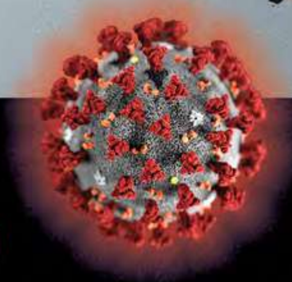

COVID-19 Pandemic, Geospatial Information, and Community Resilience

Global Applications and Lessons

edited by
Abbas Rajabifard • Daniel Paez • Greg Foliente

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ACADEMIC NETWORK

COVID-19 Pandemic, Geospatial Information, and Community Resilience

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Foreword

The COVID-19 pandemic has left no country untouched, with governments and all sectors of society impacted. As a consequence, our world is now being forced to rapidly adapt to confronting social and economic changes and challenges, from local to global levels, across all industries and sectors, and in all areas of supply and demand. However, the pandemic also presents us with a chance to rise from the challenges we face as a global community and identify new opportunities in which we can grow and build resilient and sustainable communities.

COVID-19 has reinforced the unprecedented need for data, geospatial information, enabling technologies, and insights for governments and citizens across the globe, to not only enable decision-makers to inform policies and planning, but to also minimize the risk to people, especially the most vulnerable population groups. As it continues, the pandemic has not only exacerbated our world's vulnerabilities within and among countries, it has reinforced pre-existing obstacles to realizing the SDGs – structural inequalities, socio-economic gaps, and systemic challenges and risks.

In response, and strategically led by the UN-GGIM Academic Network, this timely book brings together expertise from all around the world, presenting advanced research and case studies that raise awareness and provide valuable insights on the critical role of geospatial information and enabling technologies to better respond to and manage the global crisis we continue to face.

While COVID-19 is an unprecedented challenge, we also live in a time of unprecedented access to data, innovation and technology. This gives us the opportunity to facilitate geospatial data sharing on a scale as never before, making a real impact for all citizens of the world through delivering decision-ready solutions that not only aids decision-making during the pandemic, but creates a framework and structure that will remain in place as we recover and increase our global resilience.

Looking beyond the devastation that has occurred, we can see the truly interconnected nature of our world, further highlighting the United Nations notion that no one is safe until everyone is safe. It is imperative that at this time, we act in solidarity with our communities all around the world, particularly the most vulnerable, in order to grow our sense of humanity and build a more sustainable and resilient future.

The ideas, research and solutions shared in this book will no doubt aid in the global effort to better understand the current pandemic as we continue together to create a better future for all.

Dr. Greg Scott
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Acknowledgments

This book brought together the expertise of more than 120 leading professionals, practitioners and academic from more than 30 countries in different related fields for managing pandemic, in particular experts in the field of geospatial industry, and policy-makers and their perspectives to share their experiences and approaches to respond to CIVID-19 pandemic to improve community resilience.

The book is the result of a collaborative initiative of the United Nations Global Geospatial Information Management (UN-GGIM) Academic Network, its members and Centre for Spatial Data Infrastructures and Land Administration (CSDILA) and Centre for Disaster Management and Public Safety (CDMPS) at the University of Melbourne, Australia. Similarly, FIG Commission 7 has been another instrumental entity for the development of this book, especially in demonstrating the critical role of the geospatial community in the fight against the pandemic. The book has drawn upon the advanced research and methods implemented that aid the global effort to better understand and respond to the COVID-19 pandemic and its devastating impacts.

The editors have been privileged to have been involved with the UN-GGIM Academic Network in a leadership role, enjoying the support of the Academic Network members and a vast number of researchers, practitioners and policy makers and geospatial engineers throughout the journey for the preparation of this book.

We would like to acknowledge and thank the contribution of all chapter authors and other contributors. In particular, we would like to thank the support of Dr. Greg Scott from UN-GGIM Secretariat Team for his support and contribution.

We are grateful to the CRC Press, Taylor and Francis Group, for their support and arrangement to publish this work as Open Access, which allows all to use the experiences and research presented in this book to their own best advantage. In particular, we would like to express our sincere thanks to Ms. Irma Britton, Senior Editor, Environmental Sciences, GIS & Remote Sensing CRC Press – Taylor & Francis Group for her contribution, continuous support, and facilitation for publishing this book. We also like to thank Ms. Rebecca Pringle and the rest of the T&F publishing team for their professionalism during the preparation and publication of this book.

Finally, we would like to thank the Department of Infrastructure Engineering and the research team at the CSDILA for their support, and in particular special thanks to Dr. Farhad Laylavi, Ms. Negar Naderpajouh, Dr. Ida Jazayeri and Ms. Jemma Brewster from the CSDILA Centre for their outstanding editorial assistance in preparation of this publication.

We hope this book can contribute to the global response to the COVID-19 pandemic where we can share invaluable tools and insights and work together to not only overcome the unprecedented challenges we face but also aid in the creation of a stronger and more resilient future for all.

Abbas Rajabifard, Greg Foliente and Daniel Páez
Editors

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Part I

Setting the Scene

1

The Role and Value of Geospatial Information and Technology in a Pandemic

Abbas Rajabifard, Daniel Paez and Greg Foliente

1.1 Introduction

The coronavirus COVID-19 pandemic is the defining global crisis of our time and the most devastating challenge the world has faced since World War II, having a profoundly deep impact on the way we perceive our world and our everyday lives. While beginning as a health crisis, it has grown fast in just over few months to be an unprecedented socio-economic and environmental crisis that has spread to every continent and country. As a result, the world has been facing unprecedented social and economic changes and challenges, across all industries and sectors, at every scale (from local, to national and to global level). The COVID-19 virus is a global pandemic, as all our societies are connected, in which no country or jurisdiction is left unscathed as a result of this situation.

This book aims at covering these disciplinary intersections that happen when Geographic Information Systems (GIS) and location intelligence are used in action to respond to the crises and plans for recovery. The experiences and the information included in this book will be a learning tool for communities to being prepared, making the right decisions, and keeping informed to be able to improve community resilience and respond to future crisis.

During a pandemic political borders mean nothing, and every society has been impacted in some way. In June 2020, the World Bank forecast that global gross domestic product (GDP) would shrink by 5.2% [1] in 2020, with recessions in both advanced and emerging market economies. The devastating effects on the global economy will take years to overcome, as governments around the world grapple with the situation and make impossible decisions that aim to meet both the health and economic wars faced as a result of the virus in an attempt to save lives but also limit the financial distress faced by the global economy.

We are now living with a new norm of practice, and as each day passes, people all over the world are not only losing their lives and their health, but also employment, their livelihoods, connections with their friends and family, with no real sense of when life will return to a familiar normality. In this context, good data and statistics, in particular location information and related attributes are key for our resilience and data infrastructure for sustainable future. These data are crucial as they make essential contributions to our strategic pathways on our wider public safety. In a global crisis, our leaders and decision-makers require the fast delivery of information that is accessible and reliable, so urgent and effective responds to COVID-19 are available to make the right choices, manage the complexity and uncertainty and thus lead the world to a more resilient and sustainable future.

From a location information (location intelligence) perspective, the COVID-19 pandemic has highlighted to the world the unequivocal importance and need for geospatial information, enabling technologies, and clear and concise information for governments that enable decision-makers to keep their citizens safe, plan for the future and protect the most vulnerable in our communities.

So much of managing a pandemic is inherently a geographic and location issue. In order to manage outbreaks, perform contact-tracing and enable a robust community response to stop the spread, spatial information is required, and location information is paramount. The social and environmental factors, including population density and age, employment and lifestyle, all influence patterns of disease occurrence and prevalence.

As such, location information, mapping and related analytical tools such as GIS tools are widely used by health departments, safety and emergency management authorities and wider professionals around the world for gathering and analysing data to support informed decisions. The use of location intelligence and GIS for understanding this outbreak and its relationship to infrastructure, population, businesses and other location-based information requires both a clear understanding of the relevant geospatial principles and the relevant aspects of data monitoring, planning and mapping.

1.2 Critical Role of Location Information

The COVID-19 pandemic is proving a need for a collaborative geospatial infrastructure that will help us better understand the crisis at hand at both a local and global scale, as well as better prepare us for future pandemics worldwide. There is a growing need for real-time maps, and location information to track and share location data, and as such, a geospatial-enabled platform, along with data analytics tools and solutions play a critical role in assisting the pandemic's front lines and keeping the general public informed and prepared.

GIS for example has always been a tool in managing the response to large-scale disasters by using location technology that helps to understand the situation at hand, develop a response and prepare a road to recovery. A spatial team is of paramount importance to help create the maps, data, apps, analysis and dashboards that are required for emergency management and resource allocation.

Early in 2020, there was an extraordinary effort around the globe where GIS practitioners in every country began to work together, sharing information that helped us all grasp the situation at hand and also enabled the decision-makers in their response to the virus at local, national and global levels. The Johns Hopkins Coronavirus Dashboard, based on Esri software, was originally built by a handful of people but has evidently grown into the primary tool used to track and monitor the virus, being viewed "nearly a trillion times only a few months into the pandemic" as stated by Esri CEO, Jack Dangermond.

Location information plays a critical role managing the spread of the virus and protecting our communities by providing the tools required in collecting vital data, mapping the current crisis, simulating the results from modelling response variables, contact tracing and determining hot spots, managing high-risk locations and distributing help where it is needed most. Spatial experts around the world have come together and shared critical information that has transpired into an unprecedented effort to manage the COVID-19 pandemic in a way that has not been evident in our history. This effort has been on a global scale and as such we have evolved into a world that supports a connected and global GIS. In our new interconnected world, we all benefit from this phenomenal transformation that impacts every government, industry and citizen, where we can make better and more informed decisions about our future.

1.3 Impact of COVID-19 on the Sustainable Development Goals (SDGs)

The Sustainable Development Goals (SDGs), as outlined by the United Nations as part the global plan to create a better future for all, now play an even more critical role in providing a framework tool that puts health and prosperity at the core of the road to recovery for all nations and all people around the globe. The COVID-19 pandemic has emphasised the challenges facing governments from taking the extraordinary steps needed to attain the SDGs. The vulnerabilities and obstacles that exist in different countries when working towards achieving the SDGs are even more prominent now, including socio-economic gaps, structural inequalities, systemic challenges and risks, as well as a lack of timely fundamental data and enabling technologies to measure and monitor what is happening where, when and how (UN-GGIM White paper, COVID-19). The United Nations Committee of Experts on Global Geospatial Information Management (UN-GGIM) has been taking steps to explore how geospatial information has been used to support national response efforts, and the influence and impact of the geospatial data ecosystem in responding to the global COVID-19 pandemic.

This unprecedented time has also been the first time where geospatial data location intelligence from all around the world has been collected, visualised and made available from local to global levels, through numerous dashboards, including from the WHO and Johns Hopkins University to name a few. These geospatial visualizations clearly communicate the situation and guide decision-making, all through location-based data, and demonstrate that when the geographic dimension is considered, information can be communicated in a clearer, more effective manner, not only to governments but to every individual citizen on the globe.

Of significant importance, contact tracing applications have demonstrated hope by identifying outbreak hotspots, providing those in power with a means to identify, inform and subsequently treat those infected, limiting the spread of the pandemic among the population. In order to achieve successful contact tracing, there needs to be high-level access to geospatial information, which can be queried and classified by age, gender, demography and geography, at every level.

There is an urgent need for the work and issues raised by the UN-GGIM to be addressed and made available across the globe, including data availability, core reference data, interoperability, common geographies, integration of statistics and geography, privacy and confidentiality, the relevance of the Integrated Geospatial Information Framework (IGIF).

With the Integrated Geospatial Information Framework (IGIF) at its core, the UN-GGIM has published findings on what components are required to respond to the COVID-19 crisis, such as leadership, governance, legal and policy, data and technology. The work demonstrates that a clear connection to the IGIF will enable countries to respond in a more timely manner in a crisis where time is critical. Through its initiatives, the UN-GGIM aims to bring the international geospatial community together, along with the the statistical, public health, and development sectors to fight the current pandemic and to build a more resilient and robust global community.

As the IGIF provides a holistic and inclusive Framework, applicable to all countries and in all situations, it is able to be applied to the global COVID-19 pandemic. As an example, the IGIF is highly beneficial in disaster response, where data sharing and geospatial information are critical. Similarly, the response to COVID-19 also requires the ability to share integrated geospatial information in real-time. This ensures that the same information will be delivered to all the key players of the response at the same time. This is also critical in the responding to the aftermath of any disaster, where geospatial determines what happens next and where actions are needed. Outlined in the UN-GGIM white paper publications, the IGIF focuses on geospatial information that is integrated with any other meaningful data to solve societal and environmental problems, acts as a catalyst for economic growth and opportunity, and to provide understanding and benefit from a countries development priorities and the SDGs. While the IGIF has anchored the geospatial response to COVID-19, it is important to note that it was not developed as a response to COVID-19, only as an enabling mechanism to achieve the ambitious targets set by the SDGs. However, its usefulness has provided countries with a basis for leveraging geospatial information, either to integrate existing capacity, or through developing new capability. As a result, the IGIF has demonstrably enabled countries to determine their national geospatial response to COVID-19. The IGIF has nine strategic pathways, influenced by Governance, Technology and People, that work together as a basis and guide for developing, integrating, strengthening and maximizing geospatial information management and related resources in all countries, resulting in tangibly enabled countries to leverage geospatial information in their COVID-19 response.

The most vulnerable countries around the world that have faced the greatest challenges with achieving the SDGs, now face the greatest challenges with the COVID-19 pandemic. Collecting high-quality geospatial information as well as producing, analysing and using timely and reliable location-based data is often not possible, and in many countries where may exist in some form somewhere, it is often not discoverable, structured, interoperable or standardized. It cannot be readily accessed, shared, and more importantly, integrated with other data for decision-making.

Both in attaining SDGs and responding to the pandemic, geospatial information is the key integrator that enables informed decision-making, as well as enabling visualisation and analysis required to communicate key data to decision-makers and the general public. As such, the past few months have been a testament to the importance of collectively developing mechanisms, mobilizing resources and strengthening the global capacity of geospatial information. In this way we can then meet the challenges of COVID-19, and work to build back a stronger path forward on the road to meet the needs of the SDGs in the future.

The UN-GGIM has provided a platform for the global geospatial community and demonstrated its importance to respond to the challenge of COVID- 19. It has become evident how urgent and critical it is to have a multifaceted system that mobilises resources and ensures that all agencies, including government and the private sectors, have access to geospatial information in order to best manage the pandemic, and work towards the SDGs. Implementing the IGIF has been an important step in developing dashboards and communicating the spread and developments of COVID-19.

There is no denying that the pandemic has been a setback in achieving the SDGs around the globe, however it is also a time of great opportunity and growth as there has never been a time in history where people from every corner of the world are working together to bring solutions and advancements to better our health, our communities, our environment and the economy. This particularly effects developing countries, which may for the first time have access to geospatial data and tools that will not only benefit the management of the pandemic in such countries, but also provide their agencies with digital data for challenges that lie ahead.

1.4 Digital Innovation During a Pandemic

In times of great pressure that require solutions to distinct challenges, scientists and engineers are required to fast develop methods, technologies and innovation, and create new good practices. The pandemic has illustrated that novel innovations including dashboards and entirely new processes can be fast tracked and implemented, in a matter of weeks, rather than years. As a result, governments are able to make better and more informed decisions by understanding where the risks exist. Emerging technologies such as Artificial Intelligence (AI) help to expedite the development of a vaccine, and predict the most effective public health measures through simulation and help move much of our lives to an online environment, where we can maintain our economic and education systems to continue employment and schooling as well as our connection to one another.

This also highlights the gap across various social groups in digitally isolated countries and regions. The COVID-19 crisis reminds us that we should nurture the socially beneficial applications of digital technologies and work to improve accessibility and usage in the countries and areas which require the greatest leverage and aid. There are many examples of digital innovation across the globe including in the United Nations Educational, Scientific and Cultural Organization (UNESCO) and the International Business Machines Corporation (IBM) that support the development and deployment of public health mobile applications to help manage the pandemic by providing informed data-driven decisions and social distancing measures. There is also a push to enhance access to the Internet across the globe through UNESCO that aims to foster collaboration and partnership in developing countries.

Governments around the world are also now spending record funding (US$10.5t [2] and rising) to manage the COVID-19 pandemic which means there is a real opportunity for partnerships with businesses to emerge and fast track innovations that lead an advancement in technologies, and how we manage public health as well as how we restore the environment.

However, governments, businesses and the financial services sector need to ensure that investments in innovation create opportunities, reduce inequality and lead to net gains in employment. And governments can do more than just fund innovation; they can ensure learning is plugged back into the state. Digitalization lessons from industry, for example, can be applied to public sector services to deliver better and more effective access, while preserving provision in the face of budget deficits.

1.5 Collaboration and Engagement

Throughout the pandemic, we've seen the development of extraordinary models of collaboration that have resulted in the largest exchange of scientific data in history. It has been remarkable to see competitors work together in joint initiatives. And although there have been some level of disagreement amongst governments and international agencies, we have also observed efficient and effective collaborations between the state and private sectors to deliver technological and medical solutions at speed. This time during the pandemic has been an example of just how much we can achieve as international citizens, when we all focus on a common goal.

There has, however, been indications of an increase in the social divides, similar to the aftermath of the global financial crisis (GFC), where the recovery of many markets were uneven and the people who struggled the most fell further into crisis. The impact on jobs around the world has been dire: the International Labor Organization (ILO) estimates a decline in global working hours in the second quarter of 2020 of around 10.7% (equivalent to 305 million full-time jobs) relative to the last quarter of 2019 [3]. And the workers in poorly paid jobs, casual contracts or who are self-employed are increasing in numbers making them more vulnerable to layoffs during the economic downturn and with less access to social security safety nets. An inequality in healthcare, including access to medical attention, testing availability, access to intensive care and medication, has also been one of the crucial issues of the pandemic observed around the world. Further to this, the recent occurrence of protests that has spread from the United States across Europe to Australia demonstrates the urgent need for inequality to be addressed.

There is also the likelihood that another pandemic may happen in the future, and as such, building a close coordination between central government and local governments, and ensuring closer international collaboration, together with the sharing of digital innovation and technological advancements are of increasing importance for a sustainable future.

1.6 Opportunities Emerging from the Pandemic

Our wider society through governments, the private and the public sectors have a unique and strategic opportunity to shape the recovery and the future economy in such a way that will ensure a more sustainable and more equitable outlook for all. There is now a chance to reframe the future by building a fairer, more prosperous society founded on greener, more resilient, productive economies. While every country and region will have different priorities and starting points, the starting principle for all governments should seek to build more resilient economies while also tackling the climate change challenges and social inequalities.

Social equity is a priority that underpins sustainable economic prosperity. The opportunity to address social inequality, improve outcomes for all citizens, including fairer access to employment is an opportunity during this time that should not be missed. A sustainable recovery is not just about creating jobs; it's about creating high-quality, accessible jobs that improve peoples' lives, which in turn creates more stable societies. The pandemic has also forced the adoption of new ways of working. Organizations must reframe their work and the role of offices in creating safe, productive and enjoyable jobs and lives for employees.

The environmental opportunities in the pandemic that promote a green recovery is clear. The vast majority of the world's total GDP is moderately or highly dependent on a stable environment and is therefore susceptible to disruption due to climate change [4]. Without action to address climate change, an additional 100 million people could be pushed into poverty by 2030 and 143 million in just three regions could be displaced [5]. In the wake of COVID-19, governments and companies have an opportunity to plot greener, fairer and more sustainable days ahead. The pandemic has also raised environmental fears to the public too, as the enforced pause on industrial pollution and travel has resulted in cleaner air where CO_2 emissions are now predicted to be at the lowest level in 14 years [6]. United Nations studies also now estimate that a move to low-carbon, resilient economies could possibly create 65 million new jobs between now and 2030 [7].

1.7 Moving Forward from the Pandemic

With the lessons that we are all learning from this pandemic, our leaders in the public and private sectors, in academia must look to rise from the challenges we face and identify opportunities, in which we can find new ways to keep growing and building resilient and sustainable communities, and infrastructure.

Through the devastation, the COVID-19 pandemic has also demonstrated the interconnected nature of our world and communities, and further highlights the United Nations notion, that no one is safe until everyone is safe. We must act in solidarity with our communities all around the world, in order to save lives and overcome the devastating impacts that this virus has, not just to our health, but socially and from an economic standpoint. By demonstrating strong partnerships, we can grow our sense of humanity and inspire all generations to hope for a healthier and more prosperous future for all, where we learn from navigating through this challenging journey and work together to build greater resilience in every community.

1.8 This Book, Objectives, Chapter Outline

This book brings together the expertise of leading professionals, practitioners and academics in different related fields for managing pandemic, in particular experts in the field of geospatial industry, and policy-makers and their perspectives to share their experiences and approaches to respond to the COVID-19 pandemic, and they share their lessons for any similar pandemic in future in order to improve community resilience. The themes and objectives of the book are in line with the critical challenges that our global community is facing. It is also in line with challenges, gaps, and the work plan of the UN-GGIM Academic Network.

Over 120 authors from regions all around the world contributed to the production of this book, including contributions from more than 30 countries and country case studies.

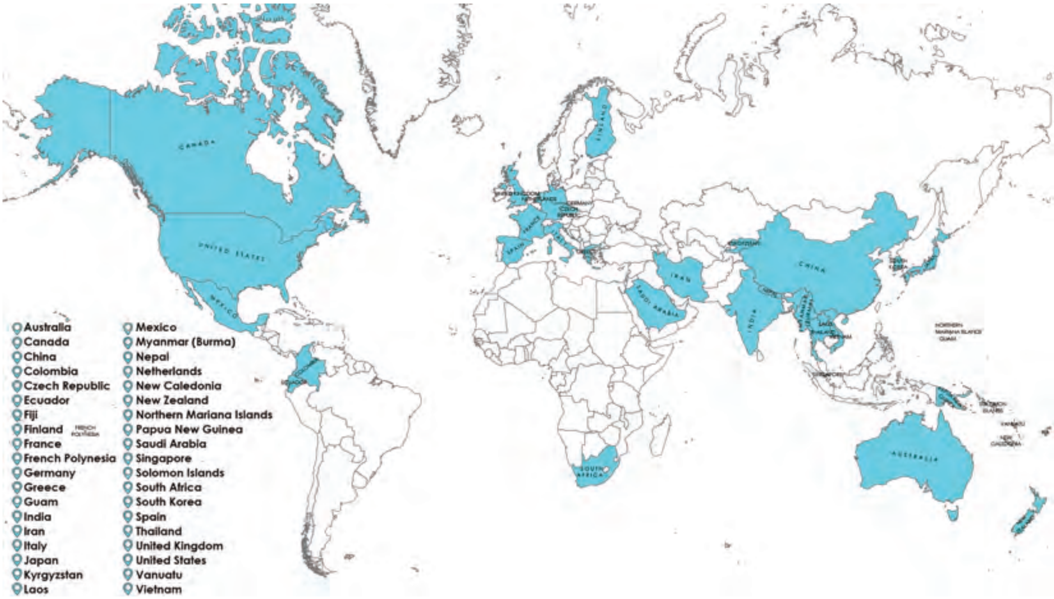

FIGURE 1.1
Contributions and country case studies

The authors have shared their observations, research and best practices in their jurisdictions and organizations that are relevant to professional lines of work or supporting training and teaching modules focusing on COVID-19 applications. This will provide the foundation that would help to reassess the field, affirm successful approaches and point to future possibilities.

The book brought together two types of contributions, scientific chapters, and industry and practitioner observations, structured into 47 chapters in 5 parts. The authors have worked together in hope of taking steps towards achieving more sustainable, safe and resilient future. In doing so, the book will address the following objectives:

- Review foundational aspects of geospatial sciences and technologies for supporting intelligent decision-making for pandemic management.
- Identify a coherent set of tools, guidelines or standards to help researchers, data producers and practitioners and authorities utilize geospatial information for decision-making during various pandemic phases.
- Provide a resource on current best practices for utilizing location intelligence for local, regional, national and global level pandemic management.
- Reflect on the lessons learnt from COVID-19 pandemic, and present a forward-looking collection of ongoing research, development and practice, with an emphasis on the role of location and geospatial science, that can improve the resilience of community, society, economy and environment.
- Provide a medium for presenting the challenges, solutions, opinions and insights from different stakeholders regarding their experience through the pandemic.

The beginning chapters of this book provide an overview of the principles and foundations for geospatial science and technologies, followed by an outline of current approaches for pandemic management and reflections for ongoing development and future prospects for geospatial data in building a more resilient community, society, economy and environment. This book is unique in that it contains observations from various countries and industries, including the challenges they faced, the solutions they came across, the opinions and insights they had during this crisis. It will help build tight bonding between industries and academics and drive more industry-oriented research opportunities.

In Chapter 2, Keith Clifford Bell and Vladimir V. Evtimov draw from the experience of the World Bank and the Food and Agriculture Organization (FAO) to discuss a way forward to ensure the resilience of countries, cities and communities through authoritative geospatial information and land administration.

Maria Antonia Brovelli and Serena Coetzee explore open geospatial data for responding to the COVID-19 challenge in Chapter 3, by examining what data is useful when studying the spatio-temporal spread of the virus and investigating the availability of such open data. In Chapter 4, Mohammad Reza Mobasheri reports on the role of remote sensing in the detection, evaluation and mapping factors relating to public health. The chapter focuses on an introduction to the importance and use of remote sensing through an examination of successful remote sensing applications.

David Green et al. explore the potential of drone technology during pandemics in Chapter 5. The study includes an overview of current drone technology and future developments, as well as investigation into the issues facing successful mainstream implementation of the use of drones for such applications, and the problems that need to be overcome to allow this technology to become mainstream. In Chapter 6, Piret Veeroja and Greg Foliente look at the role of social and built environments on social interactions in Melbourne prior to, and during, the COVID-19 pandemic and discuss possible social and built environment interventions to increase social interactions.

Farhad Laylavi reports on a study in Chapter 7, which aims to contextualise social vulnerability to pandemic situations. The study presents the preliminary indicators of social vulnerability and presents a discussion of the implications, limitations and future work. In Chapter 8, Renate Thiede and Inger Fabris-Rotelli present an algorithm for detecting informally developed roads in satellite images and quantify the uncertainty associated with the results. Such roads play an important role in the development of COVID-19 response strategies in developing countries.

In Chapter 9, Rafael Ponce Urbina et al. showcase a holistic view of the uses of GIS to monitor, analyse and disseminate knowledge pertaining to maritime geospatial data during the COVID-19 pandemic. Mark Stevenson et al. outline recent research in city design and the transmission of COVID-19 in Chapter 10. The chapter highlights the role of city design in virus transmission, particularly in high-density road networks and public transit.

In Chapter 11, Felicia N. Huang et al. discuss social media use and community resilience development during the COVID-19 pandemic in Singapore. Lesley Arnold, Zaffar Sadiq Mohamed-Ghouse and Tony Wheeler report on the role of professional bodies during a pandemic in Chapter 12, with a focus on the role of the Surveying and Spatial Sciences Institute (SSSI) in Australia. In Chapter 13, Peter Mooney et al. explore OpenStreetMap (OSM) data use cases during the early months of the pandemic. The chapter contributes to the knowledge on how volunteered geographic information (VGI) initiatives such as OSM respond and are used or accessed during a global crisis such as COVID-19.

In Chapter 14, Pravin Kokane et al. explore the utilisation of geospatial network analysis techniques for optimal route planning during the pandemic. Chryssy Potsiou discusses the critical issue of formalising informal settlements to empower residents against COVID-19 and other disasters in Chapter 15. The chapter reports on how geospatial experts can provide the means to support governments to identify and empower those most vulnerable to the pandemic, and the measures that have taken place. Abbas Rajabifard et al. provide a discussion around spatially enabled platform supporting managing pandemic, and also review of the applications and systems in place for such a spatially enabled COVID-19 in Chapter 16.

In Chapter 17, Neda Kaffash Charandabi and Amir Gholami propose a global model to help determine the important periods of each country, predict confirmed cases and to discover spatio-temporal hot/cold spots based on wavelet and neural networks. In Chapter 18, Michael Batty et al. give a report on London in Lockdown, discussing the issues of mobility in the pandemic city.

Rosario Casanova et al. in Chapter 19 discuss the Americas geospatial response to COVID-19 through an overview and analysis of the implementation of UN-GGIM global frameworks, as well as a discussion of the gaps and challenges faced. In Chapter 20, Marije Louwsma and Hartmut Müller explores spatio-temporal information management to control the pandemic in Europe. Zhixuan (Jenny) Yang reports on online higher education in Chapter 21, with a focus on how online education facilitated by Information and Communication Technology (ICT) in China has been implemented during the COVID-19 pandemic. The chapter analyses the experience of online education, and uses a case study to evaluate the critical elements involved.

In Chapter 22, Nadia Abbaszadeh Tehrani et al. provide a time-series analysis of COVID-19 in Iran, from a remote sensing (RS) perspective. The chapter discusses the novel approach that utilises remote sensing data to monitor the pandemic at a national level, as well as examining the applicability of RS coupled with time-series analysis for the study area. Alize le Roux et al. present the COVID-19 Vulnerability Dashboard for South Africa in Chapter 23, which maps out the vulnerability to the pandemic across the whole of South Africa. The study aims at helping local authorities and other stakeholders with disaster risk reduction and evidence-based decision-making.

Bola Michelle Ju et al. describe the rapid development of location-based apps in Chapter 24, focusing on the seven applications which saved lives during the pandemic in South Korea. In Chapter 25, Sultana Nasrin Baby et al. report on a spatial analysis of urban parkland and COVID-19 in the City of Whittlesea, in Victoria, Australia. Phil Bright and David Abbott describe the impact of COVID-19 to the Pacific Island Countries and Territories (PICTs) in Chapter 26.

In Chapter 27, Freya M. Shearer et al. present evidence to inform evolving COVID-19 response planning by analysing how Australians were thinking, feeling and behaving in response to the so-called "first wave" of the COVID-19 epidemic and the associated public health measures. Raul Marino et al. present the results of an investigation relating to the lack of access to public space and social interactions in three Latin-American cities in Chapter 28. David J. Coleman and Prashant Shukle provide a case study in Chapter 29 on how geospatial information and technologies were used in Canada. They highlight observations made in the early stages of Canada's response to the pandemic and provide a critical discussion and opportunities for future development and cooperation.

Milan Konecny et al. discuss the roles of geospatial intelligence in addressing COVID-19 challenges in Czechia in Chapter 30. They present three approaches to improving response to COVID-19, including visual analytics; Tracking and analysis solutions; and decision support systems. Carmen Martin and François Pérès provide an observation and analysis of COVID-19 in France in Chapter 31, with a focus on the multi-phase and multidimensional approach to a complex societal imbalance.

In Chapter 32, Richard Simpson explores the importance of a worldwide infrastructure when managing complex pandemic scenarios. He investigates the challenges faced with uncoordinated international cohesion and the accumulative crisis humanity faces as a result. In Chapter 33, Jamie Leach as an observation explores the Open Data Pandemic, and discusses the issues that arise in data sharing around the globe.

In Chapter 34, Menno-Jan Kraak addresses the challenges of mapping COVID-19, and addresses two issues including the professional cartographic design challenges and the most common cartographic mistakes witnessed in the media. In Chapter 35, Alice Kesminas also provides an observation by discussing the importance of engagement to build smarter and more resilient communities. She addresses the role that geospatial information and technology play in building community resilience and discusses the challenges faced to successfully plan and manage resilient communities.

In Chapter 36, Frank Friesecke investigates how the coronavirus could change urban planning. The study explores the changes in how we operate schools, retail, work environments and presents a first vision of the direction in which the city of the future could develop towards in light of COVID-19 and other potential pandemics in the future. In Chapter 37, Hossein Mokhtarzadeh shared his view and investigates the move towards agile strategies during the pandemic. This chapter reports on a observational study completed through a number of interviews with experts discussing how they cope with a global crisis.

Kirsikka Riekkinen provides observations from Finland in Chapter 38, with a focus on the opportunities for digitalisation, and the use of geographic information in the Finnish context. Efthimios Bakogiannis et al. report on the possible future of Greek cities in Chapter 39, with a focus on what the cities will look like after the pandemic period with a case study review analysis and best practice assessment.

Saied Pirasteh et al. explore the COVID-19 pandemic challenges and impacts on the Sustainable Development Goals 2030 in Chapter 40. The chapter discusses an understanding of the pandemic and its influences on SDGs 2030, from an Indian perspective. Malcolm Campbell et al. discuss the value of a policy-response research model in Chapter 41. The authors discuss the GeoHealth Laboratory (GHL) research model that is based on a relationship contract funding model in New Zealand.

Mark Allan outlines the lessons learned from management of the Melbourne COVID-19 pandemic in Chapter 42. His contribution chapter presents some observations made and discusses a future of co-existence with the virus.

In Chapter 43, Hassan M. Khormi explores spatial modelling concepts in Saudi Arabia as an observation. The study reports on how the Saudi authorities implement GIS concepts in controlling the spatial risks of the pandemic. Carmen Femenia-Ribera and Gaspar Mora-Navarro examine COVID-19 in Spain with a focus on the use of geospatial information in Chapter 44. Nathaniel Carpenter and Anna Dabrowski discuss the lessons learned from the COVIDSafe app in Chapter 45, a track and trace technology designed for the Australian context. The chapter focuses on understanding conditions for successful implementation of track and trace technologies. Arturo Ardila-Gomez explores sustainable transport as a key pillar to community resilience during the COVID-19 pandemic in Chapter 46.

The book then concludes in Chapter 47, with synthesis of key lessons and future work to improve our planning and preparation for the next pandemic, focusing on geospatial information and related techno-social innovations for enhanced community resilience.

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Part II

Technical and Techno-Social Solutions

2

Land Administration and Authoritative Geospatial Information: Lessons from Disasters to Support Building Resilience to Pandemics

Keith Clifford Bell and Vladimir V. Evtimov

Throughout 2020, much has been written advocating investment in geospatial information and land administration systems as solutions to pandemic resilience, but closer analyses may suggest a lack of rigor and even a tendency for hype. Resilience of countries, cities and communities in the context of land administration and geospatial information is best achieved through sustainable, authoritative, geospatial information under the framework of National Spatial Data Infrastructure (NSDI) and comprehensive and secure Land Administration Systems (LAS). However, it is becoming increasingly clear that the pandemic has severely impacted progress towards all the SDGs under the 2030 Agenda. Responding to disasters and pandemics does not afford the luxury of extended templated diagnostic assessments, economic and financial analyses and cost-benefit studies of investing in LAS and NSDI. Drawing on the experiences of the WB-FAO partnership, the Chapter discusses good practices of rapid assessments of the resilience and resilience impact of authoritative NSDI and LAS.

2.1 Introduction

> *"The COVID-19 crisis threatens to reverse much of the development progress made in recent years and throw hundreds of millions of people back into poverty. It has required countries to respond rapidly and decisively to major disruptions of their healthcare systems, their economies and the livelihoods of their citizens. I have been inspired by the World Bank Group's response – mobilizing fast to deliver urgent support to countries to minimize loss of life, mitigate severe economic hardship, protect hard-earned development gains, and protect the poorest and most vulnerable".*
> David Malpass, President of the World Bank.[1]

The COVID-19 pandemic has triggered the deepest global recession in decades, and this is well reported by both the World Bank [1] and the International Monetary Fund (IMF). This is the first recession since 1870 to be triggered solely by a pandemic. After more than a decade of uninterrupted growth, the global economy came to a sudden halt because of the pandemic. The debate continues as to how deep it will be; its duration; and how far its impacts will reach. The pandemic has

[1] World Bank President's end of year address to staff townhall, July 2, 2020.

caused contractions across the vast majority of emerging market and developing economies as well as advanced economies. Lasting damage to labor productivity and potential output are already well identified. Across the world it would seem there is strong consensus for immediate policy priorities of alleviation of the human costs and attenuation of the short-term economic losses. Thereafter, once the crisis abates, there is also consensus that it will be necessary to reaffirm a credible commitment to policies to support long-term sustainable development. The COVID-19 recession's speed and depth with which it has struck suggests the possibility of a sluggish recovery. For many emerging market and developing countries, however, effective financial support and mitigation measures are particularly hard to achieve because a substantial share of employment is in informal sectors. The speed with which countries can overcome the pandemic health crisis and pave the way for economic recovery remains to be seen.

The COVID-19 pandemic is not the first global pandemic and it will not be the last, may almost be cliché now. Countries, especially low- and middle-income countries (LIC and MIC), are at the time of writing, fully focused on dealing with the severe health and economic crises. Generally, immediate priorities are budgetary support, health and food security. Beyond recovery, all nations, and development partners, must turn their respective foci to future preparedness to ensure that nations can better withstand the shocks of any future pandemic, with the impacts minimized to the greatest extent possible and recovery enabled in the shortest possible timeframe. However, no degree of preparedness can prevent future pandemics or disasters. Preparedness should include investment in land administration systems (LAS) and national spatial data infrastructures (NSDI).

The WB and the Food and Agriculture Organization (FAO) have partnered in many countries to promote the fundamental roles of LAS and NSDI to support the 2030 Agenda for Sustainable Development and also for improving disaster resilience at the national, city and community levels, in line with the Voluntary Guidelines on the Responsible Governance of Tenure (VGGT) [2] and the Sendai Framework for Disaster Risk Reduction 2015-30 [3].

2.2 Emergencies – Disasters and Pandemics

There are some similarities between the impacts of shocks created by a natural disaster and those created by disease – but only some. No country, regardless of its level of social and economic development is immune from the increasing frequency and severity of emergencies caused by disasters and pandemics. The World Health Organization ([4], p. 22) has prepared a very comprehensive Classification of Hazards, covering disasters, pandemics, conflicts and environmental degradation. From the disaster perspective it has consistency with the Sendai Framework, which sets out the case for all development to be risk-informed in order to be sustainable.

The Disaster Management Cycle, which originates from the United States Federal Emergency Management Agency (FEMA)[2] is widely utilized. Over the past decade, the Disaster Management Cycle, has been interpreted, modified and adopted by many agencies around the world. Recently, with health crises, including the current pandemic, even WHO has adopted an equivalent 4-phase cycle [4] – Preparation, Response, Recovery and Mitigation. Understanding the cycle, enables a better appreciation of where geospatial information and land administration can be effectively applied in terms of response and building resilience, which is discussed later in this Chapter.

2.3 Economic and Financial Impacts of Disasters and Pandemics

Direct economic losses from disasters have increased by more than 150 percent over the past 20 years, with losses disproportionately borne by vulnerable developing countries. The bill from

[2] Noted by [5].

natural disasters had reached around US$200 billion per year, an increase of 4 times since the 1980s. However, it is estimated that this has now risen to around US$300 billion per year. Cumulatively, over the past 30-year period, disasters have cost nearly US$4 trillion and caused around 2.5 million deaths. Two-thirds of these losses are due to extreme storms, floods and drought [4].

WHO has advised that over the previous 30 years, more than 80 percent of deaths from natural disasters occurred in LIC and MIC and that the disaster impacts on GDP was on average 20 times higher in LIC than high-income countries (HIC). Further, and from the health perspective, WHO reported that during 2012-17, there were 1,200 health outbreaks in 168 countries, including those due to new or re-emerging infectious diseases. In 2018, a further 352 infectious disease events, including the Middle East respiratory syndrome coronavirus (MERS-CoV) and the Ebola virus disease. Estimated losses from infectious diseases, through their effects on productivity, trade and travel, have been calculated at about US$500 billion or 6 percent of global income per year [4].

The WB [6] has identified critical impacts of the current pandemic. These are summarized as follows, with specific implications for land administration and geospatial information identified by the authors of this Chapter:

- Disrupting billions of lives and livelihoods, the COVID-19 pandemic threatens decades of hard-won development gains and demands an urgent, exceptional response. The severity of the pandemic is challenging the world's health systems, while associated lockdowns and travel restrictions have upended normal life for most people – even as lockdowns ease in some countries. The pandemic is spurring changes in behaviors and trends likely to transform the post-COVID-19 world. Lockdowns require resolving homelessness and unhealthy, crowded slums.

