

Review

RETRACTED: Digital Twin Smart Cities for Disaster Risk Management: A Review of Evolving Concepts

M. R. Mahendrini Fernando Ariyachandra ^{1,*}  and Gayan Wedawatta ^{2,*}

¹ Department of Engineering, University of Cambridge, Cambridge CB2 1PZ, UK

² Department of Civil Engineering, School of Infrastructure and Sustainable Engineering, Aston University, Birmingham B4 7ET, UK

* Correspondence: mfa47@cam.ac.uk (M.R.M.F.A.); h.wedawatta@aston.ac.uk (G.W.)

Abstract: Natural hazard-induced disasters have caused catastrophic damage and loss to buildings, infrastructure, and the affected communities as a whole during the recent decades and their impact is expected to further escalate in the future. Thus, there is a huge demand for disaster risk management using digitalisation as a key enabler for effective and efficient disaster risk management systems. It is widely accepted that digital and intelligence technologies can help solve key aspects of disaster risk management such as disaster prevention and mitigation, and rescue and recovery. Digital Twin (DT) is one of the most promising technologies for multi-stage management which offers significant potential to advance disaster resilience. Smart Cities (SCs) use pervasive information and communications technology to monitor activities in the city. With increasingly large applications of DTs combined with big data generated from sensors in a SC, it is now possible to create Digital Twin Smart Cities (DTSCs). Despite the increasing prevalence of DTSC technologies and their profound impact on disaster risk management, a systematic and longitudinal view of the evolution to the current status of DTSC for disaster risk management does not exist. This review analyses 312 titles and abstracts and 72 full papers. To begin with, a scientific review of DT and SC is undertaken, where the evolution of DTSCs is reviewed. In addition, the intelligence technologies used in DTSCs for disaster risk management are assessed and their benefits are evaluated. Furthermore, the evolution and technical feasibility of DTSC-driven disaster risk management is evaluated by assessing current applications of DTSCs in disaster risk management. It was found that despite the significant potential benefits offered by DTSCs, they also add a new layer of complexities and challenges inherent to these technologies to the already complex web of complexities involved in disaster risk management. These challenges can be addressed by understanding how the process of utilising DTSCs in disaster risk reduction and sustainability is designed, which is essential for comprehending what DTSCs may offer, how it is implemented, and what it means to all involved stakeholders. This paper contributes to the knowledge by improving the understanding of the current status of DTSC technologies and their impact on disaster risk management, and articulating the challenges in implementing DTSC, which inspires the professional community to advance these technologies to address them in future research.

Keywords: digital twins; disaster risk management; preparedness; smart cities; resilience; natural hazards; vulnerability



Citation: Ariyachandra, M.R.M.F.; Wedawatta, G. RETRACTED: Digital Twin Smart Cities for Disaster Risk Management: A Review of Evolving Concepts. *Sustainability* **2023**, *15*, 11910. <https://doi.org/10.3390/su151511910>

Academic Editor: Boris A. Portnov

Received: 20 April 2023

Revised: 29 June 2023

Accepted: 24 July 2023

Published: 2 August 2023

Retracted: 15 December 2025



Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

A disaster is a ‘serious disruption of the functioning of a community or a society at any scale due to hazardous events interacting with conditions of exposure, vulnerability and capacity, leading to one or more of the following: human, material, economic and environmental losses and impacts’ [1]. Natural hazard-induced disasters can have a life-altering influence on the individuals and families fortunate enough to survive them [2]. Despite the ingenuity, the effect of natural hazard-induced disasters can be felt at the

community, city, and state level, or can even impact an entire country [3]. Over the last decade, a series of such events have caused economic losses in the tens of billions of pounds. Examples include hurricane Ida (United States) in 2021, the North American windstorm (United States, Mexico and Canada) in 2021, China floods (China) in 2020, cyclone Amphan (Eastern South Asia) in 2020, and hurricanes Harvey and Maria (United States) in 2017. In 2020 alone, direct economic losses and damages from natural hazard-induced disaster events were estimated at GBP 205 billion. Comparatively, this was well below the record-breaking highs of GBP 425 billion in losses in 2011 and GBP 370 billion in 2017 [4]. Recent storms Dudley and Eunice, which hit the UK in February 2022, are predicted to cost between GBP 2.5 billion and GBP 3.7 billion [5]. Over the last two decades, there have been over 7000 disaster events globally, claiming over 1.23 million lives (averaging over 60,000 lives per year) and affecting more than 4 billion people (many on multiple occasions) [6]. Additionally, disasters led to approximately GBP 2.26 trillion in economic losses worldwide [6]. These numbers present major demands for improving existing disaster risk management systems, including disaster response and recovery on a continuous basis [7], and there are many difficulties inherent in achieving these aims.

Such devastating and increasing social and economic impacts caused by disasters worldwide have necessitated the authorities to improve how they seek to mitigate, prepare for, respond to, and recover from disasters as a key priority at international, national, and local levels [8]. These collective efforts resulted in the establishment of emergency and disaster management systems such as the Federal Emergency Management Agency (FEMA) (United States), the Ministry of Emergency Management of China, and the United Nations Office for Disaster Risk Reduction (UNDRR) [9]. However, these systems lack technical interoperability, functional integration, and resource sharing, which currently remain obstacles to effective disaster management [10].

The increasing trend in the use of digitalisation may open new avenues to more network-centric and data-centric disaster risk management. The Coronavirus (COVID-19) pandemic is a living example which demonstrated how technology can offer substantial improvements to disaster responses in many forms; for example, improved testing and disease detection [11], improved policy and decision-making [12], improved training and education, and to efficiently manage imposed work and social distancing [13]. The role of technology in optimising risk reduction, mitigation, preparedness, response, and recovery is paramount from both an operational and strategic viewpoint, and digital innovations associated with Industry 4.0 have become key tools to use therein [14]. Hence, digital transformation and technologies have now become essential choices for disaster risk management. Among these technologies, the advent of Digital Twin (DT) and Smart City (SC) applications have emerged, presenting new opportunities for leveraging digitalisation to better manage disaster risk management.

The Digital Twin (DT) is one of the most beneficial technologies for better managing complex environments and facilitating connectivity through a variety of self-operative functionalities [15]. Digital Twin is a digital replica of a real-world asset or operation and differs from traditional Computer-Aided Design (CAD) and is based on massive, cumulative, real-world, real-time data measurements in multiple dimensions [16–18]. DTs evolve along with the physical asset or operation during their whole life cycle, enabling real-time bidirectional mappings between the virtual and physical assets or operations [19]. The term Smart City (SC) is rather ambiguous as the precise content, features, and nature of SCs tend to vary from country to country, depending on geographical conditions, ecosystems, and resource availability [20–22]. Broadly, though, a Smart City (SC) can be defined as an integrated living solution that perceptively and efficiently connects many life aspects such as power, transportation, and buildings to improve the quality of life for its citizens. A SC also looks to the future, emphasising the importance of resource and application sustainability for future generations [21,23]. Whilst there is some debate as to whether a SC is being used as a tool for smart public administration or a marketing tool [24], there is wider acceptance of the benefits associated with the concept. A Digital Twin Smart City

(DTSC) combines these two components to provide functionalities that can synthesise the unique characteristics and constraints of a community during a disaster event and predict the evolution of a community during the aftermath of a disaster, enabling better disaster risk management [25].

The extent of research on DTSC in the context of disaster management has exponentially increased over the past few years to unlock the full potential of adopting DTSC for more resilient disaster risk management systems [25–31]. Examples of that include using Light Detection and Ranging (LiDAR) to interpret real-time situational data in disaster-affected or dangerous locations [32–35], and social sensing methods such as Facebook and Twitter data to detect events and examine responses and sentiments [36–40]. On a similar note, Fan et al. [41] proposed the concept of a ‘Disaster City Digital Twin’, and discussed how a digital twin can help converge various tools in ICT and AI in disaster response. Furthermore, there are several methods through which DTSCs can assist in automatically detecting temporal and spatial information on community disruptions [42,43]. Additionally, DTSC can be used to provide localised and near-real-time information on evolving disaster situations for decision-makers, first responders, as well as local businesses and residents [44]. While the use of DTSC applications in disaster risk management is growing, there has been no review of these applications to date. Hence, there is a need for systematically reviewing and summarising state-of-the-art applications of DTSC applications in disaster risk management to inform the academic community on past works and possible future recommendations. Contextualisation of recent research developments on the topic under one roof will also benefit policymakers and practitioners.

This research aims to clarify the potential of DTSCs in disaster risk management and propose recommendations for a scientific paradigm of DTSC-driven disaster risk management. This aim will be achieved by answering the following research questions:

1. How have the DT and SC been evolved and used in disaster risk management over the last 10 years?
2. What is the current state of research in DTSC applications for disaster life cycle management?
3. What are the development needs and challenges that may hinder DTSC technologies from being fully utilised for disaster risk management?
4. What future research endeavours are necessary to address the opportunities and challenges of DTSC disaster risk management applications?

The remainder of the paper is organised as follows. Section 2 identifies the review methodology. Section 3 details the history of DTs and SCs and defines the scientific scope of DTSCs for disaster risk management. Section 4 summarises the use of technologies and the application of DTSCs in the disaster risk management life cycle. Section 5 discusses the challenges and risks inherited in the applications of DTSCs for disaster risk management and Section 6 presents the conclusions and future research directions.

2. Review Methodology

A systematic literature review is considered as a transparent, rigorous, and detailed methodology that can be used to support decision-making, which was originally used in the medical sciences to consolidate information from multiple sources [45–47]. While systematic literature reviews are constrained in terms of search method and article selection, they are effective at summarising what a large number of studies show in a specific field and can provide evidence of the effect that can be used to better inform policy and practice [48]. The outcomes can either generate new knowledge or document the current state-of-the-art [49]. This research dives deep into the concepts of DTs and SCs before documenting the current state of DTSC applications in disaster risk management research. Following that, it reveals patterns relevant to practitioners and researchers, which aids in the generation of new knowledge and the provision of future research directions.

The authors provide the following review methodology to present the status of academic publications about DTs and SCs in disaster risk management, which primarily

consists of four parts. Figure 1 illustrates the review methodology in terms of the search strings, search criteria, and article selection procedure.

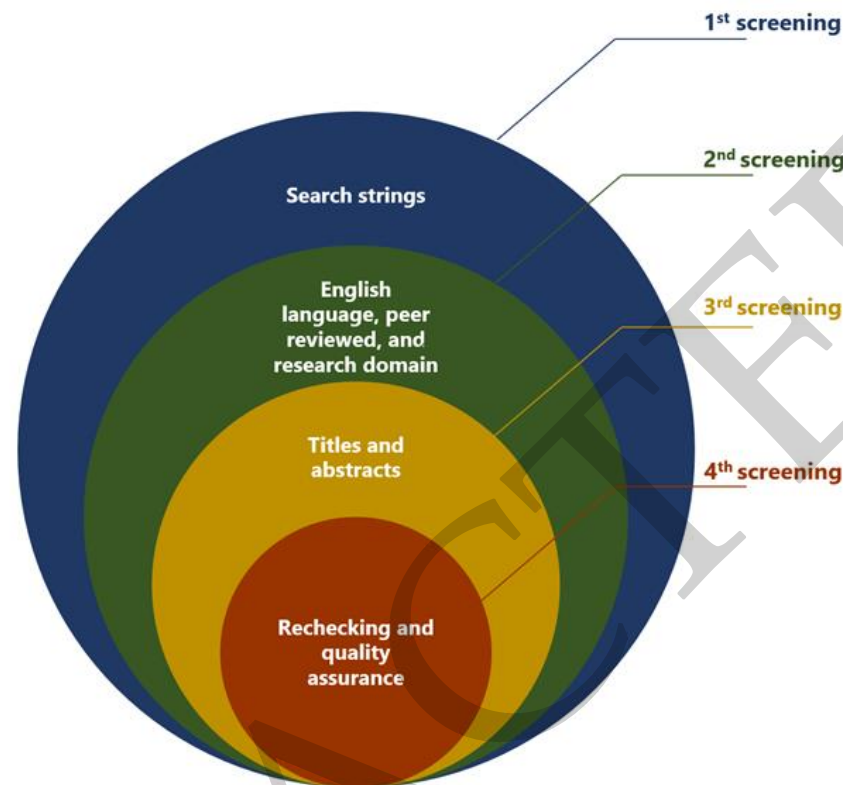


Figure 1. Methodology adopted in screening papers.

This study used articles from two of the largest academic internet databases, Web of Science (WoS) and Scopus, and was confined to peer-reviewed publications published in these two databases. Journal articles under review or in the process of publication, conference papers, books, and book chapters were excluded from the review. The exclusion of books and book chapters from systematic reviews is not uncommon because they are frequently classified as grey literature [50] or are not subject to the rigorous review process that journal articles go through [51]. The time period in this study is set as 2011–2021, as the first relevant article appeared in 2011. The sampling and filtering of the articles were done according to the following steps.

