drones

MDPI

Review

Complementarity, Interoperability, and Level of Integration of Humanitarian Drones with Emerging Digital Technologies: A State-of-the-Art Systematic Literature Review of Mathematical Models

Eleni Aretoulaki *, Stavros T. Ponis and George Plakas

School of Mechanical Engineering, National Technical University Athens, 157 73 Athens, Greece; staponis@central.ntua.gr (S.T.P.); plakasg@mail.ntua.gr (G.P.)
* Correspondence: aretoulaki@mail.ntua.gr

Abstract: The adoption of drones and other emerging digital technologies (DTs) has proven essential in revolutionizing humanitarian logistics as standalone solutions. However, the interoperability of humanitarian drones with other DTs has not yet been explored. In this study, we performed a systematic literature review to attempt to fill this gap by evaluating 101 mathematical models collected from Scopus. After conducting a descriptive analysis to identify the trends of publications in terms of year, type, source, and country of origin, a content analysis ensued to investigate the complementarity, interoperability, and level of integration of humanitarian drones with eight DTs. Next, we researched how these DTs can help drones exploit their capabilities to their full potential and facilitate the various drone operations deployed across different disaster scenarios, types, and stages. Last, the solving approaches employed by the models were examined. Overall, we shifted our research focus toward several overlooked aspects in the literature and identified multiple challenges needing to be addressed. Our work resulted in the formulation of a holistic framework aiming to standardize the cooperative utilization of DTs during the execution of humanitarian drone operations, so as to enhance their real-life application and scalability.

Keywords: humanitarian logistics; drones; unmanned aerial vehicles; digital technologies; Internet of things; big data; disaster management

Citation: Aretoulaki, E.; Ponis, S.T.; Plakas, G. Complementarity, Interoperability, and Level of Integration of Humanitarian Drones with Emerging Digital Technologies: A State-of-the-Art Systematic Literature Review of Mathematical Models. *Drones* **2023**, *7*, 301. https://doi.org/10.3390/drones7050301

Academic Editor: Tamás Bányai

Received: 23 March 2023
Revised: 27 April 2023
Accepted: 2 May 2023
Published: 4 May 2023

1. Introduction

Contemporary logistics networks, even under normal operating conditions, are inherently faced with a plethora of issues, which become even more challenging in the event of disasters and emergencies, which either disrupt existing networks by imposing additional pressure or require the creation of ad hoc humanitarian logistics (HL) networks for disaster management (DM), to relieve the affected areas and provide aid to the victims. According to the authors of [1], HL is defined as the "process of planning, implementing and controlling the efficient, cost-effective flow and storage of goods and materials as well as related information from the point of origin to the point of consumption for the purpose of alleviating the suffering of vulnerable people". Humanitarian and commercial logistics are recognized as radically different [2]. Authors [3] examined the differences between the two, concluding that HL, not being profit-driven as with commercial logistics, aims to minimize deprivation costs, i.e., the loss of well-being due to the lack of a good or service. Moreover, unlike traditional logistics, the dynamically changing environment prevalent during disasters may lead to lack of up-to-date information and may thus become a source of uncertainty regarding supply, demand, time, location, and size [4].

Even though it is not possible to completely prevent all disasters, it is widely known that leveraging emerging digital technologies (DTs) can transform HL operations deployed before, during, and after the strike of a disaster. Recently, unmanned aerial vehicles (UAVs) or "drones" have significantly changed the humanitarian landscape through their communication, monitoring, and transportation capabilities [5]. Other disruptive DTs, such as, but not limited to, big data analytics [6–11]; Internet of things (IoT) [12–14]; cloud, edge, and fog computing [15–17]; artificial intelligence (AI) [18–20]; social media and crowdsourcing [8,21–24]; robotics and cyber-physical systems (RCPSs) [25–27]; blockchain [18,28–30]; and extended reality (XR) [31,32], have also been harnessed in HL operations. However, the academic literature, to the best of our knowledge, has only focused on drones and DTs as standalone solutions, and the interoperability of drones with other DTs has so far been studied in neither the HL nor DT literature.

In the present research, we attempted to fill this particular research gap through a systematic literature review (SLR). The present paper is structured as follows: Section 2 introduces the reader to the four discrete steps of the research methodology followed in the study and provides details about the selection process of papers included in the study sample. Next, in Section 3, a descriptive analysis is outlined, and its results are provided to illustrate the trends in publications in terms of year, type, source, and country of origin. Section 4 describes the coding criteria proposed for the classification of the papers, which is detailed in Section 5, where the results are categorized and evaluated. In Section 6, the results are discussed, challenges are pinpointed, and a novel holistic integrated framework is proposed based on the review results. Finally, the paper concludes with Section 7, summarizing the study's findings as well as highlighting research limitations and future research potential.

2. Research Methodology: Systematic Literature Review

An SLR was carried out to identify and critically appraise the findings of relevant peer-reviewed research works, while ensuring transparency, objectivity, rigor, and reproducibility. The main objective of an SLR is to analyze a mass of evidence to help both academics and practitioners ameliorate their decision making by bridging the prevalent "knowing–doing" gap between research and practice [33]. SLRs differ from traditional narrative reviews in that they require a more formal and meticulous approach in terms of reporting methodology, search terms, databases used, as well as inclusion and exclusion criteria [34,35]. An SLR methodology consists of four steps, i.e., planning, searching, screening, and extraction [35]. Their implementation in the present study is detailed below.

2.1. Planning

The initial step of conducting an SLR is to develop clear, focused, and concise research questions, which set the context to our research, refined the issue under study, and guided material collection, with a view to constructing a logical argument and finding new aspects of already established results. After conducting preliminary research on HL to acquire familiarity and a deep understanding of the field, to ensure the validity of our original research idea, and to avoid duplication of previously addressed research questions, we observed that even though the research on DTs in the context of HL has been peaking over the last decade [36], there still are significant research gaps to be addressed. Indeed, according to numerous works reviewing DTs, including drones, in HL, this topic still contains various unexplored research avenues that call for additional analysis (see Table 1). The three gaps addressed in this study are described as follows:

✓ There have been multiple literature reviews concentrating on the integration of emerging technologies in HL operations, the majority of which, nevertheless, have focused on the enablers of drones [5] and other DTs [7,18,28,37–41] as standalone solutions. In fact, publications synthesizing previous research on how different DTs have been applied in tandem with drones in HL are scarce and not inclusive enough. For instance, such reviews include [42], where the coordination of drones with wireless sensor networks (WSNs); the IoT; edge, fog, and cloud computing for data gathering; and communication provision in DM was discussed. Other researchers [43] examined combined drone–truck operations for various types of drone problems in civil applications, including but not emphasizing HL. To the best of our knowledge, no study has so far holistically investigated and systematically appraised the complementarity and interoperability of drones with other emerging DTs across various disaster scenarios, types, and stages.

✓ The various types of drone problems have been the subject of much research conducted in the context of civil applications, as seen in [43], where original studies of different types of drone operations were brought together and analyzed. However, such analysis in the context of HL has been overlooked.

✓ The literature reviews of mathematical models in HL have not focused on either drones or other DTs [44–46]. Therefore, there is a need to fill this gap by highlighting the trends, state of the art, and most promising challenges in such modeling approaches.

Table 1. Summary of the most pertinent literature reviews.

Reference	Drones	DTs	Drones in Tandem with DTs	Contributions: This Paper Reviews . . .	Technology-/Model-Oriented Future Research Directions Should Address . . .	HL Context	Non-HL Context
[44–47]	-	-	-	Mathematical models developed in the field of HL.	The need for the use of metaheuristics to alleviate models' computational burdens and enable them to be used in actual disasters and filtered down into policy, practice, and procedures. The lack of holistic approaches. The infancy of technology use. The lack of use of real-time data. Narrow variety of modeling objectives.	X	-
[48]	X	-	-	Optimization problems arising in the operations planning of drones in civil applications.	Dynamic planning schemes for a range of relevant drone operations fulfilling a set of desired criteria. Approaches to deal with data uncertainty. Drone design to optimize performance, practicality, and economics. The incorporation of demand into planning models. How individual beliefs and experience impact purchasing decisions of drone technology and services, and the ways in which drones are used as well as the perceived benefit.	-	X
[49,50]	X	-	-	Trajectory and routing optimization models based on the usage of drones.	Other types of optimization problems in addition to routing ones, such as task assignments. Modeling energy consumption and kinematics, which need further investigation.	X	X
[6,7]	-	X	-	Big data in HL.	The better understanding of the environmental and social aspects of HL through big data. Big-data-assisted social media analytics. The combination of stakeholder and institutional theory from the perspective of big data use. Cost–benefit analysis of maintaining viable practices based on big data. The shift of focus from descriptive and diagnostic to predictive analytics. Improving big data quality. Securing privacy and security when integrating big data with cloud computing.	X	-
[43]	X	-	X	Optimization issues related to drone and drone–truck operations, including mathematical models, solution methods, synchronization between a drone and a truck, and implementation barriers.	Incorporating uncertainty. Relaxing operational constraints. Improving modeling techniques and solution methodologies. Addressing mixed-fleet arc routing problems.	X	X
[5]	X	-	-	Potential of drones and their role to provide operational tools for emergency responders during disastrous situations. Three important capabilities, three performance outcomes, and adoption barriers in three areas were identified.	Investigating drones' complementarity and interoperability with other emerging DTs, such as IoT, AI, blockchain, and big data analytics, other than drones as a standalone solution.	X	-

Table 1. *Cont.*

Reference	Drones	DTs	Drones in Tandem with DTs	Contributions: This Paper Reviews ...	Technology-/Model-Oriented Future Research Directions Should Address ...	HL Context	Non-HL Context
[37]	X	X	-	DTs (IoT, AI, blockchain, drones, cloud computing, big data, social media, 3D printing, robotics, AR, VR etc.) in the humanitarian supply chain (HSC) domain and their role in terms of main objectives, application domains, and deployment phases within the HSC framework.	The collection of insights from various stakeholders to explore multiple perspectives on the novelty of a specific DT within the HSC context and potentially discover new processes, methods, organizational structures, and managerial frameworks for HL operations.	X	
[42]	X	-	X	Data collection through drones and communication provision through drone-assisted ground technologies (WSN, IoT, and edge and fog computing) and their coordination for DM.	Challenges UAVs are faced with in disaster communication scenarios such as delay, coverage, quality of service (QoS) requirements, channel models, and UAV positioning and interference problems.	X	-
[28]	-	X	-	Blockchain technology in HL.	The integration of optimization models. The lack of empirical evidence. Testing simulation scenarios before performing real-life implementations.	X	-
[41]	X	X	-	DTs (IoT, image processing, AI, big data, smartphone applications, etc.) that are in use and have been proposed for DM of urban regions.	Systematization and standardization. A global database on the application of technology for HL that will act as a roadmap, highlighting the relevance of each technology as per the scenario. Training on technology. A better understanding of the legal implications of technology, data protection, privacy laws, etc.	X	-

Considering all of the above, in this study, an SLR was carried out to address the challenges that have emerged from previous studies, as presented above, by evaluating the mathematical models investigating the complementarity and interoperability of drones with other emerging DTs across various drone operations as well as disaster types and stages. The aim of the research questions posed in this SLR was to look into the aforementioned research gaps as well as identify the progress of the field under study and future research perspectives.

In particular, we raised the following research questions (RQs):

RQ1: What is the trend in the publications in terms of year, type, source, and country of origin?

RQ2: Which disaster stages and types of disasters have been discussed? What emerging DTs are being used?

RQ3: How have DTs started to complement and operate in tandem with drones in HL literature? How are these DTs diversified?

RQ4: What drone operations have been examined, and what drone capabilities have been utilized? How are drone operations approached by each DT?

RQ5: What different mathematical models have been proposed? What types of solving approaches have been proposed?

2.2. Searching

This step pertains to the identification of academic literature relevant to the RQs posed and the determination of which studies should be included in the sample after setting a number of inclusion and exclusion criteria. The data collection process in our SLR was conducted on 4 September 2022, based on papers from the Scopus database. The search query used in this study comprised three key word sets combined with the "AND" operator. The first one was used to establish the humanitarian context; the second one to include the term "UAVs" as well as synonyms and alternate terms, as shown by the authors of [5], who performed an SLR to synthesize research on drones in the HL context; and the last one was used to include various DTs, all separated by the "OR" operator.

The DTs included in our query were inspired by the research protocol followed by the authors in [37], who conducted an SLR to investigate the role of DTs in HSCs. After a comprehensive preliminary search, it was concluded that some of the DTs proposed in that study do not work in tandem with drones and were, hence, excluded from the search query. It is worth mentioning that the term "mathematical models", despite being the focus of our SLR, was not included in the query to avoid missing useful material. The query of the keyword terms used in this study was:

("Humanitarian Supply Chain" OR "Humanitarian Operation" OR "Humanitarian Logistic*" OR "Emergency Management" OR "Disaster*")* ***AND*** *(Drone* OR "Unmanned Aerial Vehicle*" OR UAV* OR "Unmanned Aircraft System*" OR UAS* OR "Remotely Piloted Aircraft*")* ***AND*** *("Big Data" OR "Big Data Analytics" OR "Cloud Computing" OR "Edge Computing" OR "Fog Computing" OR "Internet of Things" OR IoT OR "Augmented Reality" OR "Virtual Reality" OR "Extended Reality" OR "Mixed Reality" OR "Robotics" OR "Cyber-physical System*" OR "Social Media" OR "Crowdsourcing" OR "Block-chain*" OR "Blockchain*" OR "Information Technolog*" OR "Industry 4.0" OR "Smart Industry" OR "Digitalisation" OR "Digital Platform*" OR "Digital Transformation" OR "Logistics 4.0"))*

Additional reviews added on a later date to the Scopus database were, thus, not included in the present study. The proposed keyword string was entered into Scopus's default tab (Document Search form), followed by the selection of the search field "Article Title, Abstract, Keywords". Note that the use of double quotation marks ensures the inclusion of each phrase as a "loose phrase", meaning that the words must appear together in the selected search field(s). Furthermore, the use of asterisks (*) at the beginning or end of a keyword ensures the inclusion of the term in both singular and plural forms as well as its derivatives. This initial search generated 631 results.

2.3. Screening

Three exclusion criteria were then set to narrow down the development trends in mathematical models exploiting both UAVs and other DTs in the context of HL. First and foremost, our sample was limited to studies published after 2015. The reason behind this decision was twofold. On the one hand, we wanted to make sure the resulting sample was manageable enough to be carefully studied and analyzed in its entirety. The average SLR sample in the HL literature (bibliometric systematic reviews aside) was ~86 papers (see Table A1 in Appendix A), which is considerably smaller than our initial sample. On the other hand, the scope of this SLR was to collect information about the most novel solutions in the sense that novelty is inherently linked to the most recent years of technological innovation. According to the works presented in [37], the period following 2015 was the most suitable starting point for our research design including DTs and HL due to the recent increase in pertinent scientific interest, resulting in the concepts' relative maturity [6,36]. This is also corroborated by the authors of [46], who confirmed the infancy of the use of technology and sophisticated mathematical models in HL back in 2015. Taking both points into consideration, 81 papers, which were published before 2015, were rejected. The second criterion set was the exclusion of papers written in any language other than English. Sixteen of the papers yielded by the search were written in Chinese, Korean, or Ukrainian and were therefore removed from the sample. The third and last criterion applied to the type of publications and led to the exclusion of 49 magazines, conference reviews, and errata.

After rigorously examining their content, i.e., their abstract, keywords, table of contents, and main body, we also rejected 390 irrelevant papers (e.g., the majority of rejected papers deviated from the HL concept and focused on other drone applications or were describing theoretical HL contributions instead of mathematical models) as well as papers whose full text could not be retrieved. Considering all of the above, the initial sample size decreased to 101 papers. The systematic screening process described is presented in Figure 1.

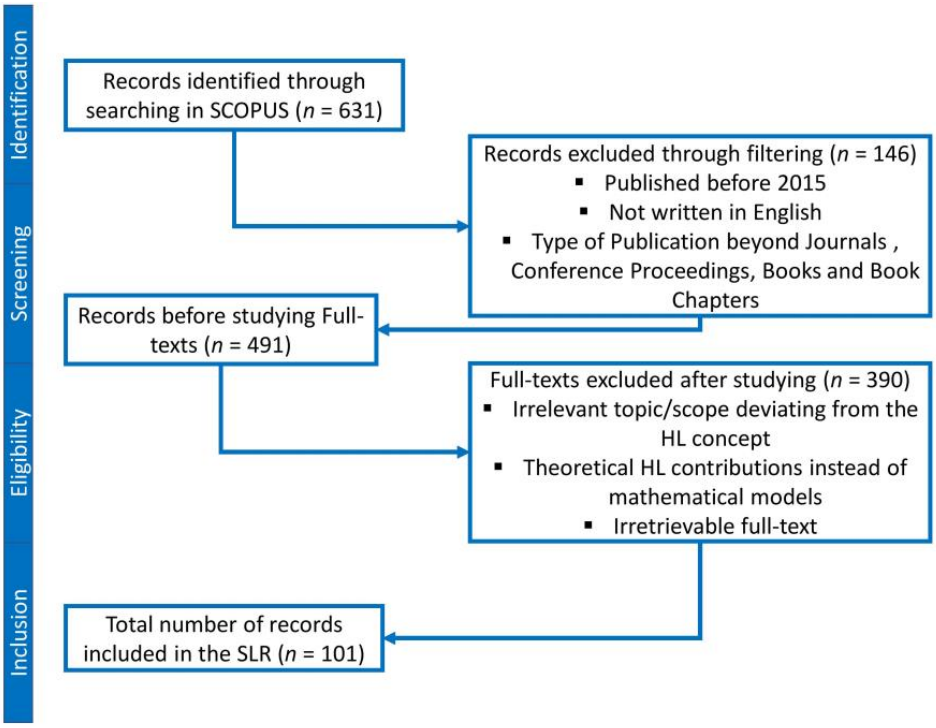

Figure 1. Systematic screening process of the SLR.

2.4. Extraction

After a descriptive analysis was conducted to answer RQ1, the 101 publications of the final SLR sample were thoroughly investigated content-wise, and coding criteria were applied to answer the remaining RQs. The ultimate classification results were processed with Microsoft Excel software, because its formulas, formatting options, and various data management and visualization tools make it a suitable tool for organizing data in an easy-to-navigate way and rapidly and accurately performing complex mathematical calculations. A list of classification abbreviations is provided in Table A2 (Appendix A), followed by a list of other abbreviations of terms used in this paper (Table A3 in Appendix A).

3. Descriptive Analysis

3.1. Number of Publications (Per Year, 2015–2022)

The chronologically first paper selected to be included in this research was [51], published in the International Conference on Informatics in Control, Automation and Robotics (ICINCO). Figure 2 illustrates the number of publications from 2015 to the present moment. From the beginning of our time frame to 2018, the number of papers published has gradually increased, while the rate of growth from 2018 to 2019 has been more than 400%. Despite this emerging trend, after 2019, the overall trend decreased for the next two years. This could be attributed to the COVID-19 pandemic as non-COVID-19 research production decreased. In fact, according to the authors of [52], non-COVID-19-related articles began to decrease in volume as COVID-19-related articles increased. Nevertheless, the trend seems to have surged again in 2022, and it will likely continue to grow in the near future as well.

3.2. Number of Publications (Per Type)

The following pie chart (Figure 3) illustrates that roughly half of the papers in our sample (n = 55, 54.46%) are journal papers, while the remaining papers (n = 45, 44.55%), apart from one book chapter, are conference proceedings. The predominance of journal papers indicates early signs of the maturing of the field.

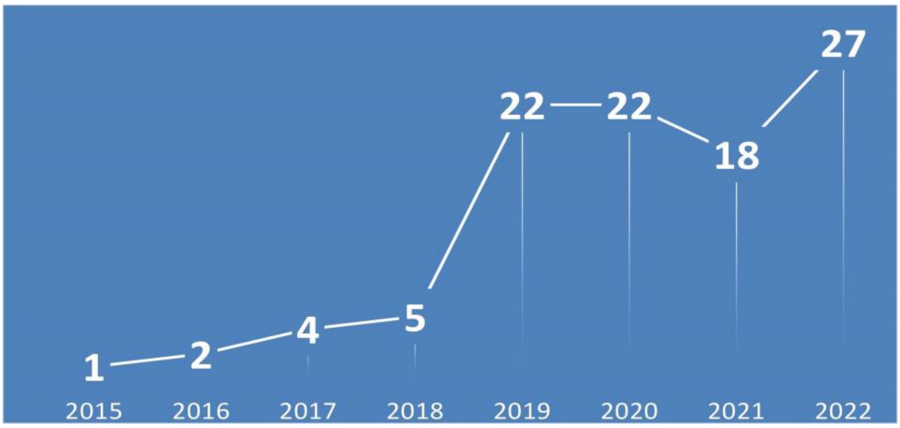

Figure 2. Number of publications per year.

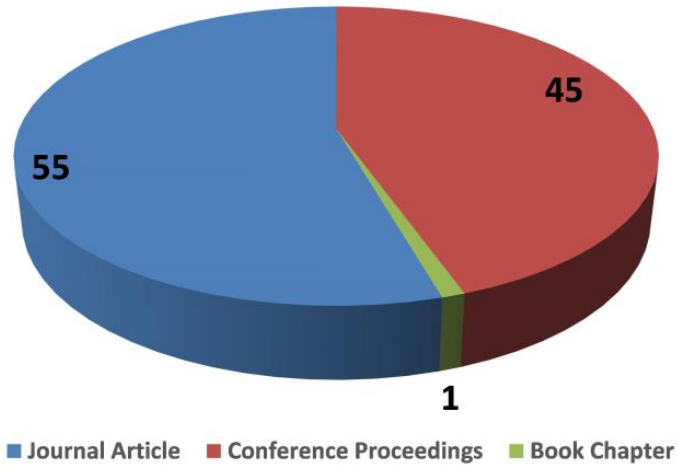

Figure 3. Number of publications (per type).

3.3. Number of Publications (Per Publishing Source)

Table 2 demonstrates how the papers included in our SLR relate to their classification by the source where they were published. A uniform distribution of papers across different sources can be seen, with no obvious pattern for a particular journal or conference in which the number of papers (*n*) is noteworthy. Out of 101, 75 (74.26%) studies were published in sources, accounting for only 1 or 2 papers in our SRL. The six sources with the majority of papers were *IEEE Internet of Things Journal* (*n* = 8, 7.92%), *IEEE Access* (*n* = 4, 3.96%), *IEEE Transactions on Vehicular Technology* (*n* = 4, 3.96%), *IEEE Conference of Computer Communications* (*n* = 4, 3.96%), *Computer Communications* (Elsevier) (*n* = 3, 2.97%), and *IEEE International Workshop on Safety, Security and Rescue Robotics* (*n* = 3, 2.97%). Overall, all of the 34 journals and 37 conferences participating in our study had a reasonably high impact factor (weighted average ~5.3) and h5 index (weighted average ~36), respectively; consequently, it was rightfully deduced that the selected studies were subject to meticulous quality control by editors and peer reviewers.

This fragmentation of academic literature pertinent to the topic under study is in accordance with the conclusions made in [5,37], which, as already mentioned, acted as motivations for this study. Moreover, all sources in our sample are technology-, applications-, and computer-science-centric and lack humanitarian foci. This contributes to our previous argument and reaffirms the conclusion drawn in [53] that the role of DTs in HL follows a technology-oriented research perspective.

Table 2. Number of publications per publishing source.

Publishing Source	# of Papers (*n*)	%
IEEE Internet of Things Journal	8	7.92%
IEEE Access	4	3.96%
IEEE Transactions on Vehicular Technology	4	3.96%
IEEE Conference on Computer Communications	4	3.96%
Computer Communications (*Elsevier*)	3	2.97%
IEEE International Workshop on Safety, Security, and Rescue Robotics	3	2.97%
IEEE Wireless Communications	2	1.98%
Wireless Communications and Mobile Computing (Wiley Hindawi)	2	1.98%
IEEE Transaction on Network Science and Engineering	2	1.98%
IEEE International Conference on Communications Workshops	2	1.98%
IEEE Transactions on Industrial Informatics	2	1.98%
IEEE Systems	2	1.98%
IEEE International Conference on Cloud Networking	2	1.98%
Sensors (MDPI)	2	1.98%
IEEE International Conference on Distributed Computing in Sensor Systems	2	1.98%
Other *	57	56.44%
All	101	100%

* Includes sources participating in the study with only one (1) paper.

3.4. Geographical Distribution of Authors

The sample size of our SLR shows that the work of authors spanned over 41 countries, with distinctly discernible clusters in east Asia, the United States, western and central Europe, as well as south and southeast Asia, along with various smaller clusters in other parts of the world, such as South America, the Middle East, eastern Europe, and Oceania (Figure 4). It is worth noting that China alone hosted over one-third of the authors. The researchers from Europe were primarily located in Italy, Spain, France, the United Kingdom, and Germany. China, Japan, and South Korea (east Asia); India and Pakistan (south Asia); as well as Vietnam, Malaysia, and Thailand (Southeast Asia) represented the Asian clusters.