- The range of growth outcomes in 2020-21 remains exceptionally uncertain, and recovery is highly dependent on global progress in containing and mitigating the pandemic. In a base case scenario, the global economy could shrink by 5.2 percent in 2020 before rebounding in 2021; in the downside scenario of prolonged shutdowns, world output could contract by almost 8 percent in 2020 (roughly equivalent to the combined GDP of France, Italy, and Spain). The recession in advanced economies is hitting developing countries hard, and the WB now projects negative growth for over 150 countries in 2020. The emerging food crisis could intensify, and food insecurity could spread much more widely. Can governments afford to invest in LAS and NSDI to build resilience to future disaster and epidemic impacts? In the short-term, especially for LIC, the answer is likely to be no, without international development assistance.

- Billions of jobs are under threat worldwide. Nearly 80 percent of the world's informal economy workers, around 1.6 billion, have now experienced COVID-19 lockdowns and slowdowns in hard-hit industries including wholesale and retail, food and hospitality, tourism, transport and manufacturing. With 740 million women globally in informal employment and a majority employed in services, women are particularly hard hit by the crisis. Remittance flows are a key source of revenues for many developing economies, and expected to fall by one-fifth in 2020. Tourism is another area hard hit. Many countries across East and South Asia are especially dependent on both tourism and remittances to a combined level of 20-30 percent of GDP. Loss of jobs places many people, renters and those with mortgages, at high risk of defaulting and subsequent eviction. Evictions create opportunities for property speculation and land grabbing, as well as governance challenges for land administration.

- The COVID-19 crisis is exacting a massive toll on the poor and vulnerable. Millions of people will fall into extreme poverty, while millions of existing poor will experience even deeper deprivation, the first increase in global poverty since 1998. This will mean an estimated additional 18 million extremely poor people in Fragile and Conflict-affected States (FCS), and the pandemic is deepening existing sources of fragility and exacerbating instability in Fragility, Conflict and Violence (FCV) settings. Land conflicts are major issues in FCS and can have long-term consequences as displaced people flee. Already the pandemic has manifested as a critical risk for refugee and resettlement camps. Homeless people are at high risk of contracting and spreading the virus and are not subjected to effective screening. Safe social distancing is largely not possible. Contact tracing of the homeless is also very difficult. Homelessness through eviction of insolvent renters is straining LIC, MIC and HIC alike.

- The scale of the financing challenge for developing countries is measured in trillions of US dollars. The sudden reversal of capital flows has helped finance the exceptional fiscal packages in the advanced economies but has left emerging market and developing economies exposed. The additional financing needs for developing countries arising from the crisis remain uncertain, but they will be exceptionally high and likely to persist over the medium term. Pandemic-related external financing gaps for active International Development Association (IDA)[3] countries could be in the range of US$25-100 billion per year – assuming that incremental financing needs arising from the crisis are in the range of 2-10 percent of GDP and that only half of these can be met internally. For WB International Bank for Reconstruction and Development (IBRD)[4] borrowers (representing approximately one-third of MIC GDP), the equivalent range is US$150-600 billion annually. This has serious implications for countries needing financing of resilience requiring investments in LAS and NSDI.

The pandemic has highlighted the urgent need for policy action to cushion its consequences, protect vulnerable populations, and improve countries' capacity to cope with similar future events. It is also critical to address the challenges posed by informality and limited safety nets and undertake reforms that enable strong, inclusive and sustainable growth. However, the pandemic's rapid global economic impacts highlight the fragility of the sustainability of SDG Goal 1, extreme poverty alleviation [1].

2.4 Overview of WB-FAO Partnership

Since 1964, the Cooperative Programme (CP) between FAO and the WB has continued to support reforms concerned with secure access to land and other natural resources, reinforced national food security and nutrition, mainstreaming responsible land governance and sustainable economic development. Rapid penetration of innovative hi-tech geomatics accelerated digitalization of LAS and advancement of e-government have naturally expanded the FAO-WB investment partnership in the land sector to encompass NSDI. The body of experiences, good practices and lessons learned during such land sector investments supported by international development partners have duly informed, and are integrated in the VGGT. In general, poor tenure security, non-recognition of legitimate land rights and interests, or lack of land and geospatial records on access rights reduce the resilience of people to natural disasters and to climate change effects. Mindful of the resilience impact of LAS and NSDI, and triggered by various recent hazards, several joint interventions of the WB and FAO pay special attention to resilience building, and/or use resilience as an entry point for investing in land sector reforms.

The WB and FAO have partnered to promote the fundamental role of LAS and NSDI infrastructure for improving disaster resilience at the community and national levels, in line with the VGGT and the Sendai Framework. The recent CP experiences have highlighted good practice rapid assessments of the resilience and resilience impact of national land administration and geospatial information systems, which are relevant to the pandemic context, over several countries, which are discussed in this Chapter.

[3] IDA is part of the World Bank Group. IDA offers concessional loans and grants to the world's poorest developing countries.

[4] IBRD is part of the World Bank Group. The IBRD offers loans to middle-income developing countries.

2.5 Resilience Enablement Through LAS and NSDI

Comprehensive and authoritative LAS and NSDI are of strategic importance for economic prosperity and inclusive growth, sustainable development, responsible governance of natural resources, and resilience – due to their potential to facilitate information synergy across multitudinous thematic domains and thus support efficient and effective decision making, as well as leveraging land as a fundamental economic factor and original source of all material wealth. In the context of national and community resilience, LAS and geospatial information are critically significant for systemic and institutional preparedness to enable the country, government and communities to mitigate hazards, adapt and recover from shocks or stresses. Such preparedness, adaption and recovery should be without compromising long-term development prospects of communities, cities, localities, regions and countries. That means digital information, secure data storage of land administration information and an NSDI providing geospatial information that is accessible, authoritative and sustainable. These are activities which must be led by the government for the benefit of all, with civil society, community, private sector professionals, investors and academic participation.

Resilience, be it for disasters or pandemics, requires a high degree of geospatial preparedness, which is best achieved through NSDI. For NSDI, countries require: (i) an agreed common geospatial framework with defined horizontal and vertical reference systems; (ii) standards, data sharing protocols and data access; (iii) fundamental mapping or geospatial datasets; (iv) an agreed lead agency mandate for the overall coordination of the NSDI and designated lead agencies for the production and maintenance of fundamental geospatial data themes; (v) communications; security; and (vi) human, technical and financial capacity to sustain the systems. In the context of a pandemic, further geospatial-related requirements may include: (i) access to mobility data from telecommunication networks, video-surveillance, urban and other sensors; (ii) tools to analyze the influx of near real-time data; (iii) spatially-enabled systems to support public health surveillance; and (iv) policies for balancing the protection of personal data privacy and confidentiality with ensuring the public good.

Many countries, especially LIC, may have very limited digital geospatial information and immature NSDI, limiting, or inhibiting, their preparedness for disasters or pandemics. For some LIC and MIC, recent wars or civil conflict have further left legacies of weak geospatial preparedness. Also, a legacy of conflict is often that LAS are either non-existent or in very poor shape due to the destruction of land records and other evidence of rights. For such countries, preparing any NSDI investment should be preceded by an assessment or stocktake of the existing systems. There is undoubtedly a geospatial preparedness inequity between countries, especially LIC, which places them at a severe disadvantage in developing resilience that requires geospatial information.

A major impediment to pandemic preparedness is often the weak street and postal addressing systems which precludes effective emergency response, contact tracing and monitoring of families and individuals for medical testing and follow-ups, vaccination programs, reliable reporting statistics, delivery and access to social benefits and so forth. For homeless people, even in advanced economies with well-developed address systems, the lack of access to an address is a major limitation and poses health risks especially where such people are mobile. Indigenous, customary and communal tenure systems are also especially vulnerable during pandemics where lack of formal records, geospatially referenced land parcels fabric and an addressing system leave inhabitants vulnerable.

As the world endures the pandemic and moves to the new norms, governments, often with international development assistance, will need to: (i) review how existing systems worked or failed during the pandemic; (ii) assess the effectiveness of geospatial information's and LAS contributions to surveillance and tracking; (iii) identify whether any non-traditional land and geospatial data sources (e.g. crowd-source data) may have government response to the pandemic; (iv) examine the effectiveness of measures used in the property markets, including valuation and government guarantee of tenure rights, addressing both ownership, leaseholds and rentals, to mitigate financial and economic downturns and ensure good governance; (v) review the impacts of land-indigence, landlessness and homelessness on the spread of the virus; (vi) study the impacts of regulated spatial planning on controlling the spread of the coronavirus and other future pandemics and health crises.

Authoritative geospatial information plays critical roles in all phases of disaster management: disaster prediction, prevention, preparedness and mitigation, emergency response, evacuation planning, search and rescue, shelter operations, and the post-disaster restoration and monitoring. Reliable and comprehensive land administration information, including land records are critical for many of the phases of disaster management including preparedness, recovery and reconstruction. Especially important for the pandemic context, is address information to enable reliable contact tracing and even social distancing. LAS and NSDI underpin economic and social recovering, supporting the minimization of the shocks of disasters and pandemics and enabling quicker recovery to return to normal.

Assessing the likely impact of disaster events requires detailed inventory of real estate assets, buildings, housing, crops, and infrastructure, including specific location-based information such as street address, and other horizontal and vertical positioning referencing data. Although, pandemics don't damage or destroy such items a spatial inventory of housing and occupancy would be expected to be beneficial.

Secure tenure is the key to reducing disaster vulnerability and risks. The more secure, formal and reconcilable the rights and systems are, the less vulnerable land users are to eviction or loss of livelihoods in the case of a disaster, and the more likely they are to receive compensation for losses sustained. Secure tenure increases investments in dwellings, which reduces risks and improves resilience through better siting and construction of buildings. Better quality housing in terms of space, ventilation, access, amongst other factors is conducive to supporting good social distancing and enhancing pandemic resilience.

Land administration and geospatial information needs to be accurate, reflect reality on the ground, and be up to date if it is to contribute to disaster preparedness and risk mitigation, and responses to disaster events. In many countries this is not the case, making them vulnerable to disasters. Street addressing transcends both land administration and geospatial information and is vital for both disaster and pandemic resilience.

Sharing land and geospatial information with disaster risk management agencies and enabling them to harness these valuable data in their planning and operations enhances the overall process and supports government-wide agendas, but often there are disconnects between a number of these key elements and a lack of interoperability. NSDI are essential to overcoming these issues. Improving interoperability means overcoming technical, capacity, legal, and cultural impediments.

LAS and NSDI can only perform their roles if they are themselves resilient – which means they must also be sustainable. Yet often LAS records are paper-based and are vulnerable to destruction. Remote storage of electronic data offers greater protection providing such data are properly secured. The organizations responsible for LAS and NSDI geospatial systems need to have business recovery plans which are regularly tested. These organizations need to be adequately resourced in terms of finances, trained personnel, equipment and facilities at all times. However, data must also be accessible. LAS and NSDI that are not able to deliver reliable, accessible information when there is no disaster or pandemic, cannot be expected to deliver during the times of disaster or pandemic.

Governance issues play an important role in the effectiveness of LAS and NSDI. Corrupt or ineffective town planning, land management, or building control systems enhance the risks from disaster events and impede recovery and reconstruction. Stakeholder involvement is needed so that all parties know the parts they must play in the event of a disaster event. Those responsible for disaster planning and mitigation and for reconstruction and recovery should be accountable to the population and respect human rights. Governance will be tested after any disaster. It is too early to assess any governance challenges from the COVID-19 pandemic, but in the near future such studies should be undertaken.

In light of the above, Table 2.1 summarizes applications for land administration and geospatial information in the emergency contexts of disasters and pandemics.

TABLE 2.1
Land Administration and Geospatial Information Uses for Disasters and Pandemics

PHASE	**DISASTER**		**PANDEMIC**	
	Geospatial	**Land Administration**	**Geospatial**	**Land Administration**
Preparation	Needs assessment Planning and response: • evacuation • communications • medical support • stockpiling resources location • logistics planning Prediction & Warning: • monitoring • forecasting • early warning • exercising Street addressing	Spatial planning Security of tenure Security of records Security of occupancy Street addressing	Needs assessment Planning and response: • evacuation • communications • medical support • stockpiling resources location • logistics planning Prediction & Warning: • monitoring • forecasting • early warning • exercising Street addressing	Spatial planning Security of tenure Security of occupancy Street addressing
Response	Coordination Situation Analysis – Appreciation Crisis maps Emergency aid - Search and rescue, Evacuation & shelters, Medical, Food, water Emergency resources dispatch Early damage assessment	Early damage assessment	Epidemiological surveillance support systems Contact tracing Situation Analysis – Appreciation Pandemic mapping Cases and deaths distribution, monitoring Testing coordination and monitoring Emergency resources dispatch Streamlining supply chains – delivery medical and food Targeting community investments to reduce risk of contagion and minimizing negative economic impacts	
Recovery	Recovery Reconstruction Rehabilitation: • coordination • damage assessment review • monitoring and evaluation Tenure security location Housing Spatial Planning Transport & infrastructure Utilities Communications and ICT Agriculture Livelihoods	Rights identification Tenure security Housing Spatial Planning Land re-allocation	Epidemiological surveillance support systems Contact tracing Pandemic mapping Cases and deaths distribution, monitoring Testing coordination and monitoring Emergency resources dispatch Streamlining supply chains – delivery medical and food Targeting community investments to reduce risk of contagion and minimizing negative economic impacts	Spatial planning Formalization of rights
Prevention and Mitigation	Hazard risk analysis Simulation & modelling Risk mapping Building & asset inventory Public awareness raising Training & capacity building	Land records digitization Data security Secure, safe facilities Online services Spatial planning Land re-allocation	Spatial planning Street addressing	Spatial planning Security of tenure

2.6 COVID-19: Specific Challenges

The pandemic has created land-tenure related and spatial challenges that have never been experienced before. These include, but are not limited to:

- Lockdown – requires a secure, serviceable, habitable place to live (dwelling) that is accessible to emergency services, power, water, sanitation. Homeless people and slum dwellers are especially at risk of contracting and spreading the virus
- Social distancing – sufficient space between people when they live and reside – again, homeless people and slum dwellers are especially at risk of contracting and spreading the virus
- Contact tracing – requires physical address – homeless people and slum dwellers are unlikely to have an address
- Privacy of personal information.

In response to the COVID-19 pandemic, many countries requested their citizens to practice social-distancing, stay-at-home and to stay safe. This has created significant challenges to implement, given the vast numbers of homeless people in both developed and developing nations. Also, for many countries housing conditions and density of informal settlements often do not allow residents to follow basic hygienic measures or to keep the minimum social distance to reduce spreading the virus. Much is being reported on the need to undertake "*formalization or regularization of slums and illegal settlements*". However, that may secure rights, but it does not improve safety, well-being, services, or quality of life.

Gender is also being reported as a specific COVID-19 challenge. Men have sustained a greater death toll from the pandemic than women. In April 2020, men accounted for 65 percent of deaths [7]. Stanley and Prettitore [8] specifically cite the gender experiences with tenure security of Aceh and North Sumatra following the December 2004 tsunami. It is well reported that in times of disasters and conflicts women may be especially vulnerable regarding tenure security and access to land rights [9]. In the longer term, reforming inheritance laws and marital property regimes will be key to improving the implementation and enforcement of women's rights to housing land and property rights, as well as ensuring that social and cultural norms also change. Titles or other rights instruments are not sufficient to bring about change and ensure the rights of women.

However, are women more vulnerable to the tenure-related shocks of the pandemic? Although Stanley and Prettitore [8] advise that women are more vulnerable, this Chapter suggests that it is probably far too soon to draw firm conclusions, but as more research and analysis is undertaken, it may also better highlight the vulnerabilities of women under a pandemic crisis. Nonetheless the tenure rights of everyone must be respected and the challenges are always there.

"*Experience from post-disaster land activities in Aceh, Indonesia, and from post-conflict land restitution programs in Colombia have shown that with willingness and a focus on women's particular barriers, we can make a difference. It's time we break down the barriers to women's access to land around the world, and make sure to protect women's rights while the pandemic places them in a precarious situation*" [8].

The United Nations Economic Commission for Europe (UNECE) Working Party on Land Administration and the International Federation of Surveyors (FIG) have admirably worked together to examine the situation of informal settlements in the pan-European region and have identified ways to formalize informal developments. The result has been the "Guidelines for the Formalization of Informal Constructions" [10], which provides a practical guide, explaining how to structure a program for the formalization of informal constructions. The Guidelines would seem to have the potential to be considered globally to assist countries in post-COVID-19 recovery. Benefits from formalizing informal settlements could contribute to economic recovery by integrating them into land markets, with clear ownership titles and registration. Security of tenure, ownership of land and property provides access to credit, and environmental, planning, construction, and utility-provision improvements can be initiated to a standard where people can live in adequate and healthy homes. The authors of this chapter would suggest that the Guidelines may have gone much further in terms of actual technical content especially regarding implications for construction, infrastructure service and utilities. Notwithstanding, these UNECE and FIG Guidelines are a useful reference for any country or jurisdiction seeking to address formalization of informal tenure. Commendably, UNECE has always been proactive when it comes to guidelines, especially in terms of improving land administration systems information in the region. Most notably, the UNECE [11] "Guidelines on Land Administration" have been referred to widely, not only in the European region, but globally.

It is well-reported that there are at least one billion urban dwellers currently living in informal settlements, which has increased from a 1996 estimate of around three-quarters of a billion. It will no doubt continue to grow as the world's urban population continues to grow. The importance of tackling this issue is undeniable and measured under several United Nations Sustainable Development Goals (SDGs). SDG target 1.4 stresses that governments should ensure that all men and women, particularly the poor and vulnerable, have equal rights to economic resources, as well as access to basic services, ownership and control over land and other forms of property and inheritance. SDG 11 stresses that cities and human settlements should be inclusive, safe, resilient and sustainable. The growth and magnitude of natural disasters around the world, of all types, have clearly identified the need for building resilience. Informal settlements have been built outside the formal system of laws and regulations that ensure tenure, legal ownership and safe, resilient structures. Informal development is not a new issue. However, over the last 30 years, informal development has become an increasingly urgent matter. UNECE reported in 2007 that more than 50 million people lived in informal settlements in 20 member-states of the UNECE region. Europe has experienced a rise of urban dwellers who cannot afford to pay rent, with housing costs rising particularly rapidly in the more prosperous large cities. This is especially the case for the Southern and Eastern parts of the region, while Western European countries are said to have more than 6 percent of their urban dwellers living in insecure housing conditions.
Slums are especially vulnerable due to:

- High population densities contribute to rapid and broader spread of infection which accelerates transmission
- Household overcrowding makes behaviors like social distancing difficult
- Poor living conditions exacerbate transmission slowing behavior
- Limited access to health services
- Reliance on crowded transport services increases contagion risk
- Working in the informal sector poses risks [12].

Renters, tenants, lessees and mortgagees are vulnerable to the economic impacts of the pandemic. All too often renters, tenants and lessees are forgotten in discussions of tenure security, as they do not hold absolute ownership rights. Rather, their tenure rights would be expected to be covered under contracts. However, often such tenure rights are not automatically inheritable, plus their security is generally subject to payment of rent, therefore they may be forfeited when rent payment defaults, leading to eviction. Similarly, mortgagees who are unable to defray mortgage repayments to the financier, may lose tenure rights and face foreclosure and eviction. Such problems are experienced globally, in both developed and developing economies. Notably some countries legislated relief periods for rents and mortgages – but periods of several months are already proving to be insufficient to people who have lost income and assets.

As the COVID-19 pandemic spreads across the globe, lives, livelihoods, food supplies and food security are being severely disrupted. In the face of this crisis, investment in agriculture and food systems provide an important way to support communities' resilience against crises and ensure robust food supply chains. This has very profound implication for land and tenure security as land is a critical factor in agriculture. Investment in the sector is crucial now more than ever, but experience shows that focusing only on more investments is not enough. The "Principles for Responsible Investment in Agriculture and Food Systems" (RAI) by the Committee on World Food Security

[13] are the main global instrument to provide guidance in this regard. The RAI have heavily drawn from guiding frameworks such as the Principles for Responsible Agricultural Investment that respects rights, livelihoods, and resources (PRAI) by FAO, International Fund for Agricultural Development (IFAD), United Nations Conference on Trade and Development (UNCTAD), and the WB, and also build on the VGGT [14].

Location of citizens has been highlighted as a very important element of managing and responding to COVID-19 cases and transmissions. In public health, contact tracing has dual roles. Firstly, contact tracing is undertaken to find all infected persons and those who have been in contact with infected persons. It has been a very effective pillar of the control of communicable diseases, e.g. contact tracing was primarily responsible for small pox eradication, rather than universal immunization. Secondly, contact tracing may be undertaken to learn more about the disease characteristics, especially the spatial context including infection clusters, locations of secondary and subsequent infection waves/spikes.[5] At the time of writing this Chapter, it has been reported that with the escalation of new cases in the USA, at around 50,000 new cases per day, contact tracing may no longer be viable.[6]

The pandemic has brought a global re-thinking of the confidentiality of personal information to better manage spread of the disease. Arguably, when the greater good is public health, new approaches to privacy of personal information are necessary. However, risks of abuse are being raised globally. In April 2020, the EU produced its "Commission Recommendation of 8.4.2020 on a common Union toolbox for the use of technology and data to combat and exit from the COVID-19 crisis, in particular concerning mobile applications and the use of anonymized mobility data". Also, in April 2020, the EU produced "Guidelines 04/2020 on the use of location data and contact tracing tools in the context of the COVID-19 outbreak". Both publications provide very useful guidance to any country or jurisdiction seeking to address personal information and also contact tracing through policy and regulatory means. Commendably, the EU has continued to be progressive in promoting sound policy with information and also NSDI. In 2007, the EU issued Directive 2007/2/EC for establishing an Infrastructure for Spatial Information in the European Community (INSPIRE). In 2016, the General Data Protection Regulation (EU)2016/679 (GDPR) was approved by the European Parliament as a regulation in EU law for data protection and privacy throughout the EU, and member countries are required to comply.

In the COVID-19 context, vulnerable communities around the world are expected to face increased land grabs, migration, displacement, corruption, and evictions. For many countries, especially LIC and MIC, it is unlikely they have sufficient capacity and resources to fully address these challenges. Technology will undoubtedly play key roles, as already has been demonstrated with smart phone applications for contact tracing. At this time, there are many questions, and clarity may only come with time:

- Can LIC and MIC afford to fund LAS and NSDI investments at sufficient levels to rebound from the pandemic in order to return society to normal, when all countries have suffered huge economic losses?

- Articulating the benefits of funding land services, protecting the land claims of vulnerable populations, and accelerating the pace of securing land and property tenure is very important. Advocating for significant investments in technology, and ensuring political support to digital transformation at a time when there may be greater financial priories, is a huge challenge. How are we seeing technology and land data playing a role in COVID-19 planning and response and perhaps more importantly, what role can it play in post-pandemic response to better prepare us for the long-term?

- What successful technology-based approaches to land governance (including land administration, land development and land use planning) and lessons learned during COVID-19 can be continued? Evidence-based advocacy, rather than rhetoric and evidence from the land sector is required. Already there is an abundance of blogs, webinars and lobbying of governments and

[5] https://en.wikipedia.org/wiki/Contact-tracing

[6] https://www.docwirenews.com/docwire-pick/hem-onc-picks/the-covid-19-pandemic-close-to-12-million-world-cases-contact-tracing-no-longer-possible-in-us-south-and-more/

international finance institutions to fund technical interventions – often claiming pandemic recovery will be quicker through quickly deploying technologies that can be used to collect and manage land and geospatial data – such as smartphones, tablets, computers, handheld GPS/GNSS, and drones to name a few – how are they being used to equitably and inclusively accelerate land administration processes?

Building resilience, through sustainable LAS and NSDI requires investment – both for the development and implementation as well as ongoing maintenance, further development and continuous improvement. It very much should remind everyone why the word "infrastructure" was included in the term NSDI – which was to ensure that soft infrastructure is funded in a similar manner to hard infrastructure. The recession and financial challenges of governments around the globe, especially in LIC and MIC, creates opportunities for alternative service delivery including public-private partnerships (PPP). Bell [15] raised opportunities such as the provision of information technology (IT) infrastructure and services, positioning infrastructure and services including Continuously Operating Reference Stations (CORS) and customer service delivery as potential areas, subject to necessary safeguarding. Loss of capacity and governance concerns may also create openings for PPP modalities to support resilience investments in LAS and NSDI. However, any such investments, must be rigorously safeguarded by government oversight to ensure reliability, sustainability, good governance, public access and affordability.

2.7 Pragmatic Rapid Assessment of LAS and NSDI Maturity in Resilience Contexts

Countries cooperate with development partners to assess their respective land and geospatial information sectors and get advice on policy, legal, institutional, capacity and technology reforms aiming to boost sustainable socio-economic growth and natural resources management, enhance resilience to adversities, and safeguard the environment. The WB and FAO have frequently partnering through their CP to respond to such requests, promoting also the fundamental role of LAS and NSDI infrastructure for improving disaster resilience at the community and national levels, in line with the VGGT and the Sendai Framework. A rapid LAS and NSDI assessment approach has shaped up through the CP and collaboration with members and others, mostly driven by pragmatic considerations and restrictions imposed by funding modalities. The recent partnership experiences have highlighted good practice rapid assessments of the resilience and resilience impact of national land administration and geospatial information systems, over several countries including Nepal, Myanmar, Lebanon, Kyrgyzstan, and Uzbekistan. The same pragmatic rapid assessment approach was also used unilaterally by the WB in Kerala, Punjab, the Solomon Islands, Lao People's Democratic Republic (see Table 2.2).

TABLE 2.2
Experiences with Pragmatic Rapid Assessment of LAS and NSDI Maturity in Resilience Contexts within Selected Countries

Country	Tailored focus	Major findings in resilience context	Advantages / benefits
Kyrgyzstan[a]	» Next generation land governance and geospatial information services › *building NSDI and geospatial data and services* › strengthening public land management › strengthening property valuation and taxation › strengthening land tenure and access to encourage investment » **LAS and NSDI as a game-changer** for: › development › integrated planning, taxation, and sustainable resource management › *disaster risk management (DRM)* › *climate resilience* › private sector investment support	» Hindrances for DRM /climate resilience identified: › limited access due to geospatial data secrecy › no obligation for data sharing or exchange › shortage of authoritative digital datasets › poor geospatial capacity across stakeholders › departmental silo culture	» highly participatory » local trust / consensus » full country ownership » use national sources » optimal speed » affordability » flexibility » recommends strategy
Myanmar[b]	» Land sector needs assessment › land policy and regulatory framework › forestland administration and management › land administration › *geospatial infrastructure and services* › property valuation and taxation » **LAS and NSDI with core geospatial datasets as a public good** underpin: › *peace building* › food security › poverty eradication › sustainable economic development › *disaster and climate resilience* › land use policy implementation › e-governance advancement	» Resilience suffers from immature LAS and NSDI: › relevant legal frame still under development › *One Map* policy initiative still not ripe › poor governance informatization / digitalization › wanting capacity, technological innovation › restrictions on access to geospatial data	» highly participatory » local trust / consensus » full country ownership » use national sources » fits absorption capacity » monitoring benchmark » recommends strategy » remedy problems » realize opportunities » pro-poor » SDG achievement in disaster risk reduction[c]
Kerala[d] India	» **Rebuild Kerala Initiative** targeting: › prepare better for future disasters › *more resilient, green, inclusive and vibrant* vision for the future › generate revenue from property taxation and value capture › prioritize *resurvey and update of land records* › unified *on-line Land Information Management System* › *interlinked digital databases*	» Weaknesses in the land and geospatial systems exacerbated the impact of natural disasters › missing *right information at the right time* › unplanned land uses and encroachments › fragmented, outdated, inconsistent land records › outdated / historical paper mapping › vulnerability of land records to destruction › insufficient local revenue from land » Poor and social underclasses are at serious risk from disasters due to lack of formal rights and poor spatial planning	» highly participatory » local trust / consensus » full state ownership » use state sources » optimal speed » affordability » fits absorption capacity » pro-poor » recommends action

TABLE 2.2
Continued – Experiences with Pragmatic Rapid Assessment of LAS and NSDI Maturity in Resilience Contexts within Selected Countries

Country	Tailored focus	Major findings in resilience context	Advantages / benefits
Nepal[e]	» Modernized, transparent and **resilient LAS and NSDI to improve national and community resilience to disasters** › *policy and legal framework for LAS and NSDI* › land registration and *LAS* › *NSDI and related systems* › land and property valuation › information and communications technologies › education & training for surveying, geospatial sciences and LAS › social review	» Resilience is best supported through a sustainable, digital LAS and an authoritative NSDI, receiving necessary budget, operational and development requirements: › review land laws; draft consolidated land code › mandate NSDI as national priority › ensure whole-of-government coordination › lead agency and data custodian designations › foundation data sets › funding › data standards › protocols for access and sharing » National DRM strategy did not consider holistically LAS or NSDI – but just for hazard risk mapping » No national coordination for NSDI » The impact of civil war 1996-2016 on the LAS were greater than the 2015 earthquake. Civil war destroyed land offiices and all land records in many districts – not yet recovered, and thus leaving communities very vulnerable. The earthquake damaged records in multiple districts, but there was no loss of services » Social underclasses are at serious risk from disasters due to lack of formal rights and poor spatial planning	» highly participatory » local trust / consensus » full country ownership » use national sources » optimal speed » affordability » flexibility » fits absorption capacity » pro-poor » recommends action
Punjab[f]	» Build a **unified land records management system** including *increased resilience to disasters* needs to: › assess legislation with consideration of the resilience angle › assess disaster resilience with land and geospatial systems	» To increase resilience to disasters, one should: › improve community resilience through enhancing tenure security › leverage the use of geospatial data » Poor and social underclasses are at serious risk from disasters due to lack of formal rights and poor spatial planning	» participatory » local trust / consensus » local ownership » optimal speed » affordability » pro-poor » recommends action

TABLE 2.2
Continued – Experiences with Pragmatic Rapid Assessment of LAS and NSDI Maturity in Resilience Contexts within Selected Countries

Country	Tailored focus	Major findings in resilience context	Advantages / benefits
Solomon	» **Land and geospatial system resilience needs assessment** › diagnosis of LAS and geospatial information system, their infrastructure and resilience impact › design *improvements for resilience* › emphasise on access to land for development › develop *LAS and NSDI investment plan*	» Resilience of land, real property and the people to land relationships requires: › community desire for better land management › register customary rights – critical for resilience › universal base map for all the Solomon Islands › share public geospatial datasets via geoportal	» participatory » local trust / consensus » local ownership » optimal speed » affordability » recommends action
Lao PDR[h]	» **Geospatial prioritization** tool to: › geographically target systematic land registration › determine geographical distribution of *natural disaster vulnerabilities* and *tenure security risks* › identify hotspots wherein interventions can achieve maximum impact › support projects design and implementation	» Natural disaster vulnerabilities must be a factor in enhancing tenure security at the local level, to: › ensure effectiveness and efficiency › reaching those who need tenure security most	» participatory » local trust / consensus » local ownership » optimal speed » affordability » recommends action

[a] World Bank (2017) Kyrgyz Republic: Next Generation Land Administration and Management Services – non lending technical assistance (P158348), Bishkek, 2017

[b] World Bank (2018) Myanmar: Towards a Sustainable Land Administration and Management System – land sector needs assessment technical assistance (P157559), Nay Pyi Taw, 2018

[c] http://www.fao.org/myanmar/news/detail-events/en/c/1033174/

[d] World Bank (2020) Solid Ground: Increasing community resilience through improved land administration and geospatial geospatial information systems, Washington DC, 2020, p. 33

[e] World Bank (2020) Nepal: Technical Assistance to Develop the Land Administration and Geospatial Information Systems (*Resilience and Resilience Impact of the Land and Geospatial Systems*, P165271), Kathmandu, 2020

[f] World Bank (2020) Improving Resilience and the Resilience Impact of National Land and Geospatial Systems - Phase II implementation support, Washington DC, 2020, pp. 7-53

[g] World Bank (2020) Improving Resilience and the Resilience Impact of National Land and Geospatial Systems - Phase II implementation support, Washington DC, 2020, pp. 54-87

[h] World Bank (2020) Improving Resilience and the Resilience Impact of National Land and Geospatial Systems - Phase II implementation support, Washington DC, 2020, p. 4

The pragmatic rapid approach allows to produce targeted outputs within a short term (a couple of weeks) and with modest workload (around a man-month of expert input per topic). The approach relies on: strong ownership by, and participation of stakeholders – coupled with international expertise knowledgeable of good practices;[7] expert analysis by brief desk review of web-sources, published documents, research, articles and statistics relying on local sources; gathering hands-on information in a limited series of face-to-face, profiling and cross-cutting technical discussions and field visits – during a short mission facilitated by the beneficiary; intensive home-based synthesis of outputs; and verification of findings and recommendations by key stakeholders. This good practice, – based on long-term WB and FAO expertise and experience – proves relevant and is appreciated by beneficiaries, since it is, among others: inherently focused on leaving no one behind, in line with good practices,[8] and endeavoring to reach the furthest behind first; affordable; very adaptable to

[7] viz. VGGT and the Sendai Framework.

[8] Land-indigence refers to land holders whose land is: (i) too small or otherwise inadequate to support healthy living, social distancing during pandemics or other health crises; and/or (ii) insufficient for a livelihood in the context of rural small farmers.

country specificity; participatory – thus capacitating in-country stakeholders; matching the needs – as its emphases, depth and detail can be tailored to the topical reform agenda; and producing outputs within tight time frames.

In assessing LAS and NSDI requirements the WB and FAO look at various tools to support and inform the work including a range of geomaturity and SDI-readiness[9] instruments, considering and evaluating also other available tools for geomaturity and NSDI-readiness, including the Integrated Geospatial Information Framework (IGIF) developed under the United Nations Initiative on Global Geospatial Information Management (UN-GGIM). UN-GGIM is currently drafting a Framework for Effective Land Administration (FELA), as reference for developing, reforming, renewing, strengthening or modernizing land administration and management systems. Early discussions with selected WB client countries suggest that there are parallels with IGIF. That is, rather than implement another costly and time-consuming framework, simply consider its key elements during the rapid assessment. FAO has communicated its doubts regarding FELA's added value in the context of other existing UN instruments. Within WB, similar doubts are shared. Experience with IGIF's NSDI diagnostic, alignment to policy drivers, socio-economic assessment, and action planning, as piloted for example in Guyana[10] (2018-19) – helps to draw parallels and inform the approaches elsewhere. However, after evaluation, it is often agreed with the governments that the pragmatic rapid approach is more suited to the resilience context especially as it is cheaper and quicker.

2.8 Build Back Better

Following a disaster event, it is not sufficient just for reconstruction to take place, but construction and land administration and geospatial information should be enhanced through building back better, so that there is greater resilience to future disaster events [1, 6]. Disaster events often reoccur so that just undertaking recovery work is an inadequate response, as it is likely to be destroyed by the next disaster event. Only by building back better can communities be protected in the future. Investment in doing so produces substantial returns on the capital employed. Similarly, following a pandemic, building back better principles should also be adopted.

Rebuilding after disaster events requires reliable, accurate geospatial data, at the appropriate levels of precision to enable engineering and construction works to be undertaken, something that volunteer geographic information cannot achieve. Following the pandemic, reliable, accurate geospatial information is also required, especially to support rehabilitation of slums and areas of homelessness to ensure they are appropriately planned and serviced to ensure health and well-being.

From the historical perspective, the concept of "Build Back Better" (BBB) was probably first coined in Indonesia in 2005 in discussions between WB, the UN Special Envoy for Tsunami (Bill Clinton) and officials of the government's reconstruction agency (WB, 2005).[11] The original concept was very much focused on physically building back better in terms of engineering of structures, assets and infrastructure, better planning, community safety, early warning as well as land rights, and gender equality. However, in the context of the pandemic, BBB has taken on broader roles including low carbon, climate change, green growth, the digital economy, addressing inequality, amongst other topics [16]. Investment in NSDI and LAS have much to contribute to this new view of BBB. Apropos SDGs 13 and 14, in the post-COVID-19 world, there is good reason to be optimistic that these and other long-standing global and regional issues will be addressed. LAS and NSDI have critical roles in contributing significantly to the solutions.

[9] Spatial-Data-Infrastructure readiness.

[10] FAO (2018), Mainstreaming Sustainable Land Development and Management in Guyana (project GCP/GUY/003/GRI).

[11] Attribution of this term's origin has been incorrectly attributed to the Sendai Framework, wherein it is reported that the term: *"was firstly defined and used officially in the UN Sendai Framework for Disaster Risk Reduction 2015-2030, which was agreed at the Third UN World Conference on Disaster Risk Reduction 14-18 March 2015, which was held in Sendai Japan, and this document was adopted by the UN General Assembly on 3 June 2015".*

2.9 Concluding Remarks

All countries, inter-governmental coordination bodies, development agencies, civil society organizations and professional bodies such as FIG have a role to play in promoting resilience through LAS and NSDI. The less hype and the more evidence-based approaches to support resilience, the better prepared communities will be to withstand the shocks of the next disaster or pandemic. Fit-for-purpose investments, that can be incrementally improved over time, which require sustainable LAS and NSDI, will enable resilience and ensure that legacy systems are not barriers to recovery after any shock. The partnership between the WB and FAO to promote the VGGT, will continue to play a leading global role in supporting the resilience of countries, cities and communities.

For the land sector, the outbreak again brings to light the very intimate, spatial relationships between land, people and communities – and how the shocks of any disaster or pandemic disrupts life and livelihoods.

The land sector can better promote the adaption of relevant technologies. There is evidence that fit-for-purpose approaches to land administration can reduce costs and promote greater transparency and accountability in the building of complete LAS, given the growing availability and reach of technologies that can be used to collect and manage data, – such as smartphones, tablets, computers, handheld GPS/GNSS, and drones to name a few. However, technology is never a solution, rather it is an enabler. Using technology to overcome development challenges is not a new phenomenon. This is particularly true in the land sector, where tools for collecting and managing data relating to land use and rights have advanced considerably in recent decades. In the post-pandemic recovery, technology is likely to prove even more critical for the collection and management of land-related data to advance land rights and tenure security for millions of people left out of formal land systems. Mere formalization of rights in over-populated, unhealthy slums, will not build resilience unless there is spatial planning.

For those working in international development, the pandemic has brought almost everything to a complete standstill. Development agency priorities are generally committed to the higher priorities of governments dealing with the economic meltdowns as well as addressing health demands and urgent needs for survival of society including food security. These priorities may see deferments of new investment projects for LAS and NSDI. Most land sector interventions take considerable time to implement and political will is paramount. The post-pandemic world presents opportunities for significant progress with carbon emission reduction, climate change, green growth and PROBLUE. LAS and NSDI have key roles to play in the resilience of the post-pandemic world by Building Back Better.

> *"Adversity has the effect of eliciting talents, which in prosperous circumstances would have lain dormant".*
> Horace, Latin Philosopher (65-8 BC).

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3

Open Geospatial Data for Responding to the COVID-19 Challenge

Maria Antonia Brovelli and Serena Coetzee

The period after the appearance of the SARS-CoV-2 virus has seen a flourishing of dynamic online maps and dashboards useful for communicating the spread of the disease, but not for the in-depth study of the phenomenon. The speed at which the disease is disseminated calls for rapid analysis and action. Data that is readily available, such as open data, or rapidly collected, e.g. by citizens, can make a significant contribution to modelling, understanding and containing the spread of a disease. This chapter explores open geospatial data responding to the COVID-19 challenge: What data is useful for studying the spatio-temporal spread of the virus? What is the availability of such open data? The chapter wants to answer these questions critically, also providing useful information to all those who want to support research, not only linked to this zoonosis, but more generally future epidemics and pandemics for which we should be better prepared.