1. The articles were retrieved using a combination of keywords. These keywords were divided into two groups. The first category was the most frequently occurring natural hazard-induced disasters between 2000 and 2019, as reported by the United Nations Office for Disaster Risk Reduction (UNDRR) (2020). Floods (44%), storms (28%), earthquakes (8%), extreme temperatures (6%), landslides (5%), droughts (5%), wildfires (3%), volcanic activity (1%), and mass movement (<1%) were identified as the disaster events to have occurred during this period [6]. The review excluded ‘mass movement’ from the first category due to the low frequency recorded compared to other disaster types. The second category of keywords used in the search string was ‘Smart City’, ‘Digital Twin’, ‘Social Sensing’, ‘Social Infrastructure’, and ‘Digitalisation’. This step returned 312 articles.
2. The articles returned were then screened using three filters: English as the language, peer-reviewed journals, and the research domain. Duplicated articles were also eliminated at this juncture. Finally, the screening step at this stage kept papers from the following domains: Environmental Studies, Construction Automation, Information Systems, Applied Sciences, and Urban Studies, and ended up with 104 articles.

3. These 104 articles were then screened based on their titles and abstracts. The exclusion criteria were as follows:
 - a. The title of the journal does not belong to any of the following categories: Disaster Risk Management, Maintenance, Built Environment, and Intelligence Domains.
 - b. The article's title and abstract do not directly specify that the study's setting is disaster risk management.
 - c. Articles that focus solely on a technical issue while ignoring the implications for buildings, infrastructure, and society.
4. The authors placed excluded articles in designated folders based on the exclusion filter identified above. In this step, the authors also included a quality assurance process. Once each author had completed the screening process, they reviewed the other author's exclusion folders to make sure that any article was excluded within reason. This step delivered 72 articles, which are the core of this systematic review.

The filtering process described above is demonstrated in the following Table 1.

Table 1. Screening and filtering process adopted.

Screening Stage	Criteria Used		No of the Articles Screened
	Keywords/Search Strings		
	Keyword	AND	
1st screening	Flood	"Digital Twin" "Social Sensing" "Social Infrastructure" "Digitalisation"	312
	Storm	"Digital Twin" "Social Sensing" "Social Infrastructure" "Digitalisation"	
	Earthquake	"Digital Twin" "Social Sensing" "Social Infrastructure" "Digitalisation"	
	"Extreme temperature"	"Digital Twin" "Social Sensing" "Social Infrastructure" "Digitalisation"	
	"Land slide"	"Digital Twin" "Social Sensing" "Social Infrastructure" "Digitalisation"	
	Drought	"Digital Twin" "Social Sensing" "Social Infrastructure" "Digitalisation"	
	Wildfire	"Digital Twin" "Social Sensing" "Social Infrastructure" "Digitalisation"	
	Volcano	"Digital Twin" "Social Sensing" "Social Infrastructure" "Digitalisation"	

Table 1. Cont.

Screening Stage	Criteria Used		No of the Articles Screened
	Keywords/Search Strings		
	Keyword	AND	
2nd screening	Filtering		
	English as the language Peer-reviewed journals, Research domain (Environmental Studies, Construction Automation, Information Systems, Applied Sciences, and Urban Studies) Duplicated articles		104
3rd screening	Title and abstract		74
4th screening	Rechecking and quality assurance		72

3. Concepts and Evolution of Digital Twin, Smart City and Disaster Risk Management

3.1. Digital Twin (DT)

A digital twin (DT) is a digital counterpart of a real-world physical asset, and it is a model with a time dimension for all its attributes. Hence, it incorporates the changes over time in the same model while representing different virtual instances at a given point in time. A DT differs from traditional Computer-Aided Design (CAD) and is based on massive, cumulative, real-time, real-world data measurements in multiple dimensions [16–18,52]. DTs evolve along with the physical asset during their whole life cycle, enabling real-time bidirectional mappings between the physical and virtual assets [19]. A DT uses the information of a digital model across the entire life cycle of an infrastructure, and its concept dates back to Dr Grieves' presentation at the University of Michigan to the industry in 2002 [53]. Industry experts predict that the DT market will reach USD 48.2 billion by 2026 [54,55]. The dynamic nature of maintenance, along with the growing application of digital twin systems to tackle the aftereffects of the COVID-19 pandemic, are the primary drivers of the digital twin market's growth.

These DTs are of four levels: Digital Twin Prototype (DTP), Digital Twin Instance (DTI), and two types of Digital Twin Environments (DTEs) known as Adaptive DT and Intelligent DT. These DTs differ depending on their relationship with the physical asset's life cycle and their dependency on the DTs' operators. The following describes the four types of DTs as defined in literature [53,56–63].

- Level 1: Digital Twin Prototype (DTP)—design engineers produce a DTP that describes the prototypical artefact for a new asset [53]. Hence, the DTP exists before there is a physical asset. This model contains design attributes such as initial designs, analyses, and processes generated by project stakeholders. DTPs hold the end-user requirements and other data necessary to define the new asset's intended function [63]. Therefore, it supports decision-making at the concept design, preliminary design, and detailed design stages of the building/infrastructure [61]. The users exploit these attributes to assess technical risks and issues in upfront engineering and later twin its physical asset in the real world.
- Level 2: Digital Twin Instances (DTIs)—project stakeholders continuously produce individual virtual instances of the physical assets known as DTIs. These DTIs represent different virtual twin variants throughout the physical asset's life cycle once the asset has been built [53]. Hence, the DTI defines the physical asset's specific correspondences at any given point in time and uses it to explore the physical asset's behaviour under various what-if scenarios [61]. Data capturing sensors (i.e. laser scanners, drones, photogrammetry) often update the DTI during alternative instances [64]. Capturing the asset's actual conditions during different asset life cycle stages is be-

yond this thesis's scope. Readers can refer to Kopsida and Brilakis [65] and Omar and Nehdi [66] for a detailed literature review of the available data-capturing solutions.

- Levels 3 and 4: Digital Twin Environment (DTEs)—Two types of DTEs exist, known as 'Adaptive DT' and 'Intelligent DT'. An Adaptive DT is a high-level DT that offers an adaptive user interface to the physical and virtual twins [61]. This user interface is sensitive to the preferences and priorities of the end-users by learning and prioritising the end-users' preferences for different instances [56,58] with supervised machine learning techniques [60]. Thus, facility managers and operators can leverage adaptive DTs for real-time planning and decision-making processes. An Intelligent DT is the most evolved version of a DT, developed with supervised and unsupervised machine learning techniques. An Intelligent DT can define assets and patterns encountered in the operational environment by itself [57] to update itself automatically; it provides benefits and abilities beyond the explicitly defined information in the existing DT versions. This DT has the highest autonomy level, allowing it to analyse more meticulous performance and maintain data from the physical asset.

The four core parts of a DT are (1) models, (2) data, (3) connections, and (4) services. As illustrated by Arup [67], physical and digital assets are interconnected in a digital twin ecosystem. The user interacts with the DT through applied intelligence, enabling the DT to perform minimal or no-human labour tasks. The digital thread in the middle connects the physical and digital assets and can be used for 3D simulations, Internet of Things (IoT) devices, networks, cloud computing, and Artificial Intelligence (AI).

3.2. Smart City (SC)

People's perceptions of SCs differ from technological perceptions. Although the SC phenomenon is widespread around the world, its definition remains elusive. Without a universally agreed definition, the SC sector is still in the 'I know it when I see it phase', which means that there is no agreed-upon definition for a SC and defining a standard global definition has proven difficult. These definitions, on the other hand, underline universal attributes and elements that may characterise SC perceptions.

For instance, some view SCs as enriching the quality of life for a certain city segment or citizens. Galán-García et al. [68] viewed the SC as a very broad concept, including social aspects that encompass physical infrastructure, human, and societal factors. This definition was emphasised further by Neirotti et al. [69] when they defined the SC as improving citizens' quality of life, with increasing importance on policymakers' agendas. They added policymakers to the definition of SCs as an additional component. In order to achieve an enhanced quality of life for a city and its people, SCs need to be utilised by information technology hardware, software, networks, and data on different services and regions. Different city components such as natural resources, infrastructures, power, transportation, education, healthcare, government, and public safety are all incorporated into these definitions. For instance, Su et al. [70] discuss the computational element of SCs and emphasise how future-oriented computing is critical to creating this SC. Their definition of a SC involves utilising future-oriented computing capabilities in all essential services such as healthcare, power grids, transportation, buildings, and utility lines, and forming the IoT through the internet. This definition was reinforced by Kitchin [71] who discusses how a city should monitor and integrate the status of all of its major infrastructures, including land and air transportation, communications, and utilities. Chourabi et al. [72] view a SC as a future paradigm of interconnected components. Their definition for a SC explains how different components such as economy, people, governance, mobility, environment, and living can be cooperated and assembled as a smart combination of endowments and activities of self-decisive, independent, and aware citizens. It is argued that this provides a more generic view that brings together all of the main aspects of a SC, making it one of the most comprehensive definitions of a SC [21].

These definitions conclude that a SC is a holistic dwelling that smartly and efficiently connects numerous life components such as power, transportation, and buildings to im-

prove the quality of life for its residents. Furthermore, the definitions concentrate on the future by highlighting the importance of resources and application sustainability for future generations. The authors observed these characteristics in every SC proposal, regardless of size, location, or available resources. It is evident that the wide landscape of SCs has eight main domains as summarised in Bellini et al. [73], that are widely used in the field of SCs such as governance, living and infrastructures, mobility and transportation, economy, industry and production, energy, environment, and healthcare. It should be noted that these eight domains are not essentially orthogonal, as they often intertwine in a variety of settings and applications.

One of the challenges of forming and sustaining a SC is the availability, size, and capabilities of such resources. Another challenge is the regulatory systems, which could have a significant impact on success. On top of that, there are technical issues that call for cutting-edge solutions. Technologies that are new and developing, on the other hand, can assist in transforming such challenges into opportunities.

3.3. Digital Twin Smart Cities (DTSC)s

Data obtained from smart city initiatives can be used to create digital twin cities [74]. The virtual version enables the simulation of spatiotemporal information in a city. A great deal of the recent advancements in global SCs has been made possible through integrating Information Communication Technology (ICT) systems into the city to make its digital replica [74,75]. A preliminary attempt to establish a DTSC was made in Singapore, also known as 'Virtual Singapore' [76]. However, this 'Virtual Singapore' had significant limitations, including the fact that the model has never been made accessible to the public, so citizens cannot engage with it or provide input, and it does not incorporate urban mobility data. A number of private companies, such as CityZenith (<https://cityzenith.com/>, accessed on 28 January 2023), Agency9, and SmarterBetterCities (<https://www.smarterbettercities.ch/>, accessed on 30 January 2023) have started to develop in the DTSC space [77]. The DTSC proposed by White et al. [78] relies on six distinct levels of data in the city. The first five levels contribute information about the city's geography, buildings, infrastructure, mobility, and IoT devices by stacking on top of each other. The smart city component gathers data from the city and sends them to the digital twin component. The data collected in the SC are used by the DT to run additional simulations on aspects such as transportation optimisation, building placement, and the design of renewable energy sources. Simulations thus play a crucial role in the implementation of DTSCs. This information is then transmitted back via the model's layers and applied in the physical world.

3.4. Disaster Risk Management

In some cultures, disasters have been viewed as an act of god, and disaster damages were considered as punishment for their misdoings [79–81]. This philosophy ignored natural global environmental change processes. Later, knowledge of the physical earth system directed the connection of disasters with natural hazards such as floods, earthquakes, and others [82]. People began to perceive the world more scientifically and rationally as economic growth and education progressed. Governments started to respond to disasters in a more logical and systematic manner [83]. Hazards, according to current knowledge, are not exceptional events, and many of them are centered on and reiterated in specific locations [84]. This has sparked a more philosophical debate about defining disasters as 'unnatural'. These natural hazards become disasters when humans fail to implement appropriate preventative and preparedness actions to mitigate their effects. According to this philosophy, disasters happen as a consequence of interactions between people and the environment [85]. This is particularly the case in urban flooding, where human-induced factors such as poor land-use planning, inadequate drainage systems, and poor flood risk management practices often contribute to fatalities and infrastructure damages [86].

The state of research in disaster management reflects that the disaster management approach should shift from reactive approaches to proactive approaches with more inter-

sectoral risk management [87]. The 1990s were designated as the 'International Decade for Natural Disaster Reduction' by the United Nations General Assembly in 1987. The goal of these steps was to improve preparedness potentials, minimise the impacts of disasters, and develop appropriate regulations. In 1994, the United Nations' Yokohama Strategy and Plan of Actions for a Safer World emphasised the importance of sustainable development in disaster reduction and prevention [88]. The World Conference on Disaster Reduction (WCDR) developed the Hyogo Framework for Action (HFA) in 2005, which called for strengthening nations' and communities' resilience to disasters. The HFA addressed issues such as community participation, capacity building, and early warning, as well as multi-hazard strategies to reduce deaths. The Sendai Framework for Disaster Risk Reduction (2015–30) was adopted at the United Nations' third disaster risk reduction conference [87]. This framework advocated for a paradigm shift from disaster management to risk management.