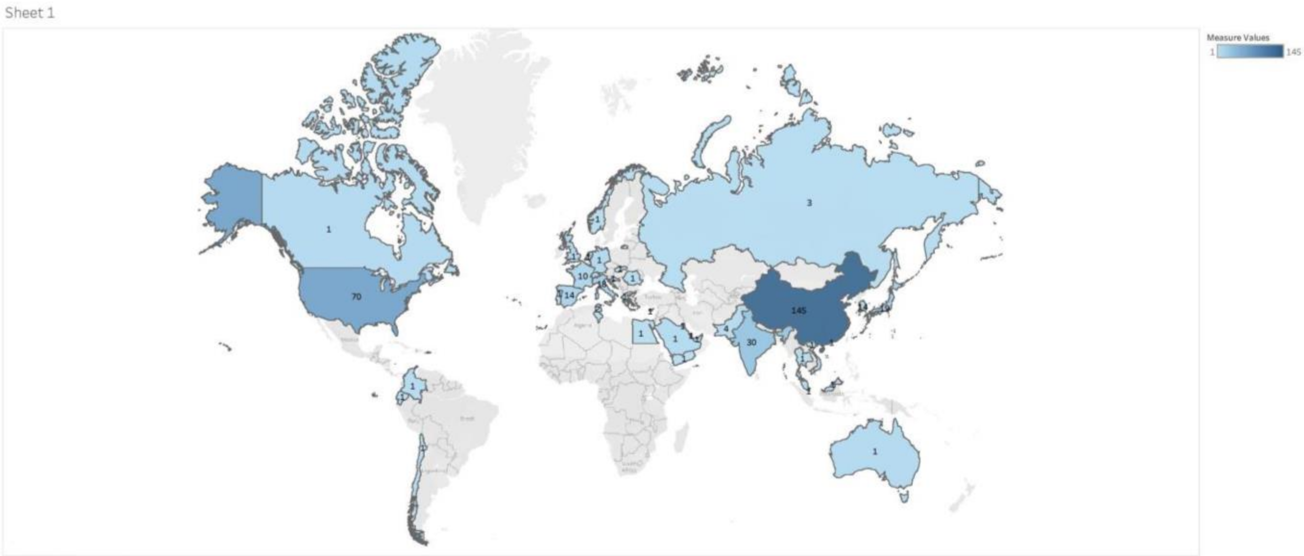

Figure 4. Geographical distribution of authors.

4. Coding Criteria Taxonomy

The descriptive analysis was followed by a content analysis based on a specific pattern of coding criteria developed, with a view to divulging meaningful themes in our sample and producing valid inferences [54]. In general, content analysis does not proceed linearly [55].

For the content analysis, the inductive method (classification after reading the selected documents) was carried out, which means that the coding criteria emerged from the content of the papers in our sample through an iterative process of criteria-building, testing, revising, and comparing [56]. Given that humanitarian drones are emerging as a promising technology [40], the use of a deductive approach would not be appropriate, because new codes have to be inferred from the data and adaptably established [57]. This process was guided by the RQs posed in the methodology section and resulted in a coding criteria taxonomy, which we used to categorize the selected publications and investigate the field's progress in terms of the integration of DTs into various drone operations across different disaster phases and types, the drone capabilities utilized, and the mathematical modeling approaches employed. The proposed coding criteria are discussed below.

4.1. Disaster Phases and Types

The first criterion was the disaster phases and types addressed by each proposed mathematical model in our sample. Leveraging DTs, including drones, in DM phases has been pinpointed in the recent literature to be a topic of paramount significance requiring further analysis [5,6,39] because they have proven to play a vital part in ameliorating efficiency, effectiveness, and continuity. In the literature, DM efforts have been classified into two stages, i.e., the pre- and postdisaster stages [58]. The predisaster stage covers the mitigation phase, which includes the steps to prevent a disaster from happening and minimize the vulnerability to its impacts; and the preparedness phase, which includes educating communities on how a disaster can impact them, so that they can appropriately react when needed and adopt a proactive stance [6,44]. On the other hand, the postdisaster stage covers the response phase, which involves resource allocation and emergency procedures aimed at protecting life and property, as well as the socioeconomic structure of a community after its immediate strike; and the recovery phase, which includes actions that support the restoration of all the damage as a result of the disaster and the stabilization of the community [6,47]. The selected contributions were also classified based on the type of the disasters, which, depending on the cause of the disruption, could be categorized into natural and human-made and further categorized into sudden- and slow-onset disasters, depending on whether their emergence was unexpected or gradual [2].

4.2. Humanitarian Digital Technologies (HDTs)

The second criterion pertains to the various DTs complementing drones in the humanitarian operations addressed by the mathematical models in our sample. These DTs include the IoT; cloud, edge, and fog computing; big data analytics; AI; social media and crowdsourcing; RCPSs; blockchain technology; and XR, which are detailed below.

4.2.1. IoT

Semantically, the IoT paradigm refers to a network of interconnected physical objects, called "things", which contain embedded technologies capable of communicating and interacting with one another [12,59], formulated to enable sensing, seamless communication, and actuation. Its capabilities, including interoperability, distributed processing, and real-time analytics, render IoT technologies capable of "smartifying" DM and providing solutions to various problems [13]. In such applications, the fundamental contributions of the IoT lie in the simultaneous and continuous exchange of real-time data, obtained from different strategically selected and reliable sources, which help crises stakeholders with decision -making before, during, or after the strike of a disaster [14,60]. In particular, the instantaneous and close-to-reality information updates from the distributed smart objects and the communication infrastructure can perfectly address the dynamic nature of the requirements during an HL operation. They contribute to disaster risk mitigation and prevention through the monitoring and design of prediction and early warning systems; to emergency response through the real-time communication for the mapping of affected areas and timely victim rescue and relief; and, finally, to disaster recovery, for example, in missing person search operations in the aftermath of a disaster [14,61,62]. Among others, IoT networks in such applications comprise sensors, gateways, mobile devices, and robots, including UAVs, computers, and satellites.

4.2.2. Cloud, Edge, and Fog Computing

Cloud, edge, and fog computing have been broadly used in IoT data management to increase data processing speed and efficiency as well as to smartify storage, control, and networking and obtain improved resource utilization and availability among connected IoT entities [63]. Cloud computing is the standard IoT computing paradigm that, instead of saving information to local servers or devices, is based on the centralization of resources. This means that all information is kept in multiple remote servers able to be accessed online from any device, which, however, increases latency, bandwidth cost, and network requirements. A new trend in computing is currently emerging with the function of clouds increasingly moving toward network edges [64]. Unlike cloud computing, in edge computing, data are directly processed and kept on edge devices without being transferred to remote servers, which prevents the transmission of irrelevant data to the cloud, eliminates the need to wait for data to return from a centralized processing system, and secures an immediate response and the lowest latency possible. Fog computing works as an intermediate layer between cloud and edge computing and works by taking on specific processing tasks from the two, hence decreasing their workload. Even though it is decentralized like edge computing, unlike it, fog computing takes place further away from the data-generating devices. In fog computing, data are analyzed within an IoT gateway, while in edge computing, data are analyzed on the devices themselves.

4.2.3. AI

AI refers to technologies that can learn from experience and adjust accordingly, thus enabling machines to imitate or even outperform human intelligence when performing human-like tasks. Machine learning (ML) is an application of AI that determines how a computer system develops its intelligence without being explicitly programmed. ML algorithms are categorized into supervised learning (SL) algorithms, which are trained by humans based on pre-existing labeled data from which the machine is expected to learn the pattern and predict the output values for new data inputs, and unsupervised learning (UL) algorithms, which learn exclusively from unlabeled data, without the need for human intervention. This conventional dichotomous separation is becoming all the more vague every day as, usually, both types of ML algorithms are used either sequentially or in a hybridized form. However, there are ML algorithms that do not require a training data set and are therefore neither supervised nor unsupervised. Examples of such algorithms include reinforcement learning (RL) algorithms, which are feedback-based, where desired behaviors are rewarded and/or undesired ones are punished, allowing the model to make mistakes and explore data within certain parameters. ML is playing an increasingly significant role in DM operations from the prediction of hazards and their escalation, vulnerability assessment, the provision of situational awareness and decision support through remote sensing (e.g., with drone aerial imagery), crowdsourcing, and the development of maps for disaster detection in real time to early warning systems, damage assessment, and beyond [19,20].

4.2.4. Social Media and Crowdsourcing

Social media is defined as a group of Internet-based applications that allow the creation and exchange of user-generated content that can be edited, shared, and interacted with [65]. It includes a broad spectrum of content formats including text, audio, video, photographs, and GPS coordinates [8]. Social media has come to play a role of paramount importance in citizen participation and crowdsourcing in the event of a crisis [21,66], as the massive volume of data generated can be mined for enhancing communications before, during, and after the occurrence of a disaster [22]. Through social media platforms, people are capable of broadcasting their needs, divulging and dispersing crisis-pertinent information [67–69], and providing real-time status updates [70], thus contributing to the planning and execution of relief operations [71,72]. The abundance of data generated by social media and their real-time analysis can help aid organizations and first responders to streamline their efforts as well as coordinate and collaborate with competent agencies and stakeholders during humanitarian operations [7]. The interactivity provided by social media [23,73] can also enable the dissemination of information, in the form of instructions and guidance, back to the citizens in danger through the design and development of early warning information systems. Human behavior can be estimated through the analysis of social big data from various services, and the efficient evacuation of victims stranded in vulnerable areas can be accomplished. Last, after the disaster has been dealt with, recovery can be aided through the sharing of locations and transmission of images of damaged infrastructures.

4.2.5. Big Data Analytics

Big data analytics involves examining and making sense out of large volumes of quickly generated, complex, and diverse data, with a view to unraveling hidden patterns and unknown correlations and ultimately improving efficiency and enhancing decision-making capabilities. These data, in their raw form, are impossible to process and analyze using traditional methods and technologies. Big data are characterized by the seven Vs, i.e., volume, designating the quantity of generated and stored data; velocity, i.e., the speed at which data are generated; variety, i.e., the nature of data; variability, i.e., the inconsistency in data; veracity, i.e., the quality of data; visualization, i.e., the visual representation of data; and value, i.e., the return resulting from data management. The ability of big data analytics to visualize, analyze, and predict disasters and their consequences renders it capable of revolutionizing humanitarian operations and emergency management [6,9,10]. In the context of humanitarian operations, the most important sources of big data include satellite imagery, UAV-based aerial imagery and videos, WSNs and the IoT, social media and crowdsourcing, as well as mobile GPS and call data records [11].

4.2.6. RCPSs

RCPSs are complex, physically aware networked systems that integrate embedded computing technologies including sensors, processors, and actuators into the physical world. These systems are designed to sense and interact with the physical world with the aim of supporting real-time monitoring, knowledge discovery, decision making, and actuation [74–76]. They are widely used in the field of HL, providing intelligent and fast responses to emergencies [76], being launched in terrestrial (unmanned ground vehicles (UGVs)), aerial (UAVs) or aquatic (unmanned underwater vehicles (UUVs) and unmanned surface vehicles (USVs)) environments. RCPSs are able to perform a multitude of operations including but not limited to the transportation of medical supplies, commodities, oxygen tanks, or even wounded victims; monitoring through video cameras or thermal imaging to spot survivors; public safety communication; search and rescue (SAR); detection and disposal of explosive ordnances; firefighting; the detection of toxic industrial chemicals or radiation; the collection of information about the temperature, humidity, and wind in the atmosphere; tethering to other devices; etc.

4.2.7. Blockchain Technology

Blockchain is a DT that started to rapidly enter the context of HL through the establishment of the permanent, immutable, and transparent recording of data and transactions across information systems and geographies with permissioned data access and identity validation. The data in blockchain are stored in a shared, distributed, and fault-tolerant database to which each and every participant in the network has access. This technology provides the ability to eliminate corruptive actions by leveraging the computational capabilities of the honest nodes, thereby rendering information exchange resilient to manipulation. Its decentralized architecture makes it robust against potential attacks, and its reliance on a public key infrastructure makes data cryptographically safe [77]. These capabilities enable blockchain to provide a solution to multiple critical DM challenges, such as the establishment of secure access to critical data generated across all HL phases, the timely exchange of verified information, the acceleration of partnership formation and collaboration between diverse organizations and agencies, the establishment of trust and reduction of corruption among stakeholders, the amelioration of resource allocation as well as coordination, and network resilience [29,30].

4.2.8. XR

XR is an umbrella term covering the spectrum of all immersive technologies merging the real and virtual worlds using augmented reality (AR), virtual reality (VR), or mixed reality (MR), which superimpose virtual objects on the real environment or/and integrate real objects into a preliminary virtual environment. In particular, AR is a solution to creating mediated reality environments in which georeferenced and context-specific computer-generated information elements in the form of text, audio, and/or graphics complement the perception of the real world [31]. VR is a solution to creating a sense of immersion and "intelligent" scenes comprising a fully virtual environment with virtual elements that obscure the physical environment and simulate real-life objects [78]. Last, in MR, also referred to as hybrid reality, the capabilities of AR and VR complement each other in such a way that digital and real objects coexist and interact with one another in real time [32]. In the context of HL, the aforementioned technologies are employed in both the pre- and postdisaster phases to deal with numerous challenges, such as achieving mass awareness by alerting the general public about disaster situations, assessing infrastructure damage, and applying efficient rescue training through realistic simulation (ibid).

4.3. Humanitarian Drone Operations (HDOs) and Capabilities (HDCs)

The third criterion was related to the HDOs performed in the studies included in our sample and the HDCs utilized during their execution. The operations we explored are inspired by the context of civil drone applications [43,48] but are here discussed across the humanitarian spectrum. It is worth mentioning that overlapping may exist between the HDOs. HDCs were first investigated in [10] and included the transportation and delivery, surveying and monitoring, and communication and integration capabilities. Briefly, transportation and delivery capabilities aim, among others, at facilitating the delivery of essentials, reducing delivery times, and enabling access to geographically, environmentally or/and, infrastructure-challenged areas, which may be unreachable by conventional transportation means [79–81]. Surveying and monitoring capabilities enable remote sensing and the collection of spatial information through the acquisition of high-resolution material even in the harsh environmental conditions of dangerous or impassable disaster-stricken areas as well as of damaged infrastructure in the aftermath of a disaster [82–84]. Last, communication and integration capabilities complement terrestrial communication and connectivity and facilitate communication between first responders and victims by providing long-range wireless connectivity for DM tasks [26,85,86]. For further details about HDCs, the reader is referred to Rejeb et al. [5]. As thoroughly analyzed in Section 5, an HDO can utilize one, two, or all three HDCs depending on the setting and objectives. Nonetheless, some HDOs are intrinsically associated with certain HDCs.

4.3.1. Area Coverage

In area coverage HL operations, one or more UAVs equipped with sensors of a limited footprint must monitor various shapes of a specified area affected by a disaster to rapidly collect spatial information [48]. Their remote sensing capabilities enable drones to provide clear and high-resolution aerial photographs or videos and assist in the surveillance of dangerous or even impassable areas, thus securing the safety of human rescue teams [83]. In such operations, the path of UAVs is designed so that unproductive movements and repeated monitoring of the same points are avoided, with common objectives being the minimization of distance [87–89], completion time [80,90], the number of turns, or energy consumption while satisfying a set of constraints [43]. Area coverage operations inherently exploit the drone's surveying and monitoring capabilities.

4.3.2. Search

Search operations in drone-assisted SAR applications involve one or multiple UAVs being launched to locate a missing person with an unknown location by partitioning a map of the search area into cells, each labeled with a different probability of finding the target [48]. The most common objectives of such operations include the maximization of the cumulative finding probability under a time constraint or the minimization of the time to find a target under a given probability. While the humanitarian drone search operations share similarities with traditional search operations [43], additional limitations have to be taken into consideration, such as the limited battery capacity, which sheds light on the need for recharging and leads to more frequent searching close to the charging station [91]; the limitations of drone sensors, which differ from the ones used by UGVs in traditional search operations [92]; and, last, the communication limitations that could arise in UAV-to-UAV, UAV-to-base station (BS), or UAV-to-UGV communication [93,94]. Search operations, by default, utilize the drone's surveying and monitoring capabilities.

4.3.3. Routing for a Set of Locations

UAV-assisted routing for a set of locations involves setting up one or several UAVs to visit a set of locations to complete a task, while minimizing cost, time, distance, energy, or other objectives, considering several limitations, including time windows, environmental conditions, payload weight and size, distance, pick-up and delivery capacity, fly zone, battery life, or fuel constraints [50]. The requirements of the locations (nodes) to be visited also have to be taken into account, as there might be no need to visit all of them based on the actual needs and available resources [95]. Routing for a set of locations might overlap with the area coverage problem because its discretized formulation can be considered as routing [48].

4.3.4. Path Planning and Trajectory Planning

Path planning and trajectory planning share similarities with routing for a set of locations, but there are significant differences worth mentioning. As stated, in routing, an optimal route needs to be found so as to fulfil a specified objective, as opposed to path planning, which pertains to the feasibility of the route to be pursued by the UAVs in a routing problem, which is a complex but crucial task. In essence, path planning involves finding a flyable collision-free geometric path for the UAV visiting a specified sequence of nodes in a two- or three-dimensional space irrespective of any specified time law or drone dynamics. On the other hand, in trajectory planning, a time law is assigned to the geometric path, and the control history of the drone is considered, while abiding by constraints pertaining to a set of equations of motion that describes the relationship between the spatiotemporal system changes as well as drone position, velocity, acceleration, and dynamics [96]. Trajectory planning is intrinsically linked to control problems. Generally, path planning is followed by trajectory planning. However, in some cases, for example, when only two nodes to be visited are specified, path and trajectory planning can be applied at the same time [97].

4.3.5. Task Assignment

UAV-assisted task assignment is relevant to the UAV routing problem. It refers to the assignment of a UAV or a swarm of UAVs to a number of tasks subject to mission requirements and environmental constraints [98]. The number of tasks does not have to be equal to the number of UAVs employed [99]. This drone operation aims at maximizing efficiency, minimizing system costs, and through cooperative work, meaning multiple UAVs supporting each other's operation through information sharing, task integration, and resource optimization, reducing overall risks and execution time as well as enhancing the quality of the completed tasks (ibid).

4.3.6. Scheduling

There is a plethora of scheduling decisions to be made in the HL operations that are assisted by multiple drones. The ultimate objective of UAV-assisted scheduling is to ensure the continuity of operations [100] by assigning drones to appropriate tasks [101,102]. These decisions may refer to multiple processes, such as drone recharging, battery swapping, refueling, predictive maintenance, safety checks, scheduling of servicing, human expert assessment and critical information collection on the fly, etc. [48]. A common objective in scheduling a drone employed to cover a disaster-stricken area is the maximization of information collected [103] for a predetermined time span; for drone delivery, a common objective is the maximization of the nodes served and minimization of delivery completion time [104]. We refer the interested reader to Zabih Ghelichi [105] on drone location and scheduling problems in HL.

4.3.7. Data Gathering and Recharging in a WSN

UAV-assisted data gathering and recharging in a WSN is the operation where UAVs are assigned to collect information from a discrete set of locations while, as opposed to routing for a set of locations, taking into account the communication range and distance, data recency, and memory capacity limitations [48]. A WSN is defined as a distributed system that gathers data from the physical environment through sensor nodes, i.e., small autonomous short-range transceivers capable of collaborating with one another using wireless communication [106]. Even though sensor nodes themselves are able to collect data from a spatially limited area, a WSN with multiple sensor nodes can cover a larger region [107]. The information collected by the sensors is conventionally transmitted to a BS, which then forwards it to a server. However, in some operations including HL operations, this would be prohibitively slow and costly. In such operations, UAVs act as an additional layer between the sensors and the BS by gathering data from the former and transmitting them or carrying them back to the latter. Apart from data gathering, UAVs can also recharge sensors inductively through wireless power transfer (WPT) by generating an electromagnetic field [108,109]. The UAVs can dynamically move around the sensors and power them, enabling information transmission. Data gathering and recharging in a WSN intrinsically takes advantage of the drone's communication and integration capabilities.

4.3.8. Resource Allocation for Mobile Devices

In the aftermath of a disaster, traditional terrestrial cellular networks may provide intermittent, poor, or no coverage owing to failure of a part or the entirety of the BS infrastructure [110–112]. This highlights the need for the deployment of reliable communication services supporting data transmission and communication between ground user devices in disaster-stricken areas, so that evacuation of trapped victims and relief operations are facilitated. Resource allocation for mobile devices refers to the UAV-assisted allocation of communication links of adequate quality and computing power to the battery-limited mobile devices participating in such emergency communication networks. UAVs play a critical role in such network, by being used as fixed or flying BSs with adaptive altitude, linking mobile devices to macrocell BSs, or even enabling UAV-to-UAV transmissions, linking mobile devices connected to one UAV to mobile devices connected to another [113–115]. Establishing communication links with a UAV requires the mobile device to be located within its communication range, which is therefore subject to deployment location limitations. This explains why the most common resource allocation objectives pertain to cost minimization, QoS maximization (interference minimization and signal-to-noise ratio maximization), and energy efficiency maximization to achieve the desired communication quality [116]. Similar to data gathering and recharging in a WSN, resource allocation uses the drone's communication and integration capabilities.

4.3.9. Other

Last but not least, in this category, other HDOs are introduced that were included in our analysis but were not addressed thus far, including supply allocation and sampling. The former refers to the delivery of essential, life-saving commodities, such as medical equipment, pharmaceuticals, and vaccines, as well as food and water. This operation has to take a variety of factors into consideration, including meeting the demand for supplies as determined by the victims of the disaster, maximization of space utilization to serve as many victims (nodes) as possible, and the consideration of time constraints. Sampling relates to the collection of water, chemical spill, or other types of samples for the testing of drinkability or/and detection of hazardous substances. Both operations are linked to the drone's transportation and delivery capabilities.

4.4. Solving Approaches

The last criterion categorizes the studies based on the problem-solving approach proposed, i.e., optimization, control, and other types of mathematical models. Obviously, various other categorizations can be employed, but we think that those chosen represent a sufficient compromise and reflect the most useful information. Additional classifications with respect to algorithmic design paradigms used and vehicle considerations examined by the studies in our analysis are introduced in Section 5. Optimization and control models are introduced below. If a mathematical model in our sample did not fall into either of the two categories, it was assigned to the "other types of mathematical model" category.

4.4.1. Optimization Models

Optimization models are used to quantitatively tackle many emerging DM challenges [117], with pertinent drone-related examples being presented in [43,48,50]. In our analysis, optimization models were categorized based on their stochasticity into exact models, which guarantee the optimal analytical solution but often suffer from high computational complexity and, therefore, inefficient execution times; and nonexact models, which provide a suboptimal but computationally reasonable solution. The latter were further categorized into heuristic models, which generate problem-dependent solutions; and metaheuristic models, whose solutions are generic and can be applied to a broad spectrum of problems. Note that due to the spread of the topic, we cannot provide details on decision variables, constraints, or objective functions for each reviewed study in the limited space of a journal article. Some other considerations are described in the following section when evaluating specific methods.

4.4.2. Control Models

Because of its nonlinear characteristics and underactuated design, UAVs seem to be an excellent platform to control systems research [118]. Control models pertain to the control of dynamic systems to drive them to a desired state while minimizing delays, the occurrence of a signal or function exceeding its target (overshooting) or steady-state error, and securing control stability [119]. A controller monitors the process variables and compares them with a reference value, whose difference is then applied as feedback to generate a control action to ensure the process variable has the same value as the reference value (ibid). Note that optimization may be part of control models, but when this is the case, emphasis is placed on the control aspect of the model.

5. Material Evaluation

In this section, the results of our analyses are presented. The evaluation of the studies of our sample was divided into categories relevant to the coding criteria introduced in Section 4. Table A4 in Appendix B succinctly lists the categorization of the papers into the proposed criteria. Notably, the foci of the papers in our sample are varied and not mutually exclusive; therefore, more than one subcategory per coding criterion may apply to each paper. The papers were examined under the lens of all subcategories into which they were classified in order to provide different insights and perspectives in terms of the integration of different HDTs, their application into the different HDOs, the exploitation of different HDCs, as well as the solving approaches pursued.

5.1. Which Disaster Phases and Types Have Been Discussed? What Emerging Technologies Are Being Used?

As illustrated in Figure 5, after investigating the sample in its entirety, we concluded that the mitigation phase was examined in 75 papers (74.26%), while the preparedness phase was analyzed in 38 papers (37.62%). Correspondingly, the response phase was covered in 99 papers (98.02%) and the recovery phase in 18 papers (17.82%). Overall, the focus on the postdisaster stage was greater in comparison. The predisaster stage received the focus in 89 papers (88.12%), whereas the postdisaster stage was investigated by all studies (100%) participating in the final sample. This means that some of the studies developed solutions applicable to more than one disaster phase/stage.

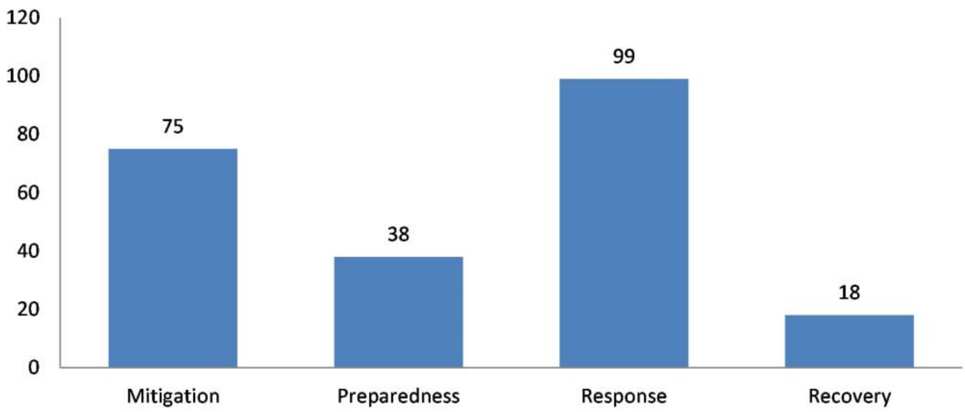

Figure 5. Categorization of the studies in our sample into disaster phases.