3.1 Introduction

The globalized society of today is challenged by various emerging diseases, in many cases, zoonoses, such as the Ebola Virus Disease (EVD), bird flu, swine flu, SARS-CoV and MERS-CoV, and these are often related to climate change. Coronavirus disease (COVID-19) caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), is a classical example. COVID-19 is a communicable disease where infections are transmitted from one person to another through little droplets, emitted when someone talks or coughs. A person can be infected through direct contact with the droplets, or by touching droplets that have settled on a surface or object and touching their face afterwards [1]. COVID-19 is therefore often transmitted when people are in close contact with each other (within 1 m) or in places that are frequented by many people. It also seems that certain demographics, e.g. older people, are more often severely affected by the disease.

On 11 March 2020, the World Health Organization (WHO) declared the COVID-19 epidemic a pandemic, and by October 2020, there were close to 35 million confirmed cases and more than a million deaths reported [2]. Governments have always had to respond to natural disasters and outbreaks of infectious diseases, the cause of loss of life and the devastation of both the environment and national economies.

The current viral epidemic is of colossal proportions and the rate of infection multiplies rapidly, favored by our densely populated urban centers and an interconnected global economy. Moreover this is not an isolated occurrence, as we have been experiencing similar situations with Ebola, HIV, dengue, SARS, MERS, Zika and West Nile. Researchers estimate [3] that zoonotic diseases account for 75% of all new or emerging diseases in humans.

The recent and dramatic evolution of the COVID-19 pandemic has highlighted and accelerated some developments that were already taking place in the scientific world and in society in general. If digitization is what immediately catches the attention, a second aspect which deserves great attention, is the use of maps in the communication of information relating to the virus spread. Our daily lives have been pervaded by dashboards with maps, a key source of information about the status of the pandemic (from the beginning of the epidemic until today), ranging in scale from hotspots in cities to provinces in a country and countries on a world map.

These dashboards, however, show only simple data visualizations (e.g. number of infections per administrative area, such as country or province), which represents, even in its powerful effectiveness, only a small part of the value of geospatial information applied to health-related information. Georeferenced data, in fact, could play a crucial role in the analysis of the phenomenon itself, leading, for example, to the production of vulnerability and resilience maps, which can help, if not to eradicate the virus, at least to study its spread, evaluate appropriate containment measures for different areas, and thus reduce its impact. Generally, geospatial information constitutes potentially decisive support for offering and making accessible a multidimensional and scalable approach, necessary for the rethinking and reorganization of our entire society in a spatial perspective. Furthermore, the UN GGIM's Strategic Framework on Geospatial Information and Services for Disasters recommends that geospatial information provided by Member States and the international community "shall be openly accessible to the disaster risk management community, as appropriate" [4].

Since the problem we are facing affects the whole world, this chapter focuses on open data with global coverage. Open geospatial data with global coverage has the advantage that anyone anywhere in the world can use the data in the same way for their specific part of the world [5]. It can therefore provide a homogeneous framework to scholars and decision makers for analysing the multifaceted aspects related to the pandemic. The Open Knowledge Foundation [6] lists three key features of open data and content: 1) availability and access at a reasonable cost and in convenient and modifiable form; 2) licence that allows reuse and distribution in machine-readable form; and 3) universal participation without discrimination against fields of endeavour (e.g. commercial or non-commercial) or against persons or groups. The notion of data being "open" is not only associated with free and unrestricted access to the data, but also with transparent and inclusive consensus-based decision-making [7], [8] identified three different kinds of open geospatial data. Firstly, there is data collected by volunteers who organize themselves into communities, e.g. OpenStreetMap. Secondly, some open geospatial data is collected by authorities and published in the spirit of freedom of access to information legislation. Thirdly, open geospatial data is also collected and published by researchers to encourage reuse of the data. Another kind of data is provided by commercial organizations for humanitarian purposes, specifically in the fight against COVID-19. This chapter provides examples of these four kinds of data. Geospatial data is useful for addressing many different humanitarian and socio-economic challenges, however, in this paper, we focus only on pandemics.

This paper should not be considered to be the final milestone nor does it claim to be complete and exhaustive, but rather a path that leads to identifying what is openly available to support the activities of experts who do not belong to the geospatial domain and who need these data to contextualize and enrich their analyses with meaning. A second aspect, addressed instead at geospatial experts, is the definition of the deficiencies in the data and information that we make openly and freely available, so that anyone can acquire a direct and immediate advantage in easily using spatio-temporal products. In the next section we describe what geospatial data is useful in the case of disasters, such as the COVID-19 pandemic. Subsequently, we present and discuss several sources of relevant open geospatial data. The chapter is concluded with an assessment of the availability and suitability of open geospatial data for responding to the COVID-19 challenge.

3.2 What Data Is Useful for Responding to the COVID-19 Challenge?

Epidemics and pandemics are disasters that cause significant damage to humans, physical structures, the economy or the environment. Risks associated with a disaster are reduced by following a risk management approach that identifies, assesses and reduces risks. Depending on the stage of the disaster, risks are managed by prediction, prevention, mitigation preparedness, response, recovery and rehabilitation [9]. To reduce risks associated with COVID-19, geospatial data can be used in many ways, e.g.

- to predict how the disease will spread, e.g. by identifying and analysing places or routes frequented by many people in close proximity to each other;
- to prevent the spread of the disease, e.g. by identifying vulnerable areas based on population density, demographics (age) and/or income, and protecting them;
- to mitigate the spread of the disease, e.g. by tracing people who visited the same locations as an infected person;
- to strengthen preparedness, e.g. by adjusting the number of planned surgical procedures in relation to the number of infections in a hospital's catchment area;
- to respond to the disease, e.g. by working out optimal routes for testing or awareness campaigns; and
- to monitor and communicate the spread of the disease at different scales, e.g. infections by country or province, or more fine-grained by street block, event or building and even location of an infected individual.

Table 3.1 matches different kinds of geospatial data to the different aspects of risk reduction. The remainder of this section elaborates on how these datasets can be used to identify, assess and reduce COVID-19-related risks.

TABLE 3.1
Geospatial data for risk management in disasters (A = Prediction, B = Prevention, C = Mitigation, D = Preparedness, E = Response, F = Monitor and Communication).

Geospatial data	**A**	**B**	**C**	**D**	**E**	**F**
COVID-19 infections	X		X		X	X
Reference information	X	X	X	X	X	X
Places frequented by many people	X	X	X	X		X
Travel networks and mobility	X	X	X	X		X
Land cover	X	X		X		
Address data	X		X		X	
Demographic data	X	X		X	X	
Air pollution	X	X		X		
Water sources	X	X	X	X	X	
Health facilities				X	X	X

Based on knowledge at the time of writing, the COVID-19 disease is mainly transmitted through close physical contact and respiratory droplets. Contamination happens either through direct contact with respiratory droplets or through droplets that have settled on a surface or object. Transmission happens when a contaminated hand touches the mouth, nose or eyes [1]. Therefore, places frequented by many people or where people are in close proximity to each other present a higher risk of transmissions. Because transmission happens through respiratory droplets emitted by people, tracking the locations visited by contaminated people and closing them for a period of time can help to contain the spread.

Geospatial information about locations and routes that are frequented by many people is of specific relevance when studying COVID-19. Examples are networks of public transport and travel by air; capacity and occupation of places or buildings where people may gather in large groups, such as socio-sanitary and social structures, educational institutions, recreational, cultural, sporting structures, penitentiary institutions, structures of social marginality, accommodation in general; places characterised by large concentrations of people, e.g. related to agriculture (e.g. markets), commerce (e.g. shopping centres) and industry (e.g. factories); and in poorer communities, communal toilets and water taps may pose a risk to COVID-19 transmission.

It has been observed that the risk of zoonosis, i.e. a pathogen such as a virus or a parasite moving from animal to humans, is higher when there are significant ecological changes in an area [10]. In such cases, humans may come into close contact with animals that previously lived far away from any human activity. Land cover datasets provide information about such ecological changes and can help with identifying areas at risk of zoonosis.

In order to study and understand the actual spread of the disease, location-based information about the infected people and the places they visited is required. Information about such locations is often provided in the form of a residential address that has to be converted into coordinates through geocoding based on geo-referenced address data. However, to protect the personal information of individuals, the information is usually published in an aggregated form, e.g. by administrative or statistical boundary. Administrative areas, place names and address data are also relevant when determining and reporting who may be affected by the predicted spread of the disease.

Older people (above 60 years) and those with underlying medical conditions, such as cardiovascular disease, chronic respiratory disease, diabetes and cancer, are at a higher risk of complications or the disease being fatal [1]. Therefore locations where these people receive care, such as old age homes, hospitals and long term care facilities, need special protection. The nature of the household may also present a vulnerability. When different generations live together in the same household, it may be difficult to isolate the older generation from the rest of the household. Similarly, when many people share the same room or ablutions, e.g. in dormitories or large families, physical distancing measures to avoid contamination may be difficult. To identify vulnerable areas that need protection, demographic and population data play an important role, including geospatial data about the socio-economic status, age, health conditions, lifestyle, household size and population density.

Another vulnerable part of the population lives in slums and informal settlements, or is displaced and lives in camps and camp-like settings. Such communities are often neglected or stigmatized and without access to health care services that are otherwise available to the general population. Satellite imagery can be used to detect such settlements, if they are not yet reflected in datasets of authorities. Satellite imagery and data contributed by volunteers, e.g. through the OpenStreetMap ecosystem, is also essential for understanding these settlements so that control measures and interventions amenable to the spatial characteristics of the settlement can be planned and implemented, e.g. routes for community health workers involved in testing campaigns or access points for delivering food parcels.

Frequent and thorough hand hygiene is one of the most important measures to prevent the spread of COVID-19 [11]. Unfortunately, a large part of the world's population does not have access to a basic hand washing facility with soap and water in their home. In 2017, three billion people were without such a facility [12]. These people are vulnerable to the COVID-19 disease and any information about access to safe drinking water can help to identify those without such access.

Other examples of vulnerabilities are non-communicable diseases, such as hypertension, diabetes and chronic respiratory disease, e.g. linked to air pollution [13]. Environmental datasets about the concentration of air pollution and data about the prevalence and spatial distribution of non-communicable diseases can help with identifying parts of the population vulnerable to COVID-19.

In the WHO's interim guidance on critical, readiness and response actions, objectives for controlling and slowing down COVID-19 infections include rapidly finding (e.g. through testing) and isolating cases, and tracing their contacts; suppressing community infections by implementing control measures at locations at risk; and reducing mortality by ensuring continuity of essential social and health services [14]. Geo-referenced address data can help with locating cases and their contacts, e.g. through geocoding, while other geospatial data layers identify locations at risk (see above) where control measures have to be implemented. Spatial accessibility and capacity of health services in response to the disease can be assessed with geospatial data about hospital locations, their available equipment (e.g. intensive care units and ventilators) and occupation (e.g. availability of beds in general wards). Additionally, the locations and capacity of places collecting and treating medical and hazardous waste, e.g. infected masks, gloves and other personal protection equipment (PPE), can be identified and assessed.

Citizen science projects involving geospatial data present the opportunity to strengthen preparedness and responses. For example, volunteers can contribute data that provides geospatial reference, such as the road network, landmarks and health facilities. They can further enhance this data by adding opening times of health facilities, such as pharmacies, in their local communities.

In summary, location-based data that helps to answer the following questions is useful for responding to the COVID-19 challenge:

- Where are locations with high risk of transmission?
- Where are the vulnerable people?
- Where are the infected people, and where were they in the past few weeks?
- Where are the healthcare facilities that can support infected people?

To communicate the answers to these questions, a base map is required for context and orientation. The base map shows reference information, such as landmarks, place names, transportation routes, administrative areas or an aerial photo as backdrop. These help the map reader with determining and orienting the location of the map. Depending on the purpose of the map, the reference information may differ; in some cases satellite imagery or aerial photography is used.

3.3 What is the Availability of such Open Data With Global Coverage?

In this section we present and discuss several sources of open geospatial data with global coverage identified as useful for responding to the COVID-19 challenge in the previous section. The link in the Annex lists URLs for datasets discussed in this section, together with the formats and licenses in which they are published.

3.3.1 COVID-19 Infections

The first datasets we have to deal with are those related to the virus evolution in time and space. The global coverage of available open data is good enough because almost all countries are included but the resolution is very poor. Data are generally available per country and not with any more detail. The first and main source of information is the dataset made freely available for non-profit public health, educational, and academic research purposes in a GitHub repository [15] by the Center for Systems Science and Engineering (CSSE) at the Johns Hopkins University (JHU). Data sources are many and various, mainly the different national agencies, and the great value of the JHU dataset is that, after their manual and automatic pre-processing, data are available in a standard format.

The folders contain daily case reports of confirmed cases (C), deaths (D), recovered cases (R) and active cases (A), where A = C-R-D.

Moreover, some computed indexes are also available, such as the Case Fatality Ratio (CFR), which allows immediate comparison between data from different countries, as well as the creation of thematic maps , e.g. choropleth, as it is the relative value of confirmed cases per 100,000 persons.

For the sake of comparing data between different countries, the European Centre for Disease Prevention and Control [16] provides new total cases and deaths day by day, as well as the population count in 2018. This data is ready for studying differences in the evolution of the virus because curves, e.g. by shifting it in such a way that all sets have the same starting outbreak point (for instance, corresponding to a certain percentage of the affected population).

The United Nations Statistics Division, in partnership with Esri, makes the layers of JHU available in various formats, including KML, GeoJSON and shapefile. The data is also accessible through an API and Geoservices [2].

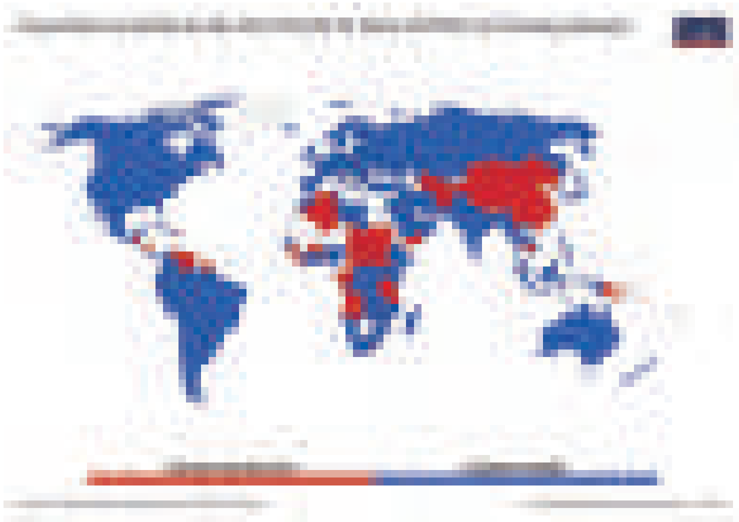

FIGURE 3.1
Countries included in the Our World in Data COVID-19 Testing Dataset (Source: Official data collated by Our World in Data [17])

Finally, information about COVID-19 testing, collected by Our World in Data [18], is published as open data. The testing dataset is updated around twice a week. The dataset includes, for the countries visible in Figure 3.1, a detailed description of how the country's data is collected [17]. Some ancillary information, such as hand washing facilities (from the United Nations Statistics Division) and hospital beds per 1,000 people (from many documented sources) are also available.

3.3.2 Reference Information

When information is communicated via a map, reference information provides context and orientation. For a thematic map, reference is usually provided by a small set of layers, e.g. country or state boundaries and their names. Depending on the scale, more (e.g. thematic map of a city) or less (e.g. thematic map of the world) reference information can be provided. Other types of maps, e.g. one that displays locations of health care services in a specific city or suburb requires much more reference information, including such features as addresses, streets, public transportation and landmarks. In some cases, an aerial photo or satellite image of the area can be useful. While data discussed in other subsections can also be used as reference information on maps (e.g. the travel network in 3.3.4), in this section we focus on base maps, imagery, place names and administrative areas.

3.3.2.1 Base Maps

OpenStreetMap is a crowdsourced dataset to which a global community of mappers contributes geospatial information and maintains it. OpenStreetMap was inspired by Wikipedia and started in the UK in 2004 as an alternative to proprietary map data with restrictions on the availability and use of data. It is maintained through an ecosystem of software, servers, tools, users, and contributors

[8]. In many parts of the world, the quality, and specifically the completeness, of OpenStreetMap data is as good as that of authoritative datasets, if not better [19], and if the quality is not good enough, the OpenStreetMap ecosystem makes it very simple for anyone to add or improve the data. In this context, OpenStreetMap has been used very successfully during disasters and humanitarian initiatives, including the COVID-19 pandemic, where volunteers added data remotely in areas where data are scarce or non-existent [20]. A large number of mapping tasks, e.g. including Peru and Botswana, were published on the task manager of the Humanitarian OpenStreetMap Team (HOT) during the COVID-19 pandemic. Volunteers from all over the world contributed map data that could subsequently be used by health workers.

The OpenStreetMap ecosystem presents another advantage: a range of tools are available for collection, maintenance, processing and visualization of data. OpenStreetMap is widely used as a basemap in COVID-19 dashboards (see e.g. [21], [22], [23], [24]) and also on websites that show emerging hotspots of infections (e.g. [25], [26]). Many of these sites were built with one of the tools in the OpenStreetMap ecosystem, such as mapbox and Leaflet.

Wikimapia is another example of a crowdsourced map with global coverage, where anyone can add geospatial features and annotate them. It was started in 2006 by two Russian Internet entrepreneurs, inspired by Wikipedia. Wikimapia is open data, but it is derived largely from aerial imagery provided by Google Maps. Copyright related to such derived data is sometimes unclear and dependent on the area of jurisdiction (country or region). Some owners of aerial photography provide licenses for the use of the data but retain the exclusive right to derive geospatial data from it. While Google has not initiated any legal court battles over this, their terms and conditions prohibit derivations without a license from Google [27].

Natural Earth is maintained by a community of volunteers, supported by the North American Cartographic Information Society. In contrast to the previous two datasets, it also includes raster data (e.g. for shaded relief and bathymetry), and some layers specifically useful for small scale maps, e.g. graticules and geographic lines (polar circles, tropical circles, the equator and the International Date Line). The data can be downloaded at scales of 1:10 m, 1:50 m, and 1:110 million, which is not as detailed as OpenStreetMap and Wikimapia, but nevertheless suitable for maps of the world or specific countries and regions. At the time of writing, the latest version (v4.1.0) was announced in 2018, therefore the data is also not as recent as the previous two datasets, however, at the available scales, the data is not likely to change frequently [28].

3.3.2.2 Imagery

A rich dataset of free and open satellite imagery, with different spatial and temporal resolutions and useful for studying different parameters, is available. Specific licenses depend on the agencies which are providing the data. Formats also depend on the satellites and, in some cases, images are available in more than one format. The best way for finding imagery is to browse portals (see relevant examples in Table 3.2), which make this satellite imagery available and often also tools for their basic processing [29].

TABLE 3.2
Portals with access to free and open satellite data

Portal	URL
USGS Earth Explorer	https://earthexplorer.usgs.gov
LANDVIEWER	https://eos.com/landviewer/
COPERNICUS OPEN ACCESS HUB	https://scihub.copernicus.eu
SENTINEL HUB	http://apps.sentinel-hub.com/eo-browser, http://apps.sentinel-hub.com/sentinel-playground
NASA EARTHDATA SEARCH	https://search.earthdata.nasa.gov
REMOTE PIXEL	https://search.remotepixel.ca
INPE IMAGE CATALOG	http://www.dgi.inpe.br/catalogo

Another interesting portal is that of OpenAerialMap [30], where one can find, apart from some openly licensed satellite imagery, also imagery from unmanned aerial vehicles (UAVs). All imagery is made available through the Humanitarian OpenStreetMap Team's Open Imagery Network (OIN) Node. The images are available for tracing in OpenStreetMap.

3.3.2.3 Place Names

GeoNames is a global database of more than 25 million names for 11 million geographical features, classified into nine categories (e.g. administrative areas, water features, parks, etc.), and further classified into 645 different feature codes. At the time of writing, GeoNames included 4.8 million populated places. GeoNames integrates data from various sources. The quality of the data depends on the source that contributed the data, therefore a wiki interface allows users to improve the quality by editing, correcting or adding new names through a wiki interface.

The GEOnet Names Server (GNS) is the official repository of standard spellings of geographic names outside the United States, sanctioned by the United States Board on Geographic Names (US BGN). At the time of writing, it included 12 million names for 7 million features, each feature described by its feature class, location, administrative division, and quality. The data can be downloaded as text files (per country or feature class or the entire dataset), or accessed through web services [31]. For a global dataset, place names in the US and Antarctica can be added by downloading them from the US BGN geographic names information system [32].

In the above sources features are represented by a point. These are useful as labels on maps or to search for a place. However, sometimes boundaries (polygons) are needed. Quattroshapes is a gazetteer of non-overlapping polygons, distinguishing it from gazetteers with simple point geometries. The gazetteer is based on data from GeoNames, Yahoo GeoPlanet, Flickr geotagged photos and EuroGeoGraphics [33].

3.3.2.4 Administrative Areas

Thematic maps show information about a specific theme, e.g. about COVID-19 infections. Such information is often displayed per administrative area, such as country, state, province, city, municipality, suburb or ward.

The World Bank publishes a dataset with administrative boundaries approved by the organization. The dataset includes international (country) boundaries, disputed areas, coastlines and lakes [34]. Sub-national boundaries for individual countries can be downloaded from the Humanitarian Data Exchange of the United Nations Office for the Coordination of Humanitarian Affairs (OCHA) [35].

For lower level administrative boundaries, GADM, a global dataset of administrative areas at all levels of sub-division, is available [36]. The GADM project sourced data for many countries from their national governments, from NGOs, and/or from maps and lists of names available on the Internet (e.g. from Wikipedia) [37]. This dataset is convenient to use because it is available as a single global layer, however, care should be taken, as it is not necessarily based on the latest authoritative sources (the website provides limited information).

Administrative boundaries are also included in some other datasets, such as Natural Earth and OpenStreetMap. Once again, care should be taken because these are not necessarily based on authoritative sources.

3.3.3 Places Frequented by many People

Because COVID-19 is mainly transmitted through close physical contact and respiratory droplets, places frequented by many people or where people are in close proximity to each other present a higher risk of transmissions. A first indicator for areas containing places frequented by many people would be data about settlement and population density. Locations of refugee camps are another way of identifying places frequented by many people. They are typically densely populated and have been identified to be COVID-19 vulnerable by the WHO. A list of refugee camps from 2014 is available in [38]. An online world map, as well as maps and statistics published as PDFs, are available on the UNHCR operational portal for refugee situations [39]. However, despite our extensive searches, including the UNHCR portal, we could not find downloadable location-based data about refugee camps.

Once areas with high settlement or population densities have been identified, data about specific places frequented by many people in these areas are useful for risk management at a larger scale. A plethora of different kinds of places could be relevant, ranging from supermarkets, restaurants, shopping centres to fitness centres, stations, schools and universities. On maps and in geospatial data, these are often referred to as points of interest.

While completeness of data in different countries and regions varies, OpenStreetMap includes an extensive set of points of interest (close to 33 million points), each identified with the "amenity" tag. At the time of writing, there were at least 71 different kinds of amenities in seven different categories: sustenance, education, transportation, financial, healthcare, entertainment, arts & culture, and others. Several tools and scripts are available for extracting points of interest from the OpenStreetMap dataset [40]. Wikimapia is another crowdsourced geospatial dataset. At the time of writing it included close to 24 million points of interest in 94 different categories [41].

Points of interest datasets are widely used, not only on maps, but also for a wide range of location-based services, e.g. for reviewing or recommending points of interest. Studies specifically about the quality of points of interest in OpenStreetMap and Wikimapia have not been conducted at a global scale; they have however been included in studies about the quality of OpenStreetMap generally. Barriers for assessing the quality of points of interest generally include the fact that no reference datasets exist against which one can compare them (apart from comparing OpenStreetMap to Wikimapia), they cannot be assessed against satellite imagery, which is possible for many other kinds of features (e.g. building and roads), and ground truthing at a global scale is just too expensive. Nevertheless, OpenStreetMap and Wikimapia are often the only available open datasets for points of interest and therefore useful. The quality of individual classes of points of interest, for which reference datasets exist, can however be assessed e.g. for transportation or health facilities. See also sections 3.3.4 and 3.3.10 in this regard.

3.3.4 Travel Networks and Mobility

The official global reference dataset for transport networks is Global Roads, version 1 (gROADSv1), based on the combination of the available, and topologically correct, road data at national level. The common data model is that of the United Nations Spatial Data Infrastructure Service (UNSDI-T). The data were collected, harmonized and homogenized over an extensive period of time, spanning a few decades. This means that updating the data and spatial accuracy may vary greatly from country to country [42].

The second dataset of interest is OpenStreetMap. The project was initiated specifically for collecting data about streets, not only their geometry, but also any features related to transportation networks. The main features related to travel networks are: arialways, aeroways, highways, public transport, railways, routes and waterways. The many different typologies and the many attributes used for the description of the features make this dataset an invaluable source of detailed information [43].

Despite its heterogeneity in spatial and semantic distribution, the dataset is rich and accurate in many developed regions [19], [44], [45] and richer than gROADSv1 in (at least some) developing countries [46] compared OpenStreetMap against gROADSv1 in Tanzania, Uganda and Kenya, finding that the former shows less roads in the ratio of 5.6, 6.5 and 2.5 respectively. Moreover, the mean spatial accuracy is 35 m for OpenStreetMap and 600 m for gROADSv1.

About mobility, recently, data was made available by Google (open data) and Facebook (upon agreement). Google trends [18] aim to provide insight into what has changed in response to policies aimed at combating COVID-19. They are based on anonymized data collected by apps such as Google Maps when the user turns on the Location History setting (which is off by default). Data are not absolute values, but rather the changes in time referred to a baseline day, which is the median value from the 5-week period between 3 January and 6 February 2020. Data are aggregated per day (starting from 16 February) and per country (where available), and represent the change in the number of visitors to specific types of location: grocery stores, pharmacies, parks, train stations, retail, recreation, and workplaces; and the duration in case of the residential category. Data per region (second administrative level) is available at [47].

In response to the COVID-19 pandemic, Facebook launched an initiative within Facebook Data for Good [48], and made available, for researchers and non-profit operators who have signed data license agreements, different typologies of maps and geospatial data: co-location maps, trends and staying at home maps, movement maps, network coverage maps and maps of the Social Connectedness Index, which measures the strength of connectedness between two geographic areas as measured by Facebook friendship ties.

Data are provided by Facebook as CSV files upon request, starting from the day of the request, on a grid that follows the Bing Tile System [49]. For the spatial resolution, in principle, the smallest allowed size guaranteeing privacy protections is Bing Tile Level 16, which is equivalent to roughly 600m near the equator, but the resolution of the requested dataset is computed on the base of the time needed for its periodical update. The calculation of the movement data is much heavier, from the computational point of view (cross matrix of calculations between all the panes) than the population count, and this is the reason why the spatial resolution of the movement datasets is coarser than that of the population density (see later section 3.3.7) and depends strongly on the size of the area of interest. As examples, in the case of Italy and the Lombardy region within Italy, pixel sizes are respectively about 7.5 km (Bing Tile Level 4 - 9.8 km at the equator) and 3.5 km (Bing Tile Level 5 - 4.9 km at the equator). Lombardy covers approximately 8% of the whole Italian territory, with 16.7% of its population (mean density equal to 422 inhabitants/km^2). The temporal resolution is 8 hours.

Apart from the above, two datasets are available to everyone: the “Change in Movement”, which compares the movement of people with respect to a baseline period; and the “Stay Put”, which provides information on the fraction of the population that appears to stay within a small area surrounding their home for an entire day. The Movement Range data is available as a CSV file only for some countries. All the maps are based on data collected from Facebook users.

3.3.5 Global High-resolution Land Cover Maps

The anthropization of the environment (deforestation, habitat degradation and fragmentation, intensification of agriculture and climate change) facilitates the passage of pathogens from animals to humans. To study the extent of these effects, the basic maps to start from are land cover maps. Thanks to the availability of open satellite images in ever increasing resolution, in recent years we have witnessed the creation of various maps that can be a valuable tools for researchers from different environmental disciplines. Some of these maps are multiclass, such as GlobeLand30 and FROM-GLC. Others represent specific elements of interest, such as urbanized areas (Global Urban Footprint and Global Human Settlement Layer), water resources (Global Surface Water) and forested areas (Forest/Non-Forest map and Global forest cover gain/loss). Some characteristics of the land cover maps can be seen in Table 3.3.

Apart from these datasets, as for the other features of interest, OpenStreetMap can be a good source of data. Specifically, in OpenStreetMap the detail of land use is reported. Therefore, from the point of view of knowledge about an area, the information is also richer than basic land cover data, even if the limitation is that it is not homogeneously distributed across the globe, because the amount of data in an area depends on the activity and contributions of volunteers in that area.

3.3.6 Address Data

Addresses are essential for locating infected cases, to trace contacts after someone tests positive, to accurately identify and respond to emerging clusters of COVID-19, and to determine households at risk as a result of these clusters. Addresses are typically maintained by local authorities [50], however, a global uniform open dataset facilitates the development of tools that can leverage economies of scale. The Universal Postal Union (UPU) [51] supports countries to develop and improve their addressing systems. The aim is to improve the coverage of addressing infrastructures globally. However, the UPU does not publish open address data.

TABLE 3.3
Global high-resolution land cover maps

	Res(m)	Year(s)	Producer
GlobeLand30 (GL30)	30	2000, 2010, 2020	National Geomatics Center of China
FROM-GLC	30	2010, 2015, 2017	Tsinghua University
Global Urban Footprint	12	2011	German Aerospace Center (DLR)
Global Human Settlement Layer (GHS BUILT-UP GRID S1)	20	2016	Joint Research Center (JRC)
Global Surface Water	30	1984-2018, every year	Joint Research Center (JRC)
Forest/Non-Forest map	25	2007-2010, 2015-2017, every year	Japan Aerospace Exploration Agency (JAXA)
Global forest cover gain	30	2000-2012, (one map for the whole period)	Hansen/UMD/Google/ USGS/NASA
Global forest cover loss	30	2001-2019, every year	Hansen/UMD/Google/ USGS/NASA

An alternative is the OpenAddresses.io initiative [52]. Data is collected from authorities all over the world, integrated into a uniform data model, and made available for downloads. Data sources can be added or improved through a GitHub site. In 2020, OpenAddresses consisted of more than 475 million addresses integrated from thousands of sources from all over the world. Figure 3.2 shows the coverage on 4 October 2020.

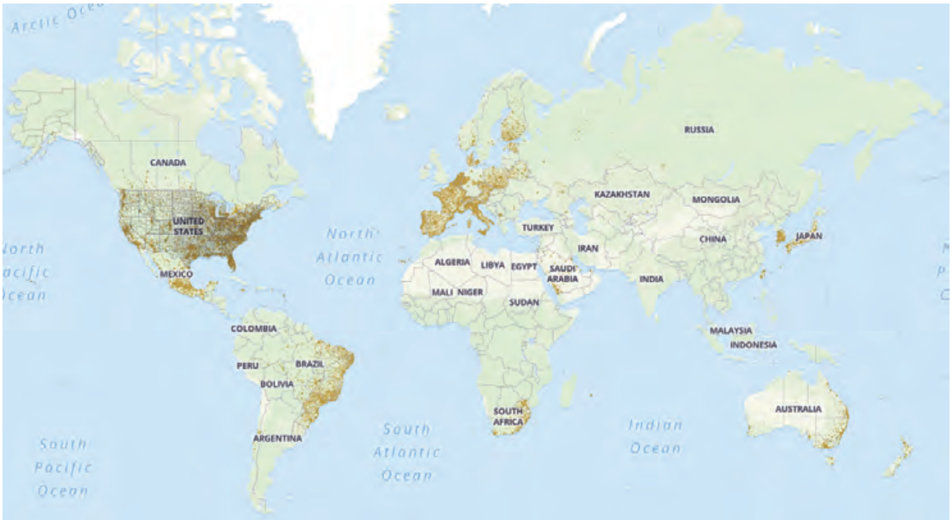

FIGURE 3.2
Global coverage of OpenAddresses.io on 4 October 2020 [52]

Addresses in OpenAddresses.io follow a rather restrictive data model, essentially comprising a number, street, city, postcode, district, region, and an additional attribute called “unit” for uniquely identifying different units at the same address. Each address has a unique identifier and a coordinate associated with it. One can specify the type (e.g. industrial or residential) of the address and add notes. The data model does not specifically cater for local variations, such as addresses without street names or addresses requiring both a suburb and a city or municipality name [53]. Following an international data model, such as that specified in ISO 19160-1 [54], would resolve this. Apart from improving issues that arise when address data is converted from source model to the OpenAddresses.io model, there are no quality checks on the address data *per se*, as this is the responsibility of the authority from where the data is sourced.

Addresses in OpenStreetMap are tagged with "addr:housenumber". Addresses can be a feature on their own or they are associated with a building, site or other area. In some parts of the world, address ranges are available, i.e. a line (called "way" in OpenStreetMap) tagged as "addr:interpolation" runs parallel to the street. The start and end nodes of the line are tagged with the numbers of the addresses closest to them. Address ranges do not provide individual address records, but in the absence of other address data, such ranges are very useful for routing and geocoding because the location of addresses with numbers between those at the start and end nodes can be interpolated along the line. Early in October 2020, there were just over 106 million "addr:housenumber" tags in OpenStreetMap, and close to 100 million fewer "addr:street" tags [55]. Challenges with the way in which addresses are represented in OpenStreetMap have been noted and improvements have been proposed [56]. Address data can be extracted and downloaded in the same way as any other OpenStreetMap data.

A single source of uniform address data across the world makes it possible to develop geocoding tools and services that can be used anywhere in the world for locating infected patients and their contacts. For example, a geocoding service based on OpenStreetMap data is available at `https://nominatim.openstreetmap.org`. Some geocoding services, such as `https://geocode.earth/sources`, are based on multiples data sources including OpenStreetMap and OpenAddresses.

3.3.7 Demographic Data

Demographics is a huge field, encompassing characteristics of the population in terms of population density, age, gender, socio-economic, health conditions, presence of vulnerable population, lifestyle, etc. General data sources, to be considered for our purposes, include open data published by the World Bank [57] and the Organisation for Economic Co-operation and Development (OECD) [58]. In the former, data are available in various formats, with various temporal extensions, and there is a special section related to COVID-19. The latter contains data of OECD countries and some non-OECD economies. The temporal coverage consists of different years, depending on the specific parameter under consideration; the most recent year is generally 2018.

Among the various characteristics of the population, the population age and its density were considered by the authors as examples, because of their importance with respect to COVID-19: the older population has more severe symptoms and density of the population is inversely related with social or physical distancing required to combat the virus.

About age, classes for population ranges 0-14 [59]; 15-64 [60]; and above 65 [61], considering male, female, total, absolute number and percentage per country were estimated by the World Bank based on the World Bank's total population and age/sex distributions of the United Nations Population Division's World Population Prospects: The 2019 Revision [62], [63]. The temporal coverage is from 1960 to 2018. If interested in the population with a certain age or within a certain age interval, these data can be found, for OECD countries and some non OECD economies, in the OECD's statistics. The temporal coverage is again from 1960 to 2018.

For population density, three global high resolution global datasets are available. The Gridded Population of the World, most recent version is GPWv4.11 [64], is a set of raster layers with the estimates of the count and density of people per 30 arc-second (around 1 km) grid cell for each of the five years: 2000, 2005, 2010, 2015 and 2020, consistent with national censuses and population registers. All estimates of population counts and population density have also been nationally adjusted to population totals from the United Nation Population Division's World Population Prospects: The 2015 Revision [65]. Data is downloadable in ASCII (text), GeoTiff and netCDF format. In addition, rasters are available for basic demographic characteristics (age and sex), geographic characteristics (land and water areas) and data quality indicators [64].

An interesting dataset, even if limited for now to 169 countries, is provided by CIESIN and the Connectivity Lab at Facebook [66]. The name of this dataset, computed for 2015, is the High Resolution Settlement Layer (HRSL) and its resolution is of 1 arc-second (approximately 30 m). The population estimates are based on recent census data and high-resolution (0.5 m) satellite imagery from DigitalGlobe.

The second global dataset is GHS_POP Global population grids at epochs 1975, 1990, 2000, 2015 and with resolution of 250 m, 1 km, 9 arcsec, 30 arcsec.

The third source of data is WorldPop [67]. Different datasets are provided, based on different methodologies [68]. Data can be downloaded per country at a resolution of 3 and 30 arc-seconds (approximately 100 m and 1 km at the equator, respectively).

The last dataset worth mentioning is a dynamic one and is available within the already mentioned initiative of Facebook Data for Good. Data about population density (more precisely, Facebook user density) has a temporal resolution of 8 hours and a spatial resolution varying on the region of interest, following the same rule seen in section 3.3.4 for mobility data. In the case of population density, the resolution is better because the time of computation for the updated data is lower. Considering the previous examples, the pixel size is that of a tile at Bing Tile Level 5 for Italy (around 3.5 km at the equator) and of Bing Tile Level 7 for Lombardy (around 1.2 km at the equator).

3.3.8 Concentration of Air Pollutants

Air pollution is one of the world's largest health and environmental problems. Even if there has been a general decrease in air pollution in rich countries in comparison to the threatening concentration of some decades ago, localised high values still remain in some areas, and in middle-income countries the death rates due to air pollution are the highest. Moreover, persistent exposure to air pollution weakens the respiratory system, creating a continuous irritation. There are two different typologies of pollution: outdoor and indoor (household).

Global data about outdoor air pollution are generally available per country. An example is the 1990-2016 series of concentrations of particulate matter with a size of less than 2.5 μm (PM2.5) and ozone (O_3), downloadable from [69]. A remarkable source of global open data for monitoring the temporal evolution of air quality is available in satellite data. Table 3.4 lists satellites, sensors and relative spatial and temporal resolution.

TABLE 3.4
Satellites, sensors for air quality monitoring, spatial and temporal resolutions (source: [70])

Satellite	**Sensor**	**Spatial resolution**	**Temporal resolution**
Aqua	Atmospheric Infrared Sounder (AIRS) Level 2 and 3 products	$1^o x 1^o$	daily, 8-day, monthly
Terra and Aqua	Moderate Resolution Imaging Spectroradiometer (MODIS)	250 m, 500 m, 1 km	1-2 days
Terra	Measurement of Pollution in the Troposphere (MOPITT)	$1^o x 1^o$	daily, monthly
Aura	Ozone Monitoring Instrument (OMI)	13 km x 24 km	daily
Suomi-NPP	Ozone Mapping and Profiler Suite (OMPS)	50 km x 50 km	101 minutes, daily
Sentinel 5-P	TROPOspheric Monitoring Instrument (TROPOMI)	7 km x 3.5 km	daily
Suomi-NPP	Visible Infrared Imaging Radiometer Suite (VIIRS)	375-750 m	1-2 days

The most recent satellite of this family is represented by Sentinel 5P, launched in 2017 by the European Space Agency within the Copernicus Initiative. The onboard TROPOMI (TROPOspheric Monitoring Instrument) spectrometer allows the monitoring of ozone (O_3), methane (CH_4), formaldehyde (HCHO), aerosol, carbon monoxide (CO), Nitrogen dioxide (NO_2) and Sulfur dioxide (SO_2). TROPOMI takes measurements every second covering an area of approximately 2600 km wide and 7 km long in a resolution of 7×7 km. Data can be freely downloaded upon registration. The first data were released in July 2018.

Using data from the Copernicus Sentinel-5P it was possible to analyse, for instance, the decline of air pollution, specifically NO_2 concentrations, in some areas of the world as a consequence of the lockdown that was implemented to prevent the spread of the coronavirus. The maps in Figure 3.3 show the NO_2 concentration over Italy before and during the lockdown.