The disaster management cycle is an indispensable tool in disaster management [89]. It is intended to guide nations in mitigating the effects of disasters and has been widely used in disaster management over the past three decades [90]. It is acknowledged that the terminology used for various stages of a disaster can be traced back to the 1930s, and also some experts used such terms in humanitarian action to better understand and improve the system [91]. Professionals from different disciplines and scientific upbringings are involved in disaster risk management. This has resulted in various viewpoints and model specifications of disaster management cycle theories [90]. This cycle illustrates how various stages of disaster management involve interconnected activities [92].

The stages of the disaster risk management cycle are three-fold: (a) pre-disaster (risk reduction), (b) during the disaster, and (c) post-disaster (recovery). Pre-disaster approaches commonly include prevention, mitigation, and preparedness, whilst response approaches include rescue and relief. Recovery and development are post-disaster activities [93]. Each of these activities contributes to the reduction in the risk of physical and human losses and enhances disaster response and recovery. Alexander [84] expanded on the disaster management cycle by categorising it into two stages: pre- and post-disaster. Preparedness and mitigation were classified as pre-disaster, while response and recovery were classified as post-disaster. Yet, there are advantages and disadvantages inherent to the disaster management cycle. Furthermore, there has been a critique of disaster management's continuous cyclic nature. As a result, experts have differed on the effectiveness of the disaster management cycle [89,90]. The cycle has been modified to allow for better management in terms of time, resources, preferences, capacities or needs, and institutional transformations. Extreme events have been linked to climate change [94,95]. Recent research highlights the importance of incorporating disaster risk reduction and climate change adaptation [96–98]. Alternative solutions, such as panarchy [99,100], and resilience, have been proposed to explain effective disaster coping mechanisms [101]. Nonetheless, despite its shortcomings, the disaster risk management cycle continues to be used due to its convenient and robust nature [102].

4. State of Practice and Research in SCDT for Prevention, Preparedness, Response, Recovery, Rehabilitation, Reconstruction, and Mitigation

With the systematic review carried out in this paper, it was identified that there are numerous practical applications for intelligent technologies to better manage disasters, considering either one or a combination of the stages of the disaster management cycle. The sections that follow provide a brief overview of DTSC applications and devices for the aforementioned seven stages: prevention, preparedness, response, recovery, rehabilitation, reconstruction, and mitigation.

4.1. Unmanned Aerial Vehicles (UAVs)

Unmanned Aerial Vehicles (UAVs), also identified as pilotless aircrafts, are powered by three main components: the UAV itself, a ground-based controlling device, and a

communication system linking the said components [103–105]. UAVs are recommended for operations in dangerous and congested areas where human life is at risk. UAVs have recently received a lot of attention, and the most recent investigations look into the likelihood of using UAVs for disaster risk management and analysis [106,107]. However, the use of UAVs for pre- and post-disaster management is extremely problematic. These challenges manifest themselves in bad weather conditions [108], mountainous terrain, and obstructed roadways caused by disasters such as floods, earthquakes, and bushfires, making UAV flying and safety challenging. High-rise structures and towers restrict UAV operations in SCs as well. Localisation of victims and path optimization are two of the most common UAV operations. Demiane et al. [109], for example, proposed an approach that used Received Signal Strength Indicators (RSSI) and a Voronoi-based system to receive RSSI measurements of Wi-Fi signals broadcast by disaster victims' smartphones. Alternatively, Yu et al. [110] suggested a Constrained Differential Evolution (CDE) algorithm for UAV path planning in the post-disaster environment [111]. This method optimised the distance and risk objective functions for UAVs. Similarly, Malandrino et al. [112] proposed a method that addressed the optimisation problem of UAV deployment in disaster-affected areas. Moreover, UAVs have been used to aid communications in disaster-stricken areas. Duong et al. [113] optimised UAV trajectories while reducing turnaround time. All of the aforementioned algorithms were proposed to create a multifaceted IoT-powered UAV-based SC management system in which all SC key components are connected and monitored to aid in catastrophe preparation and mitigation. Correspondingly, this can help to improve SC governance and keep its citizens informed in the event of a disaster.

4.2. Mobile Crowd Sensing

Mobile crowd sensing enables the general public to contribute data perceived from their mobile devices. The data are then combined and accumulated in the cloud for crowd intelligence mining and the execution of human-centric services [114]. This technology requires many more smartphones than the conventional physical sensors-based sensing paradigm [115]. For such applications, the user's location or Global Positioning System (GPS) coordinates can be collected by the smartphone. Users can use their smartphones to collect useful environmental data (i.e., images). Hence, it has been proven to be an effective approach for handling emergencies since the information provided by social sensors, such as the image of the site and the event's position, can be utilised to detect and assess the event [116].

Crooks et al. [117] utilised earthquake-related Twitter posts, which were used as hybrid forms of a dispersed sensor system to assess the earthquake's impact region. Sakaki et al. [118,119] investigated real-time earthquakes on Twitter and suggested an algorithm for recognising an occurrence through tweets. They developed a tweet classifier to process information from social sensors, as well as a probabilistic spatiotemporal model to identify the event's core location to handle spatial data. Lu et al. [120] created an earthquake alerting system, collecting data from Twitter before and after the 2011 earthquake in Japan to investigate the dynamic nature and evolution of communities in social networks in reaction to emergency occurrences. Researchers proposed methods using social sensor data in the event of fire, floods, and typhoons. For instance, Kongthon et al. [121] conducted a case study on the 2011 Thai flood to evaluate how residents responded to the crisis using social media. More sophisticated modelling methods can be categorised for trend analysis of diverse messages as well as analysis of prominent Twitter users on the flood event. Such models might be utilised to determine catastrophe response patterns in conjunction with event detection. For example, Lu et al. [122] studied the movements of 1.9 million Haitian mobile phone users. To avoid chaos, the analyses' conclusions can be utilised to guide people's movements following the accident. Similarly, Bengtsson et al. [123] tracked the daily positions of Subscriber Identity/Identification Module (SIM) cards in Haiti after the earthquake. They believed that high mobile phone use could detect population movements quickly and with possibly high validity. The 5W (What, Where, When, Who,

and Why) paradigm was proposed by Xu et al. [124], to identify and explain the real-time urban emergency occurrence. The method proposed by Liu et al. [125] investigated a Markov random field-based method for revealing event core semantics. Xu et al. [126] formed a crowdsourcing-based burst computation algorithm for an urban disaster event to effectively analyse events and communicate event information to specified organisations or institutions.

4.3. Internet of Things (IoT)

The IoT integrates with the current internet after placing sensors and equipment in appropriate locations following catastrophe characteristics [127]. The super-powerful central computer cluster is part of this integrated network and is capable of integrating people, machines, equipment, and infrastructure into the network and managing and controlling them in real-time. Based on this, people can detect and handle disaster information in a more nuanced and dynamic way, developing knowledge and bettering interactions between people and the natural world.

In recent years, research has focused heavily on disaster surveillance and early warnings based on IoT technologies, particularly for geohazards including earthquakes, flooding, volcanic eruptions, and landslides. For instance, the European Union (EU) has introduced IoT-based real-time landslide monitoring projects such as Winsoch and SLEWS [128]. A few researchers have used IoT technology for landslide monitoring to address the inadequacies of conventional methods. A Wireless Sensor Network (WSN) that measures a variety of physical factors that cause landslides, for instance, was successfully made by Sofwan et al. [129]. Wang [130] introduced an IoT-based early warning system for the autonomous monitoring of landslide surface cracks. Using WSNs, Van Khoa and Takayama [131] developed a method for remote areas to monitor landslide threats. Moulart et al. [132] described a monitoring method to identify the first indicators of rapid and catastrophic movement on slopes. An early warning system for landslides was created by Biansoongnern et al. [133] using a sensor node microcontroller. Frigerio et al. [134] developed a web-based tool for continuous and autonomous landslide monitoring.

A great deal of research has gone into developing an IoT-based monitoring and warning system for debris flows. Huang et al. [135] proposed a scheme for debris-flow monitoring that combines a 3D WebGIS-based platform with the WSN, as well as automatic continuous monitoring and early warning of debris flow. Ye et al. [136] demonstrated an effective on-site monitoring technique that captures continuous monitoring data through the use of wireless accelerometer sensor networks and cutting-edge machine-learning technologies. Ma [137] employed Bluetooth technology to create a mountain debris-flow health monitoring system, analyse and repair mountain monitoring parts, and build data collecting and processing methods.

Significant research has also been directed toward developing early warning and surveillance systems based on IoT for rockfalls [138]. Eliasson et al. [139] significantly enhanced mining activity monitoring by utilising rock anchor networks with advanced real-time monitoring.

Much research has been carried out in order to build earthquake early warning systems that make use of rapidly increasing IoT technology [140,141]. Zambrano et al. [142,143] presented a mechanism for early earthquake warning that communicates via an IoT protocol. Nachtigall and Redlich [144] presented a novel alerting protocol in response to the challenges of high robustness required by seismic early warning systems.

4.4. Artificial Intelligence (AI)

AI can forecast the occurrence of natural disasters using a variety of high-quality datasets, potentially saving thousands of lives and averting significant economic losses. Many natural calamities, such as earthquakes, floods, storms, forest fires, and volcanic eruptions can be forecasted using AI. Researchers are gathering enormous volumes of seismic data for deep-learning systems analysis for earthquake prediction. Moreover,

researchers use the data gathered from previous earthquakes to develop more accurate predictions for upcoming earthquakes.

In order to estimate the magnitude of an earthquake, Alarifi et al. [145] suggested an AI prediction system based on artificial neural networks. Seismic data can be used by AI to assess an earthquake's pattern and size, as well as to help anticipate when one will occur. Goymann et al. [146] provided a data analysis method for training, and evaluation of a neural network detecting floods and water levels. AI-based systems are more accurate in forecasting floods than conventional methods because they can learn from historical data on rainfall, climate, and flood simulation tests. The AI learning system narrows the options for decision-making and provides feedback that is extremely comparable to human judgement. Large-scale social phenomena can be understood using AI because it is necessary to study and use a lot of data for an appropriate response to complex disasters [147]. The selection of the essential real data can be accomplished through big data analysis and simulation employing AI judgement based on the available empirical data.

4.5. Geo-Parsing

Only approximately 1% of all posts linked to disasters are on social media [148], however, most disaster information mapping techniques significantly rely on these posts [149]. To compensate for this disadvantage, existing research focuses on geoparsing (or geotagging), which estimates the locations of social media posts or users based on the content of the posts and the users' social network information [150]. As explained in Ghahremanlou et al. [151], geoparsing approaches can often trace name elements in social media postings and assesses them to external geographic entity data. Middleton et al. [152] presented a real-time catastrophe mapping system that extracts street-level name entities from texts using a geoparsing technique. The study used a multi-lingual geoparsing approach, which initially tokenised the text's ngrams ($n = 2-5$) using successive combinations of one-gram tokens. Then, using known place names, street names, and area names, the location-matching algorithm matched the tokens. To disambiguate the outcomes of geoparsing techniques, heuristic rules [151] and behavioural patterns [153] are frequently applied. Cresci et al. [154] used semantic annotation techniques that are already in use to connect tweets to Wikipedia/DBpedia entries and then validate matching locales or locations.

4.6. Convolutional Neural Network (CNN)

Social media images have been used successfully to explore and monitor geographical settings [155]. Studies that have already been conducted on social media image processing primarily concentrate on image retrieval and categorisation using deep learning techniques such as convolutional neural networks (CNN) [156]. For instance, Ahmad et al. [157] used a method of data fusion using CNN image features to recover social media disaster imagery. Alam et al. [158] introduced the 'Image4Act' image processing system, which can gather, remove noise, and categorise images to help humanitarian organisations be more situationally aware. The technology used a deep neural network and user data to weed out identical and pointless images so that aid organisations may get more accurate information about the extent of disaster damage [159]. Huang et al. [160] employed a CNN to categorise flood images and tweet tags to combine textual and visual disaster information.

Numerous parts of disaster studies may benefit from automatic labelling techniques based on a fine-grained disaster social media taxonomy [161,162]. Nguyen et al. [163] demonstrated a sequence-to-sequence technique for anticipating people's demands during extreme weather and used social media data from three hurricanes [164]. With trained CNN models, Burel and Alani [165] developed an open-source Application Programming Interface (API) that supplied annotations for catastrophe-related information. The recognition of disaster-related imagery in social media posts is another vital requirement of current social sensing techniques. Retrieving disaster images from social media was one of the Multimedia Satellite subtasks at the MediaEval 2017 workshop, which was focused on combining social media data and satellite imagery for emergency responses to flooding

events [166]. Daly and Thom [167] provided a framework to determine whether a fire event occurred at a specific time and location using geotagged images. This method was utilised for modern object detection and image classification techniques in computer vision.

4.7. Other Technologies

De Nicola et al. [168] proposed a method that facilitates the creative design of Emergency Management (EM) scenarios. The method suggested a workflow of envisioning occurrences and explained those via models and stories through the creative design of scenarios. Their proposed framework aided in the tasks of collecting and organizing information about emergencies by automatically generating conceptual models based on fragments of emergencies. It enabled an algorithmic creativity approach by leveraging semantics-based techniques. For the management of disasters, Jung et al. [169] developed a conceptual framework for an Intelligent Decision Support System (IDSS), with a special focus on heat/cold waves and wildfires. To expedite the decision-making process, their IDSS technique used large data gathered via open API and AI algorithms.