With regard to the disaster types, natural disasters were addressed in 43 papers (42.57%), while 14 papers (13.86%) addressed both natural and human-made disasters. The rest of the papers (43.56%) do not explicitly specify the origin of the disaster considered by the proposed models, so it can be assumed that either disaster type could have been the application focus. It is notable that no paper in our sample had human-made disasters as the main focus. With regard to the speed of the disasters, all studies explored sudden-onset disasters, including wildfires, floods, earthquakes, and chemical spills. The only study addressing slow-onset disasters, which was in combination with sudden-onset disasters, was [120], where a model was designed for panic-based, timely, and orderly evacuation of stranded people and applied to a case study pertinent to the COVID-19 pandemic disaster. In particular, the proposed model contributes to helping with the panic-based selective testing of people with the aim of preventing panic, which is often assumed to be the natural response of people to physical danger.

Six out of eight of the DT categories introduced in Section 4 were used in all HL phases, with cloud, edge, and fog computing and XR being the two exceptions, which are not used during the recovery phase.

5.2. How Emerging DTs Have Started to Complement and Operate in Tandem with Drones in HL Literature?

In Figure 6, the classification of the 101 papers into the 8 DT categories introduced in Section 4 is depicted. Big data (n = 86, 85.15%) and IoT (n = 71, 70.3%) were studied by the majority of models in our sample, followed by AI (n = 40, 39.6%) and cloud, edge, and fog computing (n = 22, 21.78%). RCPSs were studied in 17 studies (18.81%), while blockchain, social media and crowdsourcing, and XR were utilized by 10 (0.1%), 7 (0.07%) and 4 (0.04%) studies, respectively. In the remainder of this section, the level of integration and the interoperability of each HDT with UAVs are evaluated with respect to the mathematical models presented in the literature.

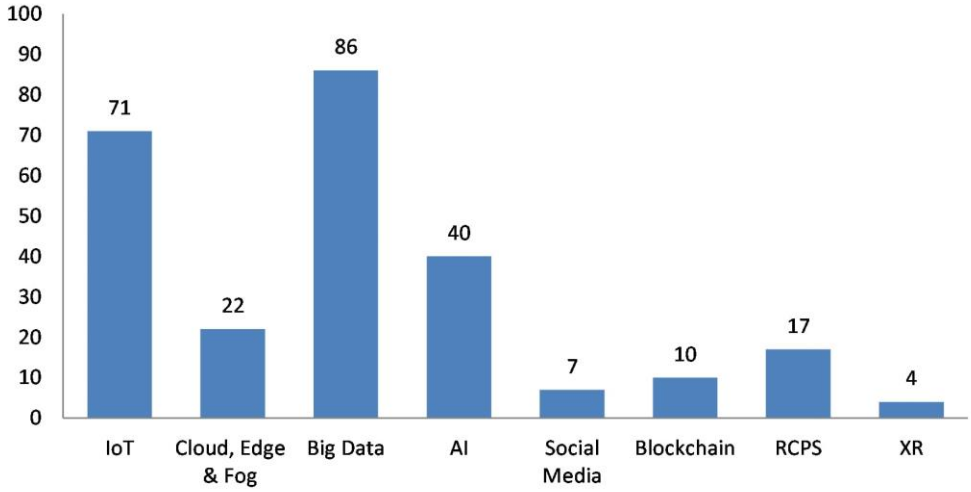

Figure 6. Classification of the 101 papers into the eight proposed DT categories.

5.2.1. IoT

The use of IoT communication networks can considerably improve the performance of DM systems through the exploitation of the massive heterogeneous data generated by various interconnected devices [121]. Nevertheless, during an emergency, where proximal BSs can potentially be damaged, overloaded, or out of the transmission range of the devices, secure communication services are compromised. Thankfully, UAVs, due to their flexibility, can establish three-dimensional mobile aerial networks in an ad hoc manner and provide reliable multihop paths able to maintain connectivity through other types of nodes [122]. UAVs are able to hover close to devices, gather IoT data, and transmit them to a remote BS or control center for processing or even immediately perform the processing on site through specialized computing units [123]. UAVs can even be equipped with devices themselves (e.g., optical, acoustic location sensors, etc.) to provide valuable audiovisual or other types of useful data [124].

Overall, according to [125], based on the nature of the application, UAVs can be integrated in different IoT–WSN architectures. As shown in Figure 7, in the IoT-enabled mathematical models in our sample, the authors have proposed links between the UAV and mobile devices (63.38%), other UAVs (29.58%), stationary sensors (28.17%), satellites (0.1%), as well as other vehicles (0.08%). Each proposed model incorporated multiple links in its architectural design, so the inclusion in one category is not exclusive.

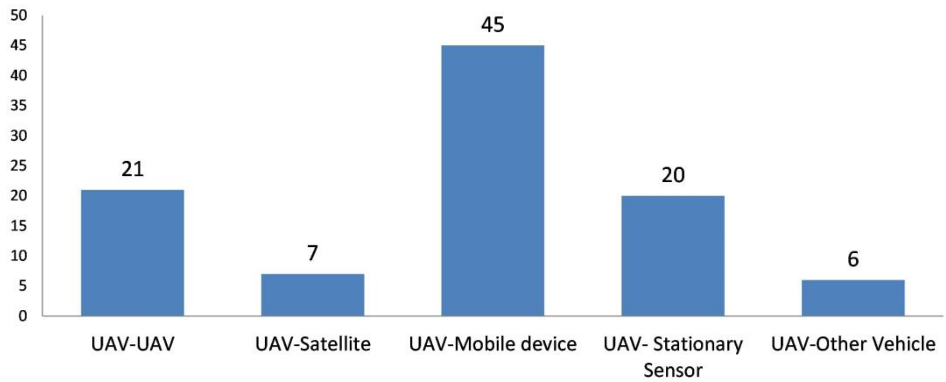

Figure 7. Categorization of papers reporting UAV-enabled IoT–WSN architectures based on the formed links.

The most prevalent link in our sample is the connection of the UAV to mobile devices, aiming at collecting data from phones, laptops, and wearable devices belonging to the victims of a disaster [94,120,121,126–165]. In some scenarios discussed in the models [127,128,130,146,159], BSs suffer severe damage, and UAVs are employed as flying BSs. This, however, is subject to a range of technical challenges, including interference as well as energy and coverage restrictions. Flying over dataless IoT nodes wastes both time and energy, both being critical resources in such urgent scenarios [94]. In this case, multihop device-to-device (D2D) communication is exploited to relay signals into the UAV's coverage area and help it extend its wireless coverage to serve more ground users with no need for additional and potentially fruitless movements. An approach to overcoming energy limitations and securing the continuous supply and exchange of data from user devices with ground terminals was proposed by the authors in [134], who considered a tethered UAV, which could only be utilized in small controlled environments. The models presented in [132,148,155] focus on the localization and crowd counting through the received signal strength indication (RSSI) measurements emitted from the devices (Wi-Fi access points). For the recharging of IoT devices, both mobile and stationary, a WPT scheme was proposed [131], where a UAV acts as a wireless charger and delivers energy to a set of energy receivers.

Stationary devices refer to sensors with limited storage, processing, and communication capabilities that are distributed at random locations over an area for the remote sensing of a disaster. Such sensors can be thermal sensors to detect active fires, chemical sensors to detect pollutants and contaminants, etc. However, many researchers have assumed a stationary node, even if the target is a user device, i.e., an inherently mobile node, because its speed is naturally much slower than that of a UAV. In the communication between a UAV and stationary sensors [111,120,121,131,138,143,148,151,153,157,158,162,166–173], the sensing area is divided into clusters and sensing nodes into cluster members, cluster heads, and relay nodes, responsible for data sensing, collection, and forwarding, respectively [172]. Clustering can reduce energy consumption, increase network scalability, extend battery life, decrease network delay, and boost throughput [174,175]. The minimization of completion time [111,120,148,170], maximization of throughput [166,173], optimization of device density [167] and drone placement [165], as well as energy-related objectives [121,131,138,151,170] are the most prominent among the proposed models. In UAV-to-UAV communication, a link is established between UAVs [121,122,126,132,133,138,144–146,151–153,164,173,176–182], forming a collaborative communication scheme. Not all UAVs are able to directly communicate with a BS due to different communication and networking requirements as well as vicinity reasons. This is the case for which UAV relay communication is used [136,140,144,150,152,173,176,181] to provide wireless coverage between IoT devices (mobile devices, stationary sensors, and gateways) and a BS without reliable direct communication links and enable spectrum sharing. Additionally, not all tasks can be handled by a single UAV due to their limited computational capacity, and offloading tasks to a server could be too time- and energy-intensive [144,146,179]. This type of network is also used when UAVs are susceptible to environmental conditions [151,152,181] and for collision avoidance [121,145,151,152,180,182].

In several models in our sample, the UAV is connected to a satellite. Satellites and UAVs, as space and aerial deployment platforms, respectively, are able to provide a flexible mode to manage the computing resources in the IoT. The flexibility mostly lies in satellites not being affected by geographical restrictions and therefore being able to achieve long communication ranges and seamless coverage for myriads of geographically sparse IoT devices and present stakeholders with an omnipresent cloud computing service [161,183]. Even though a satellite-controlled UAV can cover a large area, this method is quite expensive [184]. Such contributions are presented in [138,142,151,161,162,176]. The objectives of these models include the minimization of energy consumption for computation and transmission [138,151,161], minimization of computation delay and latency [138,142,176], as well as maximization of node-to-node connections [162] and throughput of devices [151] under various constraints. The authors of [143,169] have considered the use of high-altitude pseudosatellites (HAPs) for the purpose of dealing with high computation and transmission demands.

Last but not least, in some models, communication between UAVs and rescue vehicles takes place for safe driving and efficient rescue. The UAV-enabled Internet of vehicles (IoV) has been used [138,149,153,177,185] to assist with data sharing and recharging in disaster areas. Studies examining UAV-to-vehicle cooperation are further analyzed in the RCPS subsection.

5.2.2. Cloud, Edge, and Fog Computing

Edge computing accounts for 81.81%, cloud computing for 31.81%, and fog computing for 9.09% of the computing-oriented mathematical models of the proposed sample (Figure 8). Of course, this entails that several models have been included in more than one type of computing.

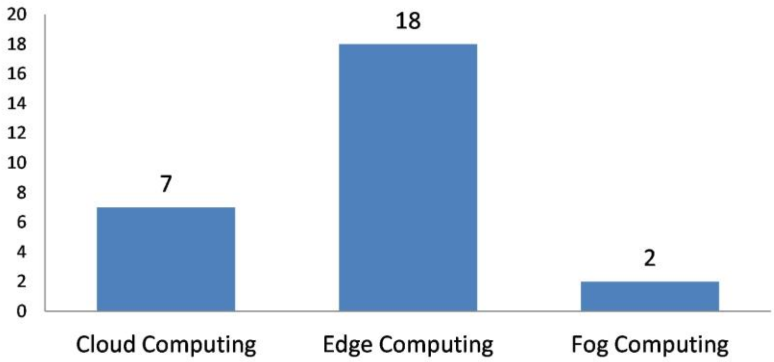

Figure 8. Categorization of the papers reporting the use of cloud, edge, and fog computing.

Mobile edge computing (MEC) has emerged as a radical paradigm in the IoT. The deployment of MEC servers, such as BSs, has enabled the execution of the real-time computation-intensive and latency-critical tasks of mobile devices at the network edge instead of the cloud, thus reducing energy consumption as well as addressing communication congestion and latency [186]. However, in disaster scenarios, terrestrial MEC networks may be compromised. In UAV-assisted MEC architectures, drones act as flying edge node carriers with cloud computing capabilities, providing controllable mobility, flexible deployment, and strong line-of-sight (LoS) channels with mobile devices [187]. Such networks have been studied by the authors of [138,188], where optimal task–UAV–edge server offloading models are proposed to minimize energy consumption and delay. In [189], UAVs were used as edge node carriers and a long-range wide area network (LoRaWAN) as a communication protocol to provide secure MEC services with increased channel capacity. In [144,164], the workload balance and communication range of UAVs have been addressed by proposing a relay control method equalizing the workload between UAVs and reducing network delay. With the aim of maximizing system stability and minimizing the energy consumption [135] and computation latency [154] of UAV-aided MEC systems, two models were proposed to optimize UAV trajectory control and users' offloaded task ratio scheduling as well as to maximize the average aggregate quality of experience (QoE) of all IoT devices. Accomplishing stability was also the focus of the authors of [130,133,185,190], where distributed and adaptive task planning models running on a network of UAVs are proposed. UAV-assisted offloading energy efficiency systems for MEC are also proposed in [146,156]. The study presented in [147] considered a novel UAV-and-BS hybrid-enabled MEC system that addresses the limited capabilities of MEC systems aided only by UAVs. In the proposed solution, multiple UAVs and one BS are used to facilitate the provisioning of MEC services either directly from UAVs or indirectly from the BS, with a view to maximizing the lifetime of all mobile devices and minimizing their energy consumption. In [143], the cooperation of UAVs and HAPs to provide the hierarchical MEC service for IoT was examined.

Space-aerial-assisted mixed cloud–edge computing models are included in the sample, where UAVs provide IoT devices with MEC services' and satellites' omnipresent access to cloud computing. The model in [191] is similar to those in [133,190] but it also integrates cloud computing, mainly for the collection of aggregated data, which is a delay-tolerant task. A pure cloud computing system was proposed [192] that collects data from WSNs and then constructs a 3D environment in near real time to reflect the incidents detected by the sensors, which is then used as a training environment for rescue teams. In [155], a cloud-terminal collaborative system for real-time crowd counting and localization using multiple UAVs is introduced. A fog-assisted cloud computing architecture is detailed in [120], where a UAV is responsible for the timely and orderly evacuation of stranded panicked people. The fog space assists in providing real-time diagnostic services and enables the optimized energy consumption of devices, while the cloud space facilitates the monitoring and prediction of panic severity of people as well as disaster mapping and geographical population analysis. Three blockchain-enhanced UAV-assisted HL applications in IoT, which are analyzed in the corresponding subsection [178,185,193], also utilize edge, cloud, and fog computing.

5.2.3. Social Media and Crowdsourcing

Social-media-driven drone sensing (SDS) is an emerging paradigm that relies on real-world observations using physical sensors on drones as well as observations collected from social media about the status of a disaster. Several researchers have attempted to address the challenges prevalent in SDS. First, in [194], a game theoretic social-media-driven energy-aware drone sensing model is proposed to jointly leverage the reliability of UAVs and scope of social sensing, with the aim of efficiently unraveling the truthful events during emergency scenarios. An RL-based UAV dispatching scheme was developed to adaptively launch an appropriate number of drones for event exploration considering the conflicting objectives of event coverage and UAV energy conservation. In [195], the exploitation of SDS for wildfire prediction was investigated. The lack of social media data in remote forest fire regions and the limited flight time capacity of UAVs were addressed through a wildfire monitoring model, which predicts the regions of fire toward which the UAVs should be guided. A game theoretic RL-assisted model is introduced in [196] to address the noisy nature of social media data. In the proposed model, signals from social media are distilled to dispatch the UAVs to target areas for event verification, the results of which are then forwarded back to enhance the sensing and distillation process and contribute to the identification of trustworthy information. The second to last SDS study in our sample introduces a spatiotemporal correlation inference model and game-theoretic UAV dispatching mechanism that leverages noisy social media signals and explores the dynamic and latent correlations among event locations [197]. Finally, the last proposed SDS model uses social media for tasking UAV swarms in SAR missions [198]. In [199], a pipeline for object detection and classification of images acquired from UAVs and labeled by a crowdsourcing effort for damage assessment and monitoring is proposed. In [200], vehicular crowdsourcing (VC) was used, where a group of UAVs and UGVs are navigated in a 3D disaster zone to collect data from several points of interest (PoIs).

5.2.4. AI

AI, and ML in particular, was the focus of approximately half of the selected studies. SL accounted for 13 papers, UL for 10 papers and RL for 20 papers in the sample (Figure 9). SL is used in multiple models in our sample for different purposes. In five studies, UAV-captured image recognition and classification were considered. In particular, deep learning (DL) has been used in the form of convolutional neural networks (CNNs) [199,201–203] and generative adversarial networks (GANs) [204] for disaster locating and monitoring as well as damage assessment. A CNN was also used to create an edge audio processing application to classify audio sent from a UAV fleet to help locate human sounds [133]. SL was also used to predict outcomes. To achieve an efficient workload distribution among UAVs, authors [190] modeled their proposed system as a network of queues, and by leveraging an autoregressive integrated moving average (ARIMA) regressor, they dynamically predicted the length of future UAV task queues to proactively migrate the tasks in case an imbalance occurs. In [120], a seasonal autoregression integrated moving average (SARIMA) model was used to predict the panic severity index (PSI) of stranded people during a disaster. In [205], a DL model was developed to predict signal blockage duration based on the mobility, location, and signal-to-interference-plus-noise ratio (SINR) values received from a UAV-node during a disaster. A vision-based intelligent neural network (NN) was used [206] for the autonomous landing of a UAV on static and moving targets in SAR applications. A decision tree was used [121] to model the UAV-collected physiological parameters of people in a disaster situation, including their heart rate, blood oxygen saturation, systolic blood pressure, respiratory rate, and temperature to determine their risk status.

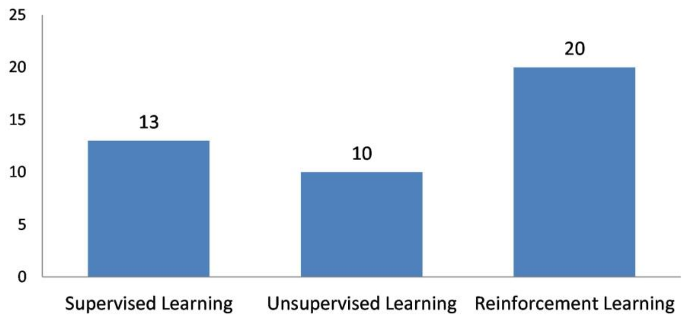

Figure 9. Categorization of the studies using ML in the AI approaches employed.

UL has been used in several models for clustering IoT devices. K-means clustering was employed in three studies aiming to group IoT devices and allocate them to UAV collectors addressing UAV path planning [111,145,170] as well as energy consumption [145,170] and completion time minimization objectives [111]. In [151], a density-based optics clustering (DBOC) algorithm was developed for increasing communication reliability between the UAV and a cluster of IoT devices. In [148], a weighted entropy-based clustering algorithm was used to find a cluster of positions where the RSSIs observed for a specific target IoT device could be used to estimate its location. Ref. [178] presents a federated learning approach, which trains an algorithm across a multitude of decentralized edge devices, keeping all training data, with the aim of improving distributed decision making during a disaster. Researchers [182,207] have proposed unsupervised algorithms to address the trajectory selection problem with the aim of minimizing the age of information collected by a UAV and the positioning of multiple BSs in scenarios with exceptionally high mobile device density.

Last, RL has been used in the majority of ML studies. Q learning, a model-free RL technique that does not require prior knowledge of system parameters, has been used for locating a missing human [208], achieving secure data sharing in UAV-aided blockchain networks [177,193], and UAV routing [180]. Deep Q learning (DQL) has been used for path planning [131,166] and task scheduling [146], while deep reinforcement learning (DRL) has been used for task-association scheduling [138,147] and task offloading [135,138] in UAV-aided MEC networks, UAV route design [163], trajectory optimization [135,154], and repositioning [162], as well as for learning consensus parameters in a blockchain-assisted network [185]. Two social-media-driven UAV networks leverage techniques from RL to exploit existing knowledge and explore different choices with a view to identifying trustworthy information [196] and generating UAV dispatching strategies based on UAV availability, number of reported events, and distances of the events from the UAVs [194]. Reinforcement-based coalition formation was employed [130] to enable the self-adaptive behavior of each IoT node to determine its role as an emergency gateway and its D2D links in the network. In [150], gradient-ascent and log-linear RL algorithms were utilized for the association of first responders to different disaster areas and UAVs, respectively.

Combinations of the abovementioned approaches have also been used [160,200,209].

5.2.5. Big Data Analytics

This DT is only mentioned for completeness, as it includes all studies mentioned in the IoT, AI, and social media and crowdsourcing categories, because these DTs inherently handle big data. Figure 10 depicts the distribution of these studies, the models presented in which were analyzed in the previous subsections, including their overlaps.

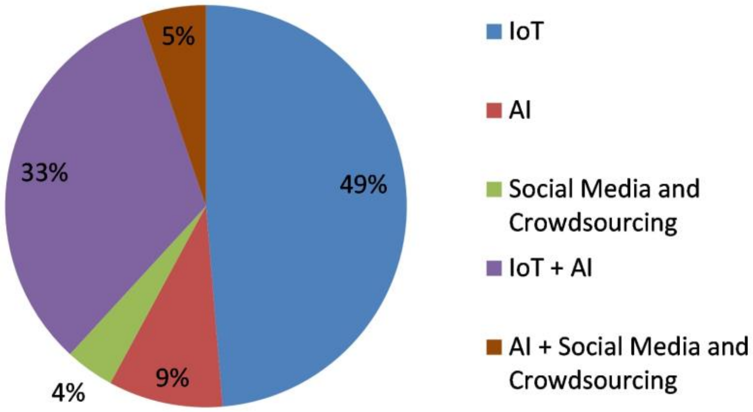

Figure 10. Categorization of studies reporting the use of big data analytics.

5.2.6. RCPSs

Heterogeneous robot cooperation is a vital aspect of UAV-assisted DM operations as it facilitates the provision of valuable information as well as the accomplishment of various SAR tasks. Employing a single robot under emergency conditions where movement in unknown environments and on unstable surfaces is required poses various challenges that can be dealt with by the joint operation of heterogeneous RCPSs, because each robot's deficiencies can be compensated for by the strengths of the others.

In UAV–UGV collaboration, UAV deployment provides high mobility, flexibility, coverage, and relief to remote or inaccessible disaster-affected areas, but UAVs have reduced flight autonomy limits and restrictive payload limitations. UGVs are able to overcome these hurdles, meeting the requirements of energy autonomy and payload; however, they have limited mobility and a reduced field of view. In [210], such a system was studied, where a model was developed for comparing three policies that assign areas of interest (AoIs) amongst a group of UGVs and a squadron of UAVs to assist a human observer collect information for disaster exploration. The UGV acts as a long-range transport, power supply, and communications station for the UAVs, which provide a set of sensors for the UGVs and act as ad hoc communication relays when needed between the UGV and the observer. Similarly, a scheme was proposed by assigning a group of UAVs and UGVs to collect data from PoIs with the aim of assisting disaster rescue in a 3D disaster work zone and maximizing the amount of data collected, geographical fairness, and energy efficiency, while minimizing data dropout [200]. In [211–213], autonomous systems are presented that enable a UAV to take off autonomously from a landing platform attached to a UGV, detect it while in the air using visual cues, follow it, and robustly land on it. In [145], a model is proposed to coordinate and specify the interrelationships between a UAV and a UGV collaborating to close a valve in a disaster-stricken industrial environment. A nested marsupial RCPS with a matryoshka (Russian nesting doll) team configuration (UGV→UAV→UGV) was introduced [214] and used to support first responders in performing a mock hazardous chemical spill investigation and sampling task within constrained spaces. Another symbiotic UAV–UGV relationship was proposed by the authors of [51], where the UGV presents the UAV with a landing area and transports it across long distances, therefore extending its battery life, while the UAV enables the UGV to surmount obstacles by lifting it across them.

In the event of a flood, rescue boats have limited visibility while searching for victims to rescue. In [215], the proposed model is aided by UAV–USV cooperation, with the former recognizing obstacles, roads, landmarks, or victims through the capturing of aerial images and the latter providing additional surface information through its acoustic sensors allowing route replanning. In the context of unmanned postdisaster construction, the AoI might not be within the operator's visual range, so a UAV can enable the teleoperation of the construction machine with direct visual observation from a safe place. In [216], a micro unmanned aerial vehicle (MUAV) was tethered to a teleoperated construction machine performing restoration tasks to provide adequate visual information and ensure human safety. The tether was also used as an energy supply, thus extending the MUAV's operation time.

Other studies [217,218] are also worth mentioning as, instead of investigating heterogeneous robotic networks, the researchers focused on homogeneous networks with heterogeneous capabilities, i.e., a group of UAVs dedicated to the inspection of a disaster zone, with the aim of locating the best areas (victim locations) for the deployment of the other group of UAVs, which was responsible for delivering supplies to the victims.

Finally, UAV–vehicle collaboration was the last aspect explored in our sample, which falls into the cyber–physical system (CPS) part of the proposed labels in our coding criterion. In [153,219], blockchain-assisted models have been used to enable vehicle-to-vehicle (V2V) charging transactions in postdisaster electric vehicle networks, where UAVs functioned as sensing and communication nodes. In [193], vehicles were used as fog nodes to offload UAVs' heavy data processing and storage tasks. In [185], a blockchain-aided hybrid UAV–truck architecture is proposed for last-mile relief distribution. The model tracks and controls the status of trucks and their on-board resources and enables them to optimally reroute and redistribute resources from damaged vehicles. The on-board UAVs, once in proximity to the AoI, deliver the resources and return. Another blockchain-enhanced solution was developed by the authors of [177], where a set of UAVs was deployed to monitor an AoI and a group of ground vehicles to carry out SAR missions. V2V links are used to increase road safety and rescue efficiency through the exchange of information pertinent to collision avoidance, road conditions, and rescue experience.