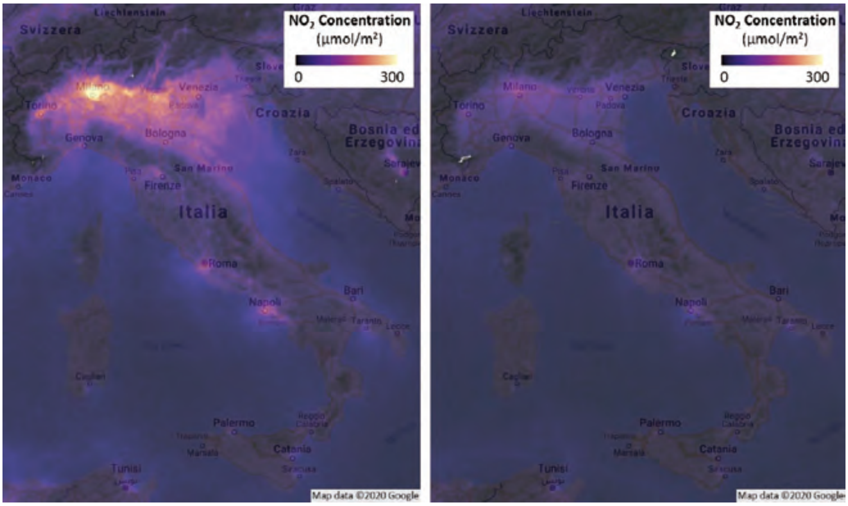

FIGURE 3.3
Concentration of NO_2 over Italy before the lockdown (average value in January 2020) and during the lockdown (average value from 9 March to 9 April 2020)

Indoor air pollution is caused mainly by the use of solid fuels for cooking. While indoor air pollution has been on the decrease since the 1990s, 40% of the world population still does not have access to clean air cooking fuels. Death rates from air pollution are highest in low-income countries. A selection of indicators about indoor air pollution are available in visualizations (maps and graphs), and also for download from [71]. Indicators are provided at the country level, and were sourced from the World Bank and from the Global Health Data Exchange.

3.3.9 Water Sources

Referring to water and sanitation, indicators for the United Nations Sustainable Development Goal (SDG) 6 are available, but again, at country scale. Maps, charts and data can be found on the UN Water geoportal [72]. Figure 3.4 is an example, showing the proportion of the population in a country using safely managed sanitation services.

The local alternative, as seen before, is to consider the features related to water available in OpenStreetMap. By using overpass turbo (`http://overpass-turbo.eu`) and browsing to the area of interest, the simple query:

```
node
  [amenity=drinking_water]
  ({{bbox}});
Out;
```

allows us, i.e. to obtain the map and data corresponding to points where drinkable water is available. The result of the query in a portion of Dar Es Salaam is shown in Figure 3.5.

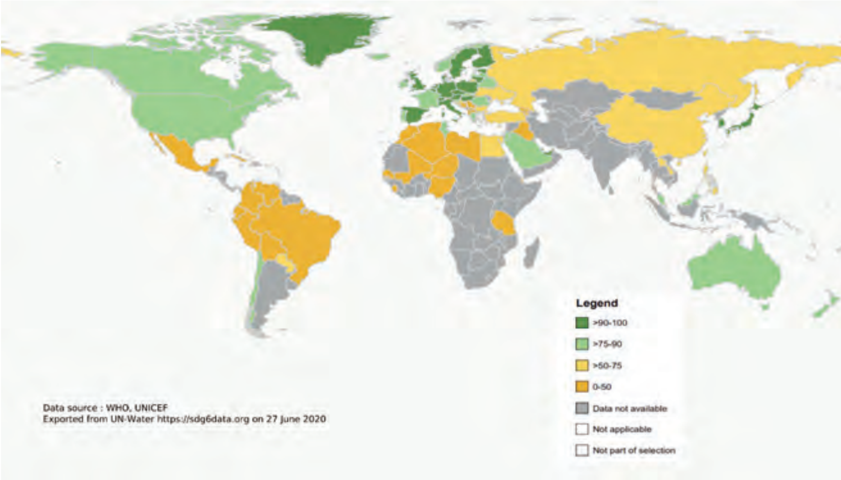

FIGURE 3.4
Proportion of population using safely managed sanitation services (Source: UN Water [73])

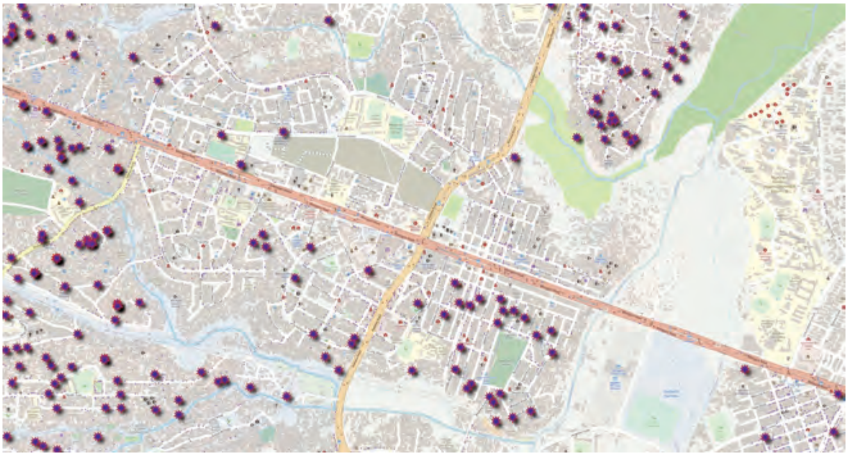

FIGURE 3.5
Drinking water locations in a portion of Dar Es Salaam (Source: OpenStreetMap contributors [74])

3.3.10 Health Facilities

General data about the health condition of the population (again at country level) can be found on the WHO website. The Global Health Observatory (GHO) [75] provides access to data and analyses for over 30 health themes ranging from health systems to disease-specific themes, as well as direct access to the full database. The same database archives data about the density of hospitals per 100,000 people (district/rural hospitals, health centres, health posts, provincial hospitals, specialized hospitals, hospitals as a whole), hospital beds (per 10,000 people), pharmacists, medical doctors, nurses and midwives (both absolute number, per 10,000 people, and density for 1,000 people). Some of this data can also be downloaded in cartographic format from the already mentioned website of the United Nations Statistics Division, in the "Healthcare Resources" section of the portal.

healthsites io.png

FIGURE 3.6
Location of health sites on 4 October 2020 (Source: HealthSites.io [76])

healthsites io graphs.png

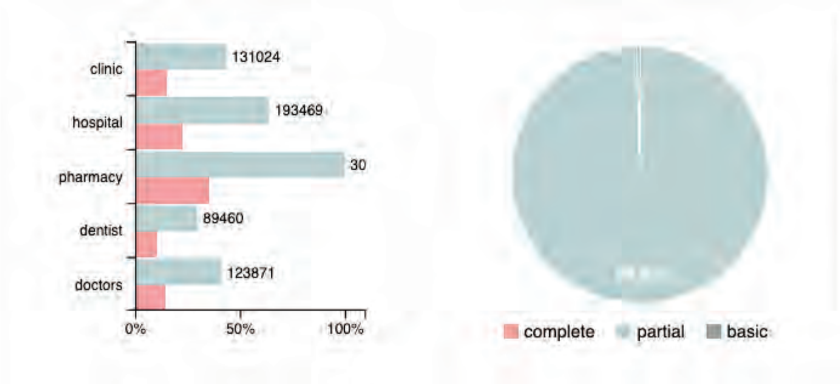

FIGURE 3.7
Number of heath sites per type (on the left) and completeness of attributes (on the right) on 4 October 2020 (Source: HealthSites.io [76])

Unfortunately, none of these datasets have local data. If one requires data at such granularity, the Global Healthsites Mapping Project [77], which is based on the OpenStreetMap data model, is a good starting point for finding locations and contact details of health facilities (clinics, doctors, hospitals, dentists, pharmacies, etc). It is a collaborative project and a long list of partners are contributing based on a citizen science or VGI (volunteered geographic information) approach. The Global Healthsites Mapping Project provides a domain specific view of OpenStreetMap data, focusing on the needs of those working with health facility data. The Heathsites.io platform [76] does not require users to be experts in the general OpenStreetMap data model and allows them to be more focused specifically on the health domain, even if the same data can be accessed from the general OpenStreetMap database and platform in various ways, e.g. with Overpass Turbo [78] or via the QuickOSM QGIS plugin [79]. Currently, 820,244 health sites are mapped (Figure 3.6), however, their descriptions are far from complete (Figure 3.7).

FIGURE 3.8
Locations of health sites in Europe on 4 October 2020 (Source: Eurostat [80])

Another interesting source of data, unfortunately only for Europe, is shared by Eurostat [80]. The dataset, which will be improved progressively, integrates the location of European healthcare services extracted from official national registers. By now it contains almost 15,000 features (Figure 3.8). When available, the capacity in terms of number of beds, rooms and practitioners and whether the healthcare site provides emergency medical services is archived. The dataset is not homogeneous neither in the level of detail nor in timeliness and update frequency. Nevertheless, it is well known that “reliable pan-European geospatial datasets for EU institutions are required to further develop GI capacities at EU level, and an important step in reducing inequalities across the EU” [81].

Global information about intensive care or ventilators is not available in any dataset. Similarly, location-based information about capacity of (and places for) collecting and treating medical and hazardous waste could not be found. To be precise, there is no data related to waste generally and again, the only source, however quite fragmented, is OpenStreetMap [82].

3.4 Discussion and Conclusion

Our study shows that global open datasets are available for many aspects of risk management before, during and after a pandemic. However, it is not always easy to find these datasets. Some of them can only be found via a (geo)portal, which often makes them inaccessible to web crawlers that search and index content for general purpose web search engines. Search engines specifically developed for datasets, such as Google’s dataset search (`https://datasetsearch.research.google.com`), which crawls and indexes metadata about datasets in schema.org format, can improve the situation. Another challenge lies in finding the license terms and conditions for using open data. For some datasets that we discussed in this paper, the licensing information was readily available and simple to understand (e.g. standardized Creative Commons licenses). For others, we struggled to locate the licensing information or, when datasets are compiled from many different sources, different licenses may apply to different parts of the dataset (see for example, OpenAddresses.io).

The UN GGIM has identified a set of 14 global fundamental geospatial data themes, amongst others, in support of the 2030 Sustainable Development Agenda and its 17 Sustainable Development Goals (SDGs). These datasets are considered to be "the minimum primary sets of data that cannot be derived from other data sets, and that are required to spatially represent phenomena, objects, or themes important for the realisation of economic, social, and environmental benefits consistently" [83]. There is considerable overlap between nine of the UN GGIM fundamental geospatial datasets and the list of datasets that we identified as useful in the case of a global pandemic: Addresses, Buildings & Settlements, Functional Areas (includes administrative areas), Geographical Names, Land Cover & Land Use, Physical Infrastructure (includes schools and hospitals), Population Distribution, Transport Networks and Water. The list of fundamental geospatial data themes presents a foundation for global geospatial information management. As a next step, detailed regional specifications are being developed. Eventually, these will lead to improved geospatial information at the national level, which can then be integrated into global datasets.

The biggest concern with the global open datasets discussed in this chapter is that many of them are not available with sufficient granularity. Fine-grained data is particularly critical in the case of a global threat, such as the current pandemic. We live in a hyper-connected world and therefore, while taking into account local differences, many challenges need to be addressed at a global level. Therefore global analyses are required, based on data with much more detail than currently provided (e.g. mostly by country). There is a definite and urgent need to move towards providing high resolution global data.

Some government agencies are already moving in this direction, for example, ESA provides satellite imagery globally down to 10 m resolution (Sentinel 2) as open data. This makes global analyses possible that were previously unthinkable. Some private companies are also moving in this direction. Consider, for example, the case of Facebook which, with the Facebook Data for Good initiative, makes many dynamic data of interest for humanitarian purposes freely available to nonprofits and universities that have signed data license agreements.

Another fundamental move towards fine-grained data is exhibited by the many initiatives related to OpenStreetMap. OpenStreetMap has been confirmed as one of the most important geospatial data projects in the last 20 years. The quality of OpenStreetMap data is often the subject to criticism. However, the wider OpenStreetMap community, which includes other communities, such as HOT, Missing Maps, Healthsites, Geochicas, etc., has equipped itself with tools and procedures that allow a solid first validation of the data. For example, during the pandemic, HOT created at least 199 projects covering approximately 124,000 km^2, many of which had been mapped and validated by the time of writing this chapter. It is in the communities' own best interest to provide the best possible data, not only because they will use their own data, but also because there is awareness among volunteers that the data will be used for humanitarian purposes and therefore the better it is, the more effective it can be. Many scientific publications have examined the quality of OpenStreetMap data in various case studies. The results are generally comforting because where OpenStreetMap communities are more developed and mature, the comparison with authoritative data [84], [85], [86] is very favourable. Where OpenStreetMap data are scarce, it is often not possible to make comparisons with reference data because these data simply do not exist or are not available [46].

Academics have approached OpenStreetMap with slowness, gathering some momentum in recent years, not only on aspects of general interest, that is the collaborative collection of data, but also the educational perspective of such an experience. In 2014, the academic community developed YouthMappers [88] to explicitly bring together and nurture the student communities and their faculty that operate within and together with the broader set of OpenStreetMap communities around youth-based identities. Founded by faculty from Texas Tech University, the George Washington University, and West Virginia University, with support from the US Agency for International Development's GeoCenter, and now administered by Arizona State University,

FIGURE 3.9
Locations of YouthMappers Chapters in October 2020 (Source: YouthMappers [87])

YouthMappers organize as chapters on university campuses, run by student leadership under the guidance of university professor mentors. By October 2020, the network had grown (Figure 3.9) to 222 campus chapters in 50 countries, linking more than 5,000 OpenStreetMap students volunteers [87]. YouthMappers' motto is "We don't just build maps. We build mappers", emphasizing the importance of mapping the world in order to get to know it better. This experience should, in the opinion of the authors of the chapter, become the heritage of all schools and universities because it would be an enrichment of global knowledge of the world and, at the same time, an enrichment of the skills of young people. Governments should encourage and support these initiatives, taking the advantage of having more detailed maps and more geographically aware young citizens. University networks, such as the UN GGIM Academic Network, could become sounding boards for the initiative itself and contribute both to its dissemination and to the design and development of procedures for data assessment, which would therefore become the heritage of all humanity.

Annex: List of datasets

The list of datasets is available at https://docs.google.com/spreadsheets/d/19amm6CbDOTOPObA8xcZ-8itdCMaOPXSu3OqUVuDQr4s/edit#gid=0.

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4

Remote Sensing and Computational Epidemiology

Mohammad Reza Mobasheri

Remote sensing techniques have been developed over the past five decades and formed an important part of an interdisciplinary approach for many interdisciplinary science including health, environment, disease monitoring, biodiversity, and determination of habitat and ambient parameters. This new approach is based on the capability of looking at multispectral views of the environment at multiple spatial and temporal scales. This new interdisciplinary ideas of remote-sensing approach, have emerged for the detection, evaluation, and mapping of factors affecting public health. Such applications have helped to achieve considerable advancement in knowledge and insight for the environmental and public health administrations to work together in teams. This synergy has enabled them to explore solutions to previously unsolved environmental issues and managerial problems. Demand for talented researchers in remote sensing, GIS, and spatial modeling are continuously increasing. This includes environmental scientists, conservation, monitoring, and assessment experts. Perhaps it is not too much to hope that we can change our view of life and justify our habits to prevent what has happened during pandemic COVID-19 again. This book chapter is written with this hope in mind. Many scientists and resource managers already recognized the importance of adopting an approach in prediction of epidemics and pandemics before their occurrences.

4.1 Introduction

Remote sensing techniques have been developed over the past five decades and formed an important part of an interdisciplinary approach for many sciences including health, environment, disease monitoring, biodiversity, and determination of habitat and ambient parameters. The remote sensing technology is based on the capability of looking at multispectral views of the environment at multiple spatial and temporal scales. The information collected through this technology is readily integrated with other forms of data, including a global positioning system (GPS), geographical information system (GIS), and field observational data. This information is essential to prepare a foundation for species-specific models to map the habitat of any creatures as small as a virus and as large as an elephant. This may include testable predictions of their population dynamics and the development of biodiversity indicators and species-environment characteristics.

Interdisciplinary remote sensing consists of concepts, methodology, technology, and innovation. These elements when integrated may provide a unique opportunity to implement novel solutions to the problems that exist at the leading edge of environmental science and management. These problems are among the most complex issues of our time.

This interdisciplinary approach of remote-sensing has emerged for the detection, evaluation, and mapping of factors affecting public health. Such applications have helped to achieve considerable advancement in knowledge and insight for the environmental and public health administrations, enabling them to work together. This synergy has also enabled them to explore solutions to previously unsolved environmental issues and managerial problems.

There are increasing belief and evidence that the health of human being and other species is adversely affected by human activities and landscape change [1–3]. Perhaps it is not too much to hope that we can change our view of life and justify our habits to prevent what has happened during pandemic COVID-19 again.

Interdisciplinary researches to understanding the environmental factors for the insects to be prepared for breeding and extraction of these factors from satellite images have shown the power of remote sensing in monitoring environmental issues. Of course not sufficient mainstream remote-sensing research texts have dealt with this emerging approach in detail to help the growing collaboration among those specializing in remote sensing, health management, and ecosystem scientists, in critical decision making and efforts on the ground. This book chapter is written with this hope in mind. Many scientists and resource managers have already recognized the importance of adopting an approach in prediction of epidemics and pandemics before their occurrences [4, 5], and in parallel with this recognition, the use of remote sensing and GIS approaches have noticeably increased [6, 7]. For example, research carried by Ahmadian et al. [4], regarding Malaria outbreak, has proved the potential of remote sensing and GIS. A section of this chapter is assigned to this work. Also, a section is assigned to Cholera epidemic prediction. Finally, an approach to the prediction of COVID-19 epidemic occurrence using remote sensing and surface data is suggested.

4.2 Remote Sensing and Health

In what follows, remote sensing technology is discussed. This is followed by an explanation on how this technology is related to the virus and some other vector disease.

4.2.1 What is a Virus?

A virus is a submicroscopic infectious agent that replicates itself only inside the living cells of an organism. Viruses can infect all types of life forms, from animals and plants to microorganisms, including bacteria and archaea [8]. Viruses are found in almost every ecosystem on Earth and are the most numerous type of biological entity [9, 10]. When infected, a host cell is forced to rapidly produce thousands of identical copies of the original virus. Most virus species have virions too small to be seen with an optical microscope as they are one hundredth the size of most bacteria.

Viruses spread in many ways. One transmission pathway is through disease-bearing organisms known as vectors: for example, viruses are often transmitted from plant to plant by insects that feed on plant sap, such as aphids; and viruses in animals can be carried by blood-sucking insects and vampire bats. The infectious dose required to produce infection in humans is less than 100 particles in Influenza viruses [11, 12] and to some extent in COVID-19. The variety of host cells that a virus can infect is called its "host range". This can be narrow or broad, meaning a virus is capable of infecting only few species, or infecting many.

Viral infections in animals provoke an immune response that usually eliminates the infecting virus. Immune responses can also be produced by vaccines, which confer an artificially acquired immunity to the specific viral infection. Some viruses, including those that cause AIDS, HPV infection, viral hepatitis, and COVID-19 evade these immune responses and result in chronic infections.

4.2.2 How is a Virus related to Remote Sensing?

In this section, the relation between different respiratory diseases (including COVID-19) and the atmospheric and environmental parameters that are investigated by different workers will be discussed. All these atmospheric and environmental parameters can be assessed by and extracted from images acquired by different sensors on board of different satellites.

Many researchers have observed a connection between the occurrence of respiratory diseases such as influenza (A and B) and COVID-19 and climatic parameters such as air temperature, air moisture content, relative humidity, wind speed, and amount of precipitation [12, 13]. Although the outbreak and epidemic, contagious on person to person, the weather conditions may play a key role in making some regions potentially suitable for the virus to be activated (Ianevski et al. 2019). This is the case for many other epidemic diseases such as Malaria and Cholera. In what follows, a few of these researches will be introduced.

Peci et al. [13], claimed that the occasion of incidence of influenza increases during rainy seasons in tropical climates and during the dry, cold months of winter in temperate climates. They found that the seasonality of influenza A and B viruses is different in most temperate climates. A negative association of both absolute humidity and temperature with influenza A and B viruses was observed.

Guo et al. [12] found an association between mean temperature, relative humidity (RH), and the atmospheric pressure with influenza cases for children between 0-17 years old. They claimed that the relative risks increase as the temperature falls below 20°C, RH lower than 50%, or higher than 80%. Also, the risk of influenza increased with rising atmospheric pressure with 1,005 hPa as the breakpoint. They found that the effect of coldness, humidity, dryness, high-pressure, and low-pressure showed statistical significance both in females and males. The cold effect increases with age while the humidity affected all ages of children, whereas, dryness mainly affects ages 4-14 years. High-pressure mainly affected the age of 0-3, whereas the low-pressure affects preschool children aged 0-6 years old.

Ianevski et al. [14] investigated the effects of meteorological parameters such as temperature, UV index, humidity, wind speed, atmospheric pressure, and precipitation (all acquirable by remote sensing technique) on IV activity in Norway, Sweden, Finland, Estonia, Latvia, and Lithuania during 2010-2018 in Influenza virus epidemics while considering the pace of global warming. They deployed correlation and machine learning analysis techniques and found that low temperature and UV radiation can preserve Influenza virus infectivity. The researchers believe that low temperature and UV index were the most suitable predictive indexes among other meteorological factors in Northern Europe. Of course, their in-vitro experiments confirmed that low temperature and UV radiation preserved Influenza virus infectivity.

Most recently, Wang et al. [15] have researched the ongoing global pandemic of COVID-19. Their aim was to predict the effect of the upcoming summer in the northern hemisphere and expected to have a reduction of the transmission intensity of COVID-19 with increasing humidity and temperature. They used data from the cases with symptom-onset dates from January 19 to February 10, 2020, for 100 Chinese cities, and cases with confirmed dates from March 15 to April 25 for 1,005 U.S. counties. The relationship between the transmissibility of COVID-19 and the temperature/humidity was assessed. They found a similar influence of the temperature and relative humidity on effective reproductive number (R values) of COVID-19 for both China and the U.S. before lockdown in both countries. There was the reduction of reproduction by increasing temperature and humidity. This reduction of transmission was not further continued until July when the temperature and humidity had risen.

In an unpublished work of Xu et al. [16], the impact of environmental factors including pollution contaminants on COVID-19 transmission was investigated. They studied the relative risk of COVID-19 due to weather conditions and ambient air pollution. In this work, the daily reproduction at 3,739 global locations was controlled for the delay between infection and detection. After that they associated these with local weather conditions and ambient air pollution. They observed a negative relationship between the estimated reproduction number and temperatures above 25°C, and a U-shaped relationship with outdoor ultraviolet exposure, with a weaker positive association with air pressure, wind speed, precipitation, diurnal temperature, SO_2, and ozone.

This was followed by a projection of the relative risk of COVID-19 transmission due to environmental factors in 1,072 global cities. The findings showed that warmer temperature and moderate outdoor ultraviolet exposure may offer a modest reduction in transmission.

Scafetta [17] investigated about COVID-19 and its possible relation to specific weather conditions. The findings showed that the 2020 winter weather in the region of Wuhan (Hubei, Central China) – where the virus first showed up in December 2019 and spread widely from January to February 2020 was very similar to that of the Northern Italian provinces of Milan, Brescia, and Bergamo, where the pandemic has been very severe from February to March 2020. According to this study such similarity may suggest the worsening of the pandemic under weather temperatures between 4°C and 11°C. Based on this result, Scafetta [17] prepared maps of world-specific isotherm to locate, month by month, the world regions that share similar temperature ranges. The analysis showed that this isotherm zone extended mostly from Central China toward Iran, Turkey, West-Mediterranean Europe (Italy, Spain, and France) up to the United State of America from January to March 2020, and coinciding with the geographic regions most affected by the pandemic in the same period. He predicted that in Autumn of the Northern hemisphere, the pandemic could return and affect the same regions again. Scafetta [17] believes that the Tropical Zone and the entire Southern Hemisphere, but in restricted southern regions, could avoid a strong pandemic because of the sufficiently warm weather during the entire year.

In a study, Njifon et al. [18] investigated the role of meteorological parameters in the seasonality of influenza viruses in tropical and subtropical regions particularly in Northern Cameroon, a region characterized by high temperatures. The researchers focused on the effect of temperature, humidity, and rainfall from January 2014 to December 2016. Their results and conclusion analysis showed that there was a statistically profound association between overall influenza activity and influenza A activity for average relative humidity. They noticed a lag between humidity rise and Influenza activity where a unit increase in humidity within a given month leads to more than 85% rise in overall influenza and influenza A activity two months later. However, they believed that none of the three meteorological variables could explain the influenza B activity.

Besides the dependence of Influenza and COVID-19 to the weather parameters, there are other vector-borne diseases such as Malaria, Cholera, Ebola, and Dengue that all proved to be dependent on some weather parameters and environmental conditions. Ahmadian et al. [4], conducted a research for the determination of high potential region for Malaria outbreak using satellite images. The findings of this research showed that the insect begins breeding when the temperature is between 25C and 35°C, relative humidity between 50 to 80%, presence of vegetation cover, and presence of water pools. All these factors were supplied using Landsat images and overlaid to find the risk potential area. The results were compared with the number of registered patients in all sentinels around within the study area. Details of the methodology are presented in the following section.

4.3 Remote Sensing Methods to Predict Health-related Outbreaks

This section is assigned to the remote sensing methods by which disease epidemic and outbreaks regions can be predicted. Numerous research has so far been conducted to predict time and regions where a disease outbreak or epidemic occurs.

4.3.1 Malaria Case Study

Based on WHO [19], in 2017, an estimated 219 million cases of malaria occurred worldwide, compared with 239 million cases in 2010 and 217 million cases in 2016. Although there were an estimated 20 million fewer malaria cases in 2017 than in 2010, data for the period 2015-2017 highlight that no significant progress in reducing global malaria cases was made in this time frame. Most malaria cases in 2017 were in the WHO African Region (200 million or 92%), followed by the WHO South-East Asia Region with 5% of the cases and the WHO Eastern Mediterranean Region with 2%.

Malaria is an infectious disease that is being transferred by the female mosquito of the species Anopheles. Out of four malaria parasites responsible for disease outbreak, Plasmodium falciparum is the most important one. The life cycle of the malaria parasite develops in the anopheline and in the human body [20, 21].

These parasites require suitable environmental parameters to complete their development cycle within the mosquito. These parameters are temperature, humidity, vegetation, and water [4]. The cycle begins when the anopheline sucks human blood usually during the night time. After two to three days the mosquito starts breeding. The breeding sites are usually water, preferably swamps or slow-flowing water bodies. In the dry and semi-dry regions, these water bodies can appear after the occurrence of heavy seasonal rain in the region. Depending on the parasite species and availability of suitable humidity and air temperature, it takes 8 to 30 days for the parasite to develop in the mosquito after which the parasitic will be ready to transmit to humans through mosquito stings.

The influence of the temperature on the feeding behavior of the mosquito, its survival, and the length of the cycle that the parasite needs to develop in the mosquito before it can be infective to humans is immense. For instance, the main mosquito species responsible for Plasmodium falciparum infections feed every second day at 25°C and every third day at lower temperatures [21].

The chance of mosquito survival is low at extreme temperatures i.e. the temperatures below 5°C and temperatures above 40°C (in some reports 35°C) are deadly for the mosquito. In this regard, the optimum mosquito survival chance is found at 32°C [21].

The environmental vulnerability of the disease is mainly determined by the effects that climatic factors can have on the abundance of malaria vectors. The population of vectors depends critically upon elements of the weather and land-use all achievable using remote sensing data [22–24]. Then epidemiological and demographic models can be deployed to relate these data to estimate the distribution of humans and parasites at a high spatial resolution [22]. Such models can in turn help in providing an empirical basis for defining the disease burden of polyparasitism and the potential health impact of removing or reducing disease risk.

In summary, a temperature range of 25°C to 35°C and a relative humidity range of 50 to 80 percent is suitable for developing malaria outbreaks. In a study conducted by Ahmadian et al. [4], a methodology for extracting temperature, humidity, water bodies, and vegetated area all from satellite images is presented and details of which are as follows.

4.3.2 Materials and Methods

In the work of Ahmadian et al. [4], when needed, weather data collected in nearby synoptic stations were used as ground truth. Also the synoptic station reports were used to select the proper satellite images after raining occurrence. Analysis of the weather stability and visibility for estimation of the severity of the atmospheric effects on the satellite images were two other important aspects of using weather data.

The Satellite images used in this work were selected upon these criteria:

- The image should contain regions where the malaria outbreaks occur
- The image should contain regions where a considerable amount of raining has happened in one to a few days before the date of image acquisition
- The visibility in the regions covered by the image scene should be greater than 10 kilometers
- The region should contain a minimum amount of cloud cover
- The image acquisition date should be between August to November and between February to May when most of the raining in the region happens
- The sensors having thermal bands were used for LST calculation
- The availability of malaria statistics for the period of the study

Taking all these conditions into account, only Landsat and ASTER images were found suitable where the former images were available. Out of five Landsat images from November 2000 to August 2005, the image of April 19, 2003 was found the most suitable one for this study. Noting that all Landsat images with acquisition dates beyond April 2003 were defected due to the malfunctioning of the 7ETM+ Scan Line Corrector [22, 25].

Geo-referencing, Radiometric calibration (Atmospheric corrections), and DN to radiance and then reflectance conversion for the visible and SWIR and DN to radiance for thermal bands were the processing steps that were taken. These images were used for producing the following products.

4.3.3 Study area

The study area was two districts located in the south of Iran right at the north of Hormuz straight in the Persian Gulf (Figure 4.1). The two districts are Minab and Kahnooj. Minab is situated between 26, 7'N and 27, 26'N and 56, 48'E and 57, 50'E with an altitude of 27m from mean sea level and approximately 104 kilometers from the Persian Gulf. Kahnooj on the other hand is located between 27, 50'N and 28, 59'N and 56, 45'E to 57, 53'E with an altitude of 469m from mean sea level approximately 330 kilometers inland. The malaria outbreaks data for these two districts were collected from the related Health and Hygiene Bureau (Table 4.1).

TABLE 4.1
Number of affected people in monthly malaria outbreaks for the period of 2003-2004

Month	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar
Minab	3	17	27	15	6	380	1020	339	95	17	1	8
Kahnooj	13	40	23	45	35	20	11	28	5	0	4	4

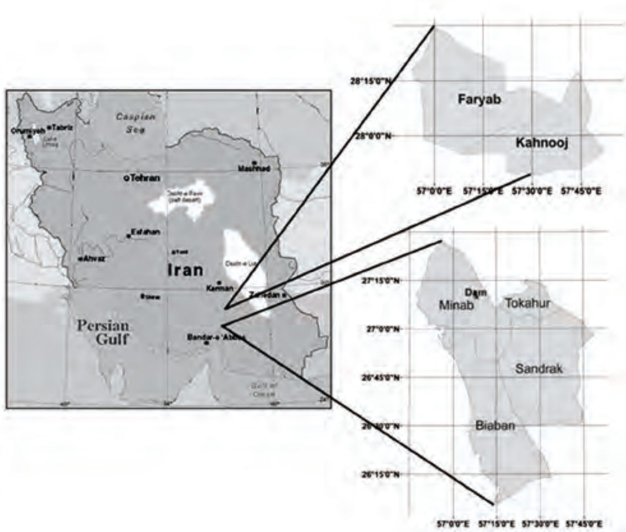

FIGURE 4.1
Location of the study area

4.3.4 Malaria Distribution Maps for Incidence Factors

Usually, three indices of Prevalence, API, and Incidence are being used in malaria outbreak investigations where the Incidence index is used in this research. The reason for this selection is the short duration required for the calculation of this index [4]. This index can be calculated using equation (4.1):

$$Incidence = \frac{M}{P_{month}} \times k \tag{4.1}$$

where M is the number of positive cases in a few months, P is the average population in the region for those months, and k is a scale factor equal to 1,000. Table 4.2 shows the health centers, region population, and calculated Incidence index for Minab and Kahnooj region respectively.

TABLE 4.2
Health centers, region population, and calculated Incidence index for Minab (left) and Kahnooj (right)

Health Center	2003 Population	*Incidence* April to June
Darpahn	6,702	0.149
Sandark	13,429	0.074
Sareni	11,481	0
Hashtbandi	11,481	0.087
Karian	13,665	0.073
Banzark	25,190	0.198
Sirik	12,439	0.241
Bemani	21,450	0
Hakami	14,305	0.070
Tiab	10,787	0.185
Haj Khademi	64,807	0.015
Minab City	62,652	0.303

Health Center	2003 Population	*Incidence* April to June
City Zone 1	12,452	2.811
City Zone 2	11,677	2.569
City Zone 3	13,048	0.077
Sahlavar	5,340	0.187
Chah Morid	5,217	0.575
Hoorani	16,455	0.425
Faryab	11,631	2.493
Dehpish	5,065	0.395

4.4 Vegetated Area Mapping

To map the vegetated area in the images, usually vegetation indices such as Normalized Difference Vegetation Index (NDVI), Simple Ratio (SR), and Enhanced Vegetation Index (EVI) or modified version of them is being used. The index used in this work was NDVI where the threshold value of 0.2 was used. This threshold was tested using ground data and other vegetation indices. A detailed discussion regarding uncertainties involved with this threshold value will be presented in the discussion and analysis section. The NDVI index takes advantage of the red edge effect in the vegetation spectral reflectance curve i.e. low reflectance in the red ρ_{R} and very high reflectance in near-infrared ρ_{NIR}. The reflectance difference in these two spectral bands can be normalized to 1 using the following equation:

$$NDVI = \frac{\rho_{\mathrm{NIR}} - \rho_{\mathrm{R}}}{\rho_{\mathrm{NIR}} + \rho_{\mathrm{R}}} \tag{4.2}$$

NDVI varies between -1 and +1 where its value for vegetated pixels is generally greater than 0.2, with values exceeding 0.65 indicating dense vegetation. Taking a flying range of mosquitoes into account a two kilometers distance around any vegetated point is considered.

4.5 Water Body Mapping

There are different methods and approaches for mapping patches of water bodies in the scenes where Normalized Difference Water Index (NDWI) and Tasselled Cap Transformation (TC) are two appropriate ones. Using field data, they found TC more appropriate for this work. This transformation takes advantage of 6 bands of 7ETM+ sensor and is of the form [26]:

$$\begin{bmatrix} Brightness \\ Greenness \\ Wetness \end{bmatrix} = \begin{bmatrix} b1 & b2 & b3 & b4 & b5 & b7 \\ g1 & g2 & g3 & g4 & g5 & g7 \\ w1 & w2 & w3 & w4 & w5 & w7 \end{bmatrix} \times \begin{bmatrix} CH1 \\ CH2 \\ CH3 \\ CH4 \\ CH5 \\ CH7 \end{bmatrix} \tag{4.3}$$

where CH1 to CH7 stands for reflectance in bands 1 to 7 (excluding band 6 which is thermal). bi, gi, and wi are coefficients of transformation for brightness, greenness, and wetness respectively, and are shown in Table 4.3.

TABLE 4.3
Tasseled cap transformation coefficients for 7ETM+ sensor

Bands	1	2	3	4	5	7
bi	0.3561	0.3972	0.3904	0.6966	0.2286	0.1596
gi	-0.3344	-0.3544	-0.4556	0.6966	-0.0242	-0.2630
wi	0.2626	0.2144	0.0926	0.0656	-0.7629	0.5388

For the regions containing patches of the water body, wetness takes a value of greater than -0.0710. Applying this threshold to the image and again taking 2 kilometers flight zone for the mosquitoes around water bodies, figures 8 and 9 for Minab and Kahnooj were produced respectively. The detected water bodies in the Kahnooj image were as small as a pixel and consequently cannot be detected visually in the figure.

4.6 Land Surface Temperature

To calculate LST, the following equation suggested by the Landsat team is used:

$$T_s = \frac{k_2}{L_n(\frac{\epsilon_{NB} k_1}{R_c} + 1)} \tag{4.4}$$

where R_c is the corrected spectral flux density that reaches the sensor (W/m^2/μm), ε_{NB} is the surface narrow-band emissivity, k_1 and k_2 are constants equal to 666.09 (Kelvin) and 1282.71 (W/m^2/μm) respectively [27]. Applying equation (4.4) to the channel 6 radiance image, the surface temperature for Minab and Kahnooj was calculated.

4.7 Air Temperature

To calculate air temperature, the Surface Energy Balance Algorithm for Land (SEBAL) is used [28]. This algorithm consists of 25 modules where a combination of empirical formulas, synoptic data from nearby weather stations, and image extracted data (such as surface temperature) are being processed in these modules. Detail of this algorithm can be found in [28]. The SEBAL algorithm output maps for air temperature for Minab and Kahnooj are shown while the temperature range of 25°C to 35°C is imposed on the image (Figure 4.2). It can be seen that except in very small areas, the other parts of the region have temperature within the 25°C to 35°C zone.

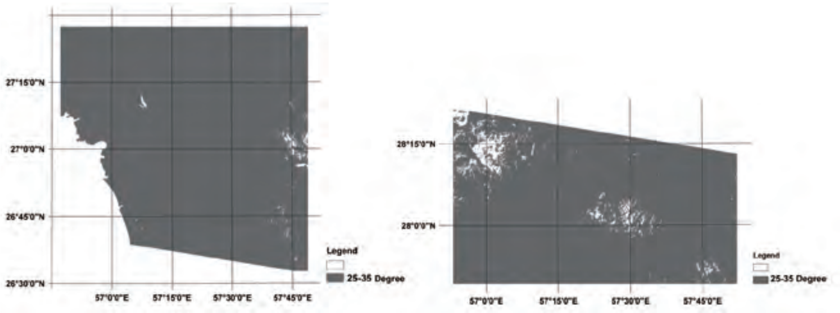

FIGURE 4.2
Satellite extracted maps of air temperature between 25°C and 35°C for Minab (left) and Kahnooj (right)

4.8 Relative Humidity

Using the calculated air temperature image in the previous step one can calculate the saturated partial water vapor pressure using the following equation [4]:

$$e_s = 6.1121 \times exp[(17.502 \times T_a)(240.97 + T_a)^{-1}] \tag{4.5}$$

where e_s is saturated partial water vapor pressure in millibar and T_a is the air temperature in degrees of Celsius. Then using partial vapor pressure e calculated from measured synoptic station data and assuming negligible horizontal gradient in e for the time of image acquisition, the relative humidity RH in the selected scene can be calculated using equation (4.6) below:

$$RH = e \times 100 \tag{4.6}$$

They produced maps of relative humidity (for 50% to 80% range).

4.9 Results and Analysis

Now all maps of parameters necessary for high-risk region determination are prepared. Since these parameters do not affect the mosquito's survival equally, then a simple overlying of these layers of information would not be appropriate and parameters such as temperature, humidity, water body, and vegetation must have different weighting coefficients. An unpublished work of suggested weighing coefficients of 0.35, 0.25, 0.25, and 0.15 for temperature, humidity, water body, and vegetation respectively. Having overlaid these layers using appropriate weighing coefficients, the resulted high-risk map is shown in Figure 4.3 where number 10 shows the highest risk.

Combining the incidence indices (Section 4.3.4) and Figure 4.3 helps compare between different calculated risk regions and calculated incidence index using field data (Figure 4.4). As can be seen, the highest risk regions can only be found in Minab. This degree of risk cannot be seen in Kahnooj mostly due to the lack of suitable humidity conditions.

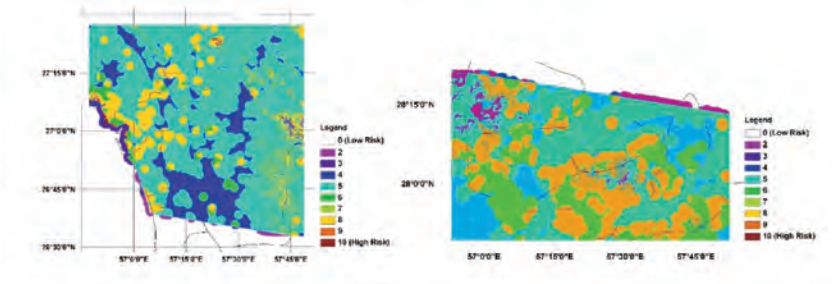

FIGURE 4.3
High-risk maps of Minab (left) and Kahnooj (right). Higher numbers represent higher risk regions

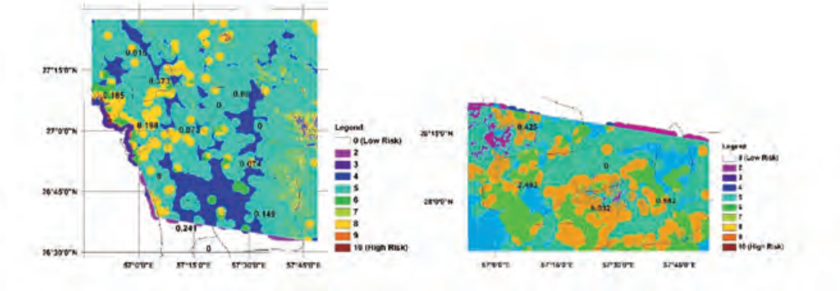

FIGURE 4.4
Comparison of different calculated risk regions (Figure 4.3) and calculated incidence index using field data. The zeros in the image are due to the lack of information for those regions.