Gosavi et al. [170] introduced a Discrete Event-Based Simulation (DEBS) model to compute the restoration time required to bring the disaster situation under control after informing the response centre. Their DEBS model can quantify the effect of resource quantities on restoration times in addition to relaxing the Markov chain model's stringent assumptions on journey time. They evaluated and verified this DEBS model in a case study from Missouri, United States. They conducted experiments that showed the model can produce numerical results quickly and be applied in real-time in a SC infrastructure.

A new reference architecture and guiding principles for a disaster-resilient smart city (DRSC) were put forth by Shah et al. [171] by combining IoT and Big Data Analytics (BDA technologies). For disaster risk management initiatives in SC incentives, the proposed architecture provided a general solution. An effective DRSC environment that supports both real-time and fine-grained analysis was developed. Data collection, aggregation, preprocessing, big data analytics, and a service platform were all components of the model's implementation. A system to detect and generate alerts for a building fire, city pollution levels, emergency evacuation routes, and the gathering of information about natural disasters was validated and evaluated using a variety of datasets in their method, including smart buildings, city pollution, traffic simulators, and Twitter. The suggested method's performance was demonstrated by measuring the system efficiency in terms of processing time and throughput.

5. Discussion on Challenges and Risks in the Implementation of DTSC for Disaster Risk Management

5.1. Quality, Quantity, Ambiguity and Complexity of Available Data

Big data techniques are viewed as a crucial tool for making cities smarter and more prepared for disaster risk management. These approaches can be used to extract accurate and sufficient information about disaster risk management [147]. However, a significant obstacle is the scant data that many governments and countries possess. For climate and emergency data, some European nations rely on the national level, but they observed that the data are limited, outdated, and deficient in standards [172]. Municipalities in under-developed nations struggle with their inability to get enough city and climatic data. For instance, municipalities lack information on population, changes in land use, and the number of buildings for the evaluation of flood risk in the Philippines [173]. Another example would be how municipalities in Thailand's Central region struggled to respond to the 2011 floods partially due to the absence of a digital elevation map across the nation [174]. Private enterprises are frequently the ones with accurate and detailed information about urban climate, but the scientific community and general public cannot access this information [175]. Therefore, enhancing collaborations and sharing data between the general public, research community, and business sectors will increase the data quantity and quality.

The use of DTs and SCs, which are developing megatrends, in a variety of sectors, including disaster risk management, is still in its infancy. The absence of a clear and general understanding of the concepts and facts that significantly increase awareness and capacity building is considered to be one of the most significant barriers to usage of DTSCs to manage disasters. This may be partially ascribed to the problem's inherent complexity and the wide range of spatial and temporal scales on which its manifestations take place [176].

5.2. Regulations, Authorities and Justice

The implementation of a DTSC for disaster risk management should be governed by laws and regulations from a variety of sectors since disaster risk management is a multifaceted issue that has an impact on many aspects of the economy and society. Bringing together different parties to secure their collaboration is a significant difficulty that arises [177]. From the standpoint of regulation, this would necessitate a coordinated policy response in numerous distinct sectors. The regulatory hurdles that DTs and SCs must overcome keep rising and getting more difficult as technology and media continue to develop. Such regulation is especially important in developing nations for establishing inexpensive access and for social potential resulting from more interconnected communities. These rules ought to at least seek to secure consumer protection, international and regional cooperation, and ubiquitous access to the established DT and SC networks. Balanced regulation and co/self-regulation may help to facilitate these requirements [178].

Justice issues are also raised when employing Industry 4.0 to assist cities in adapting to better manage disasters. According to Zuboff [179], who makes a compelling case for it, under 'surveillance capitalism', companies have steadily reduced user privacy, agency, and access to data science, leading to unfair disparities in information, social engagement, and urban planning. The use of DT and SC technologies also has an uneven impact on how robust various urban populations can become [180]. For instance, it is believed that employment is crucial to fostering resilience, yet automation may result in job losses for some populations, especially the low-skilled [181]. By employing digital tools, other stakeholders will certainly lose out monetarily while technology owners stand to gain the most. This is particularly true for the cities in the developing world where a substantial proportion of the general public lacks the knowledge and technical skills needed to use these tools. Therefore, proposers must continuously scrutinise data science sources, consider who will benefit and who will be disregarded by using digital adaption tools, and prioritise the needs of the most vulnerable individuals [182].

5.3. Public Engagement through Communication

One of the most prominent challenges is translating scientific information so that it may be properly communicated to the public after it has been retrieved precisely and efficiently. For the DTSC to be successfully implemented to manage catastrophes, it must be made simple to use for a wide variety of stakeholders. Firstly, it can be difficult to ensure the participation of all necessary stakeholders [183]. Secondly, it's even more crucial to make sure they have the abilities necessary to absorb and comprehend the information as intended and use it moving forward in the context of crisis management [184,185]. The hardest part of the process is frequently getting the needed information out to the target end user. For any DTSC to be successful in earnest, the end users will need to be at the heart of its design and implementation. End users may not have access to clear information even if the best infrastructure is built because they lack complementary personal infrastructure, such as a mobile phone, or because last mile equipment, such as warning sirens, are commonly either missing or inoperable [186]. The speed at which information is processed by the end user and disseminated from the source are additional critical elements in this chain of enablers. The information must be made as clear and understandable as possible as quickly as is feasible because the window of opportunity for emergency intervention is frequently very small. In the case of slow-onset occurrences, information may come either

too late or intangibly. It is important to make an effort to reduce time and information latency [187].

Public participation in research, and other people partaking in activities are possible ways to encourage a two-way dialogue between researchers and the general public, which has the potential to develop realistic solutions that can produce trustworthy scientific data. However, before the general public and media begin to interpret the data, researchers must be vigilant about the value of citizen science data and conduct a thorough scientific analysis of the data [188]. Additionally, formal communication training might be incorporated into undergraduate and graduate curricula to enhance communication between experts and the general public [189]. Making projects more multidisciplinary and collaborative may also aid in bringing together various stakeholders and provide forums for them to communicate, understand one another's requirements, and cooperate to meet the shared goal of disaster risk management.

5.4. Digital Literacy, Poverty, and Cultural Diversity

The significant differences in digital literacies between the wealthy and the poor present another difficulty. Wealthy and highly educated people have greater chances to access digital tools and resources. Globally, both inside and between cities, this imbalance exists. According to a study conducted in New York City, low-income and majority minority communities tended to be less digitally engaged [190]. The propensity to embrace new technologies and, eventually, the level of digital literacy of vulnerable individuals such as women and the elderly are influenced by culture and behavioural mindsets. Fostering an environment that is receptive to change is difficult given the considerable effects that DT and SC technologies have on how companies run as both the public and private sectors migrate to the digital system. Since cultural barriers may prevent the use of DTSCs, digitalisation is not simply a technical problem but also a cultural one [191,192]. A more digitalised archive of meteorological data, for instance, cannot be implemented overnight since end users must be trained in how the new system functions and how it improves their ability to do their jobs. Such comprehension is required to reduce opposition to the approaching change.

The biggest obstacles to the effective implementation of DTs and SCs include cultural and behavioural shifts [193]. Culture and technical improvements have a complicated interdependent relationship where the adoption of these advancements depends on societal demand. On the other hand, if they are created outside of the cultural context of society, technical advancements risk upsetting cultural values. Therefore, in terms of disaster risk management, cultural perceptions of gender, involvement, and power have a big impact on how DTs and SCs are used and perceived [194]. As a result, these variations must be taken into account when designing DTSC projects. Stakeholders must also take these distinctions into account when building adaptive strategies that incorporate digital solutions.

5.5. Resilience of the Digital Infrastructure

An elaborate digital and supporting infrastructure, as well as the necessary capacities, are needed to make the data information accessible to many stakeholders. The development of ICT could be very beneficial in the planning and execution of measures for disaster risk reduction and management. A prime example is the Sri Lanka Disaster Management Center's (SLDMC) creation of a tsunami warning system based on SMS [195]. In 2007, DMC made use of this technology to send out a 20-word tsunami alert through SMS sent reacting to a 7.9 magnitude earthquake that had happened at Sumatra's southern coast. The message was sent to government officials, members of the media, military personnel, police officers, and village heads who then disseminated it to the residents of their respective areas via a variety of mass media networks and sources. Civilian casualties decreased as a result. Recent digitalisation projects, such as the social media big data analytics used in the United States storm case study, offer chances to get over these restrictions by sending timely warning messages to many stakeholders promptly without relying heavily on phone

conversations. Additionally, ICT resilience is essential for effective climate change adaptation. Advanced building regulations in disaster-prone areas, increased power backup capabilities, solidified response for rapid repair of potential damage, innovative methods for managing heavier traffic during emergencies, increased network resilience, and communications via satellite as a major alternative could all improve the ICT infrastructure's resilience [196]. The current workforce in the majority of developing countries is more accustomed to conventional maps and charts, therefore considerable and ongoing guidance, as well as capacity development embracing participatory mapping, are required to facilitate a seamless switch from traditional paper-based methods to DTSCs [197].

6. Conclusions and Future Research Directions

Many facets of society are already being impacted by the digital transition, and this effect is only expected to increase going forward. The creative application of various high-tech concepts linked to DT and SC discussed in this work can promote an environmentally sound economy in both current and future cities, thereby positively contributing towards resolving socioeconomic and environmental issues, especially those related to disaster risk management. As discussed in the paper, whilst preliminary attempts have been made to establish a DTSC in contexts such as Singapore, and whilst some of the technologies discussed in the paper are being implemented in different parts of the world, the state-of-the-art is far from developing a 'Digital Twin Smart City for Disaster Risk Management' as a collective system in earnest. It is also noteworthy though that despite the significant potential benefits offered by DTSCs, they also add a new layer of complexities and challenges inherent to these technologies to the already complex web of complexities inherent to disaster risk management. The following is a summary of the key takeaways from this systematic review:

- The digital delivery of public health services and inadequate public infrastructure are some of the main issues that limit the ability of DTs and SCs to adapt.
- Digitalisation could make it easier for cities to recover from natural disasters such as earthquakes and floods. Reducing exposure will lower the likelihood of disasters, increase city resilience, and improve capacity for adaptation.
- The development of DT and SC technologies has the potential to greatly benefit emergency response planning for natural hazard-induced disasters and severe weather events. DT and SC concepts including big data analytics, social media, and mobile ICT can solve concerns about the timely transmission of early warnings and critical information to emergency response teams and communities at-risk.
- Constraints such as uncertainties about potential job losses caused by automation are required to be effectively addressed to maximise the usage of AI and ML in adaptability. Active citizen participation and awareness are required to educate communities about the complimentary functions of AI instead of their current perception of it as a danger. Relevant regulations are also necessary to quell unfavourable attitudes about intrusive digital surveillance that violates the privacy of community members.
- Given that technology, including DTs and SCs, is not neutral, it is crucial to evaluate digitalisation from the perspective of social, ecological, and technological systems, taking into account the actual difficulties and conflicts surrounding the DTSC, including the winners and losers as well as the dangers of rebound effects that could diminish the overall impact of digitalisation.

Future adaptation planning must also take into account existing and potential future challenges. Given that some of the current systems and concepts may not be wholly future-oriented, efforts to adapt to changing future disasters and technologies are crucial. As a result, it's critical to maintain the effectiveness of the current systems while also making investments in the development of dependable new ones that can quickly adjust to shifting spatiotemporal risks, vulnerabilities, and dangers. Despite the many potential advantages of DTSCs for disaster risk management, they are also susceptible to some of the current challenges preventing successful adaptation in several communities.

It may be difficult for local governments and municipalities to raise the necessary financing for the successful fusion of these for DTSCs because adaptation is a capital-intensive process, much like digitalisation. The technical sustainability of such projects depends on continuous capacity building and maintenance. Finding the necessary funding for long-term training programmes, system maintenance, and upkeep should therefore be given top priority.

Understanding how the process of utilising DTSCs in disaster risk management is designed is essential for comprehending what DTSCs may offer, how they are implemented, and what it means to all involved stakeholders. The disciplines and expertise that determine the process through which DTSCs can help disaster risk reduction, resilience, and sustainable development will be spotlighted by highlighting specific knowledge-making methods. This emphasises the significance of developing a strong knowledge infrastructure accounting for the interactions, synergies, and trade-offs between various but related stakeholders as well as the types of knowledge contributed by them to the deployment of DTSCs in building disaster resilience. It is specifically acknowledged that the design and implementation of the DTSC process into a useful tool for disaster risk management are just as important as the product itself.

The need for improved techniques to capture the spatial and temporal aspects of disruptions to the built environment and people-adjustment responses to realise the full potential of incorporating the aforementioned technologies into DTSCs for disaster resilience is noted. The DTSC paradigm's central tenet is the sensing and monitoring of the status and features of the built environment, human systems, and their interconnections, as was previously discussed. Even while social sensing is increasingly being used in disasters, very little of the work that has been done so far focuses on identifying crucial infrastructure disruptions and responses from people to such disturbances. This research is scarce for several reasons, one of which is that the information that can be collected using present social sensing techniques in the case of infrastructure disruptions is restricted to that of the disruptions themselves. As a result, outputs with a cluster of tokens are challenging to analyse in order to comprehend the status of infrastructure interruptions. This is because the outputs of current natural language processing algorithms include groupings of individual tokens. Therefore, a suitable social sensing approach for a DTSC should consider the frequency and impact of disruptions, their consequences on individuals, and the steps that have been taken to adapt to them.