5.2.7. Blockchain Technology

In [177], blockchain was used to provide secure data sharing and assist with potential security data threats in UAV-assisted IoV for disaster rescue. A credit-based delegated proof-of-stake (DpoS) consensus algorithm was designed to efficiently reach consensus in the blockchain, where the credit value was evaluated based on nodes' behaviors. Researchers [153,219] have concentrated on UAV-aided blockchain offline transactions and, in particular, presented a game theory-assisted model designed to ensure the security and effectiveness of delay-tolerant blockchain V2V charging transactions in postdisaster vehicular networks when UAVs are offline. The authors of [193] developed a secure and efficient blockchain-based information sharing scheme able to safeguard data sharing in UAV-aided disaster rescue and immutably trace misbehaving entities. A reputation-based consensus protocol was created to adapt the weakly connected environment with enhanced consensus efficiency and UAVs' honest behaviors. In hybrid UAV–truck architectures for last-mile relief distribution, there is an unpredictable demand for resources, which need to be tracked to prevent theft and maldistribution as well as fault-tolerant path planning. To address these needs, authors [185] proposed a blockchain-based algorithm for tracking and controlling the status and resources of trucks. An IOTA-based game-theory-enabled blockchain ledger, which uses no miners to validate a transaction, was employed [220] in a distributed network of charging stations and UAVs for optimal energy trading. IOTA-based blockchain is as secure and distributed as traditional blockchain, but it also provides low latency and consumes less power [137]. Energy consumption as well as blockchain latency were the focus in a study [178], in which blockchain, ML, and UAVs were combined to create a model using wireless mobile miners at UAVs for disaster response. The decisions regarding user association, UAV movement, and bandwidth allocation are crucial challenges in deploying such networks and were addressed [137], where a game-theory-enabled blockchain-based security framework for drone-mounted BSs was proposed. A sparsity-optimized and compressed-sensing-based spatiotemporal data aggregation model was proposed by the authors of [172], which focuses on UAV-aided monitoring scenarios. Its objective is to improve the security and validity of data collected through WSNs by decreasing data redundancy. Last, a network coding wireless signal transmission model combined with blockchain [221] was developed to enhance the reliability and encryption of UAV wireless signals in natural disaster scenarios.

5.2.8. XR

XR is the least employed DT in the proposed models. Three studies used VR, one used AR, and none of them used MR. A VR control scheme for decreasing the cognitive overload when controlling a UAV and addressing the lack of situational awareness of human operators was proposed [222], where a virtual UAV pilots the real UAV. In [223], VR technology was used to compare the advantages and shortcomings of several algorithms to establish a path optimization and multitarget detection model. A study [192] showcases the combined utilization of 3D VR, WSNs, cloud computing, and RCPSs for natural disaster management, where the datasets generated by the WSN and the observations of the robotic systems were used to create a realistic VR environment able to reflect actual conditions and facilitate the preparation of rescue scenarios within an acceptable time window. Last, in [224], an algorithm to improve the geographic registration accuracy of UAV imagery was designed, in which AR is implemented in thermal infrared video streams, obtained for the acquisition of information at night by collecting thermal radiation from ground objects without additional lighting measures.

5.3. What Drone Operations Have Been Examined and What Drone Capabilities Have Been Used? How Are Drone Operations Approached by Each DT?

In this section, the classification of the selected studies into the HDOs presented in Section 4 is analyzed, with a brief mention of the HDCs and HDTs exploited throughout their execution. Regarding the HDOs, path and trajectory planning (n = 38, 37.62%) has been the most pursued operation in our sample, followed by resource allocation for mobile devices (n = 27, 26.73%), task assignment (n = 22, 21.78%), search (n = 20, 19.8%), data gathering and recharging in a WSN (n = 19, 18.81%), scheduling (n = 12, 11.88%), area coverage (n = 11, 10.89%), routing for a set of locations (n = 5, 4.95%), supply allocation (n = 3, 2.97%), and sampling (n = 1, 0.99%) (Figure 11). Correspondingly, with regard to the HDCs, UAV communication and integration (n = 80, 79.2%) capabilities have been used the most, followed by surveying and monitoring (n = 40, 39.6%) and transportation and delivery (n = 7, 6.93%) capabilities (Figure 12).

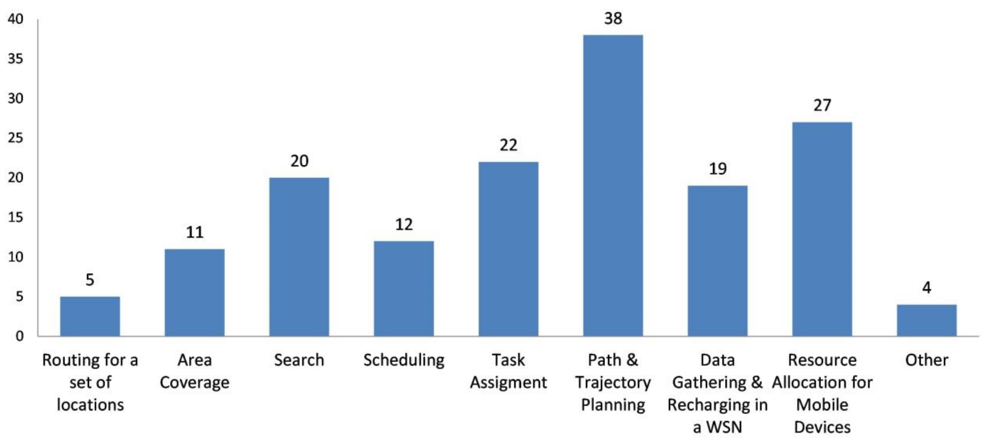

Figure 11. Categorization of the studies into the HDOs addressed by the proposed models.

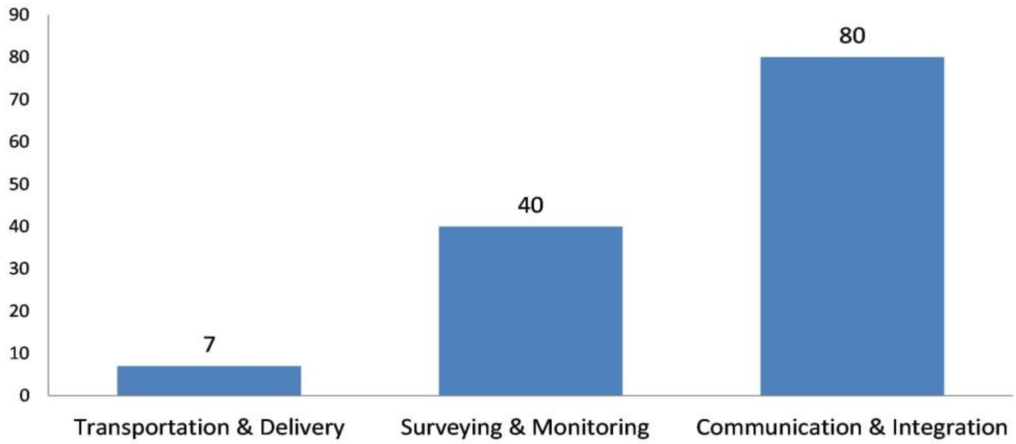

Figure 12. Categorization of the studies into the HDCs used in the proposed models.

5.3.1. Path and Trajectory Planning

The path and trajectory planning models in our sample focused on complex drone operations involving several tasks in addition to the implementation of a smooth, collision-free path from a given starting point to a given end point with no redundant path nodes. The most common objectives among the models in this category are related to energy consumption [121,130,131,135,151,152,156,170], delay or latency minimization [111,152,155,170,182,207], coverage maximization [169,217], and traveled distance minimization [215,225]. Only five studies focused exclusively on path and trajectory planning. In [223,225] and [207], path smoothness and QoS optimization were respectively pursued. In [151], three different schemes were constructed targeting covered points' maximization, PoI prioritization, and balancing the coverage and priority objectives. In [169], a dynamic, energy-efficient positioning and weather-predicting scheme is introduced. Weather conditions have also been considered [152,195,196,214,223]. In the remaining studies, resource allocation and scheduling are the most common HDOs carried out in tandem with path and trajectory planning. The synergistic optimization of path/trajectory and resource allocation has been proposed by the authors of [129–131,135,136,140,145,147,166], and joint path/trajectory and scheduling optimization models have been described by the authors of [51,94,121,124,152,177,203]. More than half (n = 22, 59.46%) of the proposed path and trajectory planning models employ multiple UAVs in their problem formulations. Path and trajectory planning operations have mostly been assisted by big data (n = 35, 92.11%), the IoT (n = 26, 68.42%), and AI (n = 19, 50%).

5.3.2. Scheduling

A multitude of scheduling decisions have been made in the models in our sample. Resource scheduling constitutes an important subject of interest among researchers. In [131], a resource scheduling scheme for a multi-UAV system was developed to provide wireless services for IoT devices in wide areas; while in [142], a fairness-aware resource scheduling solution is introduced to minimize the maximum task execution delay among IoT devices. In [179], a resource scheduling scheme is proposed to guarantee the availability of services and efficient resource utilization, taking into account the UAVs' finite lifetime and need for replacement. In [146], a task scheduling algorithm for a dispersed computing network is proposed, where the control center distributes tasks to the UAVs, which can choose to compute the tasks locally or offload them to the mobile devices. To maximize the lifetime of the mobile devices, an energy-efficient scheduling model was proposed for the studied UAV-assisted MEC system [147]. A navigation system composed of a camera-equipped UAV and offloading mobile devices was proposed by the authors of [203], consisting of visual recognition, task schedule, and fly control modules. The image captured through the UAV camera is sent to the visual recognition module, the result of which is fed to the task schedule module, which then sends flying instructions to the control module.

The scheduling of camera-equipped UAVs to collect audiovisual material from various locations was proposed [124], considering a finite number of hovering positions. A task scheduling algorithm was proposed [51] to enable the various robots of a heterogeneous robotic system to collaborate by exploiting one another's strengths and symbiotically executing complex tasks. In the UAV-enabled IoV model discussed in [177], to enhance driving safety and rescue efficiency, ground vehicles are able to receive scheduling and guidance commands from ground stations. UAV path scheduling and user scheduling have been proposed [152] and [94], with the aim of minimizing time and UAV energy consumption. The minimization of UAV energy consumption was also the focus in [121], where an energy-efficient task scheduling scheme for data collection by UAVs from the ground IoT network was developed. Scheduling has mostly been aided by big data (n = 10, 83.33%), the IoT (n = 10, 83.33%), and AI (n = 6, 50%).

5.3.3. Task Assignment

Task assignment problems emerge in multi-UAV and -vehicle missions, where inter-vehicle coordination and communication are needed. In [195], a drone task assignment (DTA) module was created to assign a set of UAVs to investigate probable fire regions obtained from a wildfire propagation prediction module. Two other DTA modules have been proposed [194,196,197], which allocate a subset of events to UAVs based on distilled social media signals and drive the UAVs to the event location to identify unreliable information before the event deadlines expire. Another social-media-driven multidrone tasking platform was introduced [198], assigning SAR tasks to UAVs. Spatiotemporally constrained tasks were also assigned to UAVs and driverless cars [200], such as the collection of environmental data from PoIs, mapping for situational awareness, searching for missing people, etc. UAV-enabled task offloading, i.e., the assignment of resource-intensive tasks to separate UAV-mounted mobile nodes, is thoroughly discussed in our study sample [133,135,138,142,156,164,176,177,188–191]. In [193], offloading tasks to moving vehicles acting as fog computing nodes was investigated. The assignment of tasks to UAV–UGV symbiotic networks has also been studied [51,192,210]. Task assignment has mostly been facilitated by big data (n = 18, 81.82%), the IoT (n = 13, 59.1%), edge computing (n = 10, 45.45%), AI (n = 9, 40.91%), and RCPSs (n = 5, 22.73%).

5.3.4. Search

Searching for a missing person is a core operation in the models in our sample. In the majority of the studies, search operations were conducted in the context of SAR missions in tandem with other operations, mostly path and trajectory planning and task assignment, where the end goal was to find a missing person during a disaster. Life searching is usually one of the tasks assigned to UAVs in task assignment operations [133,153,192,193,198,210,219]. In the selected studies, search operations were facilitated by Twitter data [198], data obtained from thermal cameras [141], LiDAR sensors [210], or other types of sensors attached to the searching vehicles [193,206,210–213,215] as well as the data from the mobile IoT devices belonging to the victims [139,148,149,155,221]. In most cases, the missing person is assumed to be moving or their mobility status is unspecified and unrelated to the problem formulation at hand, except in [208], where the person was considered immobile. The only study where the target of the search operation was not a person but a chemical sample to be collected and tested was [214]. Searches were predominantly enabled by big data (N = 17, 85%), the IoT (N = 9, 45%), RCPSs (N = 9, 45%), AI (N = 5, 25%), and blockchain (N = 4, 20%).

5.3.5. Area Coverage

In area coverage operations, UAVs are equipped with optical [199,201,202,204,209,215,216,222] or thermal cameras [141,224] for them to be able to perform the remote sensing of complex disaster environments. The models in [202,222,224] considered the azimuth or elevation [141,199,202] angles between the UAV and the camera. Several studies focused on the processing of the UAV images acquired from such operations, for map generation [215], image classification to eliminate redundant photographs [124,209], damage assessment [199], image segmentation for the detection of flooded areas [204], intelligent recognition of damaged poles [202], as well as image de-noising and feature extraction for accurate disaster identification [201]. Some area coverage models targeted the human operators and, in particular, the reduction in their cognitive workload while piloting [222] and their safety while teleoperating a construction machine from a safe distance [216]. Authors [165] proposed the future implementation of their method in communication coverage for monitoring operations as well. Exactly half of the selected models employ multiple drones, with the other half describing single-drone area coverage operations. Area coverage operations have mostly been enabled by big data (N = 10, 90.91%), AI (N = 5, 45.45%), and the IoT (N = 3, 27.27%).

5.3.6. Data Gathering and Recharging in a WSN

Data gathering and recharging in WSNs has been investigated by multiple researchers focusing on different aspects of the operation. Researchers [153,172,178,219] have emphasized the security and validity of the data collected from different clusters of ground sensor devices; in [171], UAV navigation planning was performed so that the data-gathering operation of a UAV in one cluster did not affect the same or other operations conducted by another UAV in another cluster. Energy- and time-consumption minimization during data collection from static IoT sensors by a multi-UAV network was pursued by the authors of [121,170] and [111,121,170], respectively. Energy- [120,168] and time- [120,182] consumption minimization objectives have also been studied, where both static and mobile devices attached to robots or worn by humans have been considered. Mobile ground nodes have also been considered [132,150]. Other researchers [167] targeted the optimization of the density of IoT devices and the number of UAVs covering the area, whereas in [163,166,200,210], energy-efficient approaches for the maximization of the data gathered were pursued. The recharging of IoT devices was the focus in [131], whereas UAV recharging was considered in [220], with potentially applicable results to IoT devices as well. WPT was also included in the future research steps of the study presented in [166]. Data gathering and recharging in a WSN has mostly been supported by big data (n = 18, 94.74%), the IoT (n = 17, 89.47%), AI (n = 10, 52.63%), blockchain (n = 5, 26.32%), and RCPSs (n = 4, 21.05%).

5.3.7. Resource Allocation for Mobile Devices

Resource allocation for mobile devices, in the form of communication links and computing power, has been proposed in several studies with varying objectives. The improvement in the coverage footprint to secure network connectivity has been attempted with numerous models, which optimize the drones' placement for that purpose. In [122], the authors adjusted the UAV's height and distance from other drones; in [145], the optimization of the placement of a heterogeneous team of robots was pursued to bridge disconnected networks. In [141], the drone was equipped with various optical, weather, and location sensors, enabling it to identify the optimum UAV altitudes, longitudes, and latitudes; in [205], the UAV was free to fly within a predetermined topology at a specified rate. In [158,159,162,165], the UAV altitude was fixed. In [134], the hovering region was enhanced through a tether, ensuring longer flight times. Six nonorthogonal multiple access (NOMA) schemes have been proposed by the authors in our sample, with the aim of minimizing the transmitting power of users and mobile devices [126] as well as maximizing the achievable rate of devices [129,157,166], throughput [173], and energy efficiency [130]. Researchers [127,128] have targeted the maximization of the number of connected mobile devices by extending network coverage. In [138], network computation cost minimization was pursued, while in [136,140,143,158], the authors attempted to maximize the amount of data collected. Energy consumption as well as network delay and latency reduction were the foci in [147,160,161] and [137,142,144,154,161], respectively. Resource allocation for mobile devices has mostly been aided by big data (n = 27, 100%), the IoT (n = 27, 100%), AI (n = 9, 33.33%), and edge computing (n = 7, 25.93%).

5.3.8. Routing for a Set of Locations

Routing for a set of locations was the focus of only five studies, which considered energy consumption minimization [181,200], and maximization of data collected [200] and wireless coverage extension [127]. In [181], a routing algorithm for a multi-UAV network is proposed, taking energy usage and fire sensor node information into consideration. In [200], a UAV–UGV routing algorithm is presented addressing the UGVs' inability to fully explore 3D spaces including PoIs in high altitudes as well as UAV–UGV cooperation challenges. In [127], a shortest path routing algorithm is proposed for the establishment of D2D links in an emergency UAV-aided network. In [176], latency minimization was targeted, where, unlike most routing algorithms, which are based on the drones' future location information, such as in [180], which is also included in our sample, the proposed model considers the unpredictability of drone locations due to disaster-disrupted conditions. Routing for a set of locations has mostly been assisted by big data (n = 4, 80%), the IoT (n = 4, 80%), and AI (n = 2, 40%).

5.3.9. Other

Lastly, supply allocation and sampling are the least-employed HDOs in our sample. They have all exploited RCPSs (n = 4, 100%) for loading the necessary resources for primary care and delivering them to victims guided by a leader robot agent [218], storing and delivering as many supplies as possible by maximizing space utilization [217], enabling resource tracking in last-mile UAV-aided truck delivery to prevent theft and maldistribution [185], and collecting samples with the help of a nested marsupial robotic system [214].

In Table 3, a mapping of the frequency of the utilization of the different HDTs in the different HDOs is presented.

Table 3. Mapping of the frequency of the utilization of different HDTs in different HDOs.

	Routing for a Set of Locations	Area Coverage	Search	Scheduling	Task Assignment	Path and Trajectory Planning	Data Gathering and Recharging in a WSN	Resource Allocation for Mobile Devices	Other
Social media and crowdsourcing	1	1	1	0	6	4	1	0	0
IoT	4	3	9	10	13	26	17	27	2
Big data analytics	4	10	17	10	18	35	18	27	2
AI	2	5	5	6	9	19	10	9	1
XR	0	2	1	0	1	1	0	0	0
Blockchain	0	0	4	1	2	1	5	1	1
RCPS	1	2	9	2	5	6	4	1	4
Cloud computing	0	0	2	1	3	1	1	2	1
Edge computing	0	0	1	3	10	5	1	7	1
Fog computing	0	0	1	0	1	0	1	0	0

A mapping of the frequency of the utilization of the different HDTs in the different HDOs is presented, where the darker the color, the higher the frequency. The color gradation is used to shed light on the highest frequencies.

5.4. How Are the Mathematical Models Different? What Types of Solving Approaches Have Been Proposed?

The majority of the mathematical models in our sample are optimization models (n = 61, 60.39%). Almost half of the optimization models proposed are heuristic (n = 43, 42.57%), followed by metaheuristic (n = 11, 10.89%) and exact (n = 3, 2.97%) models. These figures indicate that the integration of stochasticity into the proposed models has been a priority for researchers. The remaining optimization models (n = 4, 3.96%) use a *combination* of heuristic, metaheuristic, and exact approaches for finding solutions to different subproblems. Single-objective optimization methods outnumber multiobjective optimization methods, with the former accounting for 37 studies (36.63%) and the latter for 29 studies (28.71%). In particular, 18 models have 2 objectives, 8 models have 3 objectives, and 3 models have 4 objectives. Control models comprise the minority of our sample, accounting only for 13 studies (n = 13, 12.87%). Figure 13 depicts the distribution of the solving approaches employed in the mathematical models in our sample.

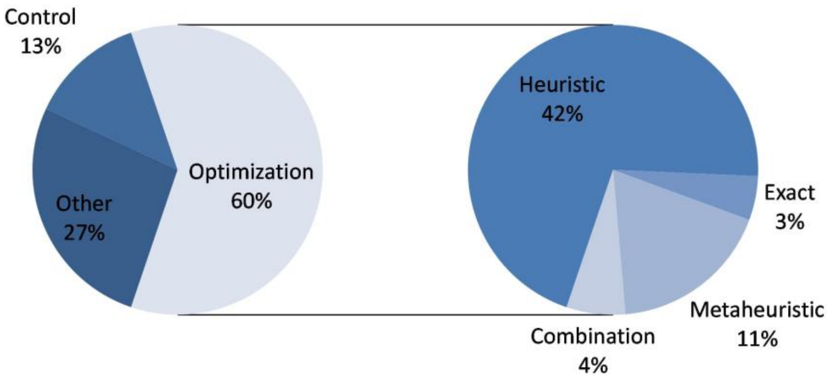

Figure 13. Categorization of the papers based on the solving approach employed in the proposed models.

5.4.1. Optimization Models

Exact models providing analytical solutions are sparse in our sample, given the fact that many of the problems formulated in the selected studies are nonconvex. The sample also includes convex, optimally and efficiently solved problems, such as [128,149,158,170,188,220]. Nonconvex problems are NP-hard, highly complex, and computationally hard problems, so can be tackled by heuristic solving approaches, including metaheuristics. In the selected studies, multiobjective nonconvex optimization problems have often been decomposed into simpler problems with single objectives and solved by various algorithms, including reweighted message-passing algorithms [126], iterative algorithms [129,136], hybrid heuristic and learning-based algorithms [147], and block coordinate descent (BCD) algorithms [142]. BCD has also been used [94,156,161] along with the bisection search technique and geometric programming-based optimization. Other approaches to such problems used by the models in our sample include approximation algorithms for the transformation of nonconvex to convex problems, followed by the utilization of low-complexity algorithms for solving the resulting convex problems, such as second-order cone programming [127], iterative algorithms [140], and the least l1 norm method [172]. Greedy heuristics [145,169], search [167], and K-means clustering algorithms [111], as well as alternative heuristic solutions [124,198], have been also proposed for handling NP-hard problems to compute suboptimal solutions.

Evolutionary algorithms, such as genetic algorithms [121,146,152,155,165,215], multi-optimization evolutionary algorithms based on decomposition (MOEA/D) [131,166], multiverse optimization algorithms [225], covariance matrix adaptation evolution strategies (CMA-ES) [173], and bio-inspired swarm mobility algorithms [132], including particle swarm optimization (PSO)-based algorithms [176,218,223] and shuffled shepherd optimization [151], have also been used to find near-optimal solutions. In [151,181], other types of metaheuristics have been proposed. It is worth mentioning that a plethora of game theoretic approaches have been employed [130,137,138,143,149,151,153,192,194–197,219,220]. Additionally, ML-driven solutions have been employed in a multitude of complex and analytically intractable optimization models in our sample, which were discussed in the AI subsection.

5.4.2. Control Models

Various control schemes have been proposed in the studies in our sample. UAV landing was the center of a study [206], where a vision-based intelligent NN controller is proposed for the autonomous landing on static and moving targets with no prior information from the external infrastructure of the target locations. UAV tracking and landing were also addressed [212]. Through the tracking of a cooperative target on a platform attached to a moving vehicle, combined with the prediction of its movement, the target the UAV needs to track is acquired; thus, stable and rapid autonomous landing can be achieved. Similar were the foci in [211], where two different approaches are proposed. The first one is based on a height-adaptive PID controller using the current position of the landing platform as target, while the second one combines this controller with a Kalman filter to predict the future positions of the platform and provide them as the input to the controller. According to the authors in [224], in the traditional Kalman filter algorithm, most input sensor data are unreliable. This realization led them to develop an improved extended Kalman filter algorithm with real-time kinematic global positioning system (RTK-GPS) data, which are usually highly accurate and can be approximated as accurate measurements relative to the usual drone operating range. In [176], the authors combined the Kalman filter with a weighted time expanded graph to address the complex network dynamics of emergency UAV networks.

RL and DL have been used for autonomous UAV navigation ([208] and [203], respectively). The models in [133,191] leverage Jackson's network model to support control operations, such as adaptive control. The authors of [222] paid attention to the lack of situational awareness of human operators when teleoperating UAVs and their increased cognitive overload owing to this fact. To address this, they developed a novel exocentric virtual control scheme with a virtual UAV piloting the real one. In [214], the authors introduce a model for autonomous planning, control, and estimation supporting vision-based manipulation and mobility for a nested marsupial RCPS fulfilling tasks in constrained environments. The control techniques currently being implemented are mostly devoted to dealing with a small number of degrees of freedom (DOFs). In [211], a Hamiltonian control system with a large number of DOFs is introduced for the control of a large-scale joint swarm of UGVs and UAVs. This global Hamiltonian control system makes use of local Lie-derivative-based controllers, i.e., the nonlinear generalization of PID controllers. Lastly, in [23], a reliable and stable control system is proposed for a UAV–UGV cooperative RCPS system fulfilling complex aerial manipulation tasks.