4.10 Discussion

There are sources of uncertainties with the extraction of any layers of information from satellite images. The amount of uncertainties compared to the field data differ for different parameters. The uncertainties are due to the unknown surface emissivity values for LST extraction of up to 2°C, uncertainties in relative humidity of up to 3% due to the assumption of uniformity for partial vapor pressure throughout the sub-scene, and the uncertainty in the air temperature. The uncertainties in vegetation and water bodies mapping are of the second order of importance because these uncertainties can be included in the 2 kilometers flying zone already considered in the maps. Adding the uncertainties in LST and relative humidity to the lower and upper limits of temperature and humidity, the effect found was a small expansion around the potential area. Since this research aimed to show the high-risk potential area to the local manager for deputing mosquitoes exterminating group to these regions, a few meters away from the high-risk region will not make much difference.

It is found that one can predict the malaria outbreak by extracting environmental parameters necessary for mosquito's parasite life cycle. These parameters were temperature (25°C to 35°C), relative humidity (50% to 80%), patches of water, and vegetation covers. Regarding 10 degrees in temperature range and 30% in humidity range, as well as 2 kilometers flying zone for the mosquito, any intrinsic uncertainties in the extraction of these parameters from satellite images due to their resolutions and intervening atmosphere - which were the sources of concern for many satellite approaches - did not affect the results seriously. A weighed overlying of the four layers of information i.e. air temperature, relative humidity, patches of water bodies, and vegetated area showed acceptable agreements with the field-collected data. Of course, there are still some uncertainties involved with the weighing coefficients for these layers which call for further investigation. Also, there are other parameters such as shadows, manmade pools, pots of water, and many other factors that may help and affect the outbreaks which each must be considered separately. However, the satellite ability in the detection of high-risk potential regions may provide non-expensive information on a routine basis not only in malaria but for other epidemics as well, where studies in those areas are the aims of these authors.

4.11 Cholera Case Study

Vibrio Cholerae (VC), a bacterium autochthonous to the aquatic environment, is the agent causing Cholera, a severe aquatic, life-threatening diarrheal disease occurring mostly in developing countries. VC has many different types of serogroups, only two of which can cause epidemic cholera. Those two serogroups are called serogroups O1 and serogroups O139 (O139 is found only in Asia) and can cause epidemic cholera if they also produce the cholera toxin. VC, including both serogroups O1 and O139, is found in association with crustacean zooplankton, mainly copepods, and notably in ponds, rivers, estuarine, and coastal region globally. Cholera bacteria attach to zooplanktons (copepods), form thin biofilms in the brackish water especially in coastal regions. Since copepods feed on phytoplankton, the proliferation of phytoplankton increases the number of cholera bacteria. (Shafiqul Islam), a member of an interdisciplinary research team from Tufts University and National Oceanic and Atmospheric Administration, US. The incidence of cholera and the occurrence of pathogenic VC strains with zooplankton were studied in many areas.

If one can measure the density of chlorophyll and track the blooming of phytoplankton, the prediction of Cholera outbreak (mostly in endemic regions) seems possible. The satellite data on chlorophyll concentration could be used to routinely monitor coastal processes and track cholera outbreaks. The privilege of using satellite data is its suitable spatial and temporal coverage as well as low expenses.

Rahimi-Doab [5] conducted research on Cholera endemic regions. He claimed that the bloom or the flowering of phytoplankton, and as a result, the flourishing of the zooplankton and feeding are closely correlated with the temperature at the sea surface (SST). The SST can be continuously monitored through thermal channels of satellite sensors. By monitoring SST and measuring the seawater chlorophyll as a sign of plankton flourishing and knowing the amount of rainfall as an agent for the transfer of micronutrient materials from shore to sea, Rahimi-Doab (2018) could predict the disease outbreak one month in advance. However, the disease has its trend in each region and the peak of the disease in each region was different in terms of time and number of patients. This requires calibrating the suggested model for each region. In Rahimi-Doab's [5] work, the statistical analysis of the log-linear Poisson Generalized Linear Model (GLM) was used to predict the appropriate time for the growth of VC in the sea and its subsequent outbreak. For this purpose, the effects of three environmental factors i.e. SST, chlorophyll concentration of seawater extracted from the products of MODIS onboard of Aqua platform, and the rainfall data supplied by TRMM satellite, were all taken as independent variables and investigated. The case study region was the 2011 outbreak in Benin, Africa and the results showed that these factors were correlated to the disease outbreak in that endemic region.

Finally, the model was applied to the outbreak cases in the southern coastal regions of Iran. The model could predict the occurrence of the outbreak, one month in advance. Although the output of the model tells us the number of patients however, this number depends on the suitability of each of the three environmental factors, which are included as independent variables in the model.

4.12 Conclusions

The two aforementioned case studies showed that the environmental factors and parameters are playing a key role in the occurrence of outbreak and/or epidemic in many cases. This includes vector-borne diseases as well as viruses including COVID-19. All these environmental parameters are acquirable from satellite images. As mentioned in previous sections, COVID-19 and other similar viruses have shown some dependencies on some environmental parameters but, the main issue in these kinds of epidemics is the behavior of the patients affected or those who carry the viruses and spread it in the ambient. Our preliminary studies show that we might be able to classify different parts of the city based on the temperature, humidity, wind speed and direction, surface cover, height, and air pressure, and some other factors and compare these classes with the results of the affected people's population in those regions. The equation that could be the basis of this investigation can be of the form of equation (4.7):

$$COVID - CF = f(Ta, LST, RH, P, Vs, Vd, SC, H) \tag{4.7}$$

Where $COVID - CF, Ta, LST, RH, P, Vs, Vd, SC$, and H are COVID-19 Contagious Factor, air temperature at 2m height, Land Surface Temperature, Relative Humidity, air pressure, wind speed, wind direction, Surface Cover, and Height of the land on that region, respectively.

The work which is currently undergoing showed the dependence of the Influenza and to some extent COVID-19 outbreaks to the air temperature, humidity, wind speed and direction, and density of the population. The results, which will be published separately, may help to highlight the hotspots and inform the people regularly.

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5

The Potential of Drone Technology in Pandemics

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In recent years, drones or Unmanned Airborne Vehicles (UAVs) have become associated with aerial data and image acquisition for many environmental applications. Unexpectedly, the COVID-19 pandemic in 2020 has led to new opportunities for drones in many new application areas, with and without the use of remote sensing imaging technology. Many unique applications have already been proposed within a short period of time, some building on existing pre-COVID-19 demonstrations and ideas, to exploring new possibilities for use. Whilst drone technology is well-established, there are still factors requiring further investigation to fully exploit drones. These include: allocation, management and control of drone air space, operation Beyond Visual Line of Sight (BVLOS), the role of existing and new telecommunication networks, safe operation in built-up areas, and societal approval and acceptance. This chapter presents an overview of current drone technology and future developments and the exploration of some existing and proposed applications. The chapter will examine the issues facing successful mainstream implementation of the use of drones for these applications, and the problems that need to be overcome to allow this technology to mature and become mainstream.

5.1 Introduction

Drones or UAVs first became popular about six years ago when Parrot, 3DR, and DJI began to market their off-the-shelf platforms to the public. Categorised mainly as ‘toys’ at first these low-cost multi-rotor aircraft rapidly became very popular for recreational flying. Their widespread appeal soon grew as they became easier to fly and could carry small cameras. The addition of GoPro Hero cameras and DJI Zenmuse gimbals helped to facilitate and reveal the potential of these small airborne platforms and sensors for aerial photography and videography.

Although the future potential of drones for applications outside remote sensing and the derived photogrammetric and visualisation products we have become so familiar with were already under consideration prior to COVID-19, the widespread impact of the pandemic has triggered a rapid escalation in interest in the role of drone technology. Already the COVID-19 pandemic has provided a new opportunity to explore the potential role of drones in other application areas, both with and without the use of remote sensing technology. Many unique applications have already been proposed within a short period of time, some capitalising on existing demonstrations and ideas, to those exploring new possibilities.

Two streams of application have been considered: (1) delivering essential goods and services, and (2) battling the spread of coronavirus. Some examples already under development and testing include: the delivery of parcels, medical supplies, and information e.g. broadcasts; personal, health and environmental monitoring, enforcing social distancing, mapping, and spraying to disinfect.

Whilst drone technology is already well-established, there are still many factors that currently require further investigation to allow this proposed potential to be fully exploited. These include the allocation, management and control of drone air space, operation Beyond the Visual Line of Sight (BVLOS), the use of new telecommunications networks, safe operation considerations in built-up areas, as well as social acceptance. With this context in mind some of the existing and proposed applications that are either already under development or being developed will be explored. This will include an overview of current drone technology and future developments. The chapter will then look at the issues facing successful implementation of the use of drones for these applications, and the problems that need to be overcome to allow this technology to become mainstream in the future.

5.2 Developments in Drone Technology

Today there are a wide range of UAV and drone platforms which include multi-rotors (quadcopter (4), hexacopter (6), and octacopter (8)), fixed wing, and Vertical Takeoff and Landing (VTOLs). In addition, some small-scale helicopters have also been used for remote sensing. High quality gimbals now support a wide range of DSLR cameras of varying different sizes, and additional camera-based sensors, such as NIR and NDVI cameras. Larger cameras and sensors can be carried by bigger drones with the required lift and battery capacity.

There are now many more options for sensors that can be mounted on small aerial platforms. Whilst RGB cameras are generally still in widespread common use, the demand for other sensors, both non-imaging and imaging, and low-cost, higher resolution systems has seen many other types of cameras/sensors become available. These include modified GoPro cameras and similar types of miniaturised cameras that can be filtered to sense the Near Infrared (NIR) and other portions of the Electromagnetic Spectrum (EMS). Examples include the range marketed by MapIR [1] and IR-Pro in the USA. Alongside these have been developments in small multi-spectral sensors specifically aimed at agricultural, horticultural crop and forest canopy monitoring. The Parrot Sequoia 5-band multi-spectral camera is one such example [2]. A larger version of this sensor, is the MicaSense RedEdge [3]. These provide the opportunity to acquire five (5) bands of imagery, and also to generate NDVI images. Other companies such as Sentera (www.sentera.com) also provide NDVI cameras based on different spectral wavelengths.

More advanced sensors are now also available to take greater advantage of the information content of the electromagnetic spectrum including thermal, hyperspectral, and Lidar instruments. Many drone manufacturers offer thermal camera-ready platforms with either their own thermal cameras e.g. Yuneec [4] and DJI [5] or ones made by a thermal camera manufacturer e.g. FLIR. Hyperspectral cameras are available for drones from a number of different manufacturers e.g. Headwall [6]. These can be useful in many applications because of the number of wavelengths that can be sensed (e.g. up to 255 channels) greatly increasing the dimensionality of the spectral dataset and resulting in the potential acquisition of more information of interest. These are expensive, often need specialist aerial platforms, and require more training to use and to extract the information. Another common sensor is Lidar (both terrestrial and bathymetric versions) which can be mounted on a number of specialist UAV platforms e.g. Riegl [7]. Terrestrial lidar has the potential to see through a vegetation canopy. Bathymetric lidar sensors can be mounted on small aerial platforms and have the capability to generate depth information in water 20-40m deep providing the water is clear and not too turbulent e.g. Riegl's Bathycopter [8]. These also have the capability to generate 3D information of underwater surfaces.

Radar systems have also been integrated into large UAV systems for navigation and image acquisition. More recently, studies have revealed success with the development of small, low-cost, high-resolution radar systems specifically designed for operation on small unmanned aerial vehicles [9–11].

In a very short period of time, drone technology has evolved from being quite basic to very advanced and increasingly customised for specific environmental applications. Several key developments in the technology have facilitated this transformation.

One of the major constraints of early platforms was the available battery technology. Early batteries provided a limited power source often only giving 6-8 minutes of flight time. This was not a major drawback for short recreational flights, but when including considerations such as operation in colder air, wind strength, and take-off, return to home, and landing requirements, the actual flight duration time was reduced quite considerably. Within a few years, however, these basic batteries have evolved into smart batteries that not only provide longer flight times e.g. 20-25 minutes, but also supply information to the controller and operator about battery status and remaining flight time. Within a few years these batteries have also become more compact and the average flight time has now increased to around 30 minutes. Considerable effort is now being put into improving the quality and battery life, as well as the development of new types of batteries [12], especially for multi-rotors. Fixed-wing aircraft by contrast typically already have longer flight times, ranging from 45 to 55 minutes, as they are lighter and offer less resistance in flight, making them more suitable for larger area coverage.

Early UAVs were usually flown manually by the pilot, often without an First Person View (FPV) device, and stereo-imagery was acquired through skilled flying by the drone pilot where overlapping flight-lines were visually assessed to provide the required stereo-imagery for generating photo-mosaics and 3D models. Today sophisticated phone and tablet Apps for both Android and iPhone operating systems, either provided by the drone companies (e.g. DJI Go4) or third party companies (e.g. Litchi [13], and Pix4D [14]), allow for varying levels of autonomous flight to be planned and executed. The phone and tablet Apps now available allow for either very basic simple autonomous flight (Litchi) or more sophisticated grid pattern flightpaths (Pix4D) to be conducted that allow the pilot to customise the overflight pattern e.g. straight line or grid, the camera tilt, speed, and the flying height of the aircraft amongst other things. Over time, the data/image capture task has now become a one-button 'push' for take-off and one for landing. The technology has therefore made it much easier to conduct repeat flights of the same area to gather multi-temporal imagery of a site. Nearly all modern drones now have autonomous flight capability, and this in turn allows them to be used for more advanced aerial survey tasks.

Additionally, some drones (e.g. the DJI Mavic Air 2) now come equipped with the new AirSense technology utilising ADS-B aviation technology for receiving signals from nearby airplanes and helicopters and displaying their locations on the on-screen map on the DJI Fly App [15].

Not surprisingly the growing number of different UAVs and the range of applications is already beginning to raise concerns about the availability and safe use of air space particularly where other industry areas will also be affected by competition for the existing air space. This will ultimately require legislation. UAV communication with the ground control system (GCS), for example, requires radio frequencies with sufficient band width. As recently as 2008, the International Telecommunication Union (ITU) had not allocated bandwidth to UAVs meaning that they have to use different radio frequencies in every country [16], something that needs to be taken into account by international operators and manufacturers.

Several drone capture methods have also been developed either to physically capture drones in a net or through 'drone snatching' using another drone in situations where illegal flights are being conducted or in emergency situations [17, 18]. All weather drone operation is now being developed and delivery drones are already able to safely operate in heavy rain and high winds [19].

5.3 The Impact of COVID-19

Prior to the COVID-19 pandemic, although drone technology was already well-established with many professional applications worldwide there were already a number of new ideas emerging for their use in a wider range of imaging and non-imaging applications.

At the time, drones were also increasingly coming under scrutiny because of the increasing occurrence of operational incidents. Though not all were substantiated, some accidents nevertheless began to have a negative impact on the perception of this technology leading to alienation of the public from supporting the continued growth of this industry. In part this was a direct result of the rapid growth in uncontrolled use of both commercial and recreational drones, with a lack of pilot training and enforcement of regulations. However, responses to concerns about privacy and safety also had many positive developments leading to improved technology, education and awareness raising, training, best practice guidelines and tighter regulations that have since helped to allay some public concern.

The COVID-19 pandemic, however, rather suddenly and unexpectedly triggered growing recognition and a new level of acceptance of drone technology, driven not so much by the increase in commercial uses prior to the outbreak of COVID-19, but by the timely emergence of new ideas that have highlighted drone technology as an important way to help deal with and, possibly even overcome, the constraints and health emergencies imposed on society by the virus in early 2020. In addition, the collection of higher resolution data that can be processed and integrated with other information for planning and decision-making.

Two new streams of application have been pursued: (1) delivering essential goods and services, and (2) battling the spread of coronavirus. Some examples already under development and being tested include: the delivery of parcels, food, medical supplies, and information e.g. broadcasts; personal, health and environmental monitoring, enforcing social distancing, mapping, and spraying to disinfect contaminated areas. These are explored below.

5.3.1 Delivering Essential Goods and Services

Prior to the arrival of COVID-19, numerous articles and press releases revealed a growing commercial interest in the use of so-called 'delivery drones' for the delivery of parcels, supplies, food. and drink. It has been predicted that by 2030 the drone package delivery market will be worth £21bn [20]. Similar forecasts have been made by others about the impact of this technology e.g. by 2026, more than a million drones could be carrying out retail deliveries, up from 20,000 today, according to new analysis from Gartner [21].

Amazon and a number of other companies were originally at the forefront of promoting these ideas, and successful demonstrations had already been carried out as proof of concept. Prime-Air, for example, was first trialled by Amazon in 2016 to demonstrate parcel delivery within a 30 minute timeframe [22]. Prime-Air development centres were set up in the United States, the United Kingdom, Austria, France and Israel. Research studies showed that drone platforms already available – albeit larger than some of the more familiar recreational drones – could easily be adapted and modified to carry small boxes and containers. Coupled with new autonomous flight capability it has since been shown possible to programme a drone to carry a cup of coffee or a meal from point A to point B. Larger platforms were also shown to be capable of carrying larger payloads such as parcels. DHL also launched drone operation tests in urban areas in China to test the so-called 'last-mile' delivery challenges being considered. Compared to road transport, the benefits of autonomous drone services were found to be significant and included a reduction in delivery times, and provided cost savings, reduced energy consumption, and a lower carbon footprint [21]. In addition, such drones were able to provide faster delivery for customers with the added benefit of giving consumers more control over the time and location of a delivery [19].

The capability of larger drones to carry boxes also opened up the possibility of carrying supplies to remote and inaccessible locations (e.g. in the event of an emergency or for delivering medical supplies) where timing is often important. Several trials have been undertaken and revealed the potential to expand drone-based deliveries to more applications. For example, in Canada, they have been delivering supplies, including medical supplies, to native communities in places where there are a lot of small, remote reserves far from resource hubs [23].

However, despite the potential there are many drone-related issues that require early solutions to allow for the practical realisation of these ideas in the future e.g. the establishment of an air traffic management system. In addition, there have been some concerns that drones maybe the target of 'hackers' who may be able to take control of a drone and steal the goods being carried.

Meantime, on a more positive note these ideas and developments have also begun to find favour with roles that might be useful to help deal with the actual and perceived impact of the COVID-19 pandemic.

The collection of high-resolution spatio-temporal data can provide the means to generate real-time information e.g. images, maps, and surveys at the community level to assist in planning and decision-making, as well as for use in an emergency response both during and after an event.

A recent report in 2020 highlights the opinion that the pandemic will be 'a catalyst for accelerating the viability and acceptance of commercial drone deliveries' [24]. 53 per cent of companies who took part in a recent survey believe commercial drone deliveries will be commonplace by 2023, helped by the public and private sector actively seeking to develop safe ways to guarantee services whilst containing the spread of any viruses [24].

Drone delivery has the potential to provide people with low-cost and near instant access to vital medical supplies, regardless of whether they live in a city or a rural community. Benefits arising will be in helping to manage chronic health conditions, enabling more home-based acute care, and reducing the number of hospitalisations and trips to accident and emergency rooms [19].

Drones have been used to deliver medical supplies in the Dominican Republic [25].

5.3.2 Battling the Spread of Coronavirus

Aside from using drones being used to carry goods, many drones are also equipped with cameras, microphones and speakers and so can be used for monitoring and to both gather and deliver information. In this respect they will utilise existing functionality that has not necessarily been used in this way before.

An area of application where there is now immense potential for drone use lies with personal, health and environmental monitoring, enforcing social distancing, mapping, and spraying to disinfect. These are all ways where drones may help to reduce the spread of the corona virus. As drones typically carry cameras - whether RGB colour or thermal - they can be used both indoors and outdoors as a remote monitoring platform.

The growing use of custom-built drone platforms carrying thermal cameras to monitor heat loss from buildings, for firefighting applications, and is also being proposed (and has already been used) to help monitor the health of people where temperature can be used as an indicator of possible infection from the corona virus. The benefit of having an airborne platform is obviously that it is in the air, far from contacting humans and can still return accurate results [26].

In Canada, Draganfly is adapting scanning technology for drones to combine thermal imaging systems and a computer program with learning algorithms to monitor temperature, heart and respiratory rate at a distance to aid in the detection of someone sneezing or coughing, and can be used for screening [27].

This is basically an extension of the more traditional use of cameras for remote sensing of surfaces that provides imagery for automated or manual interpretation. Some commercial drones (e.g. the DJI Mavic Enterprise) also carry loudspeakers that can be used to communicate information to individuals on the ground with one application being the provision of messages to help enforce social distancing in public spaces. The use of drones to communicate information and messages can also be used in many other environmental monitoring or situation scenarios. Having a remote video platform that can both record and broadcast live is a much better alternative than putting someone at risk to film by hand. You also get a more holistic picture, and can easily document dangerous gatherings from a distance without having to get close to people who are violating the pandemic regulations.

The capability to carry a larger payload also allows drones to carry other materials and equipment. One example, which is an extension of the application of drones for spraying crops, is the use of drones to carry disinfectant and spray equipment to disinfect environmental locations or internal rooms. Cities have also been using Drones such as DJI's agricultural drones to spray disinfectant on an area, which is a lot more cost-efficient than employing a team of workers using expensive and equipment to spread disinfectant by hand on the ground [28, 29]. In Scotland, a UK company Droneports has recently demonstrated the capability of drones being used to support the NHS by delivering COVID-19 test kits and medical supplies to an island off the coast of the

Scottish mainland. The demonstration showed how supplies could be delivered more quickly to the island than the normal route used by road and ferry [30].

Similar trials, which are now being fast-tracked in light of the pandemic, have also been reported in other parts of the UK [31].

During the COVID-19 crisis, drones have already been used to deliver medication and test samples in other remote locations in Ghana, Rwanda, and Chile. In Charlotte, North Caroline, USA, drones have been used to deliver personal protective equipment and supplies to frontline medical teams. This initiative was part of the North Carolina Department of Transportation's (NCDOT's) Unmanned Aircraft System Integration Pilot Program (IPP).

Unmanned aerial vehicles have also been used in several cities around the world to monitor compliance with virus-related safety measures as well as to spray disinfectant e.g. in India and China [21]. China was in fact one of the first countries to use drones in response to COVID-19 and as early as February 2020, Antwork - part of the Japanese group Terra Drone - used a drone to transport test samples and medical supplies from a local hospital in Zhejiang province to a nearby disease control centre. In 2019, Antwork were the first urban drone delivery company to obtain a license from the Civil Aviation Administration of China (CAAC). Some of the benefits arising from this demonstration were that the transport time was halved, and this in turn was found to relieve stress on medical staff.

In April 2020, Manna Aero were approved by Ireland's aviation authority to deliver medication and critical supplies to roughly a dozen households under confinement. In Switzerland, Matternet - a US company - had already been cleared to carry out autonomous, beyond-the-line-of-sight flights for the transport of blood samples between hospitals in the city of Lugarno. Another US-based drone operator, Zipline supported Ghanaian authorities by providing a 'contactless drone delivery' service to collect Coronavirus test samples from 1000 rural health facilities and to deliver them to laboratories in Accra and Kumasi [32]. These are just a few of the practical demonstrations that have already been developed to highlight the potential of autonomous aerial technology to assist in emergencies.

Other mentioned uses of drones include the delivery of non-medical products such as groceries and other food supplies to people and communities, and to extend the already well-tried data acquisition role that they have been demonstrating in the field of mapping, which sees drones providing real time imagery for emergency response and near real time mapping. The extension of the mapping role to areas that have not been mapped at certain scales also has potential in the context of COVID-19.

(a) (b) (c)

FIGURE 5.1
a) A Quadcopter Drone Lifting a Bag (Billy J. Gregory - DroneLite); b) Monitoring urban areas during lockdown (Alex R. Karachok - UCEMM); c) A thermal camera image (Billy J. Gregory - DroneLite)

5.4 Summary and Conclusions

Drones began as recreational toys, a modern-day, updated radio-controlled model aircraft but with the added benefits provided by the evolution of the technology. Recognition of their potential for many commercial applications soon raised the public profile of drones and their many uses. However, various incidents with drones involved in injuries and near misses with civilian aircraft have somewhat dented the positive perception of drone technology with the public threatening to derail future growth of the market.

With the sudden and very significant impact of COVID-19 worldwide and the need for monitoring, mapping, and social distancing to minimise contact between people and to help reduce the spread of infections, robotic technologies were soon recognised as one way by which many aspects of the pandemic could be monitored and assisted. As a direct result of this, drone technology is gradually beginning to find growing support although it is still true to say that a number of issues are still a cause for concern.

The practical experience gained so far during the COVID-19 pandemic has been both stimulating and has undoubtedly paved the way for developments needed to make better use of drone applications in the future. Furthermore, lessons learned during the crisis and from examining the use-cases that have proved to be of societal benefit during the corona virus crisis will very likely encourage updates to drone regulations that go beyond the use of drones in times of crisis enabling the wider use of drone technologies in the future.

The ability to enhance the collection of up-to-date high resolution data over both space and time using drones (aerial, terrestrial, or waterborne) will provide a basis for more detailed information that can help emergency response and planning teams in the context of building community resilience frameworks in the future.

However, significant developments in the technology are still needed to overcome some of the public concerns and to allow drone applications to reach their full potential. This includes major advances in existing telecommunications, air traffic management systems, and regulations amongst a number of other things.

Being at a stage when we are now already able to successfully utilise and adapt current drone technology to conduct numerous activities safely and remotely has been very timely in light of the COVID-19 pandemic.

The progress made during this pandemic will undoubtedly help society to function more safely and more effectively during times of crisis in the future whereby drone technology will be able to provide the data and information needed to assist in an emergency response, whilst also being able to assist communities to build future resilience.

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6

The Role of Neighbourhood Social and Built Environments on Social Interactions and Community Wellbeing Through the COVID-19 Pandemic

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This chapter looks at the role of social and built environments on social interactions in Melbourne prior to, and during, the COVID-19 pandemic and discuss possible social and built environment interventions to increase social interactions. Melbournians have experienced two COVID-19 waves of infection and two lockdowns since March 2020 and faced severe physical and social distancing restrictions. These have increased the importance of local amenities and neighbourhoods, but also the need and skills to use telecommunication services for different social (and work related) purposes. Lockdown periods provide an opportunity to upskill peoples' technical skills that can be used after the pandemic to access more resources and create balance between online and face-to-face social environments. Possibilities in urban planning to repurpose the built environment and use technology to utilise local neighbourhoods are discussed. These proposed changes in social and built environments may be beneficial in dealing with future pandemics.

6.1 Introduction

Studies show that social interactions improve people's wellbeing, satisfaction with life [1], happiness [1], mental health [2], physical health [3], longevity [4] and reduce psychological distress such as anxiety [5, 6]. Social interactions contribute to increased sense of purpose, belonging and self-worth [2, 7]. These kinds of contributions motivate people and encourage them to take better care of themselves (e.g. to engage in physical activity or reduce alcohol intake) which lead to improved mental health [2]. Lack of social interactions, on the other hand, has been found to reduce quality of life, wellbeing, mood ([8, 9] and health outcomes (such as insomnia, depression, dementia and suicide) and increase unhealthy behaviours (such as smoking, drinking alcohol, having unhealthy diet) [10].

As soon as the World Health Organisation (WHO) [11] announced that COVID-19 is a public health emergency of international concern, in response, many countries imposed restrictions such as social distancing, isolation and stay-at-home requirements. These types of restrictions may lead to loneliness and boredom [12]. Social isolation is opposite to social connectedness and has found to be related to psychological distress, such as anxiety [6, 13], depression, stress [6, 13] and loneliness [13]. Indeed, quarantine during the SARS outbreak in 2003 ([14], as cited in [13]) and the swine flu outbreak in 2009 ([15], as cited in [13]) was associated with increased depression and anxiety. Tull et al. [13] studied stay-at home restrictions and daily changed routines due to COVID-19 pandemic with mental health outcomes (n=500) in the United States. They concluded that the restrictions were associated with health related anxiety, financial worry and loneliness. Smith et al. [6] investigated the relationship between social isolation and mental health outcomes during COVID-19 pandemic (n=278) in the Unites States. They found statistical relationships between the two and concluded that higher psychological flexibility and ability to accept difficult experiences helped to reduce the negative effects of social isolation [6].

Social capital, which is formed by strong and weak social networks, is found to be necessary in effective crisis response and recovery [16]. McCrea et al. [17] found that social and amenity dimensions were the main contributors of community wellbeing, that in turn, contributed towards community resilience. Communities with higher level of social capital, for example, were found to recover faster and in a more satisfactory and sustainable fashion from earthquakes than communities with lower social capital levels [16, 18].

This chapter aims to look at the role of social and built environments on social interactions in Melbourne prior to, and during, the COVID-19 pandemic and discuss about possible social and built environment interventions during and after the pandemic to increase social interactions. The discussions follow the main phases of COVID-19, as shown in Figure 6.1 for Victoria, Australia.

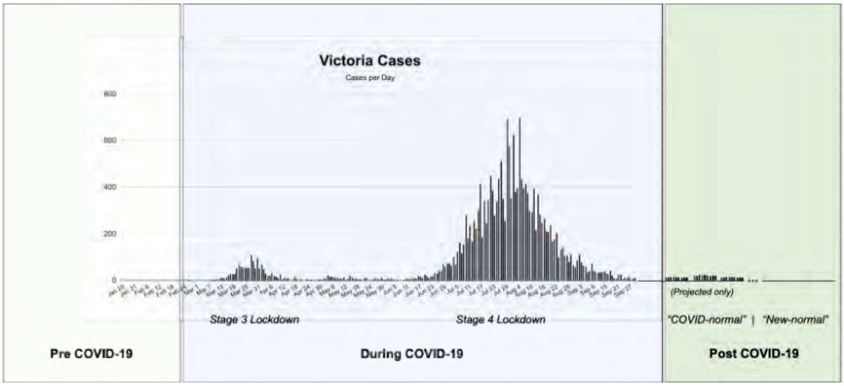

FIGURE 6.1
The Main Phases of COVID-19 Cases in the State of Victoria, Australia (Main data plot from: https://www.dhhs.vic.gov.au/victorian-coronavirus-covid-19-data)

6.2 Pre COVID-19

A previous study found that perceived social environment and especially feeling of belonging, sense of community and participation in community activities were more important to older Melbournians' (aged 55 years or above, n=476) local social interactions frequency than perceived and objective built environment measures [19]. Additionally, the importance of some types of perceived destinations for local social interactions were distinguished, such as cafes, bars and restaurants and footpaths. Looking at local social interaction satisfaction, the results were similar. Social interactions frequency, feeling of belonging and sense of community were social environment elements that contributed to older adults' local social interactions satisfaction. Perceived importance of local services for social interactions, however had a negative relationship with social interactions satisfaction [19].

Socioemotional selectivity theory explains that peoples' social networks are changing over time [20]. Younger people' s social interactions are claimed to be future-oriented with the aim of gaining information, experiences and new social contacts [21]. Older people, on the other hand, have been found to prefer smaller, but emotionally meaningful and satisfying contacts [21]. It is thus expected that the importance of social and built environments in social interactions frequency and satisfaction is different in different age groups. Therefore, a follow up study that included younger, middle aged and older Melburnians were carried out. Surprisingly, the study reached similar conclusions across different age groups [22].

6.3 During COVID-19

6.3.1 Social and Physical Distancing Restrictions in Melbourne

The Victorian premier announced a State of Emergency in mid-March 2020, and on 30 March, Victoria entered a Stage 3 lockdown (see Figure 6.1). This meant that Victorians had only four reasons to leave home: shopping for food and supplies, (essential) work or education, exercising or caregiving. Restaurants, bars and coffees were allowed to be open for take-away only; beauty, personal services, entertainment, culture and sporting venues were closed. These restrictions started to ease in the beginning of June. Shortly after the ease of restrictions, the number of COVID-19 cases rose and in the beginning of August Victoria entered a Stage 4 lockdown (Figure 6.1). Additional social and physical distancing measures were introduced in this stage: curfew from 8PM–5AM (unless seeking or giving care or essential work), Victorians were allowed to shop (once a day, one person per household) and exercise one hour per day (maximum two people) in 5 km radius from their home. By the time of writing this chapter, Regional Victoria has entered to Stage 3 lockdown and some of the Stage 4 restrictions have eased for Metropolitan Melbourne (e.g. curfew is lifted) [23].

Previous studies have found that destinations (such as parks and nature strips, shops, services, cafes/bars/restaurants and community places) encourage peoples' local social interactions [24–26]. The Stage 3 and Stage 4 restrictions in Metropolitan Melbourne (and in the rest of the Victoria) have increased the importance of local destinations (especially after applying the five-km rule). People are more than ever dependent on their neighbourhoods and presence of local amenities. For instance, inhabitants who live in a close proximity to a park (or any other type of natural environment) or are able to access footpaths that are continuous and have even surface may be better off in terms of physical and mental health than those who are not able to access these types of amenities.

6.3.2 Social Interactions During the Pandemic

The COVID-19 pandemic may have adverse personal impacts, such as worrying about catching the virus, experiencing partial or full loss of income, worrying about job or housing security, uncertainty, home schooling, increased risk of family violence, and other mental, physical and social pressures caused by the lockdown and the resulting isolation. All these factors combined can lead to mental health crisis that in turn may lead to long-term problems in wellbeing, productivity and healthcare costs [27]. Social contact and support from family and friends and community are especially important in times like these. In May 2020, the United Nations (UN) warned that the COVID-19 might turn into mental health crisis [28] and reported an increase in levels of distress that causes misery due to the COVID-19 virus and emphasised the importance of the international community to support peoples' mental health during the pandemic [29]. A study of three cities in different countries in Latin America (n=650) found that about one third of the participants missed face-to-face social interactions the most, when asked about the activities people miss due to the COVID-19 restrictions [30].

Fisher et al. [31] found that about a quarter of Australians experienced mild to moderate depressive symptoms or anxiety on the first month of COVID-19 restrictions. In 2020, there has been 66% increase in lifeline support calls compared to the previous year and two third of the calls were made by Victorians [32]. Alfred Hospital Crisis Assessment and Treatment Team have faced 50% increase in callouts after the first lockdown in March 2020 [33].

The Australian Government has provided an additional $500 million in mental health and suicide prevention funding to assist in coping with the COVID-19 pandemic since January 2020. The Government provides several free-of-charge or low-cost telephone and telehealth services, such as Lifeline, Kids Helpline, Beyond Blue, Suicide Call-Back Service, MensLine Australia, Open Arms – Veterans and Families counselling, and HeadtoHealth services for Victorians. Citizens and permanent residents can access 10 additional subsidised psychological sessions to face mental issues caused by the pandemic. For older Australians, the Government has established the Older Persons COVID-19 Support Line (phone support) and Community Visitors Scheme (telephone or online). The latter connects older adults with volunteers who spend time with them during the pandemic; but face-to-face visits are replaced with telephone or online contacts [23].

Direct face-to-face social interactions and the use of neighbourhood social and built environments (and amenities) were minimised during the first lockdown and further restricted during the second lockdown in Melbourne (Figure 6.1). During the second lockdown, the majority of Melbournians were allowed to have face-to-face contacts with people from their own households (and other neighbourhood contacts such as when grocery shopping or ordering take-away coffee when adhering social and physical distancing rules). Therefore, the importance of virtual social environment was more important than ever before.

Telehealth services, however, can only be accessed when people have the ability and opportunity to use the technologies. The less skilled Internet users may become increasingly disconnected from the society and miss out on the digital support sources [34]. More than 2.5 million Australians are not online [35]. Digital inclusion requires access to high quality and affordable Internet service, hardware and sufficient data allowance, and ability and skills to use the technology. The Australian Digital Inclusion Index [36] shows, for example, that Australians with lower income, education, and employment levels; and adults aged 65 years or older are less digitally included [35]. Moreover, about 2.7 million (34%) Australians aged 50 years or older have low digital skills or they don' t use the technology or the Internet [36]. More than half (57%) of people aged 70 years or older have low digital skills and 74% of them do not use the Internet [36].

Gorenko et al. [37] recommended considering older adults' (and other socio-demographic groups) personal preferred remote communication methods and pre-pandemic technological literacy skills when providing interventions and improving technology using skills. These could include using technology that older adults are comfortable with (e.g. telephone), providing print materials with instructions, reminders and tips, and/or involving a household member or caretaker to explain/help to set up, use and/or troubleshoot the technology [37].

The internet, social media and other mobile applications are replacing traditional media and have both positive and negative effects [38]. The use of social media and the Internet may contribute to 'infodemic', which is information overload [12]. Banerjee and Rai [12] for example, describe COVID-19 as 'digital epidemic' where all sorts of information (including false information) about the virus travels faster than the virus itself. They recommend practicing social media distancing [12]. This means that while it is crucial to increase technical literacy in different age and demographic groups, then it is necessary to include information about where to find and how to control reliability of information/sources and understand the ethics or values underpinning specific artificial intelligence (AI) applications.

Another way to increase peoples' social interactions during the pandemic could be to set up virtual physical health programs that accommodate for different physical abilities and help people to stay active; provide online courses and classes; encourage volunteering in different programs [36, 39] or send out letters and greeting cards for those who are not technologically advanced [36, 39]. Mariana Atkins and Baldassar [36] proposed to establish a buddy system where (older) adults can regularly check in and communicate with volunteers, or those with good technological literacy skills can help to set up and teach others' who are less skilled. This sort of volunteering enables people to feel they are helping others and may help to reduce their own feeling of isolation [39]. Office et al. [40], for example, investigated a phone outreach program (n=14 volunteers, 25 calls) where medical students called to older Americans during the COVID-19 pandemic. The volunteers described the calls as impactful for the students and call recipients [40]. Community and religious groups could set up regular online/telephone meetings to share information and explain it, give health and mobility tips [36].

Gehl [41] observed changes in using public spaces during the pandemic in Denmark. They found that downtown activities were dropped, but the use of public spaces is similar as before the pandemic and places that offer activities (e.g. playgrounds) were used more than ever before [41]. This differs from the Melbourne context, because the use of public spaces (e.g. playgrounds, benches) was restricted. After easing some of the restrictions, small groups of people were allowed to have picnics in Melbourne. Inspired by the New York 'social distancing circles', similar circles were drawn on the grounds of some popular parks in Melbourne, so the groups who use the park are able to stay further than 1.5m from other groups [42].

6.4 Post COVID-19

It is important to learn from the current pandemic and keep upskilling peoples' technological literacy and provide access to sufficient and affordable technology. This helps to ensure that people are able to access virtual social environment if the COVID-19 virus lingers on in the community or a similar situation occurs again in the future. Virtual social environment does not replace face-to-face community social interactions, but it may open an opportunity for members of society to be more effective, knowledgeable, resourceful and participatory in events that happen in physically distant locations. Some scholars propose that partially transforming to telehealth (e.g. mental and physical health issues, support group meetings for substance users, therapy sessions with councillors, outpatient programs, medication management programs) may be beneficial for patients and clinicians [27]. The future community social interactions may be a combination of face-to-face community social environment and virtual social environments (more accessible than it was before the pandemic). A future study could investigate the best ways to balance these modes of communication to ensure the best health and wellbeing outcomes.