An effort has been made to provide a thorough review of relevant DT and SC applications in various disaster kinds and stages, even if this study did not fully evaluate all instances of DT and SC technologies in disaster risk management internationally. Although the chosen papers might not be entirely indicative of the scope of DT and SC technologies' use in disaster risk management, they nonetheless provide insightful information on the potential of DTSC as a disaster risk management enabler in present and future cities. The varied and occasionally integrated application of several DT and SC principles offers intriguing ideas that could be reproduced elsewhere to reduce the threat of disasters. The contribution of DTSC to bolstering the socioeconomic fabric of society has been listed, and its potential to foster resilience by assisting adaptation efforts has been highlighted. Thus, this research provides a valuable addition that aims to use DT and SC principles in novel ways to address the challenge of disaster risk management in light of a changing environment. It is noteworthy that some of the conclusions have possible implications outside of disaster risk management, climate change, or cities and are applicable across a broad spectrum of domains.

Author Contributions: Conceptualization, G.W. and M.R.M.F.A.; methodology, M.R.M.F.A.; formal analysis, M.R.M.F.A.; writing—original draft preparation, M.R.M.F.A. and G.W.; writing—review and editing, G.W. and M.R.M.F.A.; supervision, G.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Not applicable.

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

References

1. United Nations Office for Disaster Risk Reduction (UNDRR). *Global Assessment Report on Disaster Risk Reduction 2022: Our World at Risk: Transforming Governance for a Resilient Future*; United Nations Office for Disaster Risk Reduction: Geneva, Switzerland, 2022.
2. Dube, E.; Wedawatta, G.; Ginige, K. Building-Back-Better in Post-Disaster Recovery: Lessons Learnt from Cyclone Idai-Induced Floods in Zimbabwe. *Int. J. Disaster Risk Sci.* **2021**, *12*, 700–712. [CrossRef]
3. United Nations. Economic Recovery after Natural Disasters. 2022. Available online: <https://www.un.org/en/chronicle/article/economic-recovery-after-natural-disasters> (accessed on 8 July 2022).
4. United Nations Office for Disaster Risk Reduction (UNDRR). Economic Impact of Natural Disasters in 2020. 2021. Available online: <https://www.preventionweb.net/news/economic-impact-natural-disasters-2020> (accessed on 12 March 2022).
5. RMS. RMS Estimates Insured Losses from Windstorms Dudley and Eunice will Likely Range between 3.0 and 4.5 Billion Euro. 2022. Available online: <https://www.rms.com/newsroom/press-releases/press-detail/2022-03-01/rms-estimates-insured-losses-from-windstorms-dudley-and-eunice-will-likely-range-between-30-and-45-billion-euro> (accessed on 8 September 2022).
6. United Nations Office for Disaster Risk Reduction (UNDRR). *Human Cost of Disasters: An Overview of the Last 20 Years 2000–2019*. Human Cost of Disasters; United Nations Office for Disaster Risk Reduction: Geneva, Switzerland, 2020.
7. Novelo-Casanova, D.A.; Suárez, G.; Cabral-Cano, E.; Fernández-Torres, E.A.; Fuentes-Mariles, O.A.; Havazli, E.; Jaimes, M.; López-Espinoza, E.D.; Martín-Del Pozzo, A.L.; Morales-Barrera, W.V.; et al. The Risk Atlas of Mexico City, Mexico: A tool for decision-making and disaster prevention. *Nat. Hazards* **2021**, *111*, 411–437. [CrossRef]
8. Alhinai, Y.S. Disaster management digitally transformed: Exploring the impact and key determinants from the UK national disaster management experience. *Int. J. Disaster Risk Reduct.* **2019**, *51*, 101851. [CrossRef]
9. Yu, D.; He, Z. Digital twin-driven intelligence disaster prevention and mitigation for infrastructure: Advances, challenges, and opportunities. *Nat. Hazards* **2022**, *112*, 1–36. [CrossRef]
10. Taubenböck, H.; Goseberg, N.; Lämmel, G.; Setiadi, N.; Schlurmann, T.; Nagel, K.; Siegert, F.; Birkmann, J.; Traub, K.P.; Dech, S.; et al. Risk reduction at the ‘Last-Mile’: An attempt to turn science into action by the example of Padang, Indonesia. *Nat. Hazards* **2013**, *65*, 915–945. [CrossRef]
11. Alshammari, M.M.; Alwan, A.A.; Nordin, A.; Abualkashik, A.Z. Disaster Recovery with Minimum Replica Plan for Reliability Checking in Multi-Cloud. *Procedia Comput. Sci.* **2018**, *130*, 247–254. [CrossRef]
12. Andriole, S.J. Five Myths About Digital Transformation. *Front. Built Environ.* **2017**, *58*, 109–120.
13. Asian Development Bank. *Digital Technologies: For Climate Action, Disaster Resilience, and Environmental Sustainability*; Asian Development Bank: Manila, Philippines, 2021.
14. Wedawatta, G.; Thurairajah, N.; Ginige, K. Foreword. In *Industry 4.0 and Disaster Resilience in the Built Environment—ARCOM Doctoral Workshop In association with CIB W120—Disasters and the Built Environment*; Wedawatta, G., Thurairajah, N., Ginige, K., Eds.; The Association of Researchers in Construction Management (ARCOM): Newcastle upon Tyne, UK, 2019.
15. Fuller, A.; Fan, Z.; Day, C.; Barlow, C. Digital Twin: Enabling Technologies, Challenges and Open Research. *IEEE Access* **2020**, *8*, 108952–108971. [CrossRef]
16. Buckley, B.; Logan, K. *SmartMarket Report The Business Value of BIM for Infrastructure*; Dodge Data & Analytics: Bedford, MA, USA, 2017.
17. Jones, D.; Snider, C.; Nassehi, A.; Yon, J.; Hicks, B. Characterising the Digital Twin: A systematic literature review. *CIRP J. Manuf. Sci. Technol.* **2020**, *29*, 36–52. [CrossRef]
18. Parrott, A.; Warshaw, L. Industry 4.0 and the Digital Twin. 2017. Available online: <https://www2.deloitte.com/us/en/insights/focus/industry-4-0/digital-twin-technology-smart-factory.html> (accessed on 14 October 2020).
19. Barricelli, B.R.; Casiraghi, E.; Fogli, D. A survey on digital twin: Definitions, characteristics, applications, and design implications. *IEEE Access* **2019**, *7*, 167653–167671. [CrossRef]
20. Hayat, P. Smart cities: A global perspective. *India Q.* **2016**, *72*, 177–191. [CrossRef]
21. Al Nuaimi, E.; Al Neyadi, H.; Mohamed, N.; Al-Jaroodi, J. Applications of big data to smart cities. *J. Internet Serv. Appl.* **2015**, *6*, 25. [CrossRef]
22. Sánchez-Corcuera, R.; Nuñez-Marcos, A.; Sesma-Solance, J.; Bilbao-Jayo, A.; Mulero, R.; Zulaika, U.; Azkune, G.; Almeida, A. Smart cities survey: Technologies, application domains and challenges for the cities of the future. *Int. J. Distrib. Sens. Netw.* **2019**, *15*, 1550147719853984. [CrossRef]
23. Cvar, N.; Trilar, J.; Kos, A.; Volk, M.; Duh, E.S. The use of iot technology in smart cities and smart villages: Similarities, differences, and future prospects. *Sensors* **2020**, *20*, 3897. [CrossRef] [PubMed]
24. Anthopoulos, L.G. Understanding smart cities: A tool for smart government or an industrial trick? In *Public Administration and Information Technology*; Springer: Cham, Switzerland, 2017; Volume 22, pp. 1–293.
25. Ford, D.N.; Wolf, C.M. Smart Cities with Digital Twin Systems for Disaster Management. *J. Manag. Eng.* **2020**, *36*, 04020027. [CrossRef]

26. De Albuquerque, J.P.; Herfort, B.; Brenning, A.; Zipf, A. A geographic approach for combining social media and authoritative data towards identifying useful information for disaster management. *Int. J. Geogr. Inf. Sci.* **2015**, *29*, 667–689. [\[CrossRef\]](#)
27. Choi, M.; Starbuck, R.; Lee, S.; Hwang, S.; Lee, S.; Park, M.; Lee, H.-S. Distributed and interoperable simulation for comprehensive disaster response management in facilities. *Autom. Constr.* **2018**, *93*, 12–21. [\[CrossRef\]](#)
28. Eid, M.S.; El-adaway, I.H. Sustainable Disaster Recovery Decision-Making Support Tool: Integrating Economic Vulnerability into the Objective Functions of the Associated Stakeholders. *J. Manag. Eng.* **2017**, *33*, 04016041. [\[CrossRef\]](#)
29. Horita FE, A.; Link, D.; De Albuquerque, J.P.; Hellingrath, B. ODMN: An integrated model to connect decision-making needs to emerging data sources in disaster management. In Proceedings of the 2016 49th Hawaii International Conference on System Sciences (HICSS), Koloa, HI, USA, 5–8 January 2016; pp. 2882–2891.
30. Ragini, J.R.; Anand PM, R.; Bhaskar, V. Big data analytics for disaster response and recovery through sentiment analysis. *Int. J. Inf. Manag.* **2018**, *42*, 13–24. [\[CrossRef\]](#)
31. Ramírez-Moreno, M.A.; Keshtkar, S.; Padilla-Reyes, D.A.; Ramos-López, E.; García-Martínez, M.; Hernández-Luna, M.C.; Mogro, A.E.; Mahlkecht, J.; Huertas, J.I.; Peimbert-García, R.E.; et al. Sensors for Sustainable Smart Cities: A Review. *Appl. Sci.* **2021**, *11*, 8198. [\[CrossRef\]](#)
32. Gong, J. Mobile LiDAR Data Collection and Analysis for Post-Sandy Disaster Recovery. In Proceedings of the 2013 ASCE International Workshop on Computing in Civil Engineering, Los Angeles, CA, USA, 23–25 June 2013; pp. 1–10.
33. McDougall, K.; Temple-Watts, P. The use of lidar and volunteered geographic information to map flood extents and inundation. In Proceedings of the XXII ISPRS Congress, Melbourne, Australia, 25 August–1 September 2012; Volume I-4, pp. 251–256.
34. She, J.; Mabi, A.; Liu, Z.; Sheng, M.; Dong, X.; Liu, F.; Wang, S. Analysis Using High-Precision Airborne LiDAR Data to Survey Potential Collapse Geological Hazards. *Adv. Civ. Eng.* **2021**, *2021*, 6475942. [\[CrossRef\]](#)
35. Yu, M.; Yang, C.; Li, Y. Big data in natural disaster management: A review. *Geosciences* **2018**, *8*, 165. [\[CrossRef\]](#)
36. Cepni, K.; Ozger, M.; Akan, O.B. Event Estimation Accuracy of Social Sensing with Facebook for Social Internet of Vehicles. *IEEE Internet Things J.* **2018**, *5*, 2449–2456. [\[CrossRef\]](#)
37. Imran, M.; Ofli, F.; Caragea, D.; Torralba, A. Using AI and Social Media Multimodal Content for Disaster Response and Management: Opportunities, Challenges, and Future Directions. *Inf. Process. Manag.* **2020**, *57*, 1–9. [\[CrossRef\]](#)
38. Kryvasheyev, Y.; Chen, H.; Moro, E.; Van Hentenryck, P.; Cebrian, M. Performance of social network sensors during Hurricane Sandy. *PLoS ONE* **2015**, *10*, e0117288. [\[CrossRef\]](#)
39. Nguyen, D.T.; Jung, J.E. Privacy-preserving discovery of topic-based events from social sensor signals: An experimental study on twitter. *Sci. World J.* **2014**, *2014*, 204785. [\[CrossRef\]](#)
40. Sakurai, M.; Murayama, Y. Information technologies and disaster management—Benefits and issues. *Prog. Disaster Sci.* **2019**, *2*, 100012. [\[CrossRef\]](#)
41. Fan, C.; Zhang, C.; Yahja, A.; Mostafavi, A. Disaster City Digital Twin: A vision for integrating artificial and human intelligence for disaster management. *Int. J. Inf. Manag.* **2021**, *56*, 102049. [\[CrossRef\]](#)
42. Mohammadi, N.; Taylor, J.E. Smart city digital twins. In Proceedings of the 2017 IEEE Symposium Series on Computational Intelligence, SSCI 2017, Honolulu, HI, USA, 27 November–1 December 2017; pp. 1–5.
43. Shahat, E.; Hyun, C.T.; Yeom, C. City digital twin potentials: A review and research agenda. *Sustainability* **2021**, *13*, 3386. [\[CrossRef\]](#)
44. Liu, Z.; Zhang, A.; Wang, W. A framework for an indoor safety management system based on digital twin. *Sensors* **2020**, *20*, 5771. [\[CrossRef\]](#)
45. Chalmers, I.; Hedges, L.V.; Boruch, B.; Clarke, M.; Glass, G.; Horn, J.; Jull, A.; Lewis, S.; Macfarlane, A.; Marks, H.; et al. A brief history of research synthesis. *Eval. Health Prof.* **2002**, *25*, 12–37. [\[CrossRef\]](#)
46. O'Hagan, E.C.; Matalon, S.; Riesenberger, L.A. Systematic reviews of the literature: A better way of addressing basic science controversies. *Am. J. Physiol.—Lung Cell. Mol. Physiol.* **2018**, *314*, 439–442. [\[CrossRef\]](#)
47. Perićić, T.P.; Tanveer, S. Why Systematic Reviews Matter: A Brief History, Overview and Practical Guide for Authors. 2019. Available online: <https://beta.elsevier.com/connect/why-systematic-reviews-matter?trial=true> (accessed on 6 May 2021).
48. Snyder, H. Literature review as a research methodology: An overview and guidelines. *J. Bus. Res.* **2019**, *104*, 333–339. [\[CrossRef\]](#)
49. Kraus, S.; Breier Dasí-Rodríguez, S. El arte de elaborar una revisión bibliográfica sistemática en la investigación sobre el espíritu empresarial. *Int. Entrep. Manag. J.* **2020**, *16*, 1023–1042. [\[CrossRef\]](#)
50. Adams, R.J.; Smart, P.; Huff, A.S. Shades of Grey: Guidelines for Working with the Grey Literature in Systematic Reviews for Management and Organizational Studies. *Int. J. Manag. Rev.* **2017**, *19*, 432–454. [\[CrossRef\]](#)
51. Clemens, E.S.; Powell, W.W.; McIlwaine, M.; Okamoto, D. Careers in Print: Books, Journals, and Scholarly Reputations. *Am. J. Sociol.* **1995**, *101*, 433–494. [\[CrossRef\]](#)
52. Shafto, M.; Conroy, M.; Doyle, R.; Glaessgen, E. *DRAFT Modeling, Simulation, Information Technology & Processing Roadmap: Technology Area 11*; NASA: Washington, DC, USA, 2010.
53. Grieves, M.; Vickers, J. Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems. In *Transdisciplinary Perspectives on Complex Systems: New Findings and Approaches*; Springer: Cham, Switzerland, 2016; pp. 85–113.
54. MarketsandMarkets. *Digital Twin Market by Technology, Type (Product, Process, and System), Application (Predictive Maintenance, and Others), Industry (Aerospace & Defense, Automotive & Transportation, Healthcare, and Others), and Geography—Global Forecast to 2026*; MarketsandMarkets: Hadapsar, India, 2021.

