required ICTs) driven AGI initiatives are important. Geographical targeting of regions currently not utilising AGI initiatives could substantially benefit smallholder farmers in areas highly impacted by changing climates. Regarding regions of high climate change vulnerability and areas predicted for severe climate impacts on agriculture, various reports identify South and Southeast Asia, Africa, Caribbean nations, and small island developing states (SIDS), such as Vanuatu, Samoa and Tonga (see [4,87–89]. Nations in some of these regions already have targeted AGI initiatives (e.g., India, Afghanistan, and parts of Africa), but many other global priority areas remain untargeted. Further research is needed to expound the reasons for these geographical gaps, and for smallholders in these countries to develop appropriate AGI strategies utilising either existing or new infrastructure, technologies, or platforms that will be most effective for the populations of those regions. Vulnerable climate regions generally coincide with areas of increasing access to ICTs, with fast-growing global internet penetration rates observed in Africa, the Middle East, Latin America, and Asia (2000–2017; [90]).

5.2. Types of Information and Information Technologies

Better understanding of the types of information and technologies that are most useful is needed to target users more effectively. A detailed SWOT (strengths, weaknesses, opportunities, threats) analysis of technologies would be valuable, specifically to determine which technological approaches would most effectively deliver AGI to smallholders impacted by digital divides, for example, impoverished and uneducated farmers, women, and those in regions where access to ICT is limited. Mobile phones and SMS can be especially useful technologies for communicating AGI to smallholder farmers as necessary infrastructure is often already present, and data requirements/costs are comparatively low; in many rural regions, mobile phones are often accessible for farmers where other technologies are limited [1,59]. However, credit costs and access to electricity for charging phones can prohibit farmers' use of mobile technologies [83]. Additionally, the information disseminated via mobile phone may be limited by the text- or voice-only format. Technological, resource (cost), and skill components required to access and use AGI will present barriers for some farmers, which also impacts the inclusion of farmer feedback and local knowledge in initiatives. If technologies can be harnessed effectively, then community information sharing could promote greater peer learning and social connectedness, and contribute to increased community resilience [86].

5.3. Independent Assessment of Initiatives

Existing initiatives and future AGI projects should be independently assessed to provide robust success evaluations of their approaches. This is essential as current non-standardised, self-evaluative techniques provide no meaningful and comparable measures of AGI initiative effectiveness, and self-published usage statistics are often more aligned with marketing. The observed asymmetrical pattern of registered and active users is not unique to AGI initiatives, and transferability of assessment approaches by other online geographic information services could be investigated, e.g., OpenStreetMap has 0.5 million registered users (2011) with 38% having undertaken some mapping, and 5% classed as active contributors [91]. There is also a need to examine impacts for users with different characteristics (considering factors, such as gender, age, income, ethnicity, social status, religion and others), as usage and impacts will not be homogeneous among heterogeneous populations [32]. Furthermore, how project success is reported and marketed may have important implications for future funding and resource allocations, agriculture and climate policies, research and development directions, and the livelihoods of farmers. Thus, independent standardised approaches to evaluating AGI initiatives with an emphasis on more nuanced measures of success beyond simple user statistics are recommended. Moreover, the trust and collaboration often needed for farmers to adopt new practices and alternative ways of thinking takes time, and processes of social change can occur over generations [44], thus longitudinal assessments are also advised over raw user statistics.

5.4. Inclusivity for Multi-Level Stakeholder Communication

Ballantyne [31] argues the need for inclusive, participatory approaches to knowledge sharing, and to successfully use ICT to support farmers and rural communities, farming communities must be empowered to define their own needs. Public participation in GIS (e.g., participatory mapping by communities) to contribute their own unique spatial knowledge, often with support from government, nongovernmental, university and other organisations engaged in development and land-related planning [92], can develop community cohesion [93] and facilitate greater local engagement in land-related decision making [94]. Combining local knowledge on coping mechanisms with top-down strategies has enhanced the capacity of rural indigenous communities in SIDS to mitigate and withstand environmental pressures [95]. Additionally, enhancing smallholder social capital can provide opportunities for more effective articulation of individual and community goals/needs to policy makers, researchers and extension providers [3]. Challenges to inclusive AGI participation (e.g., education levels, household resources, local agro-ecological conditions, market access, availability of local producer organisations, and ability/willingness to collaborate and take risks) need careful consideration, particularly regarding equality for women [3]. Baumüller [32] reports for mobile services that study of behavioural factors impacting farmers' capacity and willingness to participate and/or take risks is a significant research shortfall. Technologies that are adapted to smallholders' capacity to take risks and integrated with relevant support services [28], especially to reach marginal farmers where traditional extension activities [3] or locations where reliability of traditional farming approaches [70] fall short, may prove useful in uptake of AGI to overcome cultural and socio-economic obstacles.

Underpinning each area of potential are important considerations and limitations to AGI that warrant further understanding. Adoption of AGI and any outcomes for smallholders are limited by the capacity to act on the knowledge or information gained. For example, a farmer may receive information of a locally-relevant drought-resistant crop, but may not have the financial means to acquire it. Capacity for decision making will also influence the success of AGI initiatives, and information provision alone may not result in meaningful change. Information accessibility is just one factor among many that significantly affect adaptation [96]. Improved comprehension is needed regarding how significant livelihood change occurs when farmers adopt AGI. This requires localised studies at the level of those users most affected (smallholder farmer communities). Further, as livelihood change is not a short-term process and may vary geographically, studies should be longitudinal and undertaken in a variety of climate-impacted regions. Significantly, the potential ability for AGI provision and adoption to address long-term systemic vulnerabilities requires further research attention.

6. Summary

Learning from past experiences and innovations to promote a successful climate adaptation and development research agenda for the future is crucial [97]. Under increasing livelihood pressures associated with short term, and long term, climate stressors, we advocate that smallholder farmers require diverse and locally-relevant geographic information to aid adaptation for increased food and livelihood security. As we identify, only a small percentage of targeted users of AGI initiatives we reviewed are using and acting on the information provided, which raises questions of the appropriateness of such approaches for addressing key agro-climatic challenges. Addressing these shortcomings is important for supporting smallholders to overcome global risks of extreme weather events, natural disasters, and failures of climate change mitigation and adaptation [98]. Our analysis has identified key recommendations that will serve as a valuable guide for the success of future AGI developments whereby knowledge gaps and implementation challenges should be addressed, particularly to align with the geographically varying needs of smallholder farmers (e.g., [99,100]. Use of AGI initiatives could greatly aid smallholders to move towards climate-smart agriculture [101] for sustainably increasing productivity [44], improving environmental livelihood security [102], and enhancing landscape resilience under a changing climate [103].

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