Florida et al. [43] argued that historically, pandemics (e.g. Hispanic flue, plague) have always spread in cities (New York, London, Paris) and discussed about the ability of cities to bounce back after the virus. He argued that vulnerable people and families may be moving to suburbs, but cities will attract job seekers with higher number of jobs and salaries, and with more affordable rents than before the pandemic [43]. Joel Kotkin [43] added that cities may need to change crowded public transport with safer options (such as utilising autonomous vehicles), and it is critical to develop suburbs that produce lower emissions, provide working-from home opportunities, and lower commuting times. The provision of a metro-wide network of dedicated bicycle lanes has also attracted the attention/interest of many urban stakeholders.

The importance of the built physical environment may increase after the pandemic, and it might have a huge role to play in adjusting to the new 'COVID-19 normal' environment (Figure 6.1). Since the beginning of the pandemic, people have been asked to physically distance themselves from others. This means that urban planners need to think how to increase the amenities and infrastructure and decrease car-dependence [44]. Some urban planners and architects, however, see the opportunity in reduced use of city spaces due to COVID-19. This situation could be a turning point in how we use and think about cities. Jonathan et al. [45] see it as an opportunity to repurpose city streets for people to promote walking and cycling and create safe and attractive streets and cities or to convert street parking lots to places for street socialising. The restrictions have also further encouraged and strengthened discussions around 20-minute/15-minute cities. The concept has been proposed in Plan Melbourne [46]. These concepts refer to an idea that cities are polycentric and residents are able to access everything they need (e.g. employment, education, shopping, recreation) within 20 (or 15) minute walk, bike ride or via safe public transport from their home [47]. This sort of development, however, may mean more high-rise buildings in the areas, which may not be desirable in the future when planning for pandemic, as inhabitants would need to share lifts and common areas [48].

Chen et al. [49] propose that robotics (drones, driverless vehicles and service robots) and AI may be more useful than ever before. They concluded that facial-recognition software may offer new ways for aerial, ground and checkpoint territorial control, while admitting the possible problems with public safety, privacy and control [49]. Autonomous goods deliveries, drone transports, access to places via QR (or similar) codes and biometric screening to identify residents with high temperatures may be future solutions in urban environments if a similar pandemic occurs [49]. But these technologies require strong social acceptance and robust regulatory frameworks.

6.5 Concluding Comments

Social interactions with family, friends and the broader community are especially important for positive mental health outcomes, personal and community wellbeing during a pandemic. The use of social and built environments (and especially local destinations and amenities) have changed due to the COVID-19 pandemic. Telephone and Internet services are crucial to provide satisfying social environment, maintain social relationships with family, friends and community, and exchange information during these times. People with low income, education and employment levels and older adults, however, may not have enough means and/or skills to access these. Targeted or alternative solutions are needed, such as upskilling these societal groups to use the technology and provide affordable access to the Internet and technology during and post pandemic times. Finally, it is important to consider possibilities to repurpose and/or adapt existing built environment, better plan new ones and introduce more accessible technological innovations. Improved social and built environments may function as an opportunity for urban neighbourhood communities to recover faster via building local social capital and improved resilience when dealing with future pandemics.

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7

Social Vulnerability to COVID-19: Preliminary Indicators and Research Agenda

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Disease outbreaks and epidemics, similar to natural hazards, affect different socioeconomic groups in different ways. Understanding the varying degrees of vulnerability across socioeconomic groups, commonly referred to as social vulnerability, can lead to enhanced decision making and better resource allocation in a pandemic situation like COVID-19. This chapter reports on a study which aims to contextualise social vulnerability to pandemic situations in the wake of the COVID-19 pandemic. By building upon the existing literature and novel observations made during the pandemic, the study attempts to identify the preliminary indicators of social vulnerability to pandemics. Consequently, three main components of social vulnerability to pandemics are identified: societal determinants, built environment determinants, and individual characteristics. The latter two are discussed in detail. The chapter ends with a discussion of the implications and limitations of the study and outlines a research agenda for further work.

7.1 Introduction

Though not as frequent as natural hazards, disease outbreaks and epidemics do occur and leave behind a trail of death, destruction, and devastation. In that sense, epidemics can be thought of as natural hazards, posing public health threats and causing emergencies in the same way as earthquakes or hurricanes [1]. However, biological hazards and pandemics seem to recognise no boundaries, no particular groups, and no exceptions. Pandemics, as evidenced by the recent COVID-19 outbreak, lead to significant and long-lasting disruptive and traumatic consequences of a different nature, dynamic, and severity, compared to those of non-biological hazards. For instance, while disasters such as earthquakes and floods can inflict substantial immediate loss of life and harm the economy, mainly due to physical and infrastructural damage, epidemics cause no direct physical damage to structures or property. Instead, they pose enormous threats to humanity in terms of public health, morbidity, and mortality, as well as multifaceted socioeconomic losses due to the resultant confinement, social isolation, and suspension of economic activities.

Like natural hazards and environmental shocks, epidemics are likely to affect various demographic groups disproportionately. Lessons learned from past disasters around the world demonstrate that one's personal, social, and contextual attributes play an essential role in how one prepares for, responds to, and recovers from hazards and disasters [2–4]. The notion that the same disaster is experienced in different ways by different socioeconomic and demographic groups is generally regarded in the disaster literature as "social vulnerability" [5–7]. The development of methods and indicators to identify groups that are more susceptible to complications from health pandemics can result in better prioritisation of the response strategies, and effective resource allocation by the government and health authorities.

While the use of the term "social vulnerability" in the scientific literature can be traced back to the 1970s (e.g. [8]), it was after the mid-1990s that the concept came to be widely used in the disaster management domain [3, 5, 9]. This means that most of the systematic attempts to conceptualise, define, and measure social vulnerability in a disaster context are relatively new in many ways and are still in their conceptual or methodological adolescence. Moreover, the vast majority of the studies conducted in this area are primarily concerned with social vulnerability to natural and environmental hazards, and, to the best of the author's knowledge, little systematic attention has been paid to the assessment of social vulnerability to disease outbreaks and epidemics.

This chapter, first and foremost, intends to contextualise social vulnerability to pandemic situations in the wake of the COVID-19 crisis. To achieve this, Section 7.2 sets the scene and provides the context for social vulnerability relating to pandemics and disease outbreaks. Section 7.3 identifies preliminary indicators of social vulnerability to pandemics. Finally, implications, limitations, and an agenda for further research are discussed in Section 7.4.

7.2 Social Vulnerability and Pandemics

The scientific use of the term "vulnerability" draws its roots from geography and natural hazards literature, but it is also used in different fields, referring to diverse settings and situations [10]. "Vulnerability", in general, refers to susceptibility to threat scenarios, which can manifest itself in various ways, such as harm, powerlessness, and marginality of both physical and social systems [11, 12]. The available literature suggests that vulnerability is a broad and multifaceted concept encompassing an array of causes and contexts, such as physical, social, economic, political, and environmental.

The multi-dimensional nature of the concept of vulnerability is widely recognised and endorsed by the United Nations Office for Disaster Risk Reduction (UNDRR), where social, economic, and infrastructural vulnerabilities are considered as the constituent dimensions of the vulnerability of a specific region to hazards [13, 14]. According to UNDRR [14], infrastructural vulnerability refers to the basic infrastructures required for the production of goods and sustainability of livelihoods; economic vulnerability is associated with the economic status of individuals and communities, and social vulnerability accounts for the inability of people and society to cope with, or recover from, the devastating impacts of disasters.

Social vulnerability, among other types of vulnerability, is relatively more challenging to observe, define, and quantify [15–17]. This explains why socially created vulnerabilities are ignored or overlooked in both emergency decision-making and loss estimation reports in favour of more quantifiable factors such as human casualties and property loss [6]. The complexity surrounding the social dimension becomes even more significant during health crises like the COVID-19 pandemic. During pandemics, high levels of uncertainty and novel problems, coupled with environment-specific factors, lead to greater social, economic, and environmental complexity [18]. These all point to a need to adapt social vulnerabilities in the pandemic's context and recognise their role in coping and resource management strategies.

Although social vulnerability to pandemics has not been fully characterised, the reports from previous pandemics in 1918 and 2009 imply a link between socioeconomic factors and pandemic outcomes [19–21]. During the 1918 influenza pandemic, mortality rates in high-income countries were relatively lower than those in low-income countries. For example, in country-level analyses, the mortality rate in India was 40 times higher than in Denmark [22], and the mortality rates in some Central and South American countries were up to 20 times higher than in European countries [23].

Similar results were also found at city and community levels. Studies on the 1918 pandemic detected a considerable link between disease transmissibility and population density, illiteracy, and unemployment in Chicago [24]. Likewise, Rutter et al. [25] found an association between deprivation and the mortality rate for the 1918 pandemic in England. The results of these studies show that marginalised and disadvantaged social groups may be at greater risk from disease outbreaks. Thus, the explicit identification of populations vulnerable to disease outbreaks can be of great use in devoting attention to the groups most at risk during pandemics and their aftermath. Such a precise identification can be determined through the empirical analysis of precise indicators and variables.

The next section of this chapter is devoted to social vulnerability indicators in the context of the COVID-19 pandemic.

7.3 Social Vulnerability Indicators

Herein, social vulnerability refers to the combinations of social, cultural, economic, political, and institutional factors that account for the inability of society to cope with or withstand the impact of disasters and large-scale crises [14, 26]. There is broad agreement over the key defining factors of social vulnerability itself. Examples of such factors include [5–7, 11, 27–29]:

- poverty and economic marginalisation,
- lack of, or limited access to, resources and lifelines,
- ethnic and language minorities,
- community connectedness,
- household structure and housing conditions, and
- age and general health status.

However, as Cutter et al. [6] and Kuhlicke et al. [30] have also pointed out, there are discrepancies in specific indicators and variables representing the broader factors and the techniques used for the quantification of social vulnerability.

Despite disagreements over the indicators and variables, quantitative and statistical methods are widely used in the quantification of social vulnerabilities. Two examples are the Social Vulnerability Index (SoVI) developed in 2003 at the University of South Carolina, and the Social Vulnerability Index (SVI) developed in 2011 at the US Centres for Disease Control and Prevention (CDC). The SoVI is a place-specific and quantitative method which provides an empirically-based comparative tool to measure the capacity of social groups to cope with or recover from environmental hazards [6]. The SVI is also a well-recognised approach to facilitate the location-based quantification and comparison of social vulnerabilities to disasters [7]. Quantitative methods similar to SoVI and SVI focus on the identification of social vulnerability components associated with the specific context of the study. They then apply location-based and statistical models to the census data or other available information corresponding to the identified components.

Thus, the identification of the components of social vulnerability relating to COVID-19 could be considered as the first step towards formulating a reliable model. The rest of this chapter will be concerned with this step. Meaningful and relevant indicators are the building blocks of quantitative and empirical analysis. This study aims to identify the key social vulnerability indicators in the COVID-19 pandemic context. First of all, the preliminary indicators will be extracted from the literature or the author's observations and research during the development of the COVID-19 situation in Australia. After that, the proposed indicators will be assessed and validated by a group of emergency management and public safety experts.

It seems that COVID-19 related vulnerabilities generally arise from both the viral infection itself and the response measures, such as restrictions on the movement of people, business closures, and the subsequent economic downturn. The elderly population and people with underlying medical conditions are at higher risk if they are infected with the COVID-19 virus[1] [31]. However, the entire community appears to be more impacted by the indirect effects of COVID-19, namely, the response measures and their negative well-being and socioeconomic outcomes. To simplify the concept, this chapter will explore social vulnerability to COVID-19 as a whole without differentiating between the direct and indirect impacts of COVID-19.

Building upon the previous literature (e.g., [2, 6, 7, 32–34]), this chapter identifies three main components of social vulnerability to pandemics, namely, individual characteristics, built environment determinants, and societal determinants (Figure 7.1). Identification of the indicators associated with each component should be a prerequisite to any attempt at quantification. However, due to the time limitations, and given the intrinsic complexity of societal determinants, this chapter will focus on individual characteristics and built environment determinants. Societal determinants will be left for future work.

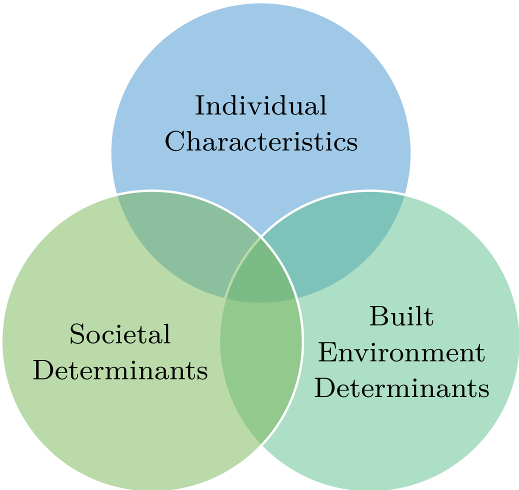


FIGURE 7.1
Main components of social vulnerability to COVID-19

7.3.1 Individual Characteristics

Individual characteristics refer to the personal attributes that may have a determinate role in an individual's susceptibility and capacity to tolerate the impacts of pandemics in general, and COVID-19 in particular. Examples of such characteristics include age, gender, ethnicity, education, disability, family conditions, and household circumstances.

7.3.1.1 Age

Those at both ends of the age spectrum are referred to as potentially more vulnerable when exposed to environmental hazards [2, 5–7, 29, 32, 35]. While people of all ages can be infected with the COVID-19 virus, older people appear to be more susceptible to it. Also, a compromised immune system or pre-existing medical condition, which can increase the severity of the infection is more common in the elderly population. Apart from the risk of exposure itself, older people are especially vulnerable to loneliness, which is the typical outcome of COVID-19 restrictions and social distancing measures. Moreover, given the prevalence of negative stereotyping of older people and age-based

[1] According to the Australian Government Department of Health, people aged 70 years and over, people aged 65 years and over with chronic medical conditions, people with compromised immune systems, and Aboriginal and Torres Strait Islander people over the age of 50, are at greater risk of more serious illness if they are infected with coronavirus (https://bit.ly/2YuIw47).

discrimination, and their potential increase during public health emergencies, the older population can face various kinds of mistreatment and barriers in accessing health care and support services.

7.3.1.2 Gender

Gender-based vulnerabilities to environmental hazards are extensively discussed in the existing literature [29, 36, 37]. In the context of the COVID-19 pandemic, early studies indicate a tendency towards higher mortality in men than women in confirmed COVID-19 cases across the world [38, 39]. Women, on the other hand, seem to be more susceptible to the socioeconomic consequences of the pandemic. Also, there are several reports of increases in the frequency and intensity of violence against women, and a significant rise in reporting of first-time family violence by women in Australia and across the world [40, 41]. This newly emerging phenomenon is referred to as "shadow pandemic" by UN Women [42]. The United Nations Population Fund (UNFPA) projections predicted that for every three months of the lockdown, 15 million cases of gender-based violence could occur globally [43].

7.3.1.3 Minority Status and Language

Race, ethnicity, religion, and language proficiency are among the factors contributing to social vulnerability to natural hazards [6, 7, 29, 44–46]. These factors can signify unequal or uncertain access to livelihood resources and health services during a pandemic and can lead to various forms of discrimination in the allocation of welfare and relief packages. Also, the author's observations and published records [47, 48] reveal a further amplification of ethnic inequality arising from a dramatic rise in racism and racially motivated attacks towards people of specific racial origins. As a result, some population groups can turn inwards and may experience a greater sense of isolation and exclusion at a time when staying connected matters most.

7.3.1.4 Family and Household Structure

Family structure refers to different forms of family or household settings, such as single-person household, shared living with non-family, a married or cohabiting couple (with or without children), single-parent families, and extended families. Previous studies suggest that overcrowded families, single-person households, and single-parent households are more vulnerable to natural hazards [6, 30, 44]. For example, according to Holand et al. [16], two-parent families can better manage the different responsibilities faced before, during, and after a hazard.

Within the context of CODIV-19, family structure can also be associated with the allocation of in-house spaces and utilities, which, if required, is critical for effective self-isolation and minimising the risk of within-household transmission [49, 50]. This issue can be more severe in families with children or in extended families where special needs such as remote schooling of children or nursing care of older adults may increase the demand for space in a house.

7.3.1.5 Disabilities and Health Conditions

In general, people with physical or mental disabilities and those suffering from chronic health conditions are considered the most vulnerable groups in society, and disasters increase this vulnerability even further [3, 5]. Also, disabled groups are less likely to receive support or benefit from disaster relief programs [30]. In addition, as outlined previously, people with a suppressed immune system or a pre-existing health condition (e.g. heart-related issues, diabetes, chronic respiratory disease, or cancer) are more likely to progress to severe forms of COVID-19.

7.3.1.6 Education

An overview of previous studies suggests that people with higher education are more resilient to the impacts of disasters. Groups with higher education have better access to the necessary information and resources and can secure government financial assistance more than those with lower education [6, 29, 51, 52]. Given the complexity of the COVID-19 pandemic and its rapid development, higher education can increase awareness of resources, facilitate access to critical information, and maximise compliance with response protocols. Moreover, people with higher education levels are expected to have higher computer competency and digital communication skills, which have proved to be crucial for staying connected, seeking practical help, online shopping, remote working, and online training.

7.3.1.7 Employment and Occupation

Employment plays a crucial role in financial security, access to resources and the overall well-being of individuals, families, and communities. It is recognised that disasters cause high levels of unemployment, especially in the short term [53, 54]. Employment instability during a disaster could decrease coping capacity and increase dependency on external financial support. For example, early studies in Australia show that casual workers and the self-employed, especially young people working in the food, hospitality and retail sectors, are likely to be disproportionately impacted by the pandemic-created economic downturn [55, 56]. Occupations with less dependency on physical movement and remote-friendly jobs appear to be more resilient during situations similar to COVID-19.

7.3.1.8 Financial Status

Financial status is a notion encompassing various financial factors such as income, expenses, assets, savings, and debts. Financial status is believed to have a significant impact on the overall health of a person or household, their social status and connectedness, and their ability to deal with and recover from crises [57, 58]. Previous studies have reported a strong tie between financial status and social vulnerability to disasters [5, 6, 29, 32, 44]. For instance, while financial commitments such as mortgages can make people more vulnerable in times of crisis, people with reasonably large savings can show better resilience to shocks from crises. Moreover, observations made during the COVID-19 pandemic indicate that better financial status can be considered as a positive factor in people's adherence to the public health guidelines and government pandemic protocols.

7.3.1.9 Insurance Coverage

Adequate insurance coverage (whether it be health insurance, income protection, life insurance, or trauma cover) can decrease susceptibility to the adverse consequences of disasters [33, 59, 60]. For example, private health cover enhances the choice of providers and improves access to timely and effective health care services and management [61, 62]. Income protection insurance or trauma cover can help families ease or avoid financial stresses caused by the COVID-19 economic downturn.

7.3.1.10 Ownership Status

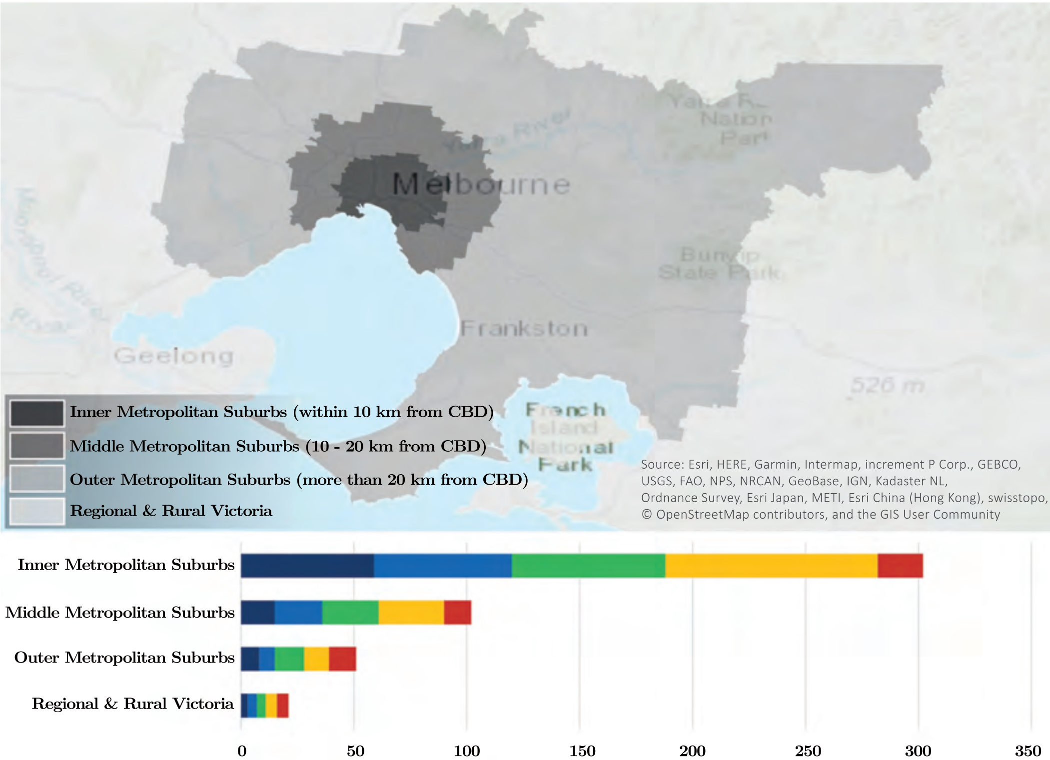
Ownership status refers to the ownership of property and motor vehicles. Various studies emphasise the role of house and car ownership in reducing the negative consequences of environmental hazards [6, 7, 32]. Regarding the COVID-19 pandemic situation, it is believed that car and house ownership, especially with no significant mortgage or car loans in place, can significantly reduce the financial stress and mental pressure caused by the pandemic's economic effects. Car ownership can provide families with better and safer commuting options and reduce their reliance on public transport – where the risk of infection is greater.

7.3.2 Built Environment Determinants

The built environment refers to the physical form of communities [63]. Some studies have demonstrated that built environment factors are significantly associated with health outcomes [33, 64]. Previous studies in the field of natural hazards attempted to measure built environment vulnerability by factors such as population density, quality of urban infrastructure, and road network density [16, 32]. Given the unique nature of the COVID-19 pandemic, this section identifies the following preliminary indicators as the pandemic's built environment determinants.

7.3.2.1 Spatial Accessibility

Spatial accessibility refers to the proximity and ease of access to essential urban services, civic amenities, and public infrastructure. Proximity to essential services and amenities such as hospitals, pharmacies, supermarkets, and parks can be a valuable resource, especially when there are limitations imposed on the movement of people and goods to prevent the spread of a virus. Studies show that people residing in inner metropolitan areas have better access to civic amenities than the residents of the outer metropolitan areas [65]. A proximity analysis conducted by the author within the state of Victoria, Australia shows that the number of essential amenities drops significantly as one moves away from the CBD (Figure 7.2). For example, the average number of essential services in a 5 km radius in the inner metropolitan suburbs of Melbourne is three times more than those in the middle metropolitan suburbs. The analysis suggests that the classification of residential areas based on their distance from the CBD can be a reliable indicator of spatial accessibility.



	Inner Suburbs	Middle Suburbs	Outer Suburbs	Regional & Rural
Health Services	59	15	8	3
Chemists & Pharmacists	61	21	7	4
Supermarkets	68	25	13	4
Grocery & Convenience Stores	94	29	11	5
Petrol Station	20	12	12	5
Total	**302**	**102**	**51**	**21**

FIGURE 7.2
Average number of essential amenities within 5 km radius of residential addresses

In order to perform the analysis, Victoria's suburbs have been classified into four zones: inner metropolitan suburbs (located within 10 km from the Melbourne CBD), middle metropolitan suburbs (located between 10 to 20 km from the Melbourne CBD), outer metropolitan suburbs (located more than 20 km from the Melbourne CBD), and regional and rural areas (suburbs located outside of the Melbourne metropolitan area). Then, the average number of accessible services is calculated, based on the mean of the number of selected essential services falling within 5 km radius of 10 random residential addresses in each zone. The analysis was produced using ArcGIS Pro 2.5.0 and data downloaded from OpenStreetMap,[2] Victoria's Department of Health and Human Services,[3] and the Australian Bureau of Statistics.[4]

7.3.2.2 Urban Infrastructure

Networks of robust urban infrastructure and essential utility systems (e.g., sewage and water networks, telecommunications, electricity, gas, road network, and public transport) play a vital role in protecting public health and the environment. The role of urban infrastructure becomes more crucial during disasters and public health emergencies, and the COVID-19 pandemic is no different. The continuity and quality of urban infrastructure and essential utility services during large-scale pandemics can provide a more convenient means for accessing essential services, complying with the stay-at-home orders, and staying connected with families, friends, and professional peers.

Evidence from previous health emergencies like the cholera epidemics during the 1800s suggests that, in some cases, contaminated water and sewage networks can contribute to the spread of disease [66]. Although this is not the case for the COVID-19 virus at the moment, some studies imply that the potential spread of COVID-19 via sewage networks must not be neglected [67]. Also, many countries have started monitoring wastewater for traces of the COVID-19 virus, and some found evidence of the virus days or even weeks before the first official case was declared [68]. It is possible, therefore, that ongoing surveillance of sewage and water systems can provide early warning of impending outbreaks and help contain the spread of contagious diseases in the early stages.

7.3.2.3 Population Density

Population density is a measurement of the population per unit area and is recognised as a key determinant of vulnerability to natural and environmental hazards [28, 29, 69]. Studies have investigated the role of population density in both the 1918 influenza pandemic [24] and the present COVID-19 pandemic [70, 71], and suggest that in cities with greater population density, the virus spreads faster than in less crowded cities, due to more frequent contacts among people.

7.3.2.4 Walkability

Walkability refers to the extent to which the built environment can provide safe and friendly conditions for walking and cycling [72, 73]. A considerable volume of published studies describes the role of walking and cycling in promoting good physical and mental health and achieving greater social equality [74–76]. With the multi-directional effects of COVID-19 on most outdoor facilities and activities, a walkable neighbourhood can greatly encourage walking, cycling, and physical activity. Recent studies like Mattioli et al. [77] and McDougall et al. [78] suggest that physical activities can play a significant role in mitigating the physical and mental health challenges presented by COVID-19.

7.4 Discussion and Conclusion Remarks

COVID-19 has created unprecedented challenges across the globe and is expected to have lasting impacts in the years to come. Understanding how pandemics influence the lives of various socioeconomic groups can help decision-makers develop a clearer perception of the situation and direct resources to where they will have the most significant effect. As outlined earlier in this

[2] https://www.openstreetmap.org/
[3] https://www.dhhs.vic.gov.au/
[4] https://www.abs.gov.au/

chapter, a large body of literature under the umbrella concept of social vulnerability is devoted to understanding how different socioeconomic groups experience crises differently. However, due to the rarity of pandemics in recent history, little work has been done on social vulnerability in the context of disease outbreaks and pandemics.

This study is an early attempt to understand social vulnerability to disease outbreaks, learning from the COVID-19 pandemic and its socioeconomic ramifications on society. Borrowing from the literature, this chapter has elaborated on the concept of social vulnerability to the COVID-19 pandemic, which was later followed by the identification of social vulnerability components in pandemic settings. Three main components have been recognised: individual characteristics, built environment determinants, and societal determinants, the first two of which have been further divided into indicators to provide a more detailed description of their role in social vulnerability to pandemics.

It should be noted that this chapter is neither an attempt to define social vulnerability to pandemics on a global scale nor to provide an exhaustive list of its indicators. The study presents several inherent limitations that should be noted before future research directions are discussed. The first limitation comes from the highly-complex nature and rapidly changing and still unfolding implications of the COVID-19 pandemic. No doubt establishing a thorough understanding of the multi-dimensional impact of the ongoing pandemic will take years. The second limitation concerns the time constraints, which restricted the study to investigate selected components of social vulnerability to pandemics and leave the detailed investigation of the societal components for future work. The third limitation originates from the jurisdiction in which this study takes place. Some of the justifications in this chapter are made through careful observations of the COVID-19 situation in Australia and may not be generalisable to other countries because of different socioeconomic or cultural circumstances.

Future directions of this study include further expansion of the concept by a detailed investigation of the societal determinants of social vulnerability to COVID-19, as well as the external validation of the outcomes through focus groups or interviews. This will be followed by studying the relationship between the indicators and the morbidity and mortality caused by the pandemic using the actual COVID-19 data, which can lead to a more thorough validation of the work. Future extensions of this study will also explore potential biases or preconceived assumptions associated with the various indicators as well as the interplay between them. For example, while high population density can contribute to pandemic-related vulnerabilities, densely populated areas are likely to have better urban infrastructure networks. Similarly, people with higher education or better financial status are expected to be less vulnerable to pandemics, but the prevalence of international and long-distance mobility in such groups may also place them on the list of highly exposed and primary long-distance carriers of disease, especially in the early stages of a pandemic. It is expected the ultimate outcomes of this ongoing research will enhance the overall awareness of pandemics and will be of considerable value in drafting future pandemic preparedness plans.

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8

Informal Road Detection and Uncertainty in Remote Sensing

Renate Thiede and Inger Fabris-Rotelli

This chapter presents an algorithm for detecting informally developed roads in satellite images, and quantifying the uncertainty associated with the results. Informal unpaved roads are common in developing countries, and arise naturally through human movement, typically in conjunction with informal housing. These roads are not authorised nor maintained by government, nor recorded in official databases or online maps. Consequently, information on their location and extent is not available to official decision-makers, severely limitating on the development of COVID-19 response strategies. This information is critical for planning the placement of testing centers and clinics, the navigation of emergency medical services, and studying the movements of the population for contact tracing and mobility purposes. The algorithm obtains these roads in a fast and efficient manner using freely available software, making it a viable solution for developing countries. The uncertainty metrics provide a measure of the reliability of the information. The algorithm is demonstrated on areas in South Africa, a developing country with one of the highest number of COVID-19 cases globally.

8.1 Introduction

Currently, the Worldometer[1] reports that South Africa is in the top ten countries worldwide for total COVID-19 cases and among the top fifteen for total deaths. Eight of the countries in the top fifteen, both for cases and deaths, are in the developing world. The Google mobility index[2] indicates that mobility generally decreased in all sectors except the residential sector, compared to a baseline day before the start of the pandemic. In South Africa, mobility in the residential sector increased by 14% compared to baseline data for the country, while the increase in Brazil and India were 10% and 14%, respectively. This highlights the need for modelling mobility within residential areas. However, much of the movement within residential areas, particularly in informal settlements, is developed by residents without government approval. These settlements arise when rapid urbanisation in developing countries leaves governments unable to meet infrastructure needs. Two-thirds of the population of the global south lives in informally developed settlements [1]. In South Africa, this population is growing at a faster rate than the population living in government-registered formal settlements [1].

[1] https://www.worldometers.info/coronavirus/#countries accessed on 28 September 2020.
[2] www.google.com/covid19/mobility/

Informal roads herein refer to any roads created by residents without government approval. These roads occur in and around a variety of settlements, which may be formal, traditional or informal. They arise naturally through human movement on foot and by vehicle, and are not authorised or maintained by government, nor commonly recorded in official databases or online maps.

The current COVID-19 pandemic highlights the need for such road data to be obtainable at short notice. The location and extent of informal roads provide crucial information regarding citizens' transport opportunities and possibilities for movement, required for government monitoring of cases. The South African government acknowledges that contact tracing is important for the COVID-19 pandemic.[3] Although the University of Cape Town in South Africa has developed a contact tracing app,[4] the population uptake of the app is unlikely to reach the requirement due to limited access to smart phones and cellular services. At this stage, they do not provide a comprehensive solution for South Africa.

The World Health Organisation[5] provides detailed advice on contact tracing which involves, for example, managing and monitoring contacts daily and direct monitoring by a contact tracing team. The knowledge of roads in informal settings are thus essential for navigation by such teams, as well as medical personnel checking on isolating cases. In addition, roads provide accessibility to services. During COVID-19 it is essential that all citizens have access to facilities such as hospitals, within a certain travel distance or travel time from their homes. Knowledge of the roads assists decision makers in optimal placing of additional emergency testing and support facilities. The same holds for other essential services such as banks and grocery stores.

In order to obtain informal-road information, remote sensing data can be utilised to provide such data rapidly, at no health or safety risk, and at low cost, as satellite images provide a comprehensive overview of settlements and infrastructure. This avoids the infection risk, as well as crime-related security risks[6] associated with land surveying. The question then becomes how to extract the information from remote sensing data. Manual digitisation of informal roads from satellite imagery is a time-consuming and complex process [2], leading to delays in data availability. An automatic or semi-automatic method for extracting informal roads from satellite imagery is therefore required. Developing such an extraction method must take into account the unique challenges posed by informal roads. Due to their unplanned nature, informal roads often occur in irregular networks, and may not have clear boundaries or centrelines. Their unpaved surfaces exhibit heterogeneous colour and fade into their surroundings, and road width may change abruptly. This contradicts many of the assumptions made by traditional formal-road extraction methods [3–5]. Furthermore, since information on these roads does not typically exist in any database, accuracy cannot be assessed using reference data. An informal-road extraction method must therefore preferably provide a measure of extraction uncertainty that does not rely on a comparison with ground truth.

This chapter presents a novel approach to extract informal unpaved roads from remote sensing images along with an associated uncertainty measure, and provides an overview of uncertainty measurement approaches. The presented approach is tailored for the unique characteristics and circumstances of informal roads. Uncertainty is quantified for each distinct road object by assessing its linearity, where more linear shapes are considered more certain to be roads. The approach is demonstrated for areas in the South African provinces of Gauteng and North West. It may be implemented using only open source software, making it ideal for the developing world.

This technique was previously presented as an unpublished Masters thesis in [6]. Here we give a broader overview of the problem, particularly with relation to the COVID-19 pandemic. Approaches for assessing uncertainty are discussed in the absence of ground truth, and sources of uncertainty around informal roads are investigated.

[3] www.sacoronavirus.co.za, 23 May 2020 Contact Tracing Toolkit; accessed on 8 July 2020.
[4] https://www.news.uct.ac.za/article/-2020-03-27-coviid-new-app-to-avoid-future-lockdowns
[5] www.who.int, Contact Tracing in the Context of COVID-19, 10 May 2020.
[6] South Africa ranks third in the world. www.numbeo.com/crime/ranking_by_country.jsp

8.2 Literature

There is limited research on informal-road extraction because of the unique challenges of informal roads, such as geometric inconsistencies of the width of roads, visually unclear road boundaries and heterogeneous surface reflectance.

Several comprehensive overviews of formal-road extraction techniques are available in the literature [7–9]. Methodologies include morphological methods [10–12], dynamic programming [13], multi-scale and multi-resolution analyses [14], and segmentation and classification [15, 16] knowledge- and logic-based techniques [17], fuzzy modeling and fuzzy logic [18], and spatial reasoning.

Deep learning approaches have become popular for road extraction in recent years. Abdollahi et al. [19] provide an overview, stating that there are four main types of deep learning used for road extraction. These are generative adversarial networks (GANs) [20], deconvolutional networks [21, 22], fully convolutional neural networks (FCNs) [23–25], and patch-based convolutional neural network (CNN) models [26]. However, deep learning methods typically require large datasets for model or network training, complex training, or large amounts of storage and memory [19]. This makes such methods infeasible for the financially constrained situations of the developing world.

The above methods were proposed to detect formal roads. The only approach in the literature developed for informal roads is that of [3], which detects roads in informal settlements in São Paolo, Brazil. Several challenges were experienced therein, such as misclassifying buildings as roads, difficulty in detecting dirty or muddy roads, and errors caused by the presence of cars and other objects on roads. There is therefore a need for further research in this area. In addition, the method in [3] requires the use of proprietary software, namely eCognition.[7] It can therefore not be implemented freely or in financially constrained situations, which may occur in the developing world.

In [27], the formal-road extraction method of [28] was able to detect some informal roads, however, this method also relied on proprietary eCognition software.

As highlighted in [3], informal roads differ from formal roads in some key characteristics. Formal roads tend to appear as long linear objects of constant width, either straight lines or regular curved shapes. Informal roads are of varying lengths and widths [3], often exhibiting sharp changes in road width. Formal, planned roads are generally laid out in regular patterns, and connect to other roads at planned junctions. Informal roads may exhibit irregular patterns [3], as their locations are influenced by convenience and environmental factors, rather than pre-planned design. They may also exhibit discontinuities. Formal roads are in general designed to be suitable for automobile navigation, and must adhere to specific standards, such as those specified by the South African National Road Traffic Act.[8] Informal roads are created ad-hoc. Their structure depends on their function, such as narrow roads being suitable for small vehicles and foot traffic, or broad roads for larger vehicles. These properties may change abruptly along the same road, depending on the way in which different stretches of the road are travelled. Formal roads are generally paved or clearly delineated, separated from their surroundings by boundaries or sidewalks. Informal roads often do not possess clearly visible boundaries, and may have similar reflectance as their surroundings, including bare soil areas and yards, or buildings with roofs made from local soil. Informal roads may exhibit heterogeneous colouring, such as brighter, harder soil on well-travelled parts of the road, or darker soil on wet or muddy patches. In the context of informal settlements, land cover may be highly heterogeneous at the scale of roads, which [3] mentions as a particular challenge for informal-road extraction.

Any approach for detecting informal roads must be able to rely on the characteristics possessed by informal roads and take their circumstances into account. The Normalised Difference Vegetation Index (NDVI) will herein be used to isolate bare soil areas.

Spectral information alone is not sufficient for informal roads. Traditional dwellings, made from

[7] https://geospatial.trimble.com/products-and-solutions/ecognition

[8] South African Legal Information Institute, National Road Traffic Act, 1996 [No. 93 of 1996] - G 17603. Available online: http://www.saflii.org/za/legis/num act/nrta1996189/

local materials, may appear spectrally similar to bare soil or vegetation, while open bare soil areas that are not roads will be spectrally identical to informal roads. Furthermore, informal roads exhibit heterogeneous reflectance across the road surface, so that uniform colour cannot be assumed as in some formal-road extraction methods [5]. Incorporating geometric and structural properties decreases the risk of confusing roads with spectrally similar areas and objects [4, 29]. Since roads are linear structures, measuring linearity will provide a way of detecting the presence of roads, even where their boundaries are not clearly visible. Detecting the linearity of roads that are not straight has proved a challenge in the past [15]. Informal roads are not necessarily straight, but may be visually erratic or winding, as determined by the navigational needs and environmental constraints from which the roads have arisen. Measuring the compactness and elongation of objects [30] allows for detecting curvilinear objects, that are linear but not straight. These measures were employed in [28] to determine whether or not image objects were roads.

Image objects appear differently at different scales [31]. The scale at which an image is analysed determines what objects will be identified [32]. Since informal roads differ in length and width, and roads of varying sizes may appear in the same area, searching for informal road segments at a single scale is not suitable. The Discrete Pulse Transform (DPT) [33] provides a multi-scale decomposition of an image by recursive application of the LULU operators [34]. It is used to find and analyse image objects of any scale. It is straightforward to extend the working of the DPT to find pulses of a certain shape, in particular linear shapes, defined by their compactness and elongation. This is efficient in terms of both computation time and simplicity. In the approach presented herein, colour and reflectance information are utilised to isolate bare soil areas, which are then further analysed using the DPT. In this way, size and shape information available in satellite imagery are combined to effectively detect unpaved informal roads of various sizes, exhibiting heterogeneous colour and irregular shapes. The only requirement is that the roads should be linear.

Aside from measuing linearity, compactness and elongation provide an additional advantage which is critical for decision-making, namely, they are used to provide a measure of certainty related to the extracted objects [28]. This is crucial in the case where road information may be used as input to a larger process, such as mobility monitoring for COVID-19 response. Many studies have focused on assessing the accuracy of the results of road extraction algorithms [35–37]. However, such uncertainty analyses are usually conducted in separate studies and not included as part of the road extraction process.

This chapter presents a practical solution to the problem of detecting informal roads and assessing their associated uncertainty. This is critical for improving mobility modelling, contact tracing and service provision during the COVID-19 pandemic. The algorithm described herein may be implemented using free open-source software, and can therefore be used in financially challenged situations, such as in developing countries. Additionally, the algorithm provides measures of certainty related to the identified road objects, rather than hard binary classification.