6. Discussion

The adoption and integration of drones and other DTs is a vital step toward delivering more value to HL operations [5,18]. Motivated by significant research gaps detected in the DM literature, we carried out an SLR to holistically evaluate relevant peer-reviewed works through various unexplored lenses. After conducting a descriptive analysis to identify the trends of publications in terms of year, type, source, and country of origin, a content analysis ensued to answer the RQs we formulated to attempt to fill the aforementioned gaps. The first and foremost issue tackled in this analysis was the investigation of the complementarity and interoperability of humanitarian drones with other emerging HDTs, including big data analytics; IoT; AI; cloud, edge, and fog computing; blockchain; RCPSs; and XR. We researched how these DTs are utilized in the UAV-assisted HL literature, across the various disaster scenarios, types, and stages in which they have been applied. Next, we looked into the different approaches through which the different HDTs facilitate the executed HDOs by exploiting different HDCs. Only mathematical models were considered in this study, so the proposed solutions were also explored, including exact and nonexact optimization as well as control models. In this section, the findings of our SLR, which were presented in Sections 3 and 5, are discussed, with a view to identifying research avenues that will shape future research endeavors.

The descriptive analysis performed indicated that the sample of 101 studies in our SLR mostly includes journal papers, followed by conference papers. The number of studies in the sample has substantially increased since 2015, with a slight decline during the COVID-19 pandemic, is authored by researchers spanning in 41 countries and dispersed across 72 sources. Amongst these observations, it is worth highlighting the comparative abundance of journal papers, which implies early signs of the maturing of the field. Despite this relative maturity, the fragmentation of studies across many different sources, which are incidentally technology- and not humanitarian-centric, impedes uniform comparisons across UAV-enabled DT operations and hinders the drawing of universal conclusions regarding the objectives in the HL spectrum. DTs' integration aside, HSCs are generally subject to a plethora of complexities and weaknesses [226–228], which either remain unexplored or have been approached by diverse multidisciplinary methodologies [229,230]. This diversity in both the HDT and non-HDT literature sheds light on the urgent need for the convergence of the different mathematical models and theoretical approaches toward a common and integrated field of study focusing on technology, information management, and processes as well as the socioeconomic, environmental, managerial, and other implications of HL.

Regarding the content analysis, all four disaster phases were considered by the mathematical models in our sample with an additional emphasis on the postdisaster stage. The predominance of post-disaster-oriented literature balances the dearth spotted in [36], in which the integration of DTs in the postdisaster stage was deemed inadequate compared with that in the predisaster stage. In particular, the response phase was studied the most often in our sample, followed by the mitigation and preparedness phases. The recovery phase was by far the least explored phase. The lack of focus on recovery has also been noted outside the UAVs–DTs collaboration spectrum [58,231–234], which can be justified due to the nonthreatening state of the disaster at that point, but should not be neglected because the restoration of normality and long-term sustainability are contingent on the success of the logistical activities and operations during that phase [235,236]. Therefore, additional emphasis on the recovery phase is required in the context of HDT-assisted HDOs.

Regarding disaster types, it is noteworthy that no study in our sample concentrated solely on human-made disasters, with their focus being on natural or a combination of both natural and human-made disasters. This lack of research on human-made disasters again confirms the statements of the authors in [231]. This could be attributed to the fact that natural disasters are considered more calamitous, less preventable, and not as easily manageable compared with human-made disasters [58]. The speed of the disasters was also taken into account in our analysis, which shows that all studies explored sudden-onset disasters, with only one paper addressing a slow-onset disaster, which was in combination with a sudden-onset disaster. Yet, although the low speed of such disasters seemingly decreases urgency, their large scale can lead to even more catastrophic repercussions than sudden-onset disasters [237]. This is also supported by the existing literature, which has primarily focused on disaster relief, overlooking continuous aid operations, most probably due to time availability permitting better planning and rendering such operations less challenging in comparison [231]. Overall, more researchers should consider the particularities and intrinsic complexities of human-made and slow-onset disasters (e.g., multiperiod approaches are required) in their mathematical formulations.

Most HDTs are used in all HL phases, which validates findings [37] that suggested that the majority of DTs are able to contribute to all four HL phases as standalone solutions. In this study, we took this a step further by showing that most DTs can be utilized in tandem with UAVs in all disaster phases. The authors of [5] systematically indicated how drones are able to improve HL phases through their capabilities, i.e., communication and integration, surveying and monitoring, and transportation and delivery capabilities. In this study, the HDCs leveraged in the various HDOs considered in the models in our sample are supported by various heterogeneous HDTs, which help stakeholders exploit them to their maximum potential. Big data analytics, IoT, and AI are the most-investigated HDTs in our sample, followed by cloud, edge, and fog computing; RCPSs; blockchain; social media and crowdsourcing; and XR.

Communication and integration are crucial aspects during emergency scenarios, with ~80% of the models utilizing such HDCs. Big data have been generated by many sources and communicated to stakeholders for efficient management of the disaster. In particular, the data generated by social media platforms or acquired during the execution of area coverage (images, audiovisual material, etc.) and data gathering (victims' physiological parameters, environmental sensor measurements, Wi-Fi access points, etc.) from IoT mobile and stationary devices have been used to a large extent in the proposed models for emergency verification and disaster identification [194–197,201], crowd counting and localization [132,148,155], search operations [141,206,210–213,215], and damage assessment [199,202,204]. Search and area coverage operations have used the surveying and monitoring HDCs, as observed in ~40% of the studies. AI has been utilized to address the large amount of redundant information and errors naturally arising from such sources and requiring data processing and analysis. Holistic models incorporating heterogeneous data from all these sources combined were not considered in our sample studies, which, can be justified given the need for more advanced approaches to deal with the increased complexity emerging from their fusion, which therefore indicates an important future research direction.

Yet, the generation, consolidation, filtering, processing, and analysis of such data are fruitless if seamless communication networks meeting QoS requirements are not in place to enable secure transmission and dissemination. Resource-allocation-focused models are abundant in our sample studies, designed to provide network coverage in the cases where BSs have been destroyed and UAV-mounted BSs or UAVs as relay nodes have been employed. Edge computing networks have been broadly utilized in such operations to address communication latency, congestion, and energy consumption, which are among the most targeted objectives amongst the models. Resource-intensive task assignment to UAV-mounted mobile nodes, i.e., task offloading, as well as resource scheduling are common topics discussed in the selected models. Another challenge in UAV communication is security and privacy within aerial networks for DM, which has been dealt with through AI solutions and blockchain technology. Resource allocation has often been combined with path and trajectory planning operations, which was the most-researched HDO in the sample. A few models focused on regular UAV routing operations, but the majority of them shifted their focus toward UAV placement and positioning to address collision avoidance and energy management. Modeling energy consumption and kinematics had needed further investigation according to [49,50], objectives that were thoroughly considered in the selected models. Only one study considered drone recharging through WPT [220], with the rest of recharging-related studies targeting mobile devices, shedding light on the need for more WPT-pertinent models in the future. Path and trajectory planning models have been assisted by AI through image recognition and the exchange of IoT data about drone speed, trajectory, and position through inter-UAV communication.

Interoperability is a core capacity in emergency situations, either when referring to data gathering from heterogeneous devices or the collaboration of different RCPSs with various configurations. Different UAV–RCPS configurations have been proposed in the studies in our sample, so that the weaknesses of the UAVs are compensated for by the strengths of other vehicles and vice versa. Task assignment and task scheduling operations have widely been employed for efficient intervehicle coordination, in response to a previous concern expressed in [49,50]. UAV–UGV, UAV–USV, UGV–UAV–UGV, as well as UAV–electric vehicle configurations have been proposed for data gathering, area coverage, search, supply allocation, and sampling operations. The last two operations exploit the transportation and delivery HDCs, which accounted for only ~7% of the studies. The lack of supply allocation operations in our sample cannot be ignored, stressing the need for producing such models in the future.

The last aspect of our analysis focused on the solving approaches employed in the mathematical models, which were mainly optimization models; according to [28], these had been much needed. Most of the rest are control models addressing path and trajectory planning. Almost half of the optimization models proposed use heuristics and metaheuristics, indicating that researchers have widely taken into consideration stochastic parameters. The level of uncertainty integrated in the models has increased to more accurately reflect the dynamic disaster conditions compared with the past, as shown in the previous literature, which has mostly dealt with deterministic approaches [43,48]. AI and metaheuristics were mainly used to reduce computational burdens and the execution times of complex multi-objective problems, filling a large research gap present in the previous optimization HL literature [44–47]. Although the proposed models were proven computationally efficient in simulation contexts, this might not be the case when applied in actual disasters, which remains to be confirmed in future studies.

In Figure 14, based on all of the above, a novel framework is proposed, illustrating how the different HDTs are able to complement the different HDOs executed in a generic disaster scenario.

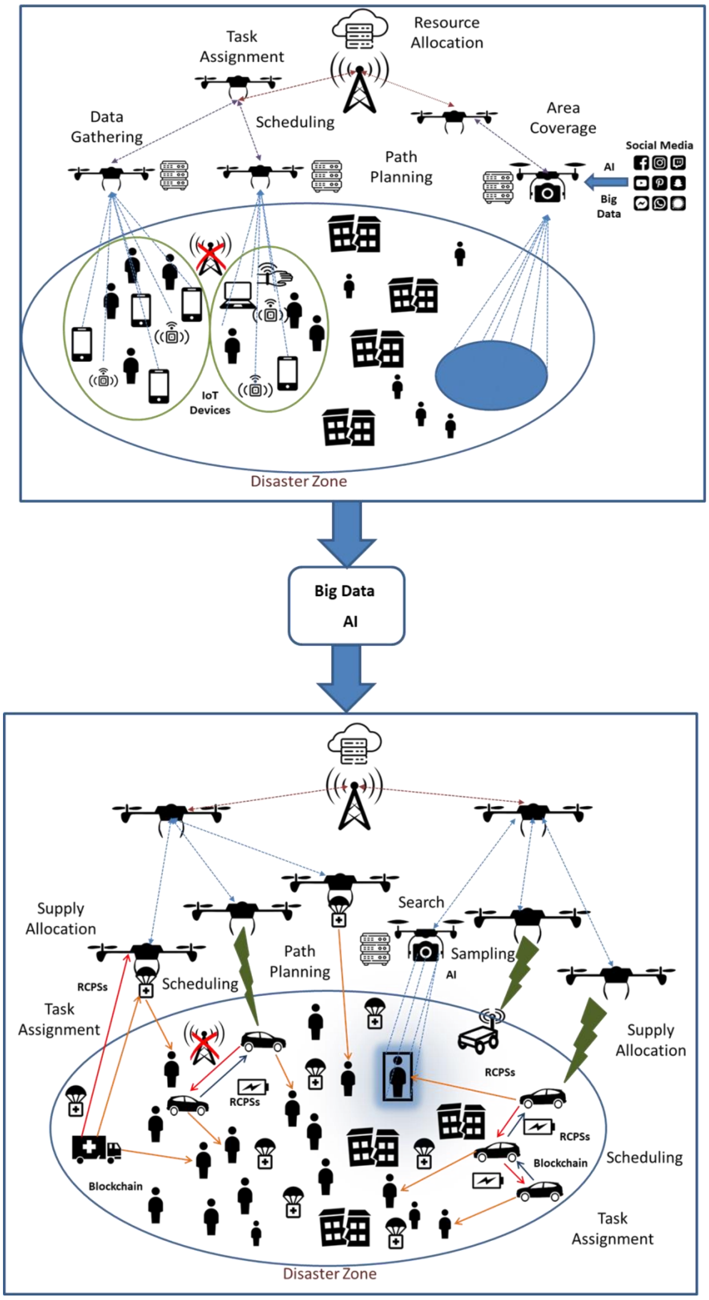

Figure 14. Proposed holistic framework for exploiting different HDTs in different HDOs executed in a generic disaster scenario.

7. Conclusions

Even though humanitarian crises cannot be approached similarly due to their inherently different characteristics and complexities, in this era of volatility, complexity, and ambivalence, standardizing the adoption of drones and their cooperative use with other HDTs during the execution of various HDOs are essential steps toward increasing their applicability and enhancing their scalability. This was the focus of this study, based on the results of which a novel holistic integrated framework was developed aiming at this overlooked aspect of the literature and contributing to the identification of several challenges needing to be addressed in the future. A step to advance the field even further is the creation of a worldwide HDT database acting as a roadmap by highlighting the relevance of each HDT per HDO for different scenarios and needs and creating awareness through the sharing of past experiences, mistakes, and measures taken, thus providing tailored options for interested stakeholders. The collection of perspectives from diverse stakeholders to gain insights into real-life applications of such models in actual disaster scenarios may lead to the establishment of new processes, organizational structures, and managerial frameworks for DM operations. However, an immense gap exists related to the exploitation of the proposed models and the integration of their results into policy frameworks, enabling real-life implementations, which should be a future research priority.

The present study, despite its contributions, is subject to limitations. The first limitation refers to the data collection source, i.e., the inclusion of studies from the Scopus database only, thus potentially leading us to omit notable non-Scopus-indexed papers. The time frame that we chose may also have led us to miss pertinent material. Moreover, even though we tried to formulate keywords that were as inclusive as possible, some studies were likely accidentally missed. Finally, our last remark pertains to the formulation of the proposed coding criteria, on which the classification of studies was based, which are both subject to human indexer bias. To mitigate such bias and ensure objectivity, the selected studies were individually examined, and the grouping decisions were then juxtaposed for us to debate and, eventually, eliminate ambiguities.

Author Contributions: Conceptualization, E.A. and S.T.P.; methodology, E.A.; writing—original draft preparation, E.A.; writing—review and editing, E.A., S.T.P. and G.P.; visualization, E.A.; supervision, S.T.P. All authors have read and agreed to the published version of the manuscript.

Funding: This study was supported by the Hellenic Foundation for Research and Innovation (HFRI) under the 3rd Call for HFRI Ph.D. Fellowships (Fellowship Number: 5910).

Data Availability Statement: Data sharing not applicable.

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

Appendix A

Table A1. Systematic literature review samples in the context of HL.

Reference	# of Papers in the Sample	Reference (Cont.)	# of Papers in the Sample (Cont.)
[238]	9	[239]	66
[33]	17	[240]	74
[241]	23	[242]	78
[243]	25	[244]	81
[245]	25	[47]	83
[7]	28	[246]	83
[247]	28	[248]	88
[249]	31	[250]	88
[251]	31	[44]	94
[252]	32	[253]	100
[254]	36	[37]	110
[255]	45	[256]	123
[257]	46	[258]	126
[259]	47	[5]	142
[260]	51	[261]	152

Table A1. *Cont.*

Reference	# of Papers in the Sample	Reference (Cont.)	# of Papers in the Sample (Cont.)
[262]	52	[231]	174
[263]	52	[264]	178
[265]	53	[266]	207
[38]	61	[267]	228
[28]	64	[36]	362

Table A2. List of classification abbreviations.

Category	Abbreviation	Details
Disaster Phase	M	Mitigation
	P	Preparedness
	Res	Response
	Rec	Recovery
Disaster Type	N	Natural disaster
	HM	Human-made disaster
Solving Approach	Opt	Optimization modeling
	Ex	Exact solution or closed form solution
	H	Heuristic algorithm solution apart from metaheuristic algorithms
	MH	Metaheuristic algorithms solution
	Co	Control theory and algorithms
	OM	Other mathematical models
	Game	Game theory (convergence to a Nash equilibrium or Stackelberg equilibrium, minority games, game engine theory, stochastic game/Markov game, matching game theory, bottom-up game theory)
	BnB, DP, LR	Branch-and-bound, dynamic programming, Lagrangian relaxation algorithms, respectively
Subject of Planning	SD	Single drone
	MD	Multiple drones
Vehicle Considerations	LF	Limited flight time/distance/payload/maximum speed/climb (descent) rate/fixed location, or height/coverage radius/intercoverage distance/fixed speed
	EqM	Equations of motion including minimum turning radius, curvature continuity constraint, maximum climbing angle constraint, and other system dynamics constraints
	EC	Energy consumption consideration
	CTC	Communication/transmission consideration
	S	Sensor related consideration (e.g., limited footprint distance/angle from device, distance between devices)
	SF	Safety concerns (presence of obstacles, collision concerns)
	W	Weather considerations
	HG	Heterogeneous vehicles, heterogeneous capabilities
HDCs.	Tran	Transportation and delivery capabilities

Table A2. *Cont.*

Category	Abbreviation	Details
	Mon	Surveying and monitoring capabilities
	Com	Communication and integration capabilities

Table A3. List of other abbreviations.

Full Term	Abbreviation
Area of Interest	AoI
Artificial Intelligence	AI
Augmented Reality	AR
Autoregressive Integrated Moving Average	ARIMA
Base Station	BS
Block Coordinate Descent	BCD
Convolutional Neural Network	CNN
Covariance Matrix Adaptation Evolution Strategy	CMA-ES
Cyber–Physical System	CPS
Deep Learning	DL
Deep Reinforcement Learning	DRL
Deep Q Learning	DQL
Degree of Freedom	DoF
Delegated Proof-of-Stake	DpoS
Density-Based Optics Clustering	DBOC
Device-to-Device	D2D
Digital Technology	DT
Disaster Management	DM
Drone Task Assignment	DTA
Extended Reality	XR
Generative Adversarial Network	GAN
High-Altitude Pseudosatellite	HAP
Humanitarian Digital Technology	HDT
Humanitarian Drone Capability	HDC
Humanitarian Drone Operation	HDO
Humanitarian Logistics	HL
Humanitarian Supply Chain	HSC
Internet of Things	IoT
Internet of Vehicles	IoV
Line of Sight	LoS
Long Range Wide Area Network	LoRaWAN
Machine Learning	ML
Micro Unmanned Aerial Vehicle	MUAV
Mixed Reality	MR
Mobile Edge Computing	MEC
Multioptimization Evolutionary Algorithm based on Decomposition	MOEA/D
Neural Network	NN
Panic Severity Index	PSI

Table A3. *Cont.*

Particle Swarm Optimization	PSO
Point of Interest	PoI
Quality of Experience	QoE
Quality of Service	QoS
Real-Time Kinematic Global Positioning System	RTK-GPS
Received Signal Strength Indication	RSSI
Reinforcement Learning	RL
Research Question	RQ
Robotics and Cyber–Physical System	RCPS
Search and Rescue	SAR
Seasonal Autoregression Integrated Moving Average	SARIMA
Signal-to-Interference-plus-Noise Ratio	SINR
Social-media-driven Drone Sensing	SDS
Supervised Learning	SL
Systematic Literature Review	SLR
Unmanned Aerial Vehicle	UAV
Unmanned Ground Vehicle	UGV
Unmanned Surface Vehicle	USV
Unmanned Underwater Vehicle	UUV
Unsupervised Learning	UL
Vehicle-to-Vehicle	V2V
Vehicular Crowdsourcing	VC
Virtual Reality	VR
Wireless Power Transfer	WPT
Wireless Sensor Network	WSN

Appendix B

Table A4. Classification of the 101 selected papers into the proposed coding criteria.

Ref.	Disaster Phase				Disaster Type			HDC		HDT	HDO	Objective	Subject of Planning		Vehicle Cons.	Solv. App.
	M	**P**	**Res**	**Rec**	**N**	**HM**	**Tran**	**Mon**	**Com**				**SD**	**MD**		
[151]	X	X	X		X	X			X	IoT, AI, big data	Path planning	Minimization of energy consumption and maximization of the throughput of IoT devices.		X	LF, EC, CTC, S, SF, W	Opt, MH, Game
[169]	X		X						X	IoT, big data	Path planning	Maximization of the number of covered points, prioritization of the points according to their visit precedence, balancing coverage and priority objectives.	X		LF, CTC, S	OM
[141]	X	X	X	X	X	X		X	X	IoT, big data	Resource allocation, search	Strong wireless connectivity, wide-coverage footprint, high-throughput transmission, low power consumption, and, thus, longer drone flight time.	X		EC, CTC, S, W	OM
[206]			X		X	X	X	X		AI, big data	Search	Autonomous landing on static and moving targets with no prior information from external infrastructure of the target locations.	X		EqM	Co
[199]		X	X	X	X			X		Crowdsourcing, AI, big data	Area Coverage	Object detection and fine-grained classification in images acquired from drones.		X	-	OM
[139]	X	X	X		X			X	X	IoT, big data	Search	Identification of the position of mobile devices and, thus, missing persons.	X		LF, CTC, SF	OM
[157]	X		X		X				X	IoT, big data	Resource allocation	Maximization of the overall sum rate of the system by optimizing the positions of UAVs for a given IoT distribution, optimization of the transmitting power of IoT devices.		X	CTC	Opt, H
[222]			X					X		VR, big data	Area coverage	Reduction in the cognitive overload when controlling drones.	X		EqM	Co
[181]	X	X	X		X			X	X	IoT, big data	Routing	Minimization of energy consumption, maximization of network lifespan.		X	EC, CTC, S	Opt, MH

Table A4. *Cont.*

Ref.	Disaster Phase				Disaster Type			HDC		HDT	HDO	Objective	Subject of Planning		Vehicle Cons.	Solv. App.
	M	**P**	**Res**	**Rec**	**N**	**HM**	**Tran**	**Mon**	**Com**				**SD**	**MD**		
[167]	X	X	X		X			X	X	IoT, big data	Data gathering	Optimization of IoT devices' density, optimization of the number of UAVs covering the forest area, such that a lower bound on wildfire detection probability is maximized.		X	LF, CTC, W	Opt, H
[192]	X	X	X		X				X	IoT, VR, cloud computing	Search, task assignment	Minimizing delivery time, energy consumption, and total costs for all robots; reducing maximum costs for all robots; balancing workload between robots/lengths of the tour/mission time/number of targets allocated.		X	EC, CTC, S, HG, W	Opt, H, Game
[158]	X		X						X	IoT, big data	Resource allocation	Maximization of the average data rate of drones through power allocation and placement of drones.		X	LF, CTC,	Opt, H, LR
[147]	X		X						X	IoT, AI, edge computing, big data	Scheduling, trajectory planning, resource allocation	Maximization of the lifetime of mobile devices by jointly optimizing drone trajectories, task associations, devices' CPU frequencies, and wireless transmitting powers.		X	LF, EC, CTC, SF	Opt, H
[160]	X		X						X	IoT, AI, big data	Resource allocation	Resumption of ground communication service in the postdisaster rescue context with the goal of optimizing energy efficiency.		X	LF, CTC	Opt, H
[111]	X		X	X	X				X	IoT, AI, big data	Path planning, data gathering	Minimization of completion time.		X	LF, EC, CTC, SF	Opt, H
[121]	X		X						X	IoT, AI, big data	Scheduling, path planning, data gathering	Minimization of drone energy consumption		X	LF, EC, CTC	Opt, MH
[149]	X		X		X	X			X	IoT, big data	Search	Maximization of the obtainable gain (in terms of meeting the demands of the applications and users in terms of performance and success rate), minimization of the consequent cost in terms of energy consumption.		X	EC, CTC, W	Opt, H, Game

Table A4. *Cont.*

Ref.	Disaster Phase				Disaster Type			HDC		HDT	HDO	Objective	Subject of Planning		Vehicle Cons.	Solv. App.
	M	P	Res	Rec	N	HM	Tran	Mon	Com				SD	MD		
[131]	X	X	X						X	IoT, AI, big data	Trajectory planning, scheduling, resource allocation	Sequential optimization of the 3D position of the drone, beam pattern, charging time to maximize energy harvested.		X	LF, EC, CTC, SF	Opt, MH, BnB
[166]	X		X						X	IoT, AI, big data	Path planning, data gathering, resource allocation, recharging	Maximization of the total uplink throughput, maximization of the total achievable rate of IoT devices, maximization of the sum rate of all IoT devices.		X	LF, CTC, S, SF	Opt, MH
[145]	X		X		X				X	IoT, AI, RCPS, big data	Path planning, resource allocation	Maximization of network coverage and exploration path		X	LF, EC, CTC, HG	Opt, H
[172]	X	X	X		X			X	X	IoT, blockchain, big data	Data gathering	Reducing data redundancy, improving sparsity, and ensuring the security of data transmission.		X	LF, EC, CTC, W	OM
[159]	X		X						X	IoT, big data	Resource allocation	Evaluation of the overall outage probability for different SINR threshold values, D2D transmit powers, distance of an IoT user from the IoT gateway, and the distance of a D2D user from a drone.	X		LF, CTC	OM
[218]	X		X		X		X			RCPS	Supply allocation	Ensuring minimal distances between agents and avoiding collisions.		X	LF, SF, HG	Opt, MH
[210]		X	X	X				X	X	RCPS, big data	Search, task assignment, data gathering	Maximization of the amount of information for a given set of responder-defined AoIs.		X	LF, EC, CTC, HG	Opt, H
[200]		X	X		X	X		X	X	Crowdsourcing, AI, RCPS, big data	Routing, task assignment, data gathering	Maximization of the amount of collected data, geographical fairness, energy efficiency, minimization of data dropout.		X	EC, CTC, S. HG	Opt, H