55. McKinsey & Company. Imagining Construction's Digital Future. 2016. Available online: <https://www.mckinsey.com/business-functions/operations/our-insights/imagining-constructions-digital-future> (accessed on 24 February 2022).
56. Alexopoulos, K.; Nikolakis, N.; Chrysosolouris, G. Digital twin-driven supervised machine learning for the development of artificial intelligence applications in manufacturing. *Int. J. Comput. Integr. Manuf.* **2020**, *33*, 429–439. [\[CrossRef\]](#)
57. Ashtari Talkhestani, B.; Jung, T.; Lindemann, B.; Sahlab, N.; Jazdi, N.; Schloegl, W.; Weyrich, M. An architecture of an Intelligent Digital Twin in a Cyber-Physical Production System. *At-Automatisierungstechnik* **2019**, *67*, 762–782. [\[CrossRef\]](#)
58. Bolender, T.; Bürvenich, G.; Dalibor, M.; Rumpe, B.; Wortmann, A. Self-Adaptive Manufacturing with Digital Twins. In Proceedings of the 2021 International Symposium on Software Engineering for Adaptive and Self-Managing Systems (SEAMS), Madrid, Spain, 18–21 May 2021; pp. 156–166.
59. Ciano, M.P.; Pozzi, R.; Rossi, T.; Strozzi, F. Digital twin-enabled smart industrial systems: A bibliometric review. *Int. J. Comput. Integr. Manuf.* **2020**, *34*, 690–708. [\[CrossRef\]](#)
60. Erkoyuncu, J.A.; del Amo, I.F.; Ariensyah, D.; Bulka, D.; Vrabič, R.; Roy, R. A design framework for adaptive digital twins. *CIRP Ann.* **2020**, *69*, 145–148. [\[CrossRef\]](#)
61. Madni, A.; Madni, C.; Lucero, S. Leveraging Digital Twin Technology in Model-Based Systems Engineering. *Systems* **2019**, *7*, 7. [\[CrossRef\]](#)
62. Maschler, B.; Braun, D.; Jazdi, N.; Weyrich, M. Transfer learning as an enabler of the intelligent digital twin. *Procedia CIRP* **2020**, *100*, 127–132. [\[CrossRef\]](#)
63. Tao, F.; Cheng, J.; Qi, Q.; Zhang, M.; Zhang, H.; Sui, F. Digital twin-driven product design, manufacturing and service with big data. *Int. J. Adv. Manuf. Technol.* **2017**, *94*, 3563–3576.
64. Gardner, P.; Dal Borgo, M.; Ruffini, V.; Hughes, A.J.; Zhu, Y.; Wagg, D.J. Towards the Development of an Operational Digital Twin. *Vibration* **2020**, *3*, 235–265. [\[CrossRef\]](#)
65. Kopsida, M.; Brilakis, I. Real-Time Volume-to-Plane Comparison for Mixed Reality-Based Progress Monitoring. *J. Comput. Civ. Eng.* **2020**, *34*, 04020016. [\[CrossRef\]](#)
66. Omar, T.; Nehdi, M.L. Data acquisition technologies for construction progress tracking. *Autom. Constr.* **2016**, *70*, 143–155. [\[CrossRef\]](#)
67. ARUP. *Digital Twin: Towards a Meaningful Framework*; Arup: London, UK, 2019.
68. Galán-García, J.L.; Aguilera-Venegas, G.; Rodríguez-Cielos, P. An accelerated-time simulation for traffic flow in a smart city. *J. Comput. Appl. Math.* **2014**, *270*, 557–563. [\[CrossRef\]](#)
69. Neirotti, P.; De Marco, A.; Cagliano, A.C.; Mangano, G.; Scorrano, F. Current trends in smart city initiatives: Some stylised facts. *Cities* **2014**, *38*, 25–36. [\[CrossRef\]](#)
70. Su, K.; Li, J.; Fu, H. Smart City and the Applications. In Proceedings of the 2011 International Conference on Electronics, Communications and Control (ICECC), Ningbo, China, 9–11 September 2011; pp. 1028–1031.
71. Kitchin, R. The Real-Time City? Big Data and Smart Urbanism. *Rob. Geojournal* **2014**, *79*, 1–14. [\[CrossRef\]](#)
72. Chourabi, H.; Nam, T.; Walker, S.; Gil-Garcia, J.R.; Mellouli, S.; Nahon, K.; Pardo, T.A.; Scholl, H.J. Understanding smart cities: An integrative framework. In Proceedings of the 2012 45th Hawaii International Conference on System Sciences, Maui, HI, USA, 4–7 January 2012; pp. 2289–2297.
73. Bellini, P.; Nesi, P.; Pantaleo, G. IoT-Enabled Smart Cities: A Review of Concepts, Frameworks and Key Technologies. *Appl. Sci.* **2022**, *12*, 1607. [\[CrossRef\]](#)
74. Mohammadi, N.; Taylor, J.E. Devising a game theoretic approach to enable smart city digital twin analytics. In Proceedings of the 52nd Hawaii International Conference on System Sciences, HICSS 2019, Hawaii, HI, USA, 8–11 January 2019.
75. White, G.; Palade, A.; Cabrera, C.; Clarke, S. Autoencoders for QoS prediction at the Edge. In Proceedings of the 2019 IEEE International Conference on Pervasive Computing and Communications, PerCom 2019, Kyoto, Japan, 11–15 March 2019; pp. 1–9.
76. Soon, K.H.; Khoo, V.H.; S. Citygml modelling for Singapore 3D national mapping. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.—ISPRS Arch.* **2017**, *42*, 37–42. [\[CrossRef\]](#)
77. Centre for Digital Built Britain (CDBB). National Digital Twin Programme | Centre for Digital Built Britain. 2022. Available online: <https://www.cdbb.cam.ac.uk/what-we-do/national-digital-twin-programme> (accessed on 20 August 2022).
78. White, G.; Zink, A.; Codecá, L.; Clarke, S. A digital twin smart city for citizen feedback. *Cities* **2021**, *110*, 103064. [\[CrossRef\]](#)
79. Dodds, G.G. 'This Was No Act of God': Disaster, Causality, and Politics. *Risk Hazards Crisis Public Policy* **2015**, *6*, 44–68. [\[CrossRef\]](#)
80. Kulatunga UWedawatta GAmaratunga, D.; Haigh, R. Evaluation of vulnerability factors for cyclones: The case of Patuakhali, Bangladesh. *Int. J. Disaster Risk Reduct.* **2014**, *9*, 204–211. [\[CrossRef\]](#)
81. Lutzer, E.Z. *An Act of God? Answers to Tough Questions about God's Role in Natural Disasters*; Tyndale Publishers, Inc.: Carol Stream, IL, USA, 2011.
82. Cannon, T. *Reducing People's Vulnerability to Natural Hazards: Communities and Resilience*; Research Paper 2008/034; UNU-WIDER: Helsinki, Finland, 2008.
83. Sylves, R.T. *Disaster Policy and Politics: Emergency Management and Homeland Security*; SAGE Publications: Thousand Oaks, CA, USA, 2020.
84. Alexander, D. *Principles of Emergency Planning and Management*; Terra Publishing: Harpenden, UK, 2002.
85. United Nations Office for Disaster Risk Reduction. *Global Assessment Report on Disaster Risk Reduction 2015. International Strategy for Disaster Reduction (ISDR)*; United Nations Office for Disaster Risk Reduction: Geneva, Switzerland, 2019.