8.3 Uncertainty Measures in Remote Sensing

In order to gauge the reliability of the results of a road extraction algorithm, some form of accuracy assessment or uncertainty evaluation is required. This is particularly important when the output of the extraction is used in further decision-making, such as mobility tracking for COVID-19 response. Informed decisions can only be made on the basis of well-understood, reliable data.

Uncertainty quantification and accuracy assessment are usually done as separate processes external to the road extraction. Methods including uncertainty measures as part of the extraction algorithm output are rare in the literature, as noted nearly twenty years ago [38]. While a wide array of accuracy assessment techniques have become available, little has changed in terms of built-in uncertainty quantification that provides uncertainty measures as part of the algorithm output.

Firstly, it is necessary to differentiate between accuracy and uncertainty. Herein, accuracy will refer to a measurement that compares the results of an extraction algorithm with some reference data that is assumed to be true [36]. Accuracy assessment gives an indication of how well the extraction approach can be expected to perform. However, it does not provide direct information about the reliability of the results on any given dataset for which no reference data is available. Uncertainty, on the other hand, is an inherent property of the extraction, resulting from intrinsic ambiguity in the data and particular extraction algorithm. Uncertainty quantifies the confidence we have in the extraction results [39]. This is of particular importance in the case of informal roads, which exhibit unique characteristics and sources of uncertainty that differ from the challenges faced by formal roads [3, 40].

A variety of specific methods is aimed at quantifying the uncertainty in remote sensing applications [41]. These methods may provide a nuanced understanding of the sources of uncertainty. While these are worth considering, the focus of this research is not to comprehensively quantify all uncertainty, but rather to present a road extraction algorithm which is coupled with its uncertainty.

Uncertainty arises from ambiguities inherent to the data and approach. It may not be possible to quantify all sources of uncertainty [42], therefore, any uncertainty measurement will exhibit some form of subjectivity. The more sources considered, the more comprehensive the uncertainty measures will be. However, this may lead to a very complicated uncertainty quantification process. Balcaen et al. [42] state that it is impossible to separate all possible sources of uncertainty present in a physical measurement. It is therefore necessary to consider sources of uncertainty, and ways of quantifying their influence, that are appropriate to the purpose and structure of the algorithm. The way in which uncertainty quantification may be incorporated into the algorithm depends on the steps followed. Fuzzy and probabilistic classification techniques provide advantages to model and quantify uncertainty [43]. Classification and feature extraction methods using Bayesian solutions tend to quantify parameter uncertainty via Markov Chain Monte Carlo approaches [44, 45], while deep learning methods such as [46] can use Monte Carlo dropout. Other approaches include the use of additional data or knowledge, such as the feature extraction approach of [47], which compares multiple images of the same places at similar times. Expert knowledge may also be used, as in [48] for assessing the uncertainty of slum boundaries, or the shoreline change detection approach of [49].

Herein, we balance the complexity of uncertainty quantification with simplicity of calculation and interpretation. We measure uncertainty based on certain physical characteristics of roads, namely their linearity, calculated via compactness and elongation, as in [50] and [28]. This is measured during the final steps of the algorithm. Uncertainty during data collection and earlier steps of the algorithm necessarily propagate and influence the final results [51]. These sources are not directly measured, but will be discussed.

Sources of uncertainty for this approach are summarised in Figure 8.1. Uncertainty may be caused by extraneous factors, including image capturing technology and circumstances on the ground. Image capturing is limited by physical factors such as atmospheric disturbance, very bright reflectance when the sun directly hits a tin roof or other reflective surface, the number of wavelengths captured by the satellite, and limited spatial resolution. This could lead to mixed pixels, caused by land cover heterogeneity or irregular road boundaries at a level too small to be captured by the pixels. Circumstances on the ground include road characteristics such as irregular networks, unclear boundaries, heterogeneous reflectance, and occlusion by trees and shadows [3, 40]. Uncertainty is also caused by parameter choices and the working of the algorithm itself. This is true for all extraction algorithms, though the exact way in which uncertainty is inherent to the algorithm, depends on the steps followed. Herein, uncertainty may arise from a loss of information during adaptive median smoothing, conversion of colour to greyscale information, adaptive thresholding, morphological opening, filtering by linearity and size, identification of image objects by the DPT, and adaptive dilation. While the process was developed to remove noise while preserving relevant detail, uncertainty is nonetheless present. The methodology is explained in the next section.

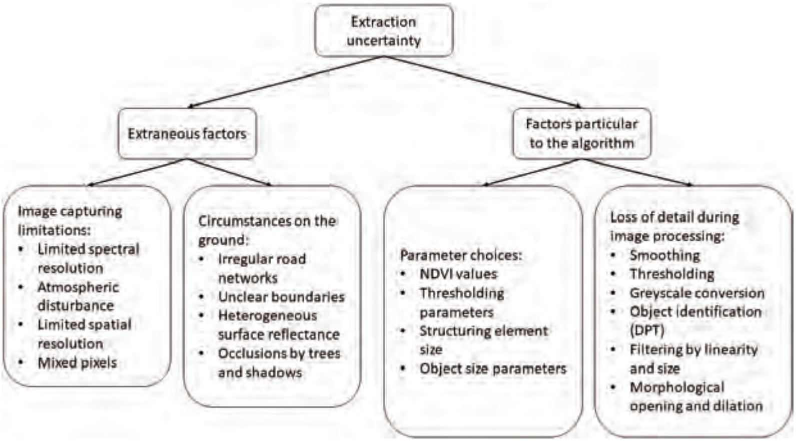


FIGURE 8.1
An overview of the sources of extraction uncertainty.

8.4 Road Extraction Algorithm

This section presents an overview of the algorithm methodology, summarised in Figure 8.2. Interested readers may refer to [6] for an in-depth discussion of the algorithm development.

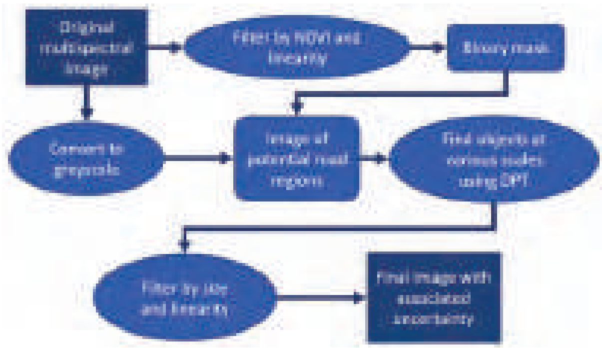


FIGURE 8.2
An overview of the road extraction algorithm.

The input to the algorithm is a multispectral satellite image with four bands, namely RGB and NIR. The NDVI is calculated from the red and NIR information, which is then used to isolate bare soil areas. A lower bound of 0.1 removes shadows and paved surfaces, while an upper bound of 0.3 removes dense vegetation. According to [52], grasslands and shrubs exhibit NDVI values in the interval [0.2,0.3], therefore, this is a lenient upper bound that allows for the inclusion of grassy paths and narrow roads bordered by grass. Optimal NDVI values for effective removal of unwanted areas may change slightly based on the individual image characteristics. This step results in a thresholded binary image containing bare soil areas. These areas are then filtered by linearity, where linearity is defined by compactness and elongation.

$$\text{Compactness} = \frac{2(\sqrt{\pi a})}{p}$$
$$\text{Elongation} = \frac{a}{\text{len}^2}$$

where a is the area of the region, p is the perimeter of the region, and len is the length of the region. Length is measured as the major axis of the smallest ellipse enclosing the region. Objects with compactness below 0.3 and elongation below 0.2 are considered potential roads [28].

The result of this filtering is a binary mask containing potential road areas. The original image is converted to greyscale and multiplied by this mask, resulting in a greyscale image containing the full grey intensity information of only those areas which are potential roads. This is done because the Discrete Pulse Transform (DPT) operates on greyscale input.

The DPT is applied to this image to extract image objects at various scales. These objects are filtered by size, elongation and compactness to identify linear pulses with a road-like shape. This requires the specification of parameters related to the size, elongation and compactness. The size parameters vary depending on the spatial resolution of the image, as well as the typical sizes of roads and objects in the image. User input is therefore required for the size parameters. The parameters used for compactness and elongation are 0.3 and 0.2 as mentioned above.

Certainty is quantified using the compactness and elongation measures, as in the method of [50], also used in [28]. For each image object, the necessity of the object being a road is calculated. The necessity specifies the degree to which it is certain that an object is a road [50], and may also be used to evaluate certainty [53]. This measure is based on compactness and elongation, used as inputs to a Z-shaped fuzzy membership function f.

$$f(x;a,b) = \begin{cases} 1 & x \leq a \\ 1 - 2(\frac{x-a}{b-a})^2 & a \leq x \leq \frac{a+b}{2} \\ 2(\frac{x-b}{b-a})^2 & \frac{a+b}{2} \leq x \leq b \\ 0 & x \geq b \end{cases} \tag{8.1}$$

This results in the measures $\mu_c = f(c_x, a_c, b_c)$, based on compactness, and $\mu_e = f(e_x, a_e, b_e)$, based on elongation, where c_x and e_x are the compactness and elongation, respectively, of an image object x. The parameters a_c and a_e are lower bounds for the compactness and elongation respectively, while b_c and b_e are upper bounds. A lower bound of 0 is used for both compactness and elongation. Since the compactness of a road object must be less than 0.3, an upper bound of $b_c = 0.6 = 2 \times 0.3$ is used. The elongation of a road object is less than 0.2, therefore an upper bound of $b_e = 0.4 = 2 \times 0.2$ is used. The necessity, or certainty that the object is a road, is quantified as follows.

$$\text{Certainty} = 1 - \max(1 - \mu_c, 1 - \mu_e)$$

Image objects with lower compactness and elongation are more likely to be roads, therefore they have a higher associated certainty, and vice versa. The ultimate output of the algorithm is the final road objects along with their associated certainty. The certainty measure is of utmost importance as it gives an indication of the reliability of the extraction inherent to a given dataset, without the need for comparison to reference data. This makes this technique highly relevant for the informal road problem, since reference data on informal roads are not generally available in official records.

8.5 Accuracy Assessment

Accuracy assessment is performed by comparing the extracted roads with a reference, assumed to represent the truth. A variety of methods exist in the literature for assessing the accuracy of the results of road extraction algorithms [35–37]. The work of [37] is seminal in assessing the accuracy of automatic road extraction. Therein, the length of roads in the extraction is compared with the length of roads in the reference. This approach has been widely used throughout the literature, either directly or as the basis of other evaluation methods [54–56]. The above-mentioned method of [35] was adapted from [37], considering edges instead of centrelines. However, since informal roads may not have clearly visible boundaries, relying on a purely edge-based approach is not suitable. In order to determine how closely the edges and centrelines, respectively, of the extraction and reference are positionally aligned, Pratt's Figure of Merit (PFOM) is calculated separately on the road edges and centrelines, providing a measure based on the distance between the extracted and reference centres.

Per-pixel measures are calculated by comparing each pixel of the extraction with each pixel of the reference. A true positive (TP) occurs when the extraction classifies a pixel as a road, and the corresponding pixel in the reference is also a road. A true negative (TN) occurs when the pixel is non-road in both the extraction and the reference. A false positive (FP) is a pixel that is classified as road in the extraction, but is non-road in the reference, while a false negative (FN) is detected as non-road by the extraction but is a road pixel in the reference. Based on the true positive, false positive and false negative counts, the completeness, correctness and quality are calculated as follows:

$$
\begin{aligned}
\text{Completeness} &= \frac{TP}{TP+FN} \\
\text{Correctness} &= \frac{TP}{TP+FP} \\
\text{Quality} &= \frac{TP}{TP+FP+FN} \\
&= \frac{\text{Compl.} \times \text{Corr.}}{\text{Compl.} + \text{Corr.} - \text{Compl.} \times \text{Corr.}}
\end{aligned}
$$

These measures all range between 0 and 1, where higher values indicate higher accuracy. A higher completeness indicates that fewer false negatives were observed, while a higher correctness indicate that fewer false positives were observed. Quality does not include extra information that the above present in completeness and correctness, but is useful for summarising the accuracy with a single measure for the sake of making comparisons.

The above measures give an estimate of the overall accuracy of the algorithm. However, they do not distinguish between possible sources of error as caused by road characteristics. Pratt's Figure of Merit (PFOM) presents a way to compare the accuracy based on road edges, with that based on road centrelines. The formula is

$$
PFOM = \frac{1}{\max\{N_R, N_E\}} \sum_{i=1}^{N_E} \frac{1}{1+\alpha+\delta_i^2}
$$

where N_R is the number of pixels of the reference edges, N_E is the number of pixels of the extracted edges, α is a scaling constant usually set equal to $\frac{1}{9}$, δ_i is the Euclidean distance between the i^{th} detected pixel and the nearest reference pixel. For a perfect match, $PFOM = 100\%$.

Herein, PFOM is calculated in two different ways. It is firstly calculated on the edges of the reference and extraction. The edges are calculated using the Laplace gradient [35]. This edge-based PFOM assesses how precisely the boundaries of objects are captured. Secondly, PFOM is calculated on the reference and extraction skeletons. The formula above is not altered, but the reference and extracted skeletons are used as the reference and extracted image, respectively. This therefore measures the distance between the centrelines. The centrelines are obtained via skeletonisation of the full road objects. The calculation of centrelines depends on the full extent of the objects, including their edges. Therefore, the edge-based and skeleton-based PFOM measures are not independent, but may be interpreted to measure different aspects of the extraction.

The accuracy assessment methods used herein are pixel-based, i.e. the extraction and reference data are compared in raster form. This choice was made for computational simplicity, as the algorithm outputs raster results. Object-based methods have become increasingly popular along with the rise of object-based image analysis [57, 58]. This requires the data to be in vector form, namely the roads are considered as polygons. Radoux et al. [59] provide an overview of some object-based accuracy assessment measures. Many of the same concepts hold as in the pixel-based case. Metrics such as completeness, correctness, quality are calculated based on the number of road objects correctly identified, rather than the number of pixels. The distinction is made between count-based and area-based approaches. For pixel-based assessment, these concepts are equivalent, given that pixels all have the same area. The number of pixels correctly classified is then equal to the area of the image that is correctly classified [59]. MacLean et al. [60] recommend the use of area-based accuracy assessment in the case where the results of an algorithm are in vector form, and incorporates the area of the polygons into the classification matrix. Object-based accuracy assessment allows for a versatile range of measures. Möller et al. [61] compare the geometric properties of extracted and reference objects [61]. Lizarazo [58] presents similarity indices which can be used to evaluate the accuracy of an extraction with regards to various aspects, namely shape, position and edges. Maxwell and Warner [62] propose a centre-weighted approach to accuracy assessment, which allows for fuzzy boundaries between objects of different classes. An object-based accuracy assessment method could be enlightening regarding potential sources of error and hence uncertainty, and could address the problem of unclear road boundaries. Performing object-based assessment on the results of this algorithm is the subject of current extended research.

8.6 Application

This section gives results of the algorithm for images of informal roads in South Africa. To demonstrate the accuracy of the algorithm, the final extracted roads are compared with reference data in this case, which were obtained via manual digitisation. The algorithm is demonstrated to be useful for extracting informal roads with associated uncertainty. This is a critical step for obtaining comprehensive information on the mobility of residents with a view on understanding and planning government response to the spread of COVID-19.

8.6.1 Study Area and Data

The three study areas considered are shown in Figure 8.3. These exhibit roads that are good candidates for formalisation. The datasets are taken from a multispectral VHR Pléiades-1B image with an estimated azimuth angle of 65° and a spatial resolution of $0.5\,m$.[9] The study areas are situated in the north-western parts of Gauteng Province and the south-eastern parts of North West Province, South Africa. The informal settlements in these areas are in many cases starting to formalise and the informal roads are beginning to take on a grid-like structure.

Figure 8.4 shows possible challenges for road extraction. The roads in area 1 are of a light colour set in dark surroundings. Challenges for this area include roads occluded by trees, circled in green, grassy roads, circled in blue, as well as light-coloured patches of sand, circled in yellow. Areas 2 and 3 both exhibit narrow roads in a semi-rural setting, lined with open yards of similar colour to the roads. Both areas also contain some paved roads, which should not be detected by the algorithm. Some of the roads in area 3 are partly vegetated, which may lead to false negatives. The trees occluding parts of the roads may lead to false negatives, while sandy patches may cause false positives. The footpaths in area 3 (circled in grey) are of particular note. Road extraction algorithms do not generally consider footpaths to be roads, and footpaths are indeed not likely to be officially recognised as roads. However, they remain conduits for travel, and may provide important information regarding mobility, especially between residential areas.

[9] Data provided by and used with permission from the CSIR.

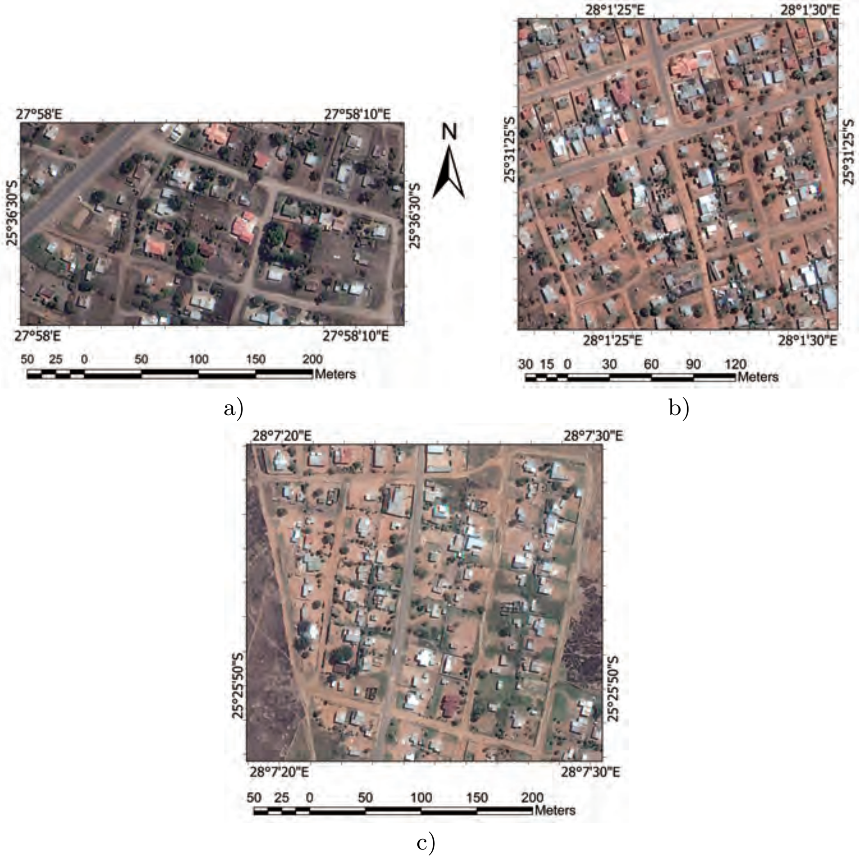


FIGURE 8.3
Areas to which the algorithm was applied. a) Hoekfontein, North West Province; b) Mabopane, North West Province; c) Soshanguve, Gauteng Province

8.6.2 Demonstration for Area 1

The process is demonstrated for area 1 (Figure 8.3 (a)). This area is characterised by narrow roads of a bright colour relative to their surroundings. There is also a paved road present in the image, which should not be detected by the algorithm.

Figure 8.5 shows the first processing steps. The original image is in (a). The image is thresholded by NDVI value in (b), and filtered by linearity in (c). This binary image is multiplied with the greyscale version of the original image, resulting in the image of potential road regions in (d).

The DPT is now applied to the image of potential road regions. This obtains image structures, or pulses, at various scales, as illustrated in Figure 8.6. At small scales, such as in (a), pulses are detected that correspond to all the larger image objects. However, pulses corresponding to unwanted non-road objects are also detected. At large scales (e.g. Figure 8.6(d)), those parts of the road network that are joined, are detected. However, roads smaller than that scale are not detected. This suggests the necessity of combining the results of the DPT at smaller and larger scales. Therefore, those pulses smaller than a given threshold, are intersected with the pulses larger than that threshold. The goal of this intersection is to remove noise and small pulses that are not part of road objects, while preserving image pulses that form part of larger objects, which may potentially be roads. The results of this step are shown in Figure 8.7. Noise and undesirable smaller objects are removed, while larger areas that might contain roads are preserved.

Lastly, any object that does not satisfy the compactness and elongation requirements is removed.

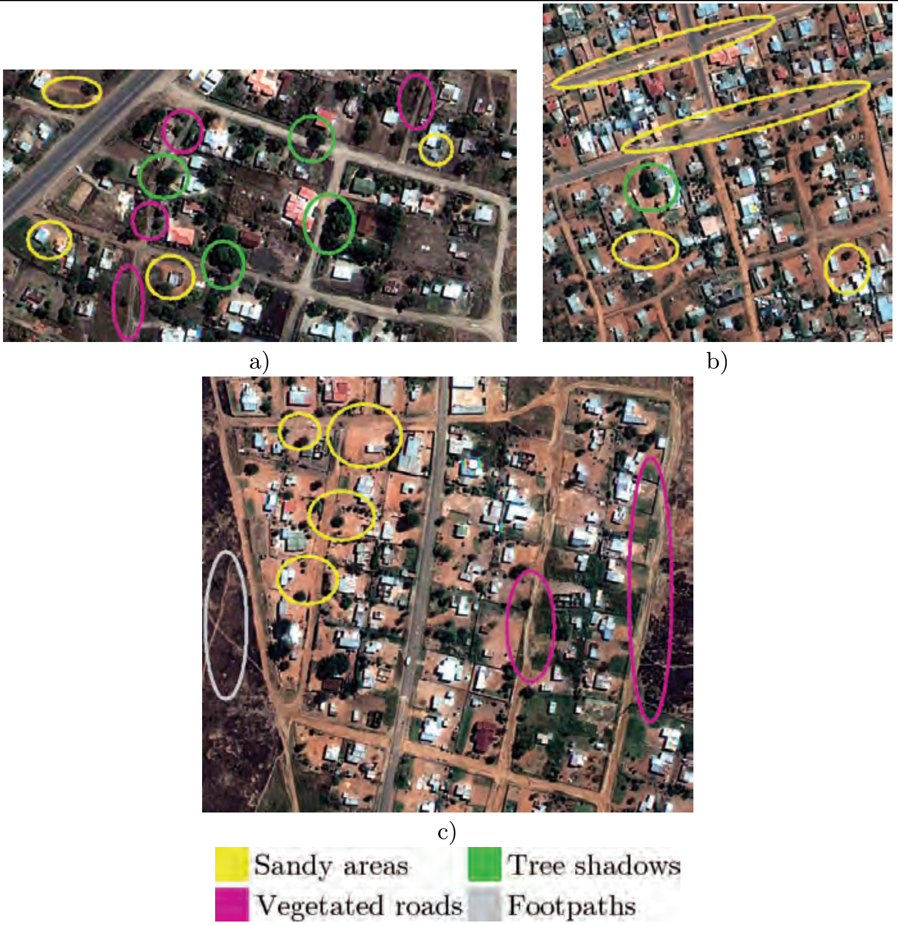


FIGURE 8.4
Possible sources of error for areas 1-3 shown in (a)-(c) respectively.

The final results are given in Figure 8.8 (a), and overlaid with the original image in (b) for illustrative purposes.

TABLE 8.1
Certainty measures for area 1.

	Minimum	Mean	Maximum	% Objects with Certainty > 50%
Certainty	60.35%	79.36%	95.80%	100.00%

The certainty associated with the extracted road objects is quantified via the certainty measure defined in Section 8.4, based on the compactness and elongation of the road objects. Figure 8.9(a) illustrates the certainty. Lighter road objects are more certain to be roads based on their compactness and elongation, while darker objects are less certain. The results are given in Table

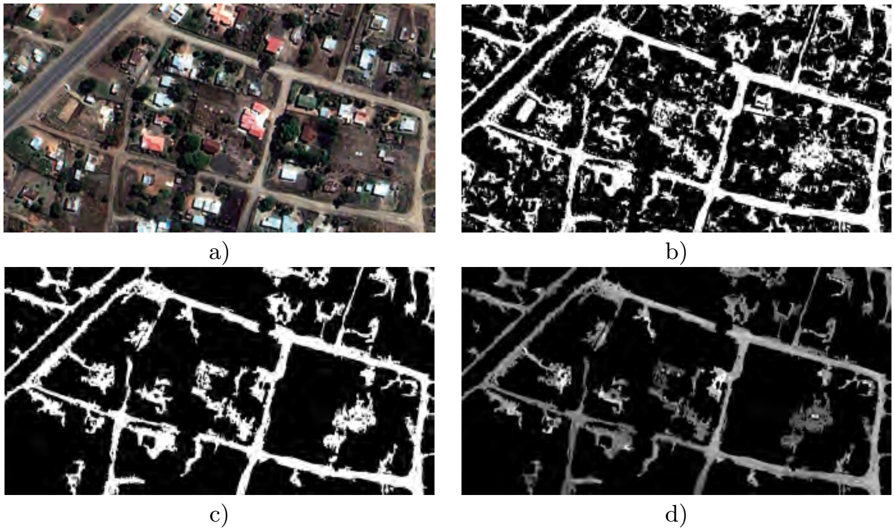


FIGURE 8.5
First steps for area 1. a) The original image. b) Areas with an NDVI below 0.1 or above 0.3 are removed, thereby isolating bare-soil areas. c) The results on the image in (b) after filtering by linearity. d) The mask in (c) overlaid with the greyscale image contains potential road regions.

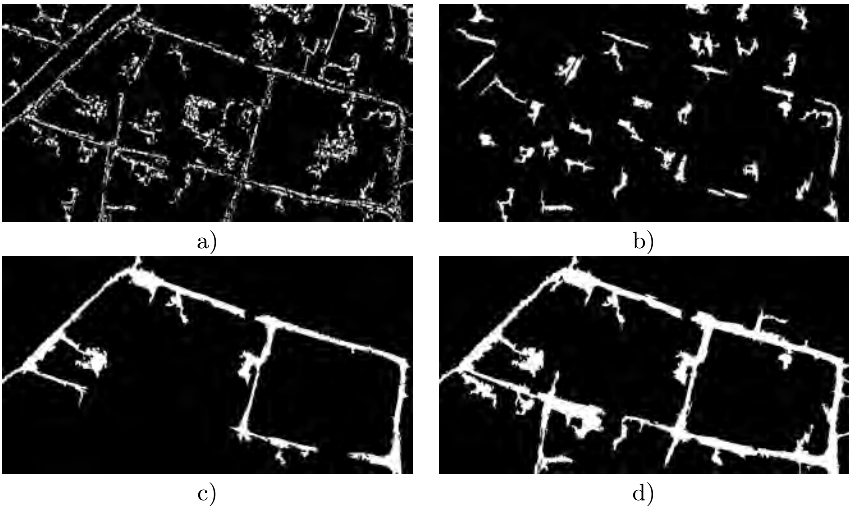
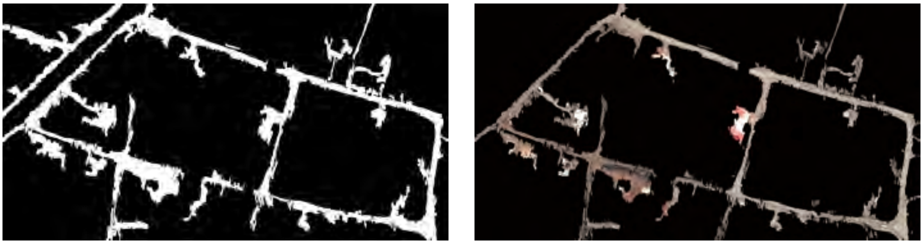


FIGURE 8.6
Image pulses of various sizes extracted using the DPT. a) Pulse sizes 0-100. b) 300-400. c) 8 000-9 000. d) 15 000-16 000.

8.1. The average certainty per image object was 79%. All road objects were more than 50% certain to be roads. The minimum certainty observed was 60%, while the maximum was 96%.

To quantify the extraction accuracy, extracted roads are compared to reference data, which was obtained via manual digitisation. Figure 8.10(a) and (b) show the extracted results and the

FIGURE 8.7
Pulses intersected by size.



a) b)

FIGURE 8.8
Results of the process. a) The binary image is the final output. b) The resulting image overlaid with the original image for illustrative purposes.

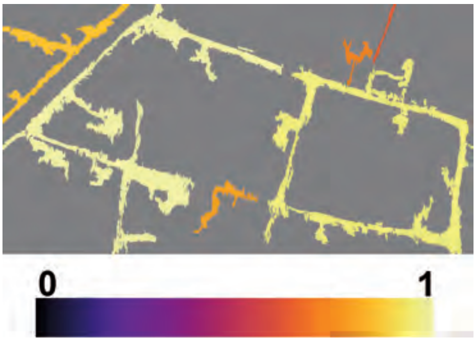


FIGURE 8.9
Certainty associated with extracted road objects. The lighter the colour of the image object, the more certain it is to be a road, as measured its by compactness and elongation.

reference roads, respectively, overlaid with the original image for illustration. The binary images are compared at pixel-level to obtain completeness, correctness and quality metrics, and at edge level and at centreline level using PFOM. The results are discussed in Section 8.6.3.

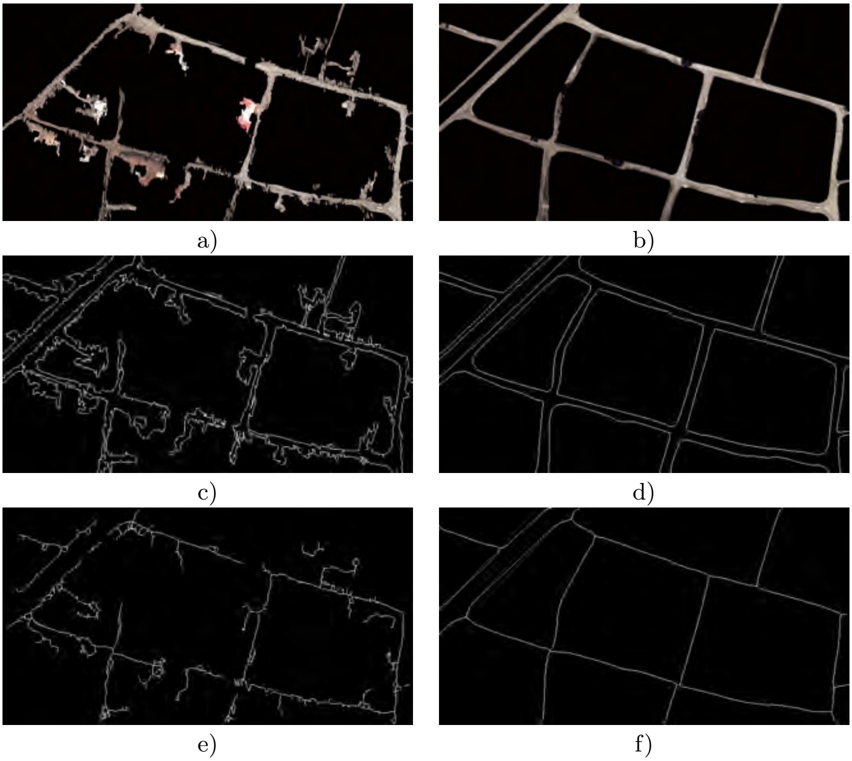


FIGURE 8.10
Comparison of results and reference. a) Extracted road objects (overlaid with the original image for illustrative purposes). b) Reference roads. c) Extracted road edges. d) Reference road edges. e) Skeleton of the extracted roads. f) Skeleton of the reference.

8.6.3 Results for All Areas

The results of the algorithm are displayed in Figure 8.11. These show which parts of the roads were detected correctly, as well as false positives and false negatives. The results the pixel-based accuracy and Pratt's Figure of Merit (PFOM) are given in Tables 8.2 and 8.3 respectively.

The pixel-based measures, quantifying accuracy in terms of overall extent, are given Table 8.2. For area 1, the completeness figure of 66.93% indicates that over two-thirds of the road pixels were accurately captured by the algorithm. The completeness was not much lower for areas 2 and 3, being above 60% in both cases. This indicates that not too many false negatives were observed. The correctness measures for areas 1, 2 and 3 were 57%, 43.33% and 38% respectively, indicating that false positives presented a greater challenge, especially in area 3. For areas 1 and 2, the per-pixel quality corresponds closely to the PFOM metric based on road edges, indicating that the extent was captured with approximately 45% accuracy for area 1, and with 34% for area 2. Area 3 experienced a 4% difference in pixel-based quality and edge-based PFOM, with a higher accuracy according to edge-based PFOM. The PFOM metrics based on road skeletons measure the alignment of extracted and reference centrelines. This gives a value of 47.60% for area 1, 33.50% for area 2 and 32% for area 3. While the presence of roads was therefore generally detected correctly, challenges were experienced at the edges. This is to be expected given the imprecise boundaries of unpaved roads and bare soil areas adjacent to roads. The skeletons-based PFOM was higher than the edge-based PFOM for areas 1 and 2, which was expected, but surprisingly the edge-based

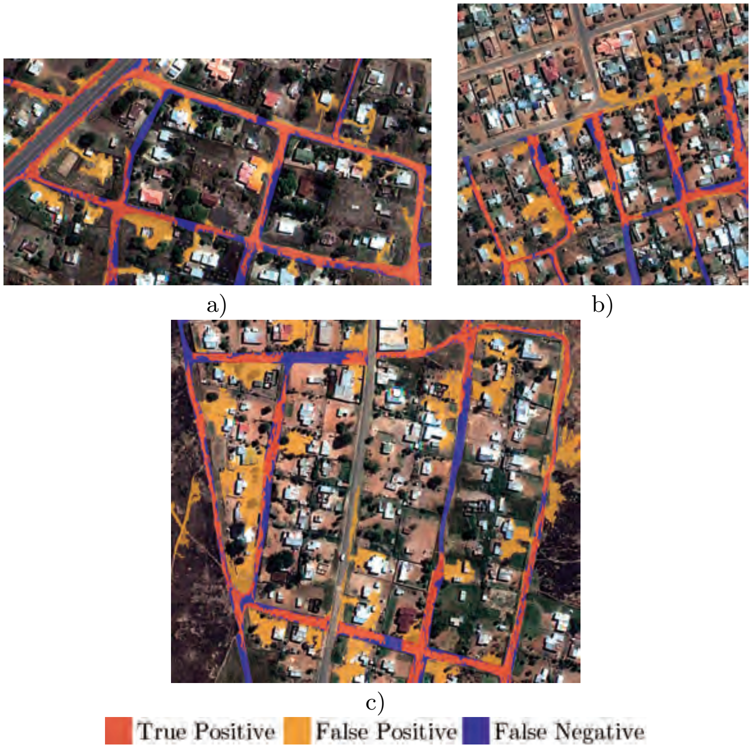


FIGURE 8.11
Results of the algorithm for areas 1-3 shown in a)-c) respectively.

TABLE 8.2
Per-pixel accuracy measures.

Area	1	2	3
Completeness	66.93%	61.56%	60.56%
Correctness	57.00%	43.33%	38.00%
Quality	44.48%	34.11%	30.46%

measure was higher for area 3. This may be due to the large number of false positives in area 3, as the centrelines of these regions would not correspond to the centrelines of any roads in the reference. This explanation also accounts for the greater similarity between the measures for area 2 as opposed to area 1, since area 2 contained more false positives than area 1. The results indicate that area 3 experienced the most false positives and negatives, while area 1 experienced the least. It is of note that area 3 outperformed area 2 in the edge-based PFOM measurement. However, the measures were low for both areas, indicating that road edges remain a challenge.

Figure 8.12 shows the certainty associated with the extracted road segments. Table 8.4 gives relevant statistics. Area 3 generally had the lowest certainty scores, except for the maximum, where the lowest was experienced by area 2. All areas had maxima of over 87%, and all means were over 75%. The highest variance was only 1.47% (area 1).

TABLE 8.3
Pratt's Figure of Merit.

	Area		
PFOM based on:	1	2	3
Edges	45.33%	33.86%	34.72%
Skeletons	47.60%	33.50%	32.00%

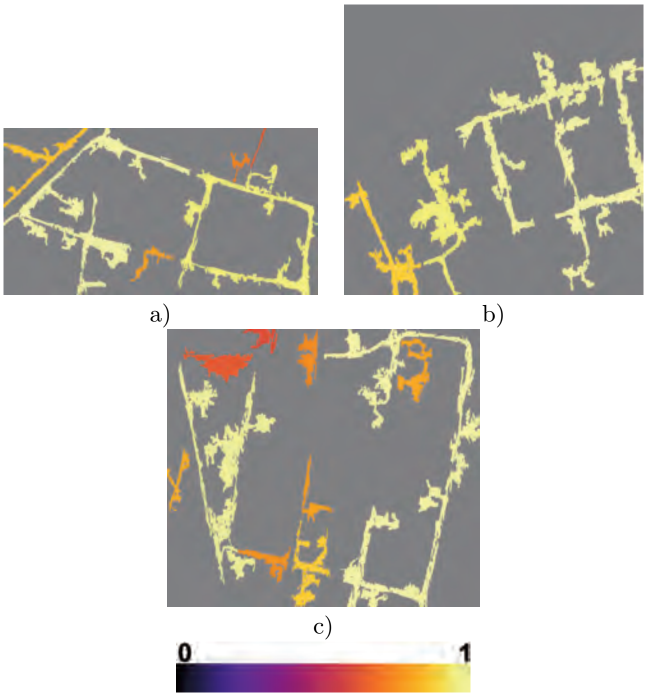


FIGURE 8.12
Certainty associated with extracted road objects. The lighter the colour of the image object, the more certain it is to be a road, as measured its by compactness and elongation. a)-c) show results for areas 1-3 respectively.

TABLE 8.4
Certainty statistics for all areas, calculated on all extracted road objects.

Area	1	2	3
Mean	79.36%	89.22%	76.58%
Minimum	60.35%	82.35%	57.65%
Maximum	95.80%	93.46%	95.63%
Percent > 50%	100.00%	100.00%	100.00%
Variance	1.47%	0.19%	1.40%

8.7 Discussion

The results indicate that the algorithm successfully detects the presence of informal roads in a variety of circumstances and for various road characteristics. Significantly, the presence of curved roads was detected accurately. Footpaths were also detected, which provide valuable information regarding the movement of people in residential areas. Improvement is needed to determine road boundaries and reduce errors, especially false positives.

Various sources of uncertainty are identified. Figure 8.13 illustrates road characteristics and environmental circumstances that led to false positives and negatives in the analysis. This is compared to the possible causes of error that were identified a priori in Figure 8.4, namely occlusions by trees, narrow and vegetated roads, road-adjacent open areas of similar colour to roads, and dusty paved roads.

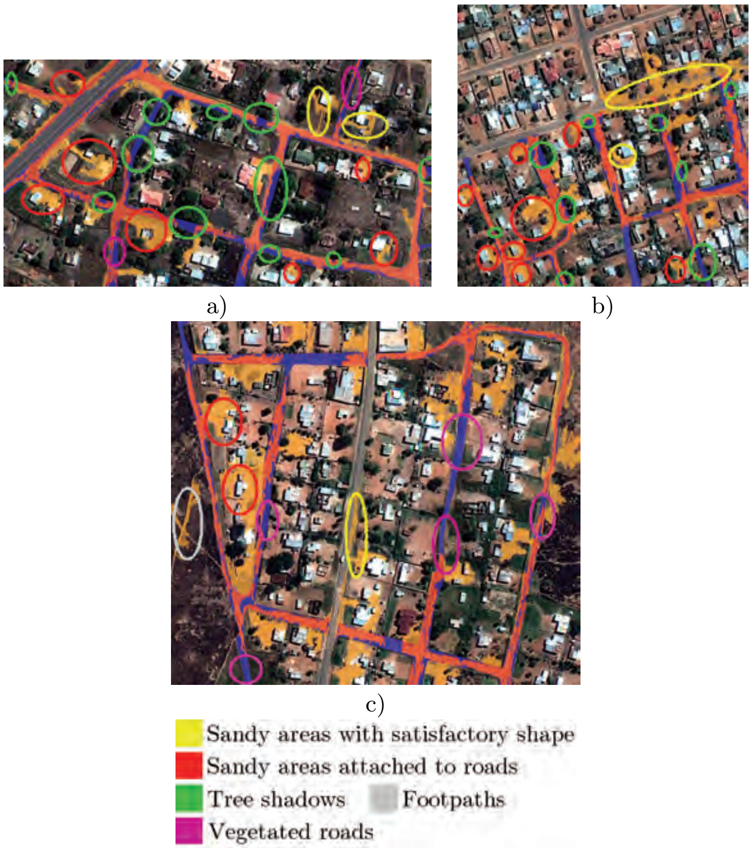


FIGURE 8.13
Results of the algorithm for areas 1-3 shown in a)-c) respectively.