Table A4. *Cont.*

Ref.	Disaster Phase				Disaster Type			HDC		HDT	HDO	Objective	Subject of Planning		Vehicle Cons.	Solv. App.
	M	**P**	**Res**	**Rec**	**N**	**HM**	**Tran**	**Mon**	**Com**				**SD**	**MD**		
[220]	X		X	X					X	IoT, blockchain, big data	Recharging	Optimal energy trading between drones and charging stations.		X	EC, CTC	OM, Game
[137]	X		X						X	IoT, blockchain, big data	Resource allocation	Optimization of cost and time parameters.		X	LF, CTC	Opt, H, Game
[209]	X	X	X		X			X		IoT, AI, big data	Area coverage	Reduction in the number of images to be processed by the first responders.		X	EC, W	OM
[213]			X	X					X	RCPS	Search	Prediction and control of a large-scale joint swarm of UGVs and UAVs performing a joint autonomous land–air operation		X	EqM, CTC, HG	Co
[221]			X		X				X	Blockchain	Search	Addition of an encryption function to a large number of data transmission models.		X	CTC	OM
[225]			X	X				X	X	Big data	Path planning	Optimization of the smoothness of path, landing accuracy at destination, distance minimization.	X	X	LF, SF	Opt, E, MH
[173]	X		X		X				X	IoT, big data	Resource allocation	Maximization of throughput.		X	LF, EC, CTC	Opt, MH
[143]	X		X						X	IoT, edge computing, big data	Resource allocation	Maximization of the total successful computed data, optimization of the usage of aerial resources.		X	CTC	Opt, H, Game
[168]	X	X	X		X	X		X	X	IoT, big data	Data gathering	Enhancement of the lifespan of the WSN.	X		LF, EC, CTC, S	OM
[188]	X		X						X	IoT, edge computing	Task assignment	Minimization of energy consumption and task completion time for optimal task–UAV–mobile edge server.		X	LF, EC, CTC	Opt, H
[216]				X	X				X	RCPS	Area coverage	Position estimation for a tethered UAV, in charge of securing the safety of the teleoperator of a construction machine.	X		LF, HG	OM
[171]	X		X	X				X	X	IoT, big data	Data gathering, trajectory planning	Use of UAVs as IoT devices for data acquisition from different clusters of sensor devices deployed in a region through geofencing.	X		CTC, S, SF	OM

Table A4. *Cont.*

Ref.	Disaster Phase				Disaster Type			HDC		HDT	HDO	Objective	Subject of Planning		Vehicle Cons.	Solv. App.
	M	**P**	**Res**	**Rec**	**N**	**HM**	**Tran**	**Mon**	**Com**				**SD**	**MD**		
[135]	X		X		X				X	IoT, AI, Edge Computing, big data	Trajectory Planning, Task Assignment	Maximization of the number of completed tasks and minimization of energy consumption.	X		LF, EC, CTC, SF	Opt, H
[154]	X		X						X	IoT, AI, Edge Computing, big data	Resource Allocation, Path Planning	Maximization of the average total QoE of all IoT devices over all time slots.		X	LF, CTC, SF	Opt, H
[162]	X		X		X				X	IoT, AI, big data	Resource Allocation	Maximization of the number of node-to-node connections while maintaining a strongly connected drone network.		X	LF, CTC, W	Opt, H
[124]		X	X		X			X		IoT, big data	Scheduling, Path Planning, Area Coverage	Maximization of non-redundant photos taken by the UAV.	X		LF, EC, SF	Opt, H
[126]	X	X	X		X				X	IoT, big data	Resource Allocation	Minimization of the hovering time of the UAV and the power consumption of the D2D network.	X		LF, CTC, S	Opt, H
[176]	X		X						X	IoT, big data	Routing, Task Assignment	Minimization of task processing latency and realization of computing while transmitting.		X	LF, CTC	Co
[142]	X		X						X	IoT, Cloud and Edge Computing, big data	Scheduling, Task Assignment, Resource Allocation	Minimization of the maximum computation delay among IoT devices.		X	LF, CTC, SF	Opt, H
[214]		X	X			X	X	X	X	RCPS, big data	Search, Sampling, Trajectory Planning	Realization of a mock hazardous chemical spill investigation and sampling task within a large shipping container requiring access to increasingly constrained spaces.	X		SF, HG, W	Co
[207]	X		X						X	IoT, AI	Path Planning	Optimization of the location of drone BSs by minimizing the collective wireless received signal strength.		X	LF, CTC, SF	Opt, H
[152]	X		X						X	IoT	Path Planning, Scheduling	Minimization of time consumption and energy consumption of UAVs.		X	LF, EC, CTC, W	Opt, MH

Table A4. *Cont.*

Ref.	Disaster Phase				Disaster Type			HDC		HDT	HDO	Objective	Subject of Planning		Vehicle Cons.	Solv. App.
	M	P	Res	Rec	N	HM	Tran	Mon	Com				SD	MD		
[217]		X	X				X	X		RCPS, big data	Path Planning, Supply Allocation	Maximization of volume of supplies and covered area.		X	LF, HG	Opt, E
[146]	X		X		X				X	IoT, AI, edge computing, big data	Scheduling	Maximization of number of tasks distributed to the UAVs and minimization of the average energy consumption.		X	EC, CTC	Opt, H. MH
[215]			X		X			X	X	RCPS, big data	Path planning, search, area coverage	Ground map generation and path distance minimization.	X		CTC, SF, HG	Opt, H, MH
[211]			X					X		RCPS, big data	Search	Autonomous take-off, tracking, and landing of a UAV on a moving landing platform, detection, and localization of the mobile target using a downward-looking camera and vision-based tracking of the mobile platform while in flight.	X		LF, EqM, S, HG	Co
[122]	X		X						X	IoT	Resource allocation	Optimization of UAV network coverage.		X	LF, EC, CTC, SF, W	OM
[51]			X	X			X		X	RCPS	Path planning, task assignment, scheduling	A reliable and stable control system for aerial manipulation, successful self-localization and mapping in 3D space, fast planning and task allocation.	X		EC, CTC, SF, HG	Co
[208]	X		X		X			X		AI, big data	Path planning, search	Autonomous UAV Navigation to locate missing human.	X		EqM, SF	Co
[178]			X		X				X	IoT, AI, blockchain, edge computing, big data	Data gathering	Minimization of energy consumption from forking events.		X	CTC	Opt, H

Table A4. *Cont.*

Ref.	Disaster Phase				Disaster Type			HDC		HDT	HDO	Objective	Subject of Planning		Vehicle Cons.	Solv. App.
	M	P	Res	Rec	N	HM	Tran	Mon	Com				SD	MD		
[204]	X	X	X		X			X		AI, big data	Area coverage	Flooded zone segmentation from aerial images that contain both water and nonwater elements.	X		S	Opt, H
[185]	X		X		X		X		X	IoT, AI, blockchain, RCPS, cloud and edge computing	Supply Allocation	Optimization of delivery times in last-mile UAV-truck networks, optimization of resource distribution to reduce the cases of surplus and deficiency of resources at affected target sites, and throughput maximization.		X	CTC, HG	Opt, H
[202]				X				X		AI, big data	Area coverage	Positioning of damaged poles with the inputs of coordinates and necessary information extracted from UAV images.			LF, S	OM
[150]	X		X						X	IoT, AI, big data	Data gathering	First responder allocation, victims' coalition formation, UAV–first responder association.		X	LF, EC, CTC	OM
[196]		X	X		X	X		X		Social media, AI, big data	Task assignment, path planning	Minimization of the discrepancy between the estimated validity of the events and their ground truth.		X	LF, EC, SF, W	OM, Game
[197]		X	X		X	X		X		Social media, big data	Task assignment, path planning	Minimization of the discrepancy between the estimated validity of events and their ground truth.		X	LF, EC, SF	OM, Game
[194]		X	X		X	X		X		Social media, AI, big data	Task assignment, path planning	Minimization of the discrepancy between the estimated truth of events and their ground truth and minimization of drone average power consumption at each sensing cycle.		X	LF, EqM, EC, SF	Opt, H, Game
[195]		X	X		X			X		Social media, big data	Task assignment, path planning	Minimization of the discrepancy between the estimated validity of events and their ground truth.		X	S, W	Opt, H, Game
[224]		X	X					X		AR, big data	Area coverage	Improvement in the geographic registration (georegistration) accuracy.	X		S, W	Co
[190]	X		X						X	IoT, AI, edge computing	Task assignment	Minimization of completion time for all tasks in the system.		X	CTC, S	Opt, H

Table A4. *Cont.*

Ref.	Disaster Phase				Disaster Type			HDC		HDT	HDO	Objective	Subject of Planning		Vehicle Cons.	Solv. App.
	M	P	Res	Rec	N	HM	Tran	Mon	Com				SD	MD		
[179]	X		X		X				X	IoT	Scheduling	Optimization of drone scheduling time.		X	EC, CTC, W	Opt, E
[133]	X	X	X		X	X		X	X	IoT, AI, edge computing, big data	Search, task assignment	Minimization of average completion time of a set of tasks.		X	CTC, S	Co
[120]	X	X	X		X	X		X	X	IoT, AI, cloud and fog computing, big data	Data gathering	Panic-based on-time and orderly evacuation of stranded persons.	X		EC, CTC, SF, W	OM
[134]	X		X	X	X				X	IoT, big data	Area coverage	Improvement in UAV coverage area.	X		LF, EC, CTC, S	OM
[138]	X		X		X				X	IoT, AI, edge computing, big data	Task assignment, resource allocation	Minimization of the overall network computation cost in terms of energy and delay.		X	EC, CTC	Opt, H, Game
[182]	X		X						X	IoT, AI, big data	Trajectory planning, data gathering	Minimization of the age of network information.		X	CTC	OM
[155]	X	X	X		X	X		X	X	IoT, cloud computing, big data	Search, trajectory planning	Crowd counting and localization.		X	SF	Opt, MH
[144]	X		X						X	IoT, edge computing, big data	Resource allocation	Delay minimization.		X	CTC	Opt, H
[164]	X		X						X	IoT, edge computing, big data	Task assignment	Service delay minimization.	X		EqM, CTC	OM
[130]	X	X	X	X					X	IoT, AI, big data	Trajectory planning, resource allocation	Maximization of the coalition head energy availability to find UAV's optimal position.	X		LF, CTC, SF	Opt, H, Game
[180]	X		X						X	IoT, AI	Routing	Proactive vehicular routing using mobility control information.		X	LF, CTC	OM

Table A4. *Cont.*

Ref.	Disaster Phase				Disaster Type		HDC			HDT	HDO	Objective	Subject of Planning		Vehicle Cons.	Solv. App.
	M	P	Res	Rec	N	HM	Tran	Mon	Com				SD	MD		
[177]	X	X	X		X			X		IoT, AI, big data, blockchain, RCPS	Scheduling, trajectory planning, task assignment	Autonomous path-finding of miniature UAVs assisted by task-offloading devices.	X		CTC, S	Co
[148]	X		X		X	X			X	IoT, AI, big data	Search, path planning	Minimization of the signal propagation exponent and the reference RSSI value.	X		S, SF	OM
[198]		X	X		X		X	X		Social media, big data	Search, task assignment	Minimization of the total fly time cost.		X	LF, EC	Opt, H
[140]	X		X		X				X	IoT, big data	Resource allocation, trajectory planning	Maximization of the total number of served IoT devices and collected throughput.	X		LF, CTC, SF	Opt, H
[132]	X	X	X	X	X				X	IoT, big data	Data gathering	Maximization of the number of connected mobile ground nodes.		X	CTC, S, SF, HG	Opt, MH
[170]	X		X						X	IoT, AI, big data	Path planning, data gathering	Minimization of completion time and total energy consumption of UAVs' deployment procedure in data collection missions.		X	CTC, S, SF	Opt, H
[191]	X	X	X		X	X		X	X	IoT, edge and cloud computing, big data	Task assignment	Creation of a management layer between the IoT application and operating system to establish and monitor network connectivity, estimate failures, and adapt task planning.		X	CTC	Co
[205]	X		X		X			X	X	IoT, AI, big data	Resource allocation	Creation of a transmission control protocol for the 5G millimeter-wave network.		X	LF, CTC, S	OM
[223]		X	X		X			X		VR, big data	Path planning	Path optimization.		X	LF, EqM, SF, W	Opt, MH
[165]	X		X						X	IoT, big data	Resource allocation	Optimization of the placement of a group of drone-cells with limited backhaul communication ranges to maximize the number of served users.		X	CTC	Opt, E, MH

Table A4. *Cont.*

Ref.	Disaster Phase				Disaster Type			HDC		HDT	HDO	Objective	Subject of Planning		Vehicle Cons.	Solv. App.
	M	P	Res	Rec	N	HM	Tran	Mon	Com				SD	MD		
[128]	X	X	X						X	IoT, big data	Resource allocation	Minimization of the transmission power for relaying data at the UAV mounted BSs to extend hovering time and, thus, maximize the number of human-portable machine-type devices to establish connectivity and send rescue messages with required data rates.	X		LF, EC, CTC	Opt, H
[127]	X	X	X	X	X				X	IoT, big data	Routing, resource allocation	Minimization of the number of hops in the uplink and downlink transmission between the UAV and mobile devices.	X		LF, EC, CTC, S	Opt, H
[163]	X		X	X					X	IoT, AI, big data	Data gathering	Creation of a task distribution mechanism to achieve trade-off between data aggregation ratio and energy cost.	X		EC, CTC	Opt, H
[212]			X	X				X		RCPS, big data	Search	Construction of an autonomous landing platform and design of cooperative target considering the rapidity and stability of landing, creation of a method that can detect and track moving targets in real time.	X		HG, W	Co
[219]	X		X		X			X	X	IoT, blockchain, RCPS, big data	Search, data gathering	Maximization of the utility of electric vehicles.		X	LF, EC, CTC, S, HG	Opt, H, Game
[153]	X		X		X			X	X	IoT, blockchain, RCPS, big data	Search, data gathering	Ensure secure blockchain offline transactions among electric vehicles.		X	EC, CTC, HG	Opt, E, Game
[203]		X	X		X			X		AI, big data	Scheduling, path planning	Autonomous path-finding of miniature UAVs assisted by task-offloading devices.	X		CTC, S, SF	Co
[189]	X	X	X		X				X	IoT, big data, edge computing	Task assignment	Minimization of service time and energy consumption.		X	EqM, EC, CTC	Opt, H
[193]	X		X		X				X	AI, blockchain, RCPS, fog computing, big data	Search, task assignment	Ensure secure, energy-efficient data sharing for UAV-aided disaster relief networks.		X	LF, EC, CTC, HG, W	OM

Table A4. *Cont.*

Ref.	Disaster Phase				Disaster Type			HDC		HDT	HDO	Objective	Subject of Planning		Vehicle Cons.	Solv. App.
	M	**P**	**Res**	**Rec**	**N**	**HM**	**Tran**	**Mon**	**Com**				**SD**	**MD**		
[94]	X		X						X	IoT, big data	Scheduling, trajectory-planning	Optimization of mission completion time and energy consumption with the goal of serving IoT nodes as much as possible based on their data needs.		X	LF, EC, CTC, SF	Opt, H, DP
[156]	X		X						X	IoT, edge computing, big data	Task assignment, trajectory planning	Minimization of the energy consumption of IoT devices.		X	LF, EC, SF	Opt, H
[136]	X		X						X	IoT, Big data	Trajectory planning, resource allocation	Maximization of the downlink achievable sum rate of users.	X		LF, CTC, SF	Opt, H
[129]	X	X	X						X	IoT, big data	Trajectory planning, resource allocation	Maximization of the uplink average achievable sum rate of IoT terminals.	X		LF, CTC, SF	Opt, H, LR
[161]	X		X		X				X	IoT, cloud and edge computing, big data	Resource allocation	Minimization of the total energy consumed by the system for computation and transmission.		X	CTC, SF	Opt, H
[201]	X	X	X	X	X			X		AI, big data	Area coverage	Intelligent identification of UAV aerial images, extraction of foreground features of disasters, and timely detection of abnormal hidden hazards.			SF, W	OM

References

1. Tomasini, R.M. The Evolutions of Humanitarian-Private Partnerships: Collaborative Frameworks Under Review. In *The Palgrave Handbook of Humanitarian Logistics and Supply Chain Management*; Kovács, G., Spens, K., Moshtari, M., Eds.; Palgrave Macmillan UK: London, UK, 2018; pp. 627–635. ISBN 978-1-137-59098-5.
2. Van Wassenhove, L.N. Humanitarian Aid Logistics: Supply Chain Management in High Gear. *J. Oper. Res. Soc.* **2006**, *57*, 475–489. [CrossRef]
3. Holguín-Veras, J.; Jaller, M.; Van Wassenhove, L.N.; Pérez, N.; Wachtendorf, T. On the Unique Features of Post-Disaster Humanitarian Logistics. *J. Oper. Manag.* **2012**, *30*, 494–506. [CrossRef]
4. Liberatore, F.; Pizarro, C.; de Blas, C.S.; Ortuño, M.T.; Vitoriano, B. Uncertainty in Humanitarian Logistics for Disaster Management. A Review. In *Decision Aid Models for Disaster Management and Emergencies*; Vitoriano, B., Montero, J., Ruan, D., Eds.; Atlantis Computational Intelligence Systems; Atlantis Press: Paris, France, 2013; Volume 7, pp. 45–74. ISBN 978-94-91216-73-2.
5. Rejeb, A.; Rejeb, K.; Simske, S.; Treiblmaier, H. Humanitarian Drones: A Review and Research Agenda. *Internet Things* **2021**, *16*, 100434. [CrossRef]
6. Akter, S.; Wamba, S.F. Big Data and Disaster Management: A Systematic Review and Agenda for Future Research. *Ann. Oper. Res.* **2019**, *283*, 939–959. [CrossRef]
7. Gupta, S.; Altay, N.; Luo, Z. Big Data in Humanitarian Supply Chain Management: A Review and Further Research Directions. *Ann. Oper. Res.* **2019**, *283*, 1153–1173. [CrossRef]
8. Joseph, J.K.; Dev, K.A.; Pradeepkumar, A.P.; Mohan, M. Chapter 16—Big Data Analytics and Social Media in Disaster Management. In *Integrating Disaster Science and Management*; Samui, P., Kim, D., Ghosh, C., Eds.; Elsevier: Amsterdam, The Netherlands, 2018; pp. 287–294. ISBN 978-0-12-812056-9.
9. Arslan, M.; Roxin, A.-M.; Cruz, C.; Ginhac, D. A Review on Applications of Big Data for Disaster Management. In Proceedings of the 2017 13th International Conference on Signal-Image Technology & Internet-Based Systems (SITIS), Jaipur, India, 4–7 December 2017; pp. 370–375.
10. Wang, J.; Wu, Y.; Yen, N.; Guo, S.; Cheng, Z. Big Data Analytics for Emergency Communication Networks: A Survey. *IEEE Commun. Surv. Tutor.* **2016**, *18*, 1758–1778. [CrossRef]
11. Yu, M.; Yang, C.; Li, Y. Big Data in Natural Disaster Management: A Review. *Geosciences* **2018**, *8*, 165. [CrossRef]
12. de França Bail, R.; Kovaleski, J.L.; da Silva, V.L.; Pagani, R.N.; de Genaro Chiroli, D.M. Internet of Things in Disaster Management: Technologies and Uses. *Environ. Hazards* **2021**, *20*, 493–513. [CrossRef]
13. Ray, P.P.; Mukherjee, M.; Shu, L. Internet of Things for Disaster Management: State-of-the-Art and Prospects. *IEEE Access* **2017**, *5*, 18818–18835. [CrossRef]
14. Sinha, A.; Kumar, P.; Rana, N.P.; Islam, R.; Dwivedi, Y.K. Impact of Internet of Things (IoT) in Disaster Management: A Task-Technology Fit Perspective. *Ann. Oper. Res.* **2019**, *283*, 759–794. [CrossRef]
15. Aljumah, A.; Kaur, A.; Bhatia, M.; Ahamed Ahanger, T. Internet of Things-Fog Computing-Based Framework for Smart Disaster Management. *Trans. Emerg. Telecommun. Technol.* **2021**, *32*, e4078. [CrossRef]
16. Tsubaki, T.; Ishibashi, R.; Kuwahara, T.; Okazaki, Y. Effective Disaster Recovery for Edge Computing against Large-Scale Natural Disasters. In Proceedings of the 2020 IEEE 17th Annual Consumer Communications & Networking Conference (CCNC), Las Vegas, NV, USA, 10–13 January 2020; pp. 1–2.
17. Jian-hua, Z.; Nan, Z. Cloud Computing-Based Data Storage and Disaster Recovery. In Proceedings of the 2011 International Conference on Future Computer Science and Education, Xi'an, China, 20–21 August 2011; pp. 629–632.
18. Rodríguez-Espíndola, O.; Chowdhury, S.; Beltagui, A.; Albores, P. The Potential of Emergent Disruptive Technologies for Humanitarian Supply Chains: The Integration of Blockchain, Artificial Intelligence and 3D Printing. *Int. J. Prod. Res.* **2020**, *58*, 4610–4630. [CrossRef]
19. Chamola, V.; Hassija, V.; Gupta, S.; Goyal, A.; Guizani, M.; Sikdar, B. Disaster and Pandemic Management Using Machine Learning: A Survey. *IEEE Internet Things J.* **2021**, *8*, 16047–16071. [CrossRef] [PubMed]
20. Linardos, V.; Drakaki, M.; Tzionas, P.; Karnavas, Y.L. Machine Learning in Disaster Management: Recent Developments in Methods and Applications. *Mach. Learn. Knowl. Extr.* **2022**, *4*, 446–473. [CrossRef]
21. Dailey, D.; Starbird, K. Social Media Seamsters: Stitching Platforms & Audiences into Local Crisis Infrastructure. In Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing, Portland, OR, USA, 25 February–1 March 2017; Association for Computing Machinery: New York, NY, USA, 2017; pp. 1277–1289.
22. Houston, J.B.; Hawthorne, J.; Perreault, M.F.; Park, E.H.; Goldstein Hode, M.; Halliwell, M.R.; Turner McGowen, S.E.; Davis, R.; Vaid, S.; McElderry, J.A.; et al. Social Media and Disasters: A Functional Framework for Social Media Use in Disaster Planning, Response, and Research. *Disasters* **2015**, *39*, 1–22. [CrossRef]
23. Landwehr, P.M.; Carley, K.M. Social Media in Disaster Relief. In *Data Mining and Knowledge Discovery for Big Data: Methodologies, Challenge and Opportunities*; Chu, W.W., Ed.; Studies in Big Data; Springer: Berlin/Heidelberg Germany, 2014; pp. 225–257. ISBN 978-3-642-40837-3.
24. Alexander, D.E. Social Media in Disaster Risk Reduction and Crisis Management. *Sci. Eng. Ethics* **2014**, *20*, 717–733. [CrossRef]
25. Murphy, R.R.; Tadokoro, S.; Kleiner, A. Disaster Robotics. In *Springer Handbook of Robotics*; Siciliano, B., Khatib, O., Eds.; Springer Handbooks; Springer: Cham, Switzerland, 2016; pp. 1577–1604. ISBN 978-3-319-32552-1.