86. Sayers, P.; Galloway, G.; Penning-Rowsell, E.; Yuanyuan, L.; Fuxin, S.; Yiwei, C.; Kang, W.; Le Quesne, T.; Wang, L.; Guan, Y. Strategic flood management: Ten 'golden rules' to guide a sound approach. *Int. J. River Basin Manag.* **2015**, *13*, 137–151. [\[CrossRef\]](#)
87. United Nations Office for Disaster Risk Reduction. *Sendai Framework for Disaster Risk Reduction 2015–2030*; United Nations Office for Disaster Risk Reduction: Geneva, Switzerland, 2015.
88. Coppola, D.P. *Introduction to International Disaster Management*; Butterworth-Heinemann Publications: Oxford, UK, 2015.
89. Sawalha, I.H. A contemporary perspective on the disaster management cycle. *Foresight* **2020**, *22*, 469–482. [\[CrossRef\]](#)
90. Coetsee, C.; Van Niekerk, D. Tracking the evolution of the disaster management cycle: A general system theory approach. *Jàmbá J. Disaster Risk Stud.* **2012**, *4*, 1–9. [\[CrossRef\]](#)
91. Neal, D.M. Reconsidering the phases of disaster. *Int. J. Mass Emerg. Disasters* **1997**, *15*, 239–264. [\[CrossRef\]](#)
92. Dewi, O.C.; Saskia, C.S.; Dewi MB, V.; Anjari, A.R.; Chairunissa, I. Fact-finding during Quick Response to Disaster: School Students' Response to the Environment. In Proceedings of the 2020 6th International Conference on Environment and Renewable Energy, Hanoi, Vietnam, 24–26 February 2020.
93. Carter, W.N. *Disaster Management a Disaster Manager's Handbook*; Asian Development Bank: Mandaluyong, Philippines, 2008.
94. Swain, D.L.; Singh, D.; Touma, D.; Diffenbaugh, N.S. Attributing Extreme Events to Climate Change: A New Frontier in a Warming World. *One Earth* **2020**, *2*, 522–527. [\[CrossRef\]](#)
95. Trenberth, K.E.; Fasullo, J.T.; Shepherd, T.G. Attribution of climate extreme events. *Nat. Clim. Chang.* **2015**, *5*, 725–730. [\[CrossRef\]](#)
96. Birkmann, J.; von Teichman, K. Integrating disaster risk reduction and climate change adaptation: Key challenges-scales, knowledge, and norms. *Sustain. Sci.* **2010**, *5*, 171–184. [\[CrossRef\]](#)
97. Rana, I.A. Disaster and climate change resilience: A bibliometric analysis. *Int. J. Disaster Risk Reduct.* **2020**, *50*, 101839. [\[CrossRef\]](#)
98. Venton, P.; La Trobe, S.; Institute of Development Studies (IDS). *Linking Climate Change Adaptation and Disaster Risk Reduction*; Tetrafund: Teddington, UK, 2008.
99. Berkes, F.; Ross, H. Panarchy and community resilience: Sustainability science and policy implications. *Environ. Sci. Policy* **2016**, *61*, 185–193. [\[CrossRef\]](#)
100. Pescaroli, G.; Alexander, D. Critical infrastructure, panarchies and the vulnerability paths of cascading disasters. *Nat. Hazards* **2016**, *82*, 175–192. [\[CrossRef\]](#)
101. Manyena, B.; Machingura, F.; O'Keefe, P. Disaster Resilience Integrated Framework for Transformation (DRIFT): A new approach to theorising and operationalising resilience. *World Dev.* **2019**, *123*, 104587. [\[CrossRef\]](#)
102. Alexander, D.E. L'Aquila, central Italy, and the 'disaster cycle', 2009–2017. *Disaster Prev. Manag. Int. J.* **2019**, *28*, 272–285. [\[CrossRef\]](#)
103. Ejaz, W.; Ahmed, A.; Mushtaq, A.; Ibnkahla, M. Energy-efficient task scheduling and physiological assessment in disaster management using UAV-assisted networks. *Comput. Commun.* **2020**, *155*, 150–157. [\[CrossRef\]](#)
104. Song, Q.; Zeng, Y.; Xu, J.; Jin, S. A survey of prototype and experiment for UAV communications. *Sci. China Inf. Sci.* **2021**, *64*, 140301. [\[CrossRef\]](#)
105. Ullah, Z.; Al-Turjman, F.; Mostarda, L.; Gagliardi, R. Applications of Artificial Intelligence and Machine learning in smart cities. *Comput. Commun.* **2020**, *154*, 313–323. [\[CrossRef\]](#)
106. Shiri, H.; Park, J.; Bennis, M. Massive autonomous UAV path planning: A neural network based mean-field game theoretic approach. In Proceedings of the 2019 IEEE Global Communications Conference, GLOBECOM 2019, Waikoloa, HI, USA, 9–13 December 2019.
107. Wu, Q.; Zeng, Y.; Zhang, R. Joint trajectory and communication design for multi-UAV enabled wireless networks. *IEEE Trans. Wirel. Commun.* **2018**, *17*, 2109–2121. [\[CrossRef\]](#)
108. Hoeppe, P. Trends in weather related disasters—Consequences for insurers and society. *Weather. Clim. Extrem.* **2016**, *11*, 70–79. [\[CrossRef\]](#)
109. Demiane, F.; Sharafeddine, S.; Farhat, O. An optimized UAV trajectory planning for localization in disaster scenarios. *Comput. Netw.* **2020**, *179*, 107378. [\[CrossRef\]](#)
110. Yu, X.; Li, C.; Zhou, J.F. A constrained differential evolution algorithm to solve UAV path planning in disaster scenarios. *Knowl.-Based Syst.* **2020**, *204*, 106209. [\[CrossRef\]](#)
111. San Juan, V.; Santos, M.; Andújar, J.M. Intelligent UAV Map Generation and Discrete Path Planning for Search and Rescue Operations. *Complexity* **2018**, *2018*, 6879419. [\[CrossRef\]](#)
112. Malandrino, F.; Chiasserini, C.F.; Casetti, C.; Landi, G.; Capitani, M. An optimization-enhanced MANO for energy-efficient 5G networks. *IEEE/ACM Trans. Netw.* **2019**, *27*, 1756–1769. [\[CrossRef\]](#)
113. Duong, T.Q.; Nguyen, L.; Nguyen, L.K. Practical Optimisation of Path Planning and Completion Time of Data Collection for UAV-enabled Disaster Communications. In Proceedings of the 2019 15th International Wireless Communications & Mobile Computing Conference (IWCMC), Tangier, Morocco, 24–28 June 2019; pp. 372–377.
114. Guo, B.; Yu, Z.; Zhou, X.; Zhang, D. From participatory sensing to Mobile Crowd Sensing. In Proceedings of the 2014 IEEE International Conference on Pervasive Computing and Communication Workshops, PERCOM WORKSHOPS 2014, Budapest, Hungary, 24–28 March 2014; pp. 593–598.
115. Ma, H.; Zhao, D.; Yuan, P. Opportunities in mobile crowd sensing. *Infocommunications J.* **2015**, *7*, 32–38. [\[CrossRef\]](#)
116. Savage, N. Twitter as Medium and Message. *Commun. ACM* **2011**, *54*, 18–20. [\[CrossRef\]](#)
117. Crooks, A.; Croitoru, A.; Stefanidis, A.; Radzikowski, J. # Earthquake: Twitter as a Distributed Sensor System. *Trans. GIS* **2013**, *17*, 124–147.

118. Sakaki, T.; Okazaki, M.; Matsuo, Y. Earthquake shakes Twitter users: Real-time event detection by social sensors. In Proceedings of the 19th International Conference on World Wide Web, WWW '10, Raleigh, NC, USA, 26–30 April 2010; pp. 851–860.
119. Sakaki, T.; Okazaki, M.; Matsuo, Y. Tweet analysis for real-time event detection and earthquake reporting system development. *IEEE Trans. Knowl. Data Eng.* **2013**, *25*, 919–931. [\[CrossRef\]](#)
120. Lu, X.; Wang, H.; Huang, M. Upper bound solution for the face stability of shield tunnel below the water table. *Math. Probl. Eng.* **2014**, *2014*, 727964. [\[CrossRef\]](#)
121. Kongthon, A.; Haruechaiyasak, C.; Pailai, J.; Kongyoung, S. The role of social media during a natural disaster: A case study of the 2011 Thai flood. *Int. J. Innov. Technol. Manag.* **2014**, *11*, 1440012. [\[CrossRef\]](#)
122. Lu, X.; Bengtsson, L.; Holme, P. Predictability of population displacement after the 2010 Haiti earthquake. *Proc. Natl. Acad. Sci. USA* **2012**, *109*, 11576–11581. [\[CrossRef\]](#) [\[PubMed\]](#)
123. Bengtsson, L.; Lu, X.; Thorson, A.; Garfield, R.; von Schreeb, J. Improved response to disasters and outbreaks by tracking population movements with mobile phone network data: A post-earthquake geospatial study in Haiti. *PLoS Med.* **2011**, *8*, e1001083. [\[CrossRef\]](#)
124. Xu, Z.; Liu, Y.; Yen, N.; Mei, L.; Luo, X.; Wei, X.; Hu, C. Crowdsourcing Based Description of Urban Emergency Events Using Social Media Big Data. *IEEE Trans. Cloud Comput.* **2020**, *8*, 387–397. [\[CrossRef\]](#)
125. Liu, W.; Luo, X.; Gong, Z.; Xuan, J.; Kou, N.M.; Xu, Z. Discovering the core semantics of event from social media. *Future Gener. Comput. Syst.* **2016**, *64*, 175–185. [\[CrossRef\]](#)
126. Xu, Z.; Liu, Y.; Xuan, J.; Chen, H.; Mei, L. Crowdsourcing based social media data analysis of urban emergency events. *Multimed. Tools Appl.* **2017**, *76*, 11567–11584. [\[CrossRef\]](#)
127. Chen, S.; Xu, H.; Liu, D.; Hu, B.; Wang, H. A vision of IoT: Applications, challenges, and opportunities with dehradun perspective. *IEEE Internet Things J.* **2014**, *1*, 349–359. [\[CrossRef\]](#)
128. Azzam, R.; Arnhardt, C.; Tomas, M.F.-S. Monitoring and Early Warning of Slope Instabilities and Deformations by Sensor Fusion in Self-Organized Wireless ad-hoc Sensor Networks. *J. SE Asian Appl. Geol.* **2010**, *2*, 163–169.
129. Sofwan, A.; Sumardi Ridho, M.; Goni, A. Najib Wireless sensor network design for landslide warning system in IoT architecture. In Proceedings of the 2017 4th International Conference on Information Technology, Computer, and Electrical Engineering, ICITACEE 2017, Semarang, Indonesia, 18–19 October 2017; pp. 280–283.
130. Wang, H.-H.; Tuo, X.-G.; Zhang, G.-Y.; Peng, F.-L. Panzhihua airport landslide (Oct. 3rd 2009) and an emergency monitoring and warning system based on the internet of things. *J. Mt. Sci.* **2013**, *10*, 873–884. [\[CrossRef\]](#)
131. Van Khoa, V.; Takayama, S. Wireless sensor network in landslide monitoring system with remote data management. *Measurement* **2018**, *118*, 214–229. [\[CrossRef\]](#)
132. Moulat MEI Debauche, O.; Mahmoudi, S.; Brahim, L.A.; Manneback, P.; Lebeau, F. Monitoring System Using Internet of Things for Potential Landslides. In Proceedings of the 15th International Conference on Mobile Systems and Pervasive Computing (MobIDPC 2018), Gran Canaria, Spain, 13–15 August 2018; pp. 26–34.
133. Biansoongnern, S.; Plungkang, B.; Susuk, S. Development of Low Cost Vibration Sensor Network for Early Warning System of Landslides. *Energy Procedia* **2016**, *89*, 417–420. [\[CrossRef\]](#)
134. Frigerio, S.; Schenato, L.; Bossi, G.; Cavalli, M.; Mantovani, M.; Marcato, G.; Pasuto, A. A web-based platform for automatic and continuous landslide monitoring: The Rotolon (Eastern Italian Alps) case study. *Comput. Geosci.* **2014**, *63*, 96–105. [\[CrossRef\]](#)
135. Huang, J.; Huang, R.; Ju, N.; Xu, Q.; He, C. 3D WebGIS-based platform for debris flow early warning: A case study. *Eng. Geol.* **2015**, *197*, 57–66. [\[CrossRef\]](#)
136. Ye, J.; Kurashima, Y.; Kobayashi, T.; Tsuda, H.; Takahara, T.; Sakurai, W. An efficient in-situ debris flow monitoring system over a wireless accelerometer network. *Remote Sens.* **2019**, *11*, 1512. [\[CrossRef\]](#)
137. Ma, H. Design and application on bluetooth-based wireless sensor network debris flow mountain health monitoring system. *Adv. Mater. Res.* **2014**, *889–890*, 829–832. [\[CrossRef\]](#)
138. Zhao, Y.; Zhang, N.; Si, G. A fiber bragg grating-based monitoring system for roof safety control in underground coal mining. *Sensors* **2016**, *16*, 1759. [\[CrossRef\]](#)
139. Eliasson, J.; Pereira, P.P.; Mäkitaavola, H.; Delsing, J.; Nilsson, J.; Gebart, J. A feasibility study of SOA-enabled networked rock bolts. In Proceedings of the 19th IEEE International Conference on Emerging Technologies and Factory Automation, ETFA 2014, Barcelona, Spain, 16–19 September 2014.
140. Picozzi, M.; Milkereit, C.; Fleming, K.; Fischer, J.; Jaekel, K.-H.; Bindi, D.; Parolai, S.; Zschau, J. Applications of a Low-Cost, Wireless, Self-Organising System (SOSEWIN) to Earthquake Early Warning and Structural Health Monitoring. In *Early Warning for Geological Disasters. Advanced Technologies in Earth Sciences*; Wenzel, F., Zschau, J., Eds.; Springer: Berlin/Heidelberg, Germany, 2014.
141. Sherki, Y.; Gaikwad, N.; Chandle, J.; Kulkarni, A. Design of real time sensor system for detection and processing of seismic waves for earthquake early warning system. In Proceedings of the 2015 IEEE International Conference on Power and Advanced Control Engineering, ICPACE 2015, Bengaluru, India, 12–14 August 2015; pp. 285–289.
142. Zambrano, A.M.; Perez, I.; Palau, C.; Esteve, M. Technologies of Internet of Things applied to an Earthquake Early Warning System. *Future Gener. Comput. Syst.* **2017**, *75*, 206–215. [\[CrossRef\]](#)