Trees and tree shadows contributed to false negatives in areas 1 and 2, as shown by the areas circled in green in Figure 8.13(a) and (b). In areas 1 and 3, some roads were not detected since they were partly overgrown. This is illustrated by the areas circled in magenta and cyan, respectively, in Figure 8.13(a) and (c). Area 3 experienced the greatest challenges with false negatives, while area 1 experienced the least. Despite some sources of false negatives, most roads were detected, as indicated visually and also by the relatively high completeness for all areas.

False positives presented a greater challenge, as evidenced by the lower correctness scores. This is confirmed visually. In area 1 (Figure 8.13(a)), some buildings were not eliminated in the NDVI thresholding step, and contributed to the false positives detected. It is possible that these roofs were made from clay tiles or some substance that was spectrally similar to bare soil. This is a challenge that should be kept in mind for future applications, especially in areas with traditional housing, where the roofs are made of local clay or grass. False positives were also caused by unpaved areas with road-like linearity. These can be seen in all areas, circled in yellow. In area 1, these non-road areas with road-like characteristics are clearly navigable and used for transport, however, they were not considered roads in the reference due to their short length and the fact that they terminate in yards. This contrasts with the shoulders of the paved road in area 1, which were captured in the reference due to their width, visual clarity, and the fact that they connect to other informal roads, implying that they are used for transport. In area 2 (Figure 8.13(b)), a high number of false positives was caused by the large section of formal road that was falsely detected as road. The road was not removed by the thresholding step due to the layer of dust over the road. In all areas, unpaved areas attached to roads caused false positives. Due to being connected with the unpaved roads, the algorithm considered them to be part of the same image object, thereby including them with the detected roads.

The footpaths in area 3 are of particular importance. These were detected as roads. From the perspective of detecting roads to monitor mobility, this is a desirable result, since footpaths are used to move within and between residential areas. Detecting footpaths is therefore relevant for understanding population mobility patterns, especially in the residential sector.

8.8 Conclusion and Future Work

The algorithm generally works well for detecting the presence of informal roads. It additionally detects road shoulders, footpaths, and elongated navigable stretches, all of which can be used for transport. Non-road areas that are connected to roads provide challenges in terms of false positives. False negatives were caused by trees, shadows, and narrow and vegetated roads. The detection of precise extents and edges of roads presented a significant challenge. At this stage, the algorithm can be used to identify the location of informal roads. It also compares favourably to other extraction algorithms, as discussed in detail in [6].

Further refinement to the algorithm is needed to reduce false positives and refine road edges. Future research could also incorporate information on the presence, orientation and connectivity of paved roads. Additional data could be used, for instance, images could be compared over time. Informal roads that broaden over time are in use, and therefore considered important by the community, while informal roads that are not in use will diminish over time. Additional covariates could also be used to predict where roads will appear, based on convenient navigability of the area under investigation. Covariates could also be included to assist in uncertainty quantification. However, incorporating information additional to the multispectral satellite image will increase the data requirement. This should be done with caution, as the goal of the algorithm is to be implemented within the constraints of the processing ability and data availability in a developing world context. Another avenue of future research is the development of comprehensive uncertainty measures, which could be integrated with road extraction methodology. Evaluating this algorithm using object-based accuracy assessment is the subject of current research. This aims to address the problem of unclear road boundaries. In the future, we aim to expand the uncertainty quantification to allow for fuzzy or indeterminate road boundaries.

Informal-road extraction provides much-needed data on informal roads that is otherwise unavailable to government and modellers. This data is critical for obtaining a comprehensive view of mobility within residential areas, and hence for mobility modelling, contact tracing and service provision. Further development of uncertainty analysis will be beneficial as understanding the uncertainty associated with this data will help decision-makers to better evaluate the reliability of the data used in planning COVID-19 response. As COVID-19 data becomes more accessible in South Africa, merging of this work with case location data will provide further insights into the spread of the disease. Such a direction is vital for a virus that will affect those most vulnerable in communities, leaving a scar on society for years to come.

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9

Management and Analysis of Maritime Geospatial Data During COVID-19: Case Studies, Opportunities and Challenges

Rafael Ponce Urbina, Orhun Aydin and Steve Snow

This chapter presents a holistic view of the uses of GIS to monitor, analyze and disseminate knowledge pertaining to maritime geospatial data during the COVID-19 pandemic are showcased. The challenges pertaining to authoritative data production during a pandemic are identified. Challenges faced by national hydrographic offices and International Maritime Organization (IMO) members to provide the most up to date information for the Safety of Life at Sea (SOLAS) during the pandemic is discussed. The value brought by analyzing and mapping such data during the pandemic is demonstrated with case studies on tracking the impacts of pandemic on maritime supply chains, continuity of operations for business and ports, and maintaining status of ship fleets. This chapter is concluded with public-facing analytical products that serve and analyze maritime data.

9.1 Introduction

COVID-19 pandemic has been disrupting human movement, travel and trade patterns on air, land and sea. Impacts of the current pandemic on maritime traffic offers challenges and opportunities to quantify the level of supply chain disruption, delineate high-risk sea routes and provide a proxy for the intercontinental spread of COVID-19.

Disruptions to maritime industry have significant consequences for the local and global economy that rely on transport and trade of goods [1]. Understanding long and short term impacts of COVID-19 on the maritime supply line disruptions is required to increase the resilience of maritime transportation systems to future pandemics, and hasten the recovery period of the maritime ecosystem.

Geographic accuracy is essential in detecting and responding to any infectious disease outbreak [2], whether is a pandemic [3], a seasonal influenza [3], or a local outbreak of food-borne illness [4]. Based on experience of GIS use supporting many health-related agencies at all levels of government, critical areas in which geospatial information is critical are summarized below:

- Assessing risks
- Evaluating threats
- Tracking outbreaks
- Maintaining situational awareness

- Documenting disparity
- Ensuring the focused allocation of resources
- Notifying communities
- Minimizing the disruption caused by necessary community health intervention

Minimizing the impacts of the COVID-19 pandemic on the maritime ecosystem can only be possible via continuous geospatial data feeds, impactful analysis and enabling artificial intelligence systems, and disseminating data and knowledge in an effective manner. We discuss the multifaceted impacts of COVID-19 maritime industry within the context of GIS.

9.1.1 The Use of Geospatial Data and Systems

Location information is critical to decision making associated with large outbreaks, determining the origins of the infection, spread (speed and direction) and measures to isolate it, how to respond to it and how to organize the work force to minimize disruption as much as possible [5].

Location intelligence becomes even more critical when the outbreak can no longer be contained through contact tracing and quarantine [6]. Location-based information can be used to inform multiple, specific community interventions and activities [7]. Using common types of GIS analysis, such as mapping where things are, mapping the “most” and “least”, mapping disease density, finding “what’s inside” or “what’s nearby”, and mapping change, authorities can prioritize interventions and re-organize their resources [8]. Time is another crucial dimension that is naturally represented inside GIS [9]. Temporal and spatio-temporal analysis of geo-enabled data pertaining to COVID-19 is essential understanding current trade delays and supply line disruptions [10].

The maritime community, especially the shipping industry and port authorities, need geospatial information to safeguard the integrity of the logistic chain to maintain the essential goods supply during the pandemic. [11].

9.1.2 Impacts on the Maritime Community

The maritime community is wide and includes many different sectors, all connected in one way or another, and all suffering the impacts of the COVID-19 pandemic [12]. In an attempt to simplify this complex ecosystem, we have divided it into those sectors that affect the so called blue economy, with two large branches: shipping and ports. In this classification, we exclude fisheries and tourism (leisure yachting) despite their importance to local and global economy. Local and partial data pertinent to fisheries and tourism makes it cumbersome to evaluate the global challenges pertinent to and the use of maritime geospatial data during the COVID-19 pandemic.

The shipping industry has been significantly impacted by the pandemic. Broadly, we can divide this impact in three main categories:

- Cargo or goods (containers and bulk)
- Oil and gas (tankers)
- Passengers (cruise liners)

The transport of goods and hydrocarbons appear to have been operating consistently, which is true in some respects. That and the global economic downturn are presenting unprecedented challenges that can cause disruptions in the supply chain. Some estimates by the International Monetary Fund estimate global GDP growth will fall 3% in 2020 [13, 14], and the World Trade Organization (WTO) expects a fall in trade between 13% and 32% [15]. Depending on the duration of the outbreak and how governments deal with it, there could be a partial recovery in 2021 [14].

According to the WTO the most affected sectors in Q2 2020 have been automobiles and containers and have seen a weak demand for goods in general as well as some constraints in the supply chain [14]. The largest container company in the world, Moller-Maersk has stated that container volumes could be around 25% lower in Q2 2020 [14].

Because of countries reducing the risk of infection of COVID-19, ship traffic has been reduced by approximately 25% in the first half of 2020. The pandemic has resulted in less demand for imports and exports of cargo between countries. Many goods that cannot store for 14 days cannot be shipped due to 14 day waiting periods in quarantine. Because of the reduced demand for cargo many companies have become bankrupt due to the pandemic.

In the oil and gas sector, besides the common impacts to navigation, ship's maintenance and crew rotation, specific situations such as the floating oil storage can be significantly affected. Because of the drop in oil prices due to high production with low demand, the need for floating storage has skyrocketed. According to S&P Global Platts, in May of 2020 there were more than 200 million barrels of oil and derived products on floating storage in tankers, which is around 5% of the global carrying capacity. These tankers will need maintenance and to fulfill contractual requirements. Many tankers are at anchor or idling near major ports around the world with the risk of getting exposed to extreme weather conditions, potential piracy activities and in some cases, to political conflict. The longer these tankers stay at sea fully loaded, the bigger the risk of cargo degradation or loss because of the extended time or worse, the risk of accidents and environmental pollution.

As per the cruise industry, it generates an estimated $150 billions in global economic activity, supporting more than one million jobs worldwide [16]. This sector is perhaps the one that is most impacted by the pandemic, with almost no activities due to several COVID-19 outbreaks on board, travel restrictions, port closures and prohibition to sail from the US Center for Disease Control (CDC) since March of 2020 [17]. With around 95 % of the global cruise fleet in lay-up, there are concerns on risks for both, ship owners and insurance companies due to the Atlantic hurricane season, considering that almost half of those ships are in and around the Americas. Similarly, for the typhoon season in the Pacific. Other important impacts are the costs of having these ships laid-up for an extended period of time, which is estimated between $1 million and $3 million per month and the costs of bringing them back to service.

Those above are perhaps the most evident impacts to the shipping industry, but there are other less visible and equally important aspects that are being impacted, such as disruptions on machinery maintenance and repairs, ship owners risk delays on scheduled maintenance and services, disruption in the supply of spare parts and other essentials such as lube-oil and hydraulic oils and travel restrictions for specialist engineers to access the ship to provide maintenance or repairs. Engines can also be damaged by delays in the analysis of sulphur emissions, because of the cap on sulphur emissions under International Maritime Organization (IMO) 2020, vessels have been using blended low-sulphur fuels, which in order to avoid engine damage, require analysis prior to be used by the ship's engines. This requires the dispatch of fuel samples to shore-based laboratories and with COVID-19 restrictions, it may not be possible to do in time. There are manuals that detail how to proceed with on board testing kits and there is the possibility to use distillate fuels as an alternative, but the normal procedures are disrupted. There are several other areas of the shipping business impacted by the COVID-19, the examples above, are meant to give a sense of the deep effects this pandemic has in the industry. The maritime ports sector has seen a reduction in containers volumes, quarantine of vessels by ports for 14 days, port closures, and port operations in general.

Reduced operations and personnel have an impact on possible cargo damage, which if stored in high risk areas without the appropriate security controls can run the risk of losses from fire or extreme weather conditions and delay in the supply chain can also result in cargo damage, mainly to perishable or temperature-sensitive goods. With vessels being quarantined and ports being quarantined cargo movement is delayed. This will also have an impact on the insurance industry, with a potential increase of claims.

9.1.3 Significance of Machine Learning for Maritime During COVID-19

Problems pertaining to every subsystem in the maritime ecosystem rely on accurate data and reproducible analysis that result in data products. In addition, maritime data has the potential to serve as a proxy for COVID-19's impact on global trade [18]. The availability and density of maritime data require scalable deployment of artifical intelligence to extract patterns [19], find anomalies [20] and forecast disruptions [21]. Live maritime data has the potential to be an early warning sign for supply line disruptions due to COVID-19 [22].

Shipping and maritime data, depending on the source, can be represented one of three ways:

1. Track/movement analysis
2. Spatio-temporal analysis
3. Time-series analysis

Depending on the aims of the maritime community all approaches have the potential to answer important questions pertinent to supply chain and trade activity during the COVID-19 pandemic. Movement prediction is another useful data product obtained from track-level analysis of vessel movement [23]. Anomalies and movement prediction are important components for maritime community to ensure safe navigation, an ever important topic during a pandemic and associated supply line disruption [22]. Spatial analysis of maritime data has provided proxies for secondary sources of information on ship movement that is not available publicly in real time. In particular, satellite imagery from ship emissions and ship wakes are used to reconstruct ship tracts which in turn can be used for further analysis [24]. Track and movement analysis for maritime data is performed at the agent level and movement anomaly detection methods are frequently used to identify unexpected movement of vessels [25].

Spatio-temporal analysis of ship traffic using Getis-Ord statistic [26] has shown to effectively detect bottlenecks of ship traffic at natural and artificial confinements, such as ports and straits [27]. In addition, space-time analysis of ship tracks from AIS feeds has been found useful for delineating areas where shipping volume is observed to drop unexpectedly. Despite differences in their formulation and uses, operationalizing artificial intelligence during the COVID-19 pandemic requires uninterrupted data streams, near real-time data curation and resilient analysis networks to ensure information flow on issues of vital importance to communities on supply-line disruption.

9.1.4 The Maritime Ecosystem's Needs for Data & Challenges

As discussed above, maritime transport is more important than ever, ships must keep moving, ports need to stay open and cross-border trade flowing. Besides the challenges in maintaining the supply chain, there is a human factor that is no less important. The shipping industry normally replaces crews every certain time, this operation is becoming very difficult. The International Maritime Organization (IMO) has promoted the key role seafarers play during the pandemic and the need to recognize them as key or essential workers, by identifying the dangers they face while doing their jobs.

This pandemic has created an unprecedented crisis for ship crews, with the difficulties to travel and restrictions imposed by governments and port authorities, the normal crew change that periodically has to happen has been interrupted and in many cases seafarers are stuck at sea way passed the due time, creating health risks and safety issues.

Normally more than 100,000 seafarers must be changed monthly in order to comply with international regulations for crew welfare and safe working hours. In the current situation, it is estimated that around 400,000 seafarers are being impacted by the COVID-19 restrictions.

The International Transport Workers' Federation (ITF), that represents about 1.4 million seafarers, has decided not to celebrate the 2020 Day of the Seafarer, due to the humanitarian crisis that the travel restrictions have created at sea. The global supply chain could be at risk.

The IMO together with the United Nations Conference on Trade and Development (UNCTAD) are encouraging governments and maritime industry stakeholders to take a pragmatic approach, such as granting exceptions and waivers where they are appropriate. Also, the use of technology and electronic means for communications between ships and shore, encouraging governments and maritime industry stakeholders to take a pragmatic approach, such as granting exceptions and waivers where they are appropriate. Here is where the use of Geospatial Information in the application of IMO e-Navigation principles should be used in order to provide maritime services that facilitate and expedite administrative, commercial and operational activities. E-Navigation is a way to systematically ensure "berth-to-berth navigation", improving efficiency when a ship is approaching the port.

In this sense, the "Single Window" concept, at least for some of the most important activities should be implemented. The e-Navigation concept for a "single window" is where a ship (or a shipping company) can access a series of services from registered service providers before arriving the Port.

In this topic there are important geospatial aspects to consider from another organization, the International Association of Marine Aids to Navigation and Lighthouse Authorities (IALA), which standards such as the IHO S-200 series and organizations like the PortCDM Council (Collaborative Decision Making) will contribute in improving efficiency coming in to and going out of a port.

The International Hydrographic Organization (IHO) is the entity in charge of developing standards and specifications to be applied to products and services used in the maritime world. They have developed the S-100 standard, officially called the Universal Hydrographic Data Model, from which many new product specifications are being developed. Most if not all national hydrographic offices around the world follow IHO standards in one way or another. As per the COVID-19 pandemic, IHO has not emitted any specific guidelines or recommendations to its members, but they have suspended all in person meetings and activities, including the General Assembly meeting that did not take place in 2020 as scheduled.

While normally the bulk of the organization's work happens by correspondence, there is important work that occurs during technical working group physical meetings, that has the advantage of isolating themselves from the day to day work for one week to make significant advancements in developing standards and make key decisions with all the relevant stakeholders present in the same room. These on-site meetings have been replaced with webcasts in an effort to continue with their working plans and minimize the effects of the pandemic on their work.

National hydrographic offices are the authoritative government agencies, equivalent to national mapping agencies on land, in charge of producing navigational charts and other complementary information products for safety of navigation. Some of these agencies in general have experienced challenges for keeping up with their regular production and updating services, and they have been adapting to the pandemic circumstances in different ways. As we will see in the NOAA use case below, some agencies have implemented enterprise systems that allow them to work remotely and continue with their regular activities as close as possible to the normal times.

Hydrographic surveying activities in general cannot be performed in the office, there are many phases of this type of surveys that need to be performed on the field, and sometimes physical distancing between hydrographers is almost not possible, if we consider a small hydrographic survey boat with two or three hydrographers on board collecting data together for long periods of time or a larger hydrographic survey ship at sea with crew confined in small compartments for several weeks in a row.

Similar situation and risks are being experienced by land surveyors, and many governments around the world have implemented guidelines to increase safety of their workers while in the field. Although these measures and guidelines are often generic and not specific to surveyors, much less to hydrographic surveyors.

Oftentimes hydrographic surveys are not on the top of the list of priorities during a pandemic, but the need to keep the navigational routes mapped and up to date is as important as keeping the shipping fleets moving. There is no hard evidence that the hydrographic surveying activities around the world have diminished to the point to consider them in crisis, but there are signs of some reduction of activities, this is true for both government and private organizations. Because a pandemic is not the same as a meteorological phenomenon such as a hurricane or typhoon, the characteristics of coastal waters haven't been affected, then there is not an immediate or emergency need and surveying activities can be planned carefully following all the appropriate measures.

On the other hand, nautical chart and related information production are activities that can be done remotely or from home. Many national hydrographic offices around the world have implemented telework measures in order to keep up with the necessary production updates and distribution of digital publications. Thus, nautical data products can be effectively served with the exception of some activities that require onsite labor such as the distribution of printed nautical charts and other paper nautical publications.

9.1.5 Challenges Faced by Information Product Providers

The standards related to the S-100 Universal Hydrographic Data Model [28], are geospatial data standards that can support a wide variety of hydrographic-related digital data sources. S-100 is fully aligned with mainstream international geospatial standards, specifically the ISO 19000 series of geographic standards. This alignment enables easier integration of hydrographic data and applications into geospatial solutions. S-100 is more flexible than the old S-57 and enables the use of imagery and gridded data types, enhanced metadata and many encoding formats. It also provides a flexible and dynamic maintenance regime for features, their attributes and portrayal through a dedicated Registry online. One can think of S-100 as a framework of components that provides instructions for building standardized Product Specifications for hydrographic data, enabling true interoperability between different data standards and systems.

The IMO e-Navigation [29] is defined as the harmonized collection of marine information, its integration and exchange for "presentation and analysis both on board, and ashore by electronic means to enhance berth to berth navigation and related services for safety and security at sea and protection of the marine environment" [30].

The term "Single Window" can be understood as the point of contact for communication in relation to ship-to-shore and shore-to-ship. In this sense, it's mentioned in the IMO resolution A.950(23) "Maritime Assistance Service" (MAS) adopted on 05 December 2003. "Single Window" can also mean a service or institution on land that collects all information related to safety of navigation before sending them to ships, as defined in IMO documents on e-Navigation. The information products and services to be provided by the IMO e-Navigation single window concept should be based on standards that would allow them to be used anywhere in the world. In this sense, the IHO S-100 series are perhaps the most important one.

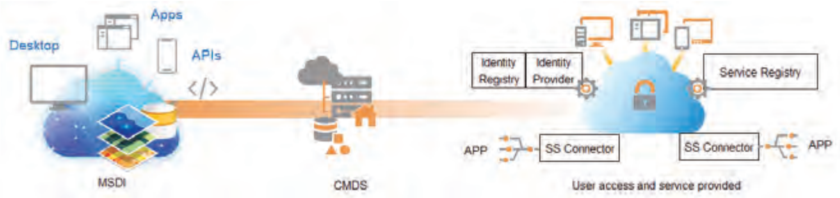

FIGURE 9.1
Geospatial Information to the e-Nav "Single Window" concept (Source: https://www.esri.com/)

By adopting S-100 standards, there are new products and services that can be provided following the e-Navigation concept from which the Maritime Service Portfolios (MSPs) can be developed and shared through a Common Maritime Data Structure (CMDS), which could be considered a derivation or extension of a Marine Spatial Data Infrastructure (MSDI). The Hydrospatial Agency not necessarily has to create the CMDS, but the MSDI should provide the "connectors" to feed a CMDS with their products and services.

The role is not anymore constrained to producing nautical charts (and in some cases Sailing Directions, Notice to Mariners, Tide Tables and related information), through this type of infrastructure, authorities and service providers can go beyond that. Bathymetric Surfaces, Near Real Time Tides and Currents, Under the Keel Clearance Management, Marine Protected Areas, and more necessary information can be provided through MSPs. Port Authorities and Administrations will benefit from this, Port Pilots, Dredging Operations, Port Security, Port Services, Port Logistics, will certainly be improved through these MSPs.

The right side of the graphic above shows the e-Nav concept for a "single window" where a ship (or a shipping company) can access these services from registered service providers before arriving the Port. The PortCDM Council (Collaborative Decision Making) has taken the role of developing the S-200 series of standards for IALA, being the first one developed the S-211 standard for Port Call Messages, standardizing sharing of data on Intentions and Outcomes of Movements, Services and Administrative events.

All the above mentioned systems are an integral part of what is commonly known as "Port

Community Systems" (PCS), which are open and neutral platforms that can connect multiple systems together with the purpose to provide intelligent and secure exchange of information between different organizations that participate in a seaport community, such as agents and shipping lines, customs and excise, logistics providers, terminal and warehouse operators. A PCS can integrate into a national single window or act as a national single window.

9.1.6 Working Remotely and Disconnected

The COVID-19 outbreak has made maritime organizations and geospatial authorities rethink how the modern workplace can operate during major disruptions.

Maritime software, such as ArcGIS will support the management and production of maritime data that is compliant with the International Hydrographic Organization's (IHO) S-4, S-57 and S-100 series of standards.

With the COVID-19 crisis engulfing and disrupting businesses, it has become necessary for our national mapping agencies and industry leaders and experts, to reevaluate ways for maintaining successful business continuity.

As the workforce adapted the organization's senior leadership team implemented powerful operational tools that ensured production was maintained and tracked across environments. Two actions that were taken were

1. Enablement of virtual and disconnected environments
2. Automated apps and dashboards that optimized the organizations' communication responsiveness.

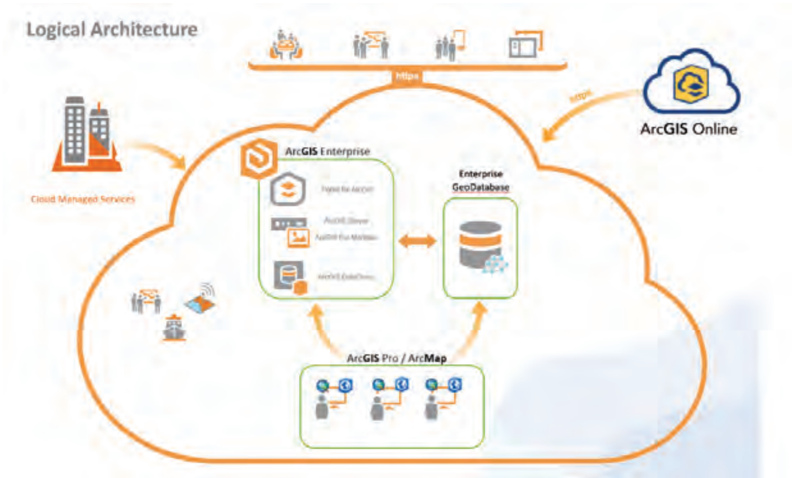

FIGURE 9.2
Leveraging Virtual, Disconnected, and Cloud Environments with ArcGIS (Source: https://www.esri.com/)

First action requires leveraging virtual environments and disconnected editing. This offered GIS users the advantage of working remotely with large amounts of geospatial information including maps, statistics, imagery, and other forms of remotely sensed data which exists across multiple distributed networks or in the cloud. This was done using via virtualization and disconnected work loads. Virtualization allows remotely connecting to a server GIS (such as ArcGIS Enterpise) with desktop virtualization. This provides the ability to collaborate directly with colleagues in a multi-user environment. Disconnectedness enables completing tasks, projects, and production. Reconnect later to synchronize work with the larger workforce.

The second action requires leveraging automated templates for apps and dashboards that optimize communication and workflows. Organization are now driven to adapt to unexpected yet urgent catastrophes like the COVID-19 pandemic, with accurate ready-to-use apps and dashboards, for building and reporting critical information to stakeholders, constituents and at-risk groups. Customized (COTS) out of the box Operations Dashboards, tools, GIS software, predesigned templates, libraries of reusable widgets and applications like the WebApp Builder give instant ability for performing time-sensitive decision making and building optimized workflow communication strategies.

9.2 Case Studies

The importance of maritime data acquisition, analysis via machine learning and AI and data product dissemination is elaborated with three case studies, one from NOAA and two from ESRI, respectively.

9.2.1 National Oceanic and Atmospheric Administration – Office of Coast Survey

The pandemic has forced the NOAA Office of Coast Survey (US National Hydrographic Office) to re-organize the way they conduct business. The safety of navigation in US waters is one of Coast Survey's main responsibilities and updating navigational charts is one of their most essential functions. Prior to the COVID-19, Coast Survey's Marine Chart Division (MCS) had developed an on-site sever-based system that allowed their staff and contractors to work remotely when needed, so when the pandemic struck and the need to establish physical distance for everyone, they could quickly shift one hundred percent of its workforce (more than 100 cartographers) to a work-from-home status. During this period the Division has continued to apply updates to nautical charts and has made progress on its effort to rescheme the suite of nautical charts in the United States according to their cartographic plan.

The MCD system relies on Citrix, allowing users to connect to a virtual server or desktop application remotely, so there is no need for a program to be installed on the local or physical system. MCD cartographers connect to their IT services from home via internet connection. Security is ensured by using VPN and a single sign-on (SSO) and advanced security controls. Using an application called XenApp, that facilitates the installation of applications on a server that can be accessed without having to install anything on the client machine, except for the Citrix client software, cartographers access the ArcGIS-based enterprise chart production system, called "Nautical Chart System II" (NCPSII).

In this way, all the processing happens on the server, through mouse clicks and keystrokes from the client that feels like if the production software is running locally, and the client screen refreshes from the responses to the server through a remote display protocol called "Independent Computing Architecture" (ICA).

The configuration of Citrix, together with the ArcGIS-based NCSII, was a key step in preparing the workforce to work remotely. However, a very important factor might be the general willingness of the users and management to work remotely before the pandemic started. NOAA OCS had already set up infrastructure - hardware, software and the user's understanding of how to work from home. Every staff member was provided with a laptop with the appropriate software installed to enable them to work remotely even if they were not currently teleworking.

They also benefit from robust virtual meeting capabilities that allow system administrators to work directly with the users to run upgrades and troubleshoot problems. This enabled OCS to keep the virtual convenience of working shoulder to shoulder.

With this arrangement, the Marine Chart Division has kept up with their usual production activities. They have been updating charting products and have been applying all critical (dangers to navigation) corrections to their products. In addition, MCD has also reschemed 259 ENCs during

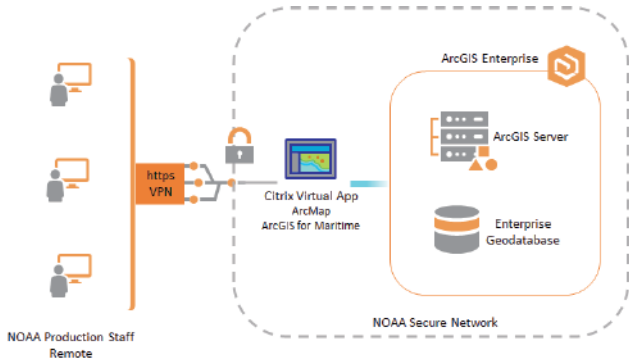

FIGURE 9.3
NOAA's Nautical Chart System for remote work diagram (Source: https://www.esri.com/)

the work from home period, continuing with their modernization plans that include retiring paper nautical charts.

Working remotely has been a positive experience, thanks to the NCPSII platform capabilities and flexibility, the overall productivity has not been affected, these results are causing OCS to consider the possibility to increasing their flexibility with regard to telework, although there is no official guidance for the post-pandemic activities.

9.2.2 Space-Time Analytics for Quantying Impacts of COVID-19 on Shipping Trade

Restrictions due to COVID-19 measures impact maritime traffic and all sectors of the economy that rely on maritime transport of goods. Live space-time data plays an essential role to for modeling and pattern mining studies to quantify current status of traffic restrictions, expected delays of transported goods and changes to port activity.

We use time series clusters and space-time patterns in the Oxford COVID-19 Government Response Tracker's (OxCGRT) stringency index which quantifies the extent to which governments take actions to restrict day to day activities [31]. The index is the average of 17 selected mitigation and suppression measures employed by different countries [31].

Daily stringency index mapped at the county-level is aggregated into a space-time structure, the space-time cube. Space-time patterns of the stringency index are mined by classfying the local changes to the Getis-Ord Statistics, namely the G_i^* statistics (Getis and Ord, 1992). The G_i^*tatistic is a z-score where extreme values imply significantly high (hot-spot) or significantly low (cold-spot) in a spatial neighborhood compared to the global average of stringency index. G_i^* values close to zero implies stringency index in the area is similar to the global average at a given time.

Stringency index space-time patterns are depicted in Figure 9.4. Space-time patterns indicate Russia and parts of South America as Oscillating Hot-Spot. This pattern means these countries and their neighbors oscillate around global average for stringency for extended periods of time and go above the global average for short periods of time. Locations that are classified as sporadic hot spots go above the global average for stringency at certain times and fall back to the average. Majority of Europe exhibits oscillating cold spot which indicates stringency is lower than global average at certain times.

Space-time patterns of stringency informs the expected maritime opening and closures of an entire region using data from neighboring countries. This space-time metric gives a clear idea of how regions of the world may open up over time and which regions are still under high stringency measures.

We also performed a time-series analysis of stringency per country to assess when maritime traffic may return back to normal as stringency measures are lifted at the country level.

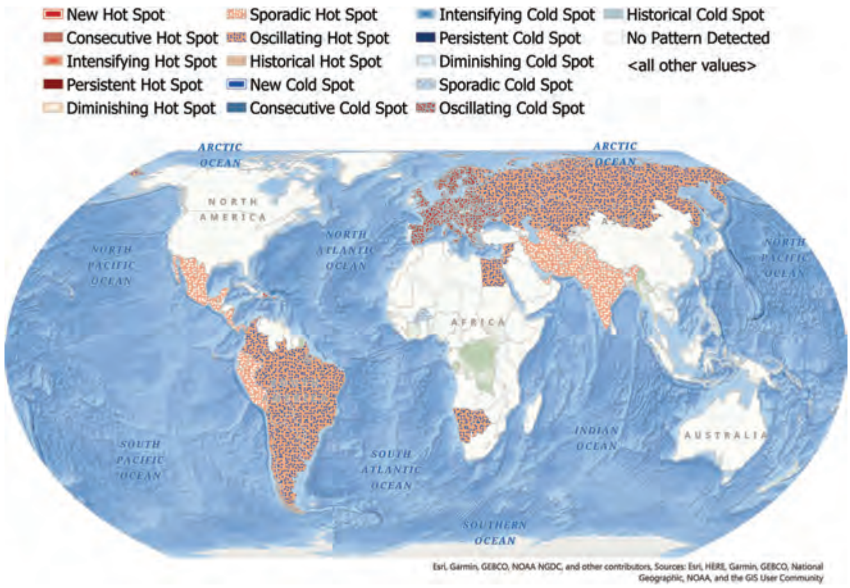

FIGURE 9.4
Emerging Hot Spot Classes of Oxford's COVID-19 Government Response Tracker (OxCGRT) Stringency Index (Display variable)

Three clusters identified in Figure 9.5 indicate change of stringency of countries over time. Blue time series clusters show a high rate of increase in the stringency index, this can imply reduced ship traffic from these countries. Red cluster indicates countries that started their stringency measures later on increase at a higher rate. Green countries are the ones with stabilizing and a lower level of stringency.

FIGURE 9.5
Time-Series Clusters of Oxford's COVID-19 Government Response Tracker (OxCGRT) Stringency Index (Display variable)

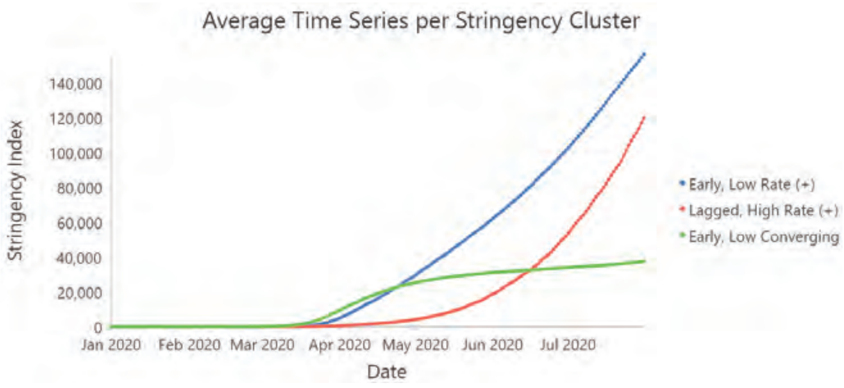

FIGURE 9.6
Time Series Clusters (same coloring scheme as Figure 9.5 of Oxford's COVID-19 Government Response Tracker (OxCGRT) Stringency Index (Display variable)

Figure 9.6 demonstrates the challenges awaiting the maritime industry due to COVID-19 as some countries are getting ready to resume regular daily activities and others deeper into the pandemic with strict measures. Three distinct time series are labelled with respect to when stringency measures were imposed and the rate of increase in their stringency measures over times. Note that countries symbolized with blue in Figure 9.5 started stringency measures earlier and their measures have been increasing ever since. Red group countries started lock-downs later but they have been ramping up efforts at a high rate. Green countries have a converging profile for their stringency measures which are not extensive as the countries in blue and red groups.

The spatial heterogeneity of imposed lock-downs and reductions to business activity indicate that even after the pandemic is declared to be over, a significant lag is to be expected for supply chains to return back to normal. Countries marked with green in Figure 9.5 are expected to ramp up their trade activities as the pandemic is under control, however countries with large trade volumes such as United States and China that fall under the blue category will need more time for their maritime operations to go back to normal.

9.2.3 Disseminating Live Traffic Data During the Pandemic: ESRI Ireland

One threat to maritime was the occurrence of outbreaks on vessels. The effects of such outbreaks had a major impact on economic and trade activities. In 2018 the cruise ship industry was estimated to be worth over $29.4 billion dollars and it is predicted to carry over 19 million passengers annually. An important tool used to monitor and measure global vessel movement is the Automatic Identification System (AIS). AIS uses ship transponders and satellite communications which feed into Vessel Traffic Services (VTS). From these data feed ships with known outbreaks were tracked and monitored.

In early 2020, COVID-19 hit the leisure cruise ship industry which resulted in many issues of quarantine and the need to provide medical assistance to those in dire need. In Europe, ESRI Ireland created a web-based Global Vessel Dashboard dashboard using vessel traffic from the AISHub to monitor the situation. The AIS hub collates and shares vessel data collected from approximately 750 tracking stations run by the AISHub community. ESRI Ireland enriched the raw vessel data with information on cruise ships that reported COVID-19 outbreaks using public data.

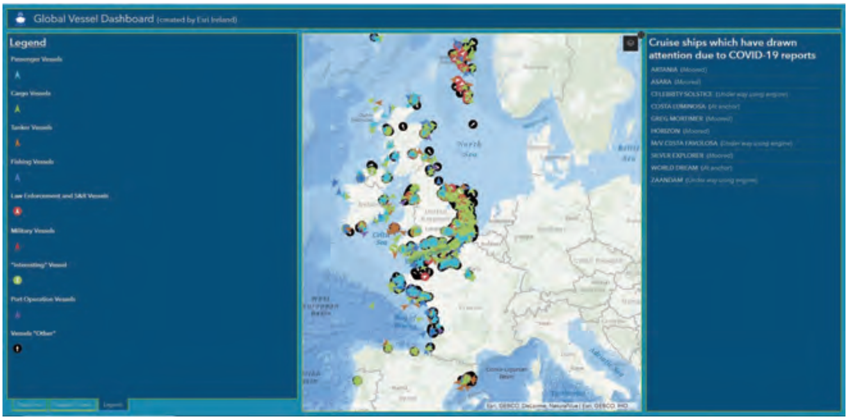

FIGURE 9.7
ESRI Ireland's Maritime Dashboard for Vessel Traffic in Europe

9.3 Conclusions

By leveraging geospatial technology using existing GIS capabilities, national mapping agencies and geospatial authorities can address continuity of operations, leverage virtual and disconnected environments, and optimize communications and workflows. These approaches can be used individually or collectively to ensure mission and business success during a time of crisis. NOAA's work on implementing data standards and virtualization is a representative example of opportunities in maritime for operationalizing geospatial servers that leverage maritime data conforming to international standards. It is important to note that the remote infrastructure for data collection, mapping and dissemination has resulted in positive outcomes for the scale that is required by a large organization such as NOAA. ESRI Ireland's data dissemination method through dashboards shows the value of geospatial maritime data visualization and interactive data dissemination during the COVID-19 pandemic.

Challenges with respect to changing type of work environment and establishing uninterrupted data streams during the pandemic are important to quantify the impact of the pandemic on maritime activity and global trade in general. Our showcase of the importance of AI and machine learning as it pertains to stringency index demonstrates spatiotemporal heterogeneity in factors that impact maritime traffic and supply lines. The stringency as a proxy for maritime activity shows that vessel activity between countries may not go back to normal immediately after the pandemic due to different levels of stringency measures throughout the world. Thus, concerted efforts taken by international organizations are required to restore the maritime traffic and intercontinental supply lines. As prolonged supply line disruptions are expected to cause major alterations to supply routes and trade deals, COVID-19 serves the latest pandemic of the digital age, where live maritime data and remote work can keep organizations and country levels afloat during time of crisis. A better understanding of the logistical chain and identification of weak points along the way as well as prioritization of essential goods will be key. This extends to terrestrial transportation, warehousing and distribution centers. The crew change system has to be reviewed and adapted to the circumstances based on how the pandemic is being addressed and controlled around the world, and the recognition of ship's crew as essential workers is also very important in maintaining operations.

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