26. Jara-Olmedo, A.; Medina-Pazmiño, W.; Tozer, T.; Aguilar, W.G.; Pardo, J.A. E-Services from Emergency Communication Network: Aerial Platform Evaluation. In Proceedings of the 2018 International Conference on eDemocracy & eGovernment (ICEDEG), Ambato, Ecuador, 4–6 April 2018; pp. 251–256.
27. Scerri, P.; Kannan, B.; Velagapudi, P.; Macarthur, K.; Stone, P.; Taylor, M.; Dolan, J.; Farinelli, A.; Chapman, A.; Dias, B.; et al. Flood Disaster Mitigation: A Real-World Challenge Problem for Multi-Agent Unmanned Surface Vehicles. In *Advanced Agent Technology*; Dechesne, F., Hattori, H., ter Mors, A., Such, J.M., Weyns, D., Dignum, F., Eds.; Springer: Berlin/Heidelberg, Germany, 2012; pp. 252–269.
28. Hunt, K.; Narayanan, A.; Zhuang, J. Blockchain in Humanitarian Operations Management: A Review of Research and Practice. *Socio-Econ. Plan. Sci.* **2022**, *80*, 101175. [CrossRef]
29. Hunt, K.; Zhuang, J. Blockchain for Disaster Management. In *Big Data and Blockchain for Service Operations Management*; Emrouznejad, A., Charles, V., Eds.; Studies in Big Data; Springer: Cham, Switzerland, 2022; pp. 253–269. ISBN 978-3-030-87304-2.
30. Zwitter, A.; Boisse-Despiaux, M. Blockchain for Humanitarian Action and Development Aid. *Int. J. Humanit. Action* **2018**, *3*, 16. [CrossRef]
31. Nunes, I.L.; Lucas, R.; Simões-Marques, M.; Correia, N. Augmented Reality in Support of Disaster Response. In Proceedings of the Advances in Human Factors and Systems Interaction, Los Angeles, CA, USA, 17−21 July 2017; Nunes, I.L., Ed.; Springer: Cham, Switzerland, 2018; pp. 155–167.
32. Khanal, S.; Medasetti, U.S.; Mashal, M.; Savage, B.; Khadka, R. Virtual and Augmented Reality in the Disaster Management Technology: A Literature Review of the Past 11 Years. *Front. Virtual Real.* **2022**, *3*, 30. [CrossRef]
33. Heaslip, G.; Kovács, G.; Grant, D.B. Servitization as a Competitive Difference in Humanitarian Logistics. *JHLSCM* **2018**, *8*, 497–517. [CrossRef]
34. Ghadge, A.; Dani, S.; Kalawsky, R. Supply Chain Risk Management: Present and Future Scope. *Int. J. Logist. Manag.* **2012**, *23*, 313–339. [CrossRef]
35. Tranfield, D.; Denyer, D.; Smart, P. Towards a Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review. *Br. J. Manag.* **2003**, *14*, 207–222. [CrossRef]
36. Behl, A.; Dutta, P. Humanitarian Supply Chain Management: A Thematic Literature Review and Future Directions of Research. *Ann. Oper. Res.* **2019**, *283*, 1001–1044. [CrossRef]
37. Marić, J.; Galera-Zarco, C.; Opazo-Basáez, M. The Emergent Role of Digital Technologies in the Context of Humanitarian Supply Chains: A Systematic Literature Review. *Ann. Oper. Res.* **2021**, *319*, 1003–1044. [CrossRef]
38. Modgil, S.; Singh, R.K.; Foropon, C. Quality Management in Humanitarian Operations and Disaster Relief Management: A Review and Future Research Directions. *Ann. Oper. Res.* **2020**, *319*, 1045–1098. [CrossRef] [PubMed]
39. Pyakurel, U.; Dhamala, T.N. Continuous Dynamic Contraflow Approach for Evacuation Planning. *Ann. Oper. Res.* **2017**, *253*, 573–598. [CrossRef]
40. Sandvik, K.B.; Jumbert, M.G.; Karlsrud, J.; Kaufmann, M. Humanitarian Technology: A Critical Research Agenda. *Int. Rev. Red Cross* **2014**, *96*, 219–242. [CrossRef]
41. Munawar, H.S.; Mojtahedi, M.; Hammad, A.W.A.; Kouzani, A.; Mahmud, M.A.P. Disruptive Technologies as a Solution for Disaster Risk Management: A Review. *Sci. Total Environ.* **2022**, *806*, 151351. [CrossRef]
42. Khan, A.; Gupta, S.; Gupta, S.K. Emerging UAV Technology for Disaster Detection, Mitigation, Response, and Preparedness. *J. Field Robot.* **2022**, *39*, 905–955. [CrossRef]
43. Chung, S.H.; Sah, B.; Lee, J. Optimization for Drone and Drone-Truck Combined Operations: A Review of the State of the Art and Future Directions. *Comput. Oper. Res.* **2020**, *123*, 105004. [CrossRef]
44. Habib, M.S.; Lee, Y.H.; Memon, M.S. Mathematical Models in Humanitarian Supply Chain Management: A Systematic Literature Review. *Math. Probl. Eng.* **2016**, *2016*, 1–20. [CrossRef]
45. Hezam, I.M.; Nayeem, M.K. A Systematic Literature Review on Mathematical Models of Humanitarian Logistics. *Symmetry* **2020**, *13*, 11. [CrossRef]
46. Özdamar, L.; Ertem, M.A. Models, Solutions and Enabling Technologies in Humanitarian Logistics. *Eur. J. Oper. Res.* **2015**, *244*, 55–65. [CrossRef]
47. Anaya-Arenas, A.M.; Renaud, J.; Ruiz, A. Relief Distribution Networks: A Systematic Review. *Ann. Oper. Res.* **2014**, *223*, 53–79. [CrossRef]
48. Otto, A.; Agatz, N.; Campbell, J.; Golden, B.; Pesch, E. Optimization Approaches for Civil Applications of Unmanned Aerial Vehicles (UAVs) or Aerial Drones: A Survey. *Networks* **2018**, *72*, 411–458. [CrossRef]
49. Coutinho, W.P.; Battarra, M.; Fliege, J. The Unmanned Aerial Vehicle Routing and Trajectory Optimisation Problem, a Taxonomic Review. *Comput. Ind. Eng.* **2018**, *120*, 116–128. [CrossRef]
50. Rojas Viloria, D.; Solano-Charris, E.L.; Muñoz-Villamizar, A.; Montoya-Torres, J.R. Unmanned Aerial Vehicles/Drones in Vehicle Routing Problems: A Literature Review. *Int. Trans. Oper. Res.* **2021**, *28*, 1626–1657. [CrossRef]
51. Petrovic, T.; Haus, T.; Arbanas, B.; Orsag, M.; Bogdan, S. Can UAV and UGV Be Best Buddies? Towards Heterogeneous Aerial-Ground Cooperative Robot System for Complex Aerial Manipulation Tasks. In Proceedings of the 2015 12th International Conference on Informatics in Control, Automation and Robotics (ICINCO), Colmar, France, 21–23 July 2015; Volume 01, pp. 238–245.

52. Shan, J.; Ballard, D.; Vinson, D.R. Publication Non Grata: The Challenge of Publishing Non-COVID-19 Research in the COVID Era. *Cureus* **2020**, *12*, e11403. [CrossRef]
53. Dubey, R.; Gunasekaran, A.; Childe, S.J.; Roubaud, D.; Fosso Wamba, S.; Giannakis, M.; Foropon, C. Big Data Analytics and Organizational Culture as Complements to Swift Trust and Collaborative Performance in the Humanitarian Supply Chain. *Int. J. Prod. Econ.* **2019**, *210*, 120–136. [CrossRef]
54. Krippendorff, K. *Content Analysis: An Introduction to Its Methodology*; SAGE Publications: Thousand Oaks, CA, USA, 2018; ISBN 978-1-5063-9567-8.
55. Polit, D.F.; Beck, C.T. *Nursing Research: Principles and Methods*; Lippincott Williams & Wilkins: Philadelphia, PA, USA, 2004; ISBN 978-0-7817-3733-3.
56. Mayring, P. *A Companion to Qualitative Research*; SAGE: London, UK, 2004; ISBN 978-0-7619-7374-4.
57. Saunders, M.; Lewis, P.; Thornhill, A. *Research Methods for Business Students*; Pearson Education: London, UK, 2009; ISBN 978-0-273-71686-0.
58. Altay, N.; Green, W.G. OR/MS Research in Disaster Operations Management. *Eur. J. Oper. Res.* **2006**, *175*, 475–493. [CrossRef]
59. Lee, I.; Lee, K. The Internet of Things (IoT): Applications, Investments, and Challenges for Enterprises. *Bus. Horiz.* **2015**, *58*, 431–440. [CrossRef]
60. Adeel, A.; Gogate, M.; Farooq, S.; Ieracitano, C.; Dashtipour, K.; Larijani, H.; Hussain, A. A Survey on the Role of Wireless Sensor Networks and IoT in Disaster Management. In *Geological Disaster Monitoring Based on Sensor Networks*; Durrani, T.S., Wang, W., Forbes, S.M., Eds.; Springer Natural Hazards; Springer: Singapore, 2019; pp. 57–66. ISBN 9789811309922.
61. Velev, D.; Zlateva, P.; Zong, X. Challenges of 5G Usability in Disaster Management. In Proceedings of the 2018 International Conference on Computing and Artificial Intelligence, Chengdu, China, 12–14 March 2018; Association for Computing Machinery: New York, NY, USA, 2018; pp. 71–75.
62. Amiri, I.S.; Prakash, J.; Balasaraswathi, M.; Sivasankaran, V.; Sundararajan, T.V.P.; Hindia, M.H.D.N.; Tilwari, V.; Dimyati, K.; Henry, O. DABPR: A Large-Scale Internet of Things-Based Data Aggregation Back Pressure Routing for Disaster Management. *Wirel. Netw.* **2020**, *26*, 2353–2374. [CrossRef]
63. Qian, L.; Luo, Z.; Du, Y.; Guo, L. Cloud Computing: An Overview. In Proceedings of the Cloud Computing, Beijing, China, 1–4 December 2009; Jaatun, M.G., Zhao, G., Rong, C., Eds.; Springer: Berlin/Heidelberg, Germany, 2009; pp. 626–631.
64. Chiang, M.; Zhang, T. Fog and IoT: An Overview of Research Opportunities. *IEEE Internet Things J.* **2016**, *3*, 854–864. [CrossRef]
65. Surowiecki, J. *The Wisdom of Crowds*; Knopf Doubleday Publishing Group: New York, NY, USA, 2005; ISBN 978-0-307-27505-9.
66. Soden, R.; Palen, L. Infrastructure in the Wild: What Mapping in Post-Earthquake Nepal Reveals about Infrastructural Emergence. In Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems, San Jose, CA, USA, 7–12 May 2016; Association for Computing Machinery: New York, NY, USA, 2016; pp. 2796–2807.
67. Kogan, M.; Palen, L.; Anderson, K.M. Think Local, Retweet Global: Retweeting by the Geographically-Vulnerable during Hurricane Sandy. In Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing, Vancouver, BC, Canada, 14–18 March 2015; Association for Computing Machinery: New York, NY, USA, 2015; pp. 981–993.
68. Palen, L.; Liu, S.B. Citizen Communications in Crisis: Anticipating a Future of ICT-Supported Public Participation. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, San Jose, CA, USA, 28 April–3 May 2007; Association for Computing Machinery: New York, NY, USA, 2007; pp. 727–736.
69. Qu, Y.; Huang, C.; Zhang, P.; Zhang, J. Microblogging after a Major Disaster in China: A Case Study of the 2010 Yushu Earthquake. In Proceedings of the ACM 2011 Conference on Computer Supported Cooperative Work, Hangzhou, China, 19–23 March 2011; Association for Computing Machinery: New York, NY, USA, 2011; pp. 25–34.
70. Vieweg, S.; Hughes, A.L.; Starbird, K.; Palen, L. Microblogging during Two Natural Hazards Events: What Twitter May Contribute to Situational Awareness. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, Atlanta, GA, USA, 10–15 April 2010; Association for Computing Machinery: New York, NY, USA, 2010; pp. 1079–1088.
71. Starbird, K.; Palen, L. "Voluntweeters": Self-Organizing by Digital Volunteers in Times of Crisis. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, Vancouver, BC, Canada, 7–12 May 2011; Association for Computing Machinery: New York, NY, USA, 2011; pp. 1071–1080.
72. Torrey, C.; Burke, M.; Lee, M.; Dey, A.; Fussell, S.; Kiesler, S. Connected Giving: Ordinary People Coordinating Disaster Relief on the Internet. In Proceedings of the 2007 40th Annual Hawaii International Conference on System Sciences (HICSS'07), Waikoloa, HI, USA; 2007; p. 179a.
73. Jaeger, P.T.; Shneiderman, B.; Fleischmann, K.R.; Preece, J.; Qu, Y.; Fei Wu, P. Community Response Grids: E-Government, Social Networks, and Effective Emergency Management. *Telecommun. Policy* **2007**, *31*, 592–604. [CrossRef]
74. Wang, Z.; Song, H.; Watkins, D.W.; Ong, K.G.; Xue, P.; Yang, Q.; Shi, X. Cyber-Physical Systems for Water Sustainability: Challenges and Opportunities. *IEEE Commun. Mag.* **2015**, *53*, 216–222. [CrossRef]
75. Gunes, V.; Peter, S.; Givargis, T.; Vahid, F. A Survey on Concepts, Applications, and Challenges in Cyber-Physical Systems. *KSII Trans. Internet Inf. Syst.* **2014**, *8*, 4242–4268. [CrossRef]
76. Gelenbe, E.; Wu, F.-J. Future Research on Cyber-Physical Emergency Management Systems. *Future Internet* **2013**, *5*, 336–354. [CrossRef]
77. Liang, X.; Shetty, S.; Tosh, D.; Kamhoua, C.; Kwiat, K.; Njilla, L. ProvChain: A Blockchain-Based Data Provenance Architecture in Cloud Environment with Enhanced Privacy and Availability. In Proceedings of the 2017 17th IEEE/ACM International Symposium on Cluster, Cloud and Grid Computing (CCGRID), Madrid, Spain, 14–17 May 2017; pp. 468–477.

78. Anderson, A.; Boppana, A.; Wall, R.; Acemyan, C.Z.; Adolf, J.; Klaus, D. Framework for Developing Alternative Reality Environments to Engineer Large, Complex Systems. *Virtual Real.* **2021**, *25*, 147–163. [CrossRef]
79. Escribano Macias, J.; Angeloudis, P.; Ochieng, W. Optimal Hub Selection for Rapid Medical Deliveries Using Unmanned Aerial Vehicles. *Transp. Res. Part C Emerg. Technol.* **2020**, *110*, 56–80. [CrossRef]
80. Nedjati, A.; Izbirak, G.; Vizvari, B.; Arkat, J. Complete Coverage Path Planning for a Multi-UAV Response System in Post-Earthquake Assessment. *Robotics* **2016**, *5*, 26. [CrossRef]
81. Rabta, B.; Wankmüller, C.; Reiner, G. A Drone Fleet Model for Last-Mile Distribution in Disaster Relief Operations. *Int. J. Disaster Risk Reduct.* **2018**, *28*, 107–112. [CrossRef]
82. Gärtner, A.C.; Ferriero, D.; Bayrak, A.E.; Papalambros, P.Y. Integrated System Design of a Modular, Autonomous, Aerial and Ground Vehicle Fleet for Disaster Relief Missions—A Case Study. In Proceedings of the DS 92: DESIGN 2018 15th International Design Conference, Dubrovnik, Croatia, 21–24 May 2018; pp. 735–746. Available online: https://www.designsociety.org/publication/40488/INTEGRATED+SYSTEM+DESIGN+OF+A+MODULAR%2C+AUTONOMOUS%2C+AERIAL+AND+GROUND+VEHICLE+FLEET+FOR+DISASTER+RELIEF+MISSIONS+-+A+CASE+STUDY (accessed on 12 April 2023).
83. Lei, T.; Zhang, Y.; Wang, X.; Fu, J.; Li, L.; Pang, Z.; Zhang, X.; Kan, G. The Application of Unmanned Aerial Vehicle Remote Sensing for Monitoring Secondary Geological Disasters after Earthquakes. In Proceedings of the Ninth International Conference on Digital Image Processing (ICDIP 2017), Hong Kong, China, 19–22 May 2017; SPIE: Bellingham, WA, USA, 2017; Volume 10420, pp. 736–742.
84. Oruc, B.E.; Kara, B.Y. Post-Disaster Assessment Routing Problem. *Transp. Res. Part B Methodol.* **2018**, *116*, 76–102. [CrossRef]
85. Kim, D.; Lee, K.; Moon, I. Stochastic Facility Location Model for Drones Considering Uncertain Flight Distance. *Ann. Oper. Res.* **2019**, *283*, 1283–1302. [CrossRef]
86. Reynaud, L.; Guérin-Lassous, I. Physics-Based Swarm Intelligence for Disaster Relief Communications. In Proceedings of the Ad-hoc, Mobile, and Wireless Networks, Lille, France, 4–6 July 2016; Mitton, N., Loscri, V., Mouradian, A., Eds.; Springer: Cham, Switzerland, 2016; pp. 93–107.
87. Dille, M.; Singh, S. Efficient Aerial Coverage Search in Road Networks. In Proceedings of the AIAA Guidance, Navigation, and Control (GNC) Conference, Boston, MA, USA, 19–22 August 2013; American Institute of Aeronautics and Astronautics: Boston, MA, USA, 2013.
88. Oh, H.; Kim, S.; Tsourdos, A.; White, B.A. Coordinated Road-Network Search Route Planning by a Team of UAVs. *Int. J. Syst. Sci.* **2014**, *45*, 825–840. [CrossRef]
89. Torres, M.; Pelta, D.A.; Verdegay, J.L.; Torres, J.C. Coverage Path Planning with Unmanned Aerial Vehicles for 3D Terrain Reconstruction. *Expert Syst. Appl.* **2016**, *55*, 441–451. [CrossRef]
90. Avellar, G.S.C.; Pereira, G.A.S.; Pimenta, L.C.A.; Iscold, P. Multi-UAV Routing for Area Coverage and Remote Sensing with Minimum Time. *Sensors* **2015**, *15*, 27783–27803. [CrossRef]
91. Sujit, P.B.; Saripalli, S.; Sousa, J.B. Unmanned Aerial Vehicle Path Following: A Survey and Analysis of Algorithms for Fixed-Wing Unmanned Aerial Vehicless. *IEEE Control Syst. Mag.* **2014**, *34*, 42–59. [CrossRef]
92. Lanillos, P.; Gan, S.K.; Besada-Portas, E.; Pajares, G.; Sukkarieh, S. Multi-UAV Target Search Using Decentralized Gradient-Based Negotiation with Expected Observation. *Inf. Sci.* **2014**, *282*, 92–110. [CrossRef]
93. Ji, X.; Wang, X.; Niu, Y.; Shen, L. Cooperative Search by Multiple Unmanned Aerial Vehicles in a Nonconvex Environment. *Math. Probl. Eng.* **2015**, *2015*, e196730. [CrossRef]
94. Yang, H.; Ruby, R.; Pham, Q.-V.; Wu, K. Aiding a Disaster Spot via Multi-UAV-Based IoT Networks: Energy and Mission Completion Time-Aware Trajectory Optimization. *IEEE Internet Things J.* **2022**, *9*, 5853–5867. [CrossRef]
95. Murray, C.C.; Chu, A.G. The Flying Sidekick Traveling Salesman Problem: Optimization of Drone-Assisted Parcel Delivery. *Transp. Res. Part C Emerg. Technol.* **2015**, *54*, 86–109. [CrossRef]
96. Mechali, O.; Xu, L.; Wei, M. *UAV Path Planning: Technical Report*; University of Electronic Science and Technology of China: Chengdu, China, 2018.
97. Gasparetto, A.; Boscariol, P.; Lanzutti, A.; Vidoni, R. Path Planning and Trajectory Planning Algorithms: A General Overview. In *Motion and Operation Planning of Robotic Systems: Background and Practical Approaches*; Carbone, G., Gomez-Bravo, F., Eds.; Mechanisms and Machine Science; Springer: Cham, Switzerland, 2015; pp. 3–27. ISBN 978-3-319-14705-5.
98. Khamis, A.; Hussein, A.; Elmogy, A. Multi-Robot Task Allocation: A Review of the State-of-the-Art. In *Cooperative Robots and Sensor Networks 2015*; Koubâa, A., Martínez-de Dios, J.R., Eds.; Studies in Computational Intelligence; Springer: Cham, Switzerland, 2015; pp. 31–51. ISBN 978-3-319-18299-5.
99. Miao, Y.; Zhong, L.; Yin, Y.; Zou, C.; Luo, Z. Research on Dynamic Task Allocation for Multiple Unmanned Aerial Vehicles. *Trans. Inst. Meas. Control* **2017**, *39*, 466–474. [CrossRef]
100. Peng, K.; Lin, F.; Chen, B.M. Online Schedule for Autonomy of Multiple Unmanned Aerial Vehicles. *Sci. China Inf. Sci.* **2017**, *60*, 072203. [CrossRef]
101. Peters, J.R.; Bertuccelli, L.F. Robust Task Scheduling for Multi-Operator Supervisory Control Missions. *J. Aerosp. Inf. Syst.* **2016**, *13*, 393–406. [CrossRef]
102. Torabbeigi, M.; Lim, G.J.; Kim, S.J. Drone Delivery Scheduling Optimization Considering Payload-Induced Battery Consumption Rates. *J. Intell. Robot. Syst.* **2020**, *97*, 471–487. [CrossRef]

103. Xia, J.; Wang, K.; Wang, S. Drone Scheduling to Monitor Vessels in Emission Control Areas. *Transp. Res. Part B Methodol.* **2019**, *119*, 174–196. [CrossRef]
104. Mbiadou Saleu, R.G.; Deroussi, L.; Feillet, D.; Grangeon, N.; Quilliot, A. The Parallel Drone Scheduling Problem with Multiple Drones and Vehicles. *Eur. J. Oper. Res.* **2022**, *300*, 571–589. [CrossRef]
105. Ghelichi, Z. Drone Location and Scheduling Problems in Humanitarian Logistics. *Electron. Diss.* 2021. [CrossRef]
106. Jondhale, S.R.; Maheswar, R.; Lloret, J. Fundamentals of Wireless Sensor Networks. In *Received Signal Strength Based Target Localization and Tracking Using Wireless Sensor Networks*; Jondhale, S.R., Maheswar, R., Lloret, J., Eds.; EAI/Springer Innovations in Communication and Computing; Springer: Cham, Switzerland, 2022; pp. 1–19. ISBN 978-3-030-74061-0.
107. Dargie, W.; Poellabauer, C. *Fundamentals of Wireless Sensor Networks: Theory and Practice*; John Wiley & Sons: Hoboken, NJ, USA, 2010; ISBN 978-0-470-97568-8.
108. Griffin, B.; Detweiler, C. Resonant Wireless Power Transfer to Ground Sensors from a UAV. In Proceedings of the 2012 IEEE International Conference on Robotics and Automation, St Paul, MN, USA, 14–18 May 2012; pp. 2660–2665.
109. Hui, S.Y.R.; Zhong, W.; Lee, C.K. A Critical Review of Recent Progress in Mid-Range Wireless Power Transfer. *IEEE Trans. Power Electron.* **2014**, *29*, 4500–4511. [CrossRef]
110. Mase, K. How to Deliver Your Message from/to a Disaster Area. *IEEE Commun. Mag.* **2011**, *49*, 52–57. [CrossRef]
111. Duong, T.Q.; Nguyen, L.D.; 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.
112. Deepak, G.C.; Ladas, A.; Sambo, Y.A.; Pervaiz, H.; Politis, C.; Imran, M.A. An Overview of Post-Disaster Emergency Communication Systems in the Future Networks. *IEEE Wirel. Commun.* **2019**, *26*, 132–139. [CrossRef]
113. Mozaffari, M.; Saad, W.; Bennis, M.; Debbah, M. Unmanned Aerial Vehicle with Underlaid Device-to-Device Communications: Performance and Tradeoffs. *IEEE Trans. Wirel. Commun.* **2016**, *15*, 3949–3963. [CrossRef]
114. Pang, Y.; Zhang, Y.; Gu, Y.; Pan, M.; Han, Z.; Li, P. Efficient Data Collection for Wireless Rechargeable Sensor Clusters in Harsh Terrains Using UAVs. In Proceedings of the 2014 IEEE Global Communications Conference, Austin, TX, USA, 8–12 December 2014; pp. 234–239.
115. Mozaffari, M.; Saad, W.; Bennis, M.; Debbah, M. Mobile Internet of Things: Can UAVs Provide an Energy-Efficient Mobile Architecture? In Proceedings of the 2016 IEEE Global Communications Conference (GLOBECOM), Washington, DC, USA, 4–8 December 2016; pp. 1–6.
116. Choi, D.H.; Kim, S.H.; Sung, D.K. Energy-Efficient Maneuvering and Communication of a Single UAV-Based Relay. *IEEE Trans. Aerosp. Electron. Syst.* **2014**, *50*, 2320–2327. [CrossRef]
117. Caunhye, A.M.; Nie, X.; Pokharel, S. Optimization Models in Emergency Logistics: A Literature Review. *Socio-Econ. Plan. Sci.* **2012**, *46*, 4–13. [CrossRef]
118. Priya, P.; Kamlu, S.S. *Robust Control Algorithm for Drones*; IntechOpen: London, UK, 2022; ISBN 978-1-80355-301-6.
119. Kruse, R.; Mostaghim, S.; Borgelt, C.; Braune, C.; Steinbrecher, M. *Computational Intelligence: A Methodological Introduction*; Springer: Cham, Switzerland, 2022; ISBN 978-3-030-42227-1.
120. Sahil; Sood, S.K. Fog-Assisted Energy Efficient Cyber Physical System for Panic-Based Evacuation during Disasters. *Comput. J.* **2022**, *65*, 1540–1559. [CrossRef]
121. 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]
122. Park, K.-N.; Kang, J.-H.; Cho, B.-M.; Park, K.-J.; Kim, H. Handover Management of Net-Drones for Future Internet Platforms. *Int. J. Distrib. Sens. Netw.* **2016**, *12*, 5760245. [CrossRef]
123. Jawhar, I.; Mohamed, N.; Al-Jaroodi, J.; Agrawal, D.P.; Zhang, S. Communication and Networking of UAV-Based Systems: Classification and Associated Architectures. *J. Netw. Comput. Appl.* **2017**, *84*, 93–108. [CrossRef]
124. Liang, Y.; Xu, W.; Liang, W.; Peng, J.; Jia, X.; Zhou, Y.; Duan, L. Nonredundant Information Collection in Rescue Applications via an Energy-Constrained UAV. *IEEE Internet Things J.* **2019**, *6*, 2945–2958. [CrossRef]
125. Li, J.; Kacimi, R.; Liu, T.; Ma, X.; Dhaou, R. Non-Terrestrial Networks-Enabled Internet of Things: UAV-Centric Architectures, Applications, and Open Issues. *Drones* **2022**, *6*, 95. [CrossRef]
126. Liu, M.; Yang, J.; Gui, G. DSF-NOMA: UAV-Assisted Emergency Communication Technology in a Heterogeneous Internet of Things. *IEEE Internet Things J.* **2019**, *6*, 5508–5519. [CrossRef]
127. Liu, X.; Li, Z.; Zhao, N.; Meng, W.; Gui, G.; Chen, Y.; Adachi, F. Transceiver Design and Multihop D2D for UAV IoT Coverage in Disasters. *IEEE Internet Things J.* **2019**, *6*, 1803–1815. [CrossRef]
128. Liu, X.; Ansari, N. Resource Allocation in UAV-Assisted M2M Communications for Disaster Rescue. *IEEE Wirel. Commun. Lett.* **2019**, *8*, 580–583. [CrossRef]
129. Na, Z.; Liu, Y.; Shi, J.; Liu, C.; Gao, Z. UAV-Supported Clustered NOMA for 6G-Enabled Internet of Things: Trajectory Planning and Resource Allocation. *IEEE Internet Things J.* **2021**, *8*, 15041–15048. [CrossRef]
130. Sikeridis, D.; Tsiropoulou, E.E.; Devetsikiotis, M.; Papavassiliou, S. Wireless Powered Public Safety IoT: A UAV-Assisted Adaptive-Learning Approach towards Energy Efficiency. *J. Netw. Comput. Appl.* **2018**, *123*, 69–79. [CrossRef]
131. Feng, W.; Tang, J.; Yu, Y.; Song, J.; Zhao, N.; Chen, G.; Wong, K.-K.; Chambers, J. UAV-Enabled SWIPT in IoT Networks for Emergency Communications. *IEEE Wirel. Commun.* **2020**, *27*, 140–147. [CrossRef]