143. Zambrano, A.; Perez, I.; Palau, C.; Esteve, M. Quake detection system using smartphone-based wireless sensor network for early warning. In Proceedings of the 2014 IEEE International Conference on Pervasive Computing and Communication Workshops, PERCOM Workshops 2014, Budapest, Hungary, 24–28 March 2014; pp. 297–302.
144. Nachtigall, J.; Redlich, J.P. Wireless alarming and routing protocol for Earthquake Early Warning Systems. In Proceedings of the 2011 4th IFIP International Conference on New Technologies, Mobility and Security, NTMS 2011, Paris, France, 7–10 February 2011.
145. Alarifi AS, N.; Alarifi NS, N.; Al-Humidan, S. Earthquakes magnitude prediction using artificial neural network in northern Red Sea area. *J. King Saud Univ.—Sci.* **2012**, *24*, 301–313. [\[CrossRef\]](#)
146. Goymann, P.; Herrling, D.; Rausch, A. Flood Prediction through Artificial Neural Networks A case study in Goslar, Lower Saxony. In Proceedings of the ADAPTIVE 2019: The Eleventh International Conference on Adaptive and Self-Adaptive Systems and Applications, Venice, Italy, 5–9 May 2019; pp. 56–62.
147. Arslan, M.; Roxin, A.M.; Cruz, C.; Ginhac, D. A review on applications of big data for disaster management. In Proceedings of the 13th International Conference on Signal-Image Technology and Internet-Based Systems, SITIS 2017, Jaipur, India, 4–7 December 2017; pp. 370–375.
148. Granell, C.; Ostermann, F.O. Beyond data collection: Objectives and methods of research using VGI and geo-social media for disaster management. *Comput. Environ. Urban Syst.* **2016**, *59*, 231–243. [\[CrossRef\]](#)
149. Pond, P. International Journal of Disaster Resilience in the Built Environment Article information. *Int. J. Disaster Resil. Built Environ.* **2016**, *6*, 102–116.
150. Avvenuti, M.; Cresci, S.; Nizzoli, L.; Tesconi, M. GSP (Geo-Semantic-Parsing): Geoparsing and Geotagging with Machine Learning on Top of Linked Data. In Proceedings of the 15th International Conference, ESWC 2018, Heraklion, Greece, 3–7 June 2018; Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). Springer: Cham, Switzerland, 2018; pp. 17–32.
151. Ghahremanlou, L.; Sherchan, W.; Thom, J.A. Geotagging twitter messages in crisis management. *Comput. J.* **2014**, *58*, 1937–1954. [\[CrossRef\]](#)
152. Middleton, S.E.; Middleton, L.; Modafferi, S. Real-time crisis mapping of natural disasters using social media. *IEEE Intell. Syst.* **2014**, *29*, 9–17. [\[CrossRef\]](#)
153. Kumar, S.; Morstatter, F.; Zafarani, R.; Liu, H. Whom should I follow? Identifying relevant users during crises. In Proceedings of the 24th ACM Conference on Hypertext and Social Media, Paris, France, 1–3 May 2013; pp. 139–147.
154. Cresci, S.; Cimino, A.; Dell’Orletta, F.; Tesconi, M. Crisis Mapping During Natural Disasters via Text Analysis of Social Media Messages. In Proceedings of the Web Information Systems Engineering—WISE 2015: 16th International Conference, Miami, FL, USA, 1–3 November 2015, Part II.
155. Cervone, G.; Sava, E.; Huang, Q.; Schnebele, E.; Harrison, J.; Waters, N. Using Twitter for tasking remote-sensing data collection and damage assessment: 2013 Boulder flood case study. *Int. J. Remote. Sens.* **2016**, *37*, 100–124. [\[CrossRef\]](#)
156. Nguyen, D.T.; Al Mannai, K.A.; Joty, S.; Sajjad, H.; Imran, M.; Mitra, P. Rapid Classification of Crisis-Related Data on Social Networks using Convolutional Neural Networks Dat. In Proceedings of the 11th International Conference on Web and Social Media, ICWSM 2017, Montreal, QC, Canada, 15–18 May 2017; pp. 632–635.
157. Ahmad, S.; Ahmad, K.; Ahmad, N.; Conci, N. Convolutional neural networks for disaster images retrieval. In Proceedings of the MediaEval 2017, Dublin, Ireland, 13–15 September 2017.
158. Alam, F.; Imran, M.; Ofli, F. Image4Act: Online social media image processing for disaster response. In Proceedings of the 2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, ASONAM 2017, Sydney, Australia, 31 July 2017–3 August 2017; pp. 601–604.
159. Alam, F.; Ofli, F.; Imran, M. Processing Social Media Images by Combining Human and Machine Computing during Crises. *Int. J. Hum.-Comput. Interact.* **2018**, *34*, 311–327. [\[CrossRef\]](#)
160. Huang, X.; Li, Z.; Wang, C.; Ning, H. Identifying disaster related social media for rapid response: A visual-textual fused CNN architecture. *Int. J. Digit. Earth* **2020**, *13*, 1017–1039. [\[CrossRef\]](#)
161. Ghosh, S.; Sriji, P.K.; Desarkar, M.S. Using social media for classifying actionable insights in disaster scenario. *Int. J. Adv. Eng. Sci. Appl. Math.* **2017**, *9*, 224–237. [\[CrossRef\]](#)
162. Hofmann, M.; Betke, H.; Sackmann, S. Process-oriented disaster response management: A structured literature review. *Bus. Process Manag. J.* **2015**, *2*, 966–987. [\[CrossRef\]](#)
163. Nguyen, L.; Yang, Z.; Li, J.; Pan, Z.; Cao, G.; Jin, F. Forecasting People’s Needs in Hurricane Events from Social Network. *IEEE Trans. Big Data* **2018**, *8*, 229–240. [\[CrossRef\]](#)
164. Nguyen, D.T.; Ofli, F.; Imran, M.; Mitra, P. Damage assessment from social media imagery data during disasters. In Proceedings of the 2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, ASONAM 2017, Sydney, Australia, 31 July 2017–3 August 2017; pp. 569–576.
165. Burel, G.; Alani, H. Crisis event extraction service (CREES)—Automatic detection and classification of crisis-related content on social media. In Proceedings of the 15th ISCRAM Conference, Rochester, NY, USA, 20–23 May 2018; pp. 597–608.
166. Bischke, B.; Helber, P.; Zhao, Z.; De Bruijn, J.; Borth, D. The multimedia satellite task at MediaEval 2018 emergency response for flooding events. In Proceedings of the MediaEval’18, Sophia Antipolis, France, 29–31 October 2018.

167. Daly, S.; Thom, J.A. Mining and classifying image posts on social media to analyse fires. In Proceedings of the 13th International Conference on Information Systems for Crisis Response and Management, Rio de Janeiro, Brazil, 22–25 May 2016.
168. De Nicola, A.; Melchiori, M.; Villani, M.L. Creative design of emergency management scenarios driven by semantics: An application to smart cities. *Inf. Syst.* **2019**, *81*, 21–48. [\[CrossRef\]](#)
169. Jung, D.; Tuan, V.T.; Tran, D.Q.; Park, M.; Park, S. Conceptual framework of an intelligent decision support system for smart city disaster management. *Appl. Sci.* **2020**, *10*, 666. [\[CrossRef\]](#)
170. Gosavi, A.; Fraioli, G.; Sneed, L.H.; Tasker, N. Discrete-Event-Based Simulation Model for Performance Evaluation of Post-Earthquake Restoration in a Smart City. *IEEE Trans. Eng. Manag.* **2020**, *67*, 582–592. [\[CrossRef\]](#)
171. Shah, S.A.; Seker, D.Z.; Rathore, M.M.; Hameed, S.; Ben Yahia, S.; Draheim, D. Towards Disaster Resilient Smart Cities: Can Internet of Things and Big Data Analytics Be the Game Changers? *IEEE Access* **2019**, *7*, 91885–91903. [\[CrossRef\]](#)
172. Jayawardene, V.; Huggins, T.J.; Prasanna, R.; Fakhruddin, B. The role of data and information quality during disaster response decision-making. *Prog. Disaster Sci.* **2021**, *12*, 100202. [\[CrossRef\]](#)
173. Ohara, M.; Nagumo, N.; Shrestha, B.; Sawano, H. Flood risk assessment in Asian flood prone area with limited local data: Case study in Pampanga river basin, Philippines. *J. Disaster Res.* **2016**, *11*, 1150–1160. [\[CrossRef\]](#)
174. Marks, D. Assembling the 2011 Thailand floods: Protecting farmers and inundating high-value industrial estates in a fragmented hydro-social territory. *Political Geogr.* **2019**, *68*, 66–76. [\[CrossRef\]](#)
175. Oxoli, D.; Ronchetti, G.; Minghini, M.; Molinari, M.E.; Lotfian, M.; Sona, G.; Brovelli, M.A. Measuring urban land cover influence on air temperature through multiple geo-data—The case of Milan, Italy. *Int. J. Geo-Inf.* **2018**, *7*, 421. [\[CrossRef\]](#)
176. Iglesias, C.A.; Favenza, A.; Carrera, Á. A big data reference architecture for emergency management. *Information* **2020**, *11*, 569. [\[CrossRef\]](#)
177. TARU; SMC; SCCT. End to End Early Warning Systems for Ukai and Local Floods in Surat City. 2015. Available online: https://smartnet.niua.org/sites/default/files/resources/End%20to%20End%20EWS_Surat.pdf (accessed on 5 July 2021).
178. United Nations Development Programme. *Effective Law and Regulation for Disaster Risk Reduction: A Multi-Country Report (Summary)*; United Nations Development Programme: New York, NY, USA, 2014.
179. Zuboff, S. *The Age of Surveillance Capitalism: The Fight for a Human Future at the New Frontier of Power*; Profile Books: London, UK, 2019.
180. Grove, K.; Krivý, M.; Rickards, L.; Schliwa, G.; Collier, S.J.; Cox, S.; Gandy, M. Interventions on design and political geography. *Political Geogr.* **2019**, *74*, 102017. [\[CrossRef\]](#)
181. Gulrud, N.M.; Raymond, C.M.; Rutt, R.L.; Olafsson, A.S.; Plieninger, T.; Sandberg, M.; Beery, T.H.; Jönsson, K.I. ‘Rage against the machine’? The opportunities and risks concerning the automation of urban green infrastructure. *Landsc. Urban Plan.* **2018**, *180*, 85–92. [\[CrossRef\]](#)
182. Cretney, R. Resilience for whom? Emerging critical geographies of socio-ecological resilience. *Geogr. Compass* **2014**, *8*, 627–640. [\[CrossRef\]](#)
183. AL-Fazari, S.; Kasim, N. Role of Stakeholders in Mitigating Disaster Prevalence: Theoretical Perspective. *MATEC Web Conf.* **2018**, *266*, 03008. [\[CrossRef\]](#)
184. Ningtyas, T.; Larasati, E.; Warsono, H.; Purnaweni, H. Multi-stakeholder Participation Challenges In Local Disaster Management Policies: A Case from Bojonegoro District, Indonesia. In Proceedings of the 6th International Conference on Social and Political Sciences (ICOSAPS 2020), Online, 1 January 2020; pp. 417–424.
185. Panneer, S.; Kantamaneni, K.; Pushparaj RR, B.; Shekhar, S.; Bhat, L.; Rice, L. Multistakeholder participation in disaster management—The case of the covid-19 pandemic. *Healthcare* **2021**, *9*, 203. [\[CrossRef\]](#) [\[PubMed\]](#)
186. Post, J.; Zosseder, K.; Strunz, G.; Birkmann, J.; Gebert, N.; Setiadi, N.; Anwar, H.Z.; Harjono, H.; Nur, M.; Siagian, T. Risk and vulnerability assessment to tsunami and coastal hazards in Indonesia: Conceptual framework and indicator development. In Proceedings of the 2007 International Symposium on Disaster in Indonesia. Problems and Solutions, Padang, Indonesia; 2007.
187. Zhang, N.; Ni, X.Y.; Huang, H.; Zhao, J.L.; Duarte, M.; Zhang, J. The impact of interpersonal pre-warning information dissemination on regional emergency evacuation. *Nat. Hazards* **2016**, *80*, 2081–2103. [\[CrossRef\]](#)
188. Golumbic, Y.N.; Orr, D.; Baram-Tsabari, A.; Fishbain, B. Between Vision and Reality: A Study of Scientists’ Views on Citizen Science. *Citiz. Sci. Theory Pract.* **2017**, *2*, 6. [\[CrossRef\]](#)
189. Brownell, S.E.; Price, J.V.; Steinman, L. Science communication to the general public: Why we need to teach undergraduate and graduate students this skill as part of their formal scientific training. *J. Undergrad. Neurosci. Educ.* **2013**, *12*, 6–10.
190. Sanders, C.K.; Scanlon, E. The Digital Divide Is a Human Rights Issue: Advancing Social Inclusion Through Social Work Advocacy. *J. Hum. Rights Soc. Work* **2021**, *6*, 130–143. [\[CrossRef\]](#)
191. Abdeen, F.; Fernando, T.; Kulatunga, U.; Hettige, S.; Ranasinghe, K.A. Challenges in multi-agency collaboration in disaster management: A Sri Lankan perspective. *Int. J. Disaster Risk Reduct.* **2021**, *62*, 102399. [\[CrossRef\]](#)
192. Appleby-Arnold, S.; Brockdorff, N.; Jakovljević, I.; Zdravković, S. Disaster preparedness and cultural factors: A comparative study in Romania and Malta. *Disasters* **2021**, *45*, 664–690. [\[CrossRef\]](#)
193. Broo, D.G.; Schooling, J. Digital twins in infrastructure: Definitions, current practices, challenges and strategies. *Int. J. Constr. Manag.* **2021**, *23*, 1–10. [\[CrossRef\]](#)

194. Thomalla, F.; Smith, R.; Schipper, E. Cultural Aspects of Risk to Environmental Changes and Hazards: A Review of Perspectives. In *Disaster's Impact on Livelihood and Cultural Survival: Losses, Opportunities, and Mitigation*; Companion, M., Ed.; CRC Press: Boca Raton, FL, USA, 2015; pp. 3–18.
195. Goyder, H.; Perera, R. External Evaluation of the UNISDR-Coordinated Tsunami Early Warning Systems Initiative. 2009. Available online: https://www.preventionweb.net/files/9580_UNISDRtsunamievaluation.pdf (accessed on 10 July 2021).
196. UNESCAP. *Role of Information and Communications Technology in the Implementation of the Hyogo Framework for Action*; United Nations Economic and Social Commission for Asia and the Pacific: Bangkok, Thailand, 2010.
197. Gaillard, J.; Maceda, E.A. Participatory three- dimensional mapping for disaster risk reduction. *Development* **2018**, *60*, 109–118.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.