132. Trotta, A.; Montecchiari, L.; Felice, M.D.; Bononi, L. A GPS-Free Flocking Model for Aerial Mesh Deployments in Disaster-Recovery Scenarios. *IEEE Access* **2020**, *8*, 91558–91573. [CrossRef]
133. Sacco, A.; Flocco, M.; Esposito, F.; Marchetto, G. An Architecture for Adaptive Task Planning in Support of IoT-Based Machine Learning Applications for Disaster Scenarios. *Comput. Commun.* **2020**, *160*, 769–778. [CrossRef]
134. Saif, A.; Dimyati, K.; Noordin, K.A.; Shah, N.S.M.; Alsamhi, S.H.; Abdullah, Q. Energy-Efficient Tethered UAV Deployment in B5G for Smart Environments and Disaster Recovery. In Proceedings of the 2021 1st International Conference on Emerging Smart Technologies and Applications (eSmarTA), Sana'a, Yemen, 10–12 August 2021; pp. 1–5.
135. Zhang, L.; Zhang, Z.-Y.; Min, L.; Tang, C.; Zhang, H.-Y.; Wang, Y.-H.; Cai, P. Task Offloading and Trajectory Control for UAV-Assisted Mobile Edge Computing Using Deep Reinforcement Learning. *IEEE Access* **2021**, *9*, 53708–53719. [CrossRef]
136. Na, Z.; Mao, B.; Shi, J.; Wang, J.; Gao, Z.; Xiong, M. Joint Trajectory and Power Optimization for UAV-Relay-Assisted Internet of Things in Emergency. *Phys. Commun.* **2020**, *41*, 101100. [CrossRef]
137. Hassija, V.; Saxena, V.; Chamola, V. A Blockchain-Based Framework for Drone-Mounted Base Stations in Tactile Internet Environment. In Proceedings of the IEEE INFOCOM 2020—IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS), Toronto, ON, Canada, 6–9 July 2020; pp. 261–266.
138. Seid, A.M.; Boateng, G.O.; Mareri, B.; Sun, G.; Jiang, W. Multi-Agent DRL for Task Offloading and Resource Allocation in Multi-UAV Enabled IoT Edge Network. *IEEE Trans. Netw. Serv. Manag.* **2021**, *18*, 4531–4547. [CrossRef]
139. Avanzato, R.; Beritelli, F. An Innovative Technique for Identification of Missing Persons in Natural Disaster Based on Drone-Femtocell Systems. *Sensors* **2019**, *19*, 4547. [CrossRef] [PubMed]
140. Tran, D.-H.; Nguyen, V.-D.; Chatzinotas, S.; Vu, T.X.; Ottersten, B. UAV Relay-Assisted Emergency Communications in IoT Networks: Resource Allocation and Trajectory Optimization. *IEEE Trans. Wirel. Commun.* **2022**, *21*, 1621–1637. [CrossRef]
141. Almalki, F.A.; Soufiene, B.O. Modifying Hata-Davidson Propagation Model for Remote Sensing in Complex Environments Using a Multifactional Drone. *Sensors* **2022**, *22*, 1786. [CrossRef]
142. Mao, S.; He, S.; Wu, J. Joint UAV Position Optimization and Resource Scheduling in Space-Air-Ground Integrated Networks With Mixed Cloud-Edge Computing. *IEEE Syst. J.* **2021**, *15*, 3992–4002. [CrossRef]
143. Jia, Z.; Wu, Q.; Dong, C.; Yuen, C.; Han, Z. Hierarchical Aerial Computing for Internet of Things via Cooperation of HAPs and UAVs. *IEEE Internet Things J.* **2022**, *10*, 5676–5688. [CrossRef]
144. Shimada, H.; Kawamoto, Y.; Kato, N. Novel Computation and Communication Resources Allocation Using Relay Communications in UAV-Mounted Cloudlet Systems. *IEEE Trans. Netw. Sci. Eng.* **2021**, *8*, 3140–3151. [CrossRef]
145. Ferranti, L.; D'Oro, S.; Bonati, L.; Cuomo, F.; Melodia, T. HIRO-NET: Heterogeneous Intelligent Robotic Network for Internet Sharing in Disaster Scenarios. *IEEE Trans. Mob. Comput.* **2022**, *21*, 4367–4380. [CrossRef]
146. Niu, Z.; Liu, H.; Lin, X.; Du, J. Task Scheduling With UAV-Assisted Dispersed Computing for Disaster Scenario. *IEEE Syst. J.* **2022**, *16*, 6429–6440. [CrossRef]
147. Dai, B.; Niu, J.; Ren, T.; Hu, Z.; Atiquzzaman, M. Towards Energy-Efficient Scheduling of UAV and Base Station Hybrid Enabled Mobile Edge Computing. *IEEE Trans. Veh. Technol.* **2022**, *71*, 915–930. [CrossRef]
148. Sun, Y.; Xu, D.; Huang, Z.; Zhang, H.; Liang, X. LIDAUS: Localization of IoT Device via Anchor UAV SLAM. In Proceedings of the 2020 IEEE 39th International Performance Computing and Communications Conference (IPCCC), Austin, TX, USA, 6–8 November 2020; pp. 1–11.
149. Esposito, C.; Zhao, Z.; Alcarria, R.; Rizzo, G. Game Theoretic Optimal User Association in Emergency Networks. In Proceedings of the Ad-Hoc, Mobile, and Wireless Networks, Luxembourg, 1–3 October 2019; Palattella, M.R., Scanzio, S., Coleri Ergen, S., Eds.; Springer: Cham, Switzerland, 2019; pp. 18–31.
150. Rael, K.; Fragkos, G.; Plusquellic, J.; Tsiropoulou, E.E. UAV-Enabled Human Internet of Things. In Proceedings of the 2020 16th International Conference on Distributed Computing in Sensor Systems (DCOSS), Marina del Rey, CA, USA, 25–27 May 2020; pp. 312–319.
151. Khan, A.; Zhang, J.; Ahmad, S.; Memon, S.; Qureshi, H.A.; Ishfaq, M. Dynamic Positioning and Energy-Efficient Path Planning for Disaster Scenarios in 5G-Assisted Multi-UAV Environments. *Electronics* **2022**, *11*, 2197. [CrossRef]
152. Muthanna, M.S.A.; Muthanna, A.; Nguyen, T.N.; Alshahrani, A.; Abd El-Latif, A.A. Towards Optimal Positioning and Energy-Efficient UAV Path Scheduling in IoT Applications. *Comput. Commun.* **2022**, *191*, 145–160. [CrossRef]
153. Xing, R.; Su, Z.; Luan, T.H.; Xu, Q.; Wang, Y.; Li, R.; Benslimane, A. UAVs Assisted Secure Blockchain Offline Transactions for V2V Charging Among Electric Vehicles in Disaster Area. In Proceedings of the ICC 2022—IEEE International Conference on Communications, Seoul, Republic of Korea, 16–20 May 2022; pp. 4211–4216.
154. Zhang, L.; Jabbari, B.; Ansari, N. Deep Reinforcement Learning Driven UAV-Assisted Edge Computing. *IEEE Internet Things J.* **2022**, *9*, 25449–25459. [CrossRef]
155. Shen, S.; Ma, Z.; Liu, M.; Liu, Q.; Bai, Y.; Xiong, M. A Cloud-Terminal Collaborative System for Crowd Counting and Localization Using Multi-UAVs. In Proceedings of the IEEE INFOCOM 2022—IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS), New York, NY, USA, 2–5 May 2022; pp. 1–6.
156. Yu, X.-Y.; Niu, W.-J.; Zhu, Y.; Zhu, H.-B. UAV-Assisted Cooperative Offloading Energy Efficiency System for Mobile Edge Computing. *Digit. Commun. Netw.* 2022. [CrossRef]
157. Barick, S.; Singhal, C. Multi-UAV Assisted IoT NOMA Uplink Communication System for Disaster Scenario. *IEEE Access* **2022**, *10*, 34058–34068. [CrossRef]

158. Chen, R.; Sun, Y.; Liang, L.; Cheng, W. Joint Power Allocation and Placement Scheme for UAV-Assisted IoT With QoS Guarantee. *IEEE Trans. Veh. Technol.* **2022**, *71*, 1066–1071. [CrossRef]
159. Ghosh, S.; Roy, S.D.; Kundu, S. A T-BS and a UAV Based IoT Enabled D2D Network for Disaster Management. In Proceedings of the 2021 IEEE 18th India Council International Conference (INDICON), Guwahati, India, 19–21 December 2021; pp. 1–7.
160. Ding, Y.; Yu, P.; Li, W.; Feng, L.; Zhou, F. Optimal Deployment Methods of Multi-UAVs for Capacity Enhancement under Weak Coverage. In Proceedings of the 2021 Computing, Communications and IoT Applications (ComComAp), Shenzhen, China, 26–28 November 2021; pp. 280–285.
161. Zhang, Z.; Cui, Q.; Li, X.; Li, X.; Tao, X. Satellite/UAV-Assisted Computing and Offloading IoT Networks with Spectrum Sharing: An Energy-Efficient Design. In Proceedings of the 2021 26th IEEE Asia-Pacific Conference on Communications (APCC), Kuala Lumpur, Malaysia, 11–13 October 2021; pp. 185–191.
162. Lee, I.; Babu, V.; Caesar, M.; Nicol, D. Deep Reinforcement Learning for UAV-Assisted Emergency Response. In Proceedings of the MobiQuitous 2020—17th EAI International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services, Darmstadt, Germany, 7–9 December 2020; Association for Computing Machinery: New York, NY, USA, 2021; pp. 327–336.
163. Wang, X.; Hu, J.; Lin, H. An Intelligent UAV Based Data Aggregation Strategy for IoT after Disaster Scenarios. In Proceedings of the 2nd ACM MobiCom Workshop on Drone Assisted Wireless Communications for 5G and Beyond, London, UK, 25 September 2020; Association for Computing Machinery: New York, NY, USA, 2020; pp. 97–101.
164. Shimaday, H.; Kawamotoy, Y.; Katoy, N. Novel Workload Balancing Method for UAV-Based Edge Cloud Computing Systems with Handover. In Proceedings of the ICC 2020–2020 IEEE International Conference on Communications (ICC), Dublin, Ireland, 7–11 June 2020; pp. 1–6.
165. Li, X.; Xing, L. Efficient Optimal Backhaul-Aware Placement of Multiple Drone-Cells Based on Genetic Algorithm. In Proceedings of the 2019 IEEE International Conference on Robotics and Biomimetics (ROBIO), Dali, China, 6–8 December 2019; pp. 332–339.
166. Feng, W.; Tang, J.; Zhao, N.; Fu, Y.; Zhang, X.; Cumanan, K.; Wong, K.-K. NOMA-Based UAV-Aided Networks for Emergency Communications. *China Commun.* **2020**, *17*, 54–66. [CrossRef]
167. Bushnaq, O.M.; Chaaban, A.; Al-Naffouri, T.Y. The Role of UAV-IoT Networks in Future Wildfire Detection. *IEEE Internet Things J.* **2021**, *8*, 16984–16999. [CrossRef]
168. Karunanithy, K.; Bhanumathi, V. Unmanned Aerial Vehicle Based Reliable and Energy Efficient Data Collection from Red Alerted Area Using Wireless Sensor Networks with IoT. *J. Inf. Sci. Eng.* **2019**, *35*, 521–536. [CrossRef]
169. Abdelhamid, S. UAV Path Planning for Emergency Management in IoT. In Proceedings of the 2018 IEEE International Conference on Communications Workshops (ICC Workshops), Kansas City, MO, USA, 20–24 May 2018; pp. 1–6.
170. Van Huynh, D.; Do-Duy, T.; Nguyen, L.D.; Le, M.-T.; Vo, N.-S.; Duong, T.Q. Real-Time Optimized Path Planning and Energy Consumption for Data Collection in Unmanned Ariel Vehicles-Aided Intelligent Wireless Sensing. *IEEE Trans. Ind. Inform.* **2022**, *18*, 2753–2761. [CrossRef]
171. Kumar, J.S.; Pandey, S.K.; Zaveri, M.A.; Choksi, M. Geo-Fencing Technique in Unmanned Aerial Vehicles for Post Disaster Management in the Internet of Things. In Proceedings of the 2019 Second International Conference on Advanced Computational and Communication Paradigms (ICACCP), Gangtok, India, 25–28 February 2019; pp. 1–6.
172. Li, G.; He, B.; Wang, Z.; Cheng, X.; Chen, J. Blockchain-Enhanced Spatiotemporal Data Aggregation for UAV-Assisted Wireless Sensor Networks. *IEEE Trans. Ind. Inform.* **2022**, *18*, 4520–4530. [CrossRef]
173. Nguyen, L.-M.-D.; Vo, V.N.; So-In, C.; Dang, V.-H. Throughput Analysis and Optimization for NOMA Multi-UAV Assisted Disaster Communication Using CMA-ES. *Wirel. Netw* **2021**, *27*, 4889–4902. [CrossRef]
174. Arafat, M.Y.; Moh, S. Localization and Clustering Based on Swarm Intelligence in UAV Networks for Emergency Communications. *IEEE Internet Things J.* **2019**, *6*, 8958–8976. [CrossRef]
175. Arafat, M.Y.; Moh, S. Bio-Inspired Approaches for Energy-Efficient Localization and Clustering in UAV Networks for Monitoring Wildfires in Remote Areas. *IEEE Access* **2021**, *9*, 18649–18669. [CrossRef]
176. Ma, B.; Ren, Z.; Cheng, W. Credibility Computation Offloading Based Task-Driven Routing Strategy for Emergency UAVs Network. In Proceedings of the 2021 IEEE Global Communications Conference (GLOBECOM), Madrid, Spain, 7–11 December 2021; pp. 1–6.
177. Su, Z.; Wang, Y.; Xu, Q.; Zhang, N. LVBS: Lightweight Vehicular Blockchain for Secure Data Sharing in Disaster Rescue. *IEEE Trans. Dependable Secur. Comput.* **2022**, *19*, 19–32. [CrossRef]
178. Pokhrel, S.R. Federated Learning Meets Blockchain at 6G Edge: A Drone-Assisted Networking for Disaster Response. In Proceedings of the 2nd ACM MobiCom Workshop on Drone Assisted Wireless Communications for 5G and Beyond, London UK, 25 September 2020; Association for Computing Machinery: New York, NY, USA, 2020; pp. 49–54.
179. Tipantuña, C.; Hesselbach, X.; Sánchez-Aguero, V.; Valera, F.; Vidal, I.; Nogales, B. An NFV-Based Energy Scheduling Algorithm for a 5G Enabled Fleet of Programmable Unmanned Aerial Vehicles. *Wirel. Commun. Mob. Comput.* **2019**, *2019*, e4734821. [CrossRef]
180. Sliwa, B.; Schüler, C.; Patchou, M.; Wietfeld, C. PARRoT: Predictive Ad-Hoc Routing Fueled by Reinforcement Learning and Trajectory Knowledge. In Proceedings of the 2021 IEEE 93rd Vehicular Technology Conference (VTC2021-Spring), Helsinki, Finland, 25–28 April 2021; pp. 1–7.

181. Bharany, S.; Sharma, S.; Frnda, J.; Shuaib, M.; Khalid, M.I.; Hussain, S.; Iqbal, J.; Ullah, S.S. Wildfire Monitoring Based on Energy Efficient Clustering Approach for FANETS. *Drones* **2022**, *6*, 193. [CrossRef]
182. Shehzad, M.K.; Hassan, S.A.; Luque-Nieto, M.A.; Otero, P. UAV Trajectory Optimization and Choice for UAV Placement for Data Collection in Beyond 5G Networks. In *Intelligent Unmanned Air Vehicles Communications for Public Safety Networks*; Kaleem, Z., Ahmad, I., Duong, T.Q., Eds.; Unmanned System Technologies; Springer: Singapore, 2022; pp. 133–144. ISBN 978-981-19129-2-4.
183. Cheng, N.; Lyu, F.; Quan, W.; Zhou, C.; He, H.; Shi, W.; Shen, X. Space/Aerial-Assisted Computing Offloading for IoT Applications: A Learning-Based Approach. *IEEE J. Sel. Areas Commun.* **2019**, *37*, 1117–1129. [CrossRef]
184. Aljehani, M.; Inoue, M.; Watanbe, A.; Yokemura, T.; Ogyu, F.; Iida, H. UAV Communication System Integrated into Network Traversal with Mobility. *SN Appl. Sci.* **2020**, *2*, 1057. [CrossRef]
185. Prathiba, S.B.; Raja, G.; Anbalagan, S.; Narayanan, R.; Venkata Karthik, K.B. SOSChain: Self Optimizing Streamchain for Last-Mile 6G UAV-Truck Networks. In Proceedings of the 1st Workshop on Artificial Intelligence and Blockchain Technologies for Smart Cities with 6G, New Orleans, LA, USA, 25–29 October 2021; Association for Computing Machinery: New York, NY, USA, 2021; pp. 19–24.
186. Mao, Y.; You, C.; Zhang, J.; Huang, K.; Letaief, K.B. A Survey on Mobile Edge Computing: The Communication Perspective. *IEEE Commun. Surv. Tutor.* **2017**, *19*, 2322–2358. [CrossRef]
187. Cheng, N.; Xu, W.; Shi, W.; Zhou, Y.; Lu, N.; Zhou, H.; Shen, X. Air-Ground Integrated Mobile Edge Networks: Architecture, Challenges, and Opportunities. *IEEE Commun. Mag.* **2018**, *56*, 26–32. [CrossRef]
188. Kim, K.; Hong, C.S. Optimal Task-UAV-Edge Matching for Computation Offloading in UAV Assisted Mobile Edge Computing. In Proceedings of the 2019 20th Asia-Pacific Network Operations and Management Symposium (APNOMS), Matsue, Japan, 18–20 September 2019; pp. 1–4.
189. Xu, J.; Ota, K.; Dong, M. Big Data on the Fly: UAV-Mounted Mobile Edge Computing for Disaster Management. *IEEE Trans. Netw. Sci. Eng.* **2020**, *7*, 2620–2630. [CrossRef]
190. Sacco, A.; Esposito, F.; Marchetto, G. Resource Inference for Task Migration in Challenged Edge Networks with RITMO. In Proceedings of the 2020 IEEE 9th International Conference on Cloud Networking (CloudNet), Piscataway, NJ, USA, 9–11 November 2020; pp. 1–7.
191. Ventrella, A.V.; Esposito, F.; Sacco, A.; Flocco, M.; Marchetto, G.; Gururajan, S. APRON: An Architecture for Adaptive Task Planning of Internet of Things in Challenged Edge Networks. In Proceedings of the 2019 IEEE 8th International Conference on Cloud Networking (CloudNet), Coimbra, Portugal, 4–6 November 2019; pp. 1–6.
192. Cheikhrouhou, O.; Koubaa, A.; Zarrad, A. A Cloud Based Disaster Management System. *J. Sens. Actuator Netw.* **2020**, *9*, 6. [CrossRef]
193. Wang, Y.; Su, Z.; Xu, Q.; Li, R.; Luan, T.H. Lifesaving with RescueChain: Energy-Efficient and Partition-Tolerant Blockchain Based Secure Information Sharing for UAV-Aided Disaster Rescue. In Proceedings of the IEEE INFOCOM 2021—IEEE Conference on Computer Communications, Vancouver, BC, Canada, 10–13 May 2021; pp. 1–10.
194. Rashid, M.T.; Zhang, D.Y.; Shang, L.; Wang, D. SEAD: Towards A Social-Media-Driven Energy-Aware Drone Sensing Framework. In Proceedings of the 2019 IEEE 25th International Conference on Parallel and Distributed Systems (ICPADS), Tianjin, China, 4–6 December 2019; pp. 647–654.
195. Rashid, M.T.; Zhang, Y.; Zhang, D.; Wang, D. CompDrone: Towards Integrated Computational Model and Social Drone Based Wildfire Monitoring. In Proceedings of the 2020 16th International Conference on Distributed Computing in Sensor Systems (DCOSS), Marina del Rey, CA, USA, 25–27 May 2020; pp. 43–50.
196. Rashid, M.T.; Zhang, D.Y.; Wang, D. SocialDrone: An Integrated Social Media and Drone Sensing System for Reliable Disaster Response. In Proceedings of the IEEE INFOCOM 2020—IEEE Conference on Computer Communications, Toronto, ON, Canada, 6–9 July 2020; pp. 218–227.
197. Rashid, M.T.; Zhang, D.; Liu, Z.; Lin, H.; Wang, D. CollabDrone: A Collaborative Spatiotemporal-Aware Drone Sensing System Driven by Social Sensing Signals. In Proceedings of the 2019 28th International Conference on Computer Communication and Networks (ICCCN), Valencia, Spain, 29 July–1 August 2019; pp. 1–9.
198. Terzi, M.; Kolios, P.; Panayiotou, C.; Theocharides, T. Towards a Social-Media Driven Multi-Drone Tasking Platform. In Proceedings of the 2020 International Conference on Unmanned Aircraft Systems (ICUAS), Athens, Greece, 1–4 September 2020; pp. 573–581.
199. Attari, N.; Ofli, F.; Awad, M.; Lucas, J.; Chawla, S. Nazr-CNN: Fine-Grained Classification of UAV Imagery for Damage Assessment. In Proceedings of the 2017 IEEE International Conference on Data Science and Advanced Analytics (DSAA), Tokyo, Japan, 19–21 October 2017; pp. 50–59.
200. Wang, H.; Liu, C.H.; Dai, Z.; Tang, J.; Wang, G. Energy-Efficient 3D Vehicular Crowdsourcing for Disaster Response by Distributed Deep Reinforcement Learning. In Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining, San Francisco, CA, USA, 13–17 August 2016; Association for Computing Machinery: New York, NY, USA, 2021; pp. 3679–3687.
201. Zhou, F.; Huang, J.; Sun, B.; Wen, G.; Tian, Y. Intelligent Identification Method for Natural Disasters along Transmission Lines Based on Inter-Frame Difference and Regional Convolution Neural Network. In Proceedings of the 2019 IEEE Intl Conf on Parallel & Distributed Processing with Applications, Big Data & Cloud Computing, Sustainable Computing & Communications, Social Computing & Networking (ISPA/BDCloud/SocialCom/SustainCom), Xiamen, China, 16–18 December 2019; pp. 218–222.

202. Wang, R.; Zhao, J.; Wu, W.; Chen, B.; Liu, B. Recognition and Locating of Damaged Poles in Distribution Network Through Images Shot by Unmanned Aerial Vehicle (UA V). In Proceedings of the 2020 IEEE International Conference on Information Technology, Big Data and Artificial Intelligence (ICIBA), Chongqing, China, 6–8 November 2020; Volume 1, pp. 1048–1052.
203. Xu, J.; Ota, K.; Dong, M. LUNA: Lightweight UAV Navigation Based on Airborne Vision for Disaster Management. In Proceedings of the 2019 International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData), Atlanta, GA, USA, 14–17 July 2019; pp. 315–322.
204. Popescu, D.; Ichim, L.; Stoican, F. Flooded Area Segmentation from UAV Images Based on Generative Adversarial Networks. In Proceedings of the 2018 15th International Conference on Control, Automation, Robotics and Vision (ICARCV), Singapore, 18–21 November 2018; pp. 1361–1366.
205. Na, W.; Bae, B.; Cho, S.; Kim, N. DL-TCP: Deep Learning-Based Transmission Control Protocol for Disaster 5G MmWave Networks. *IEEE Access* **2019**, *7*, 145134–145144. [CrossRef]
206. Almeshal, A.M.; Alenezi, M.R. A Vision-Based Neural Network Controller for the Autonomous Landing of a Quadrotor on Moving Targets. *Robotics* **2018**, *7*, 71. [CrossRef]
207. Morocho-Cayamcela, M.E.; Lim, W.; Maier, M. An Optimal Location Strategy for Multiple Drone Base Stations in Massive MIMO. *ICT Express* **2022**, *8*, 230–234. [CrossRef]
208. Pham, H.X.; La, H.M.; Feil-Seifer, D.; Van Nguyen, L. Reinforcement Learning for Autonomous UAV Navigation Using Function Approximation. In Proceedings of the 2018 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR), Philadelphia, PA, USA, 6–8 August 2018; pp. 1–6.
209. Hernández, D.; Cano, J.-C.; Silla, F.; Calafate, C.T.; Cecilia, J.M. AI-Enabled Autonomous Drones for Fast Climate Change Crisis Assessment. *IEEE Internet Things J.* **2022**, *9*, 7286–7297. [CrossRef]
210. Gregory, J.M.; Brookshaw, I.; Fink, J.; Gupta, S.K. An Investigation of Goal Assignment for a Heterogeneous Robotic Team to Enable Resilient Disaster-Site Exploration. In Proceedings of the 2017 IEEE International Symposium on Safety, Security and Rescue Robotics (SSRR), Shanghai, China, 11–13 October 2017; pp. 133–140.
211. Palafox, P.R.; Garzón, M.; Valente, J.; Roldán, J.J.; Barrientos, A. Robust Visual-Aided Autonomous Takeoff, Tracking, and Landing of a Small UAV on a Moving Landing Platform for Life-Long Operation. *Appl. Sci.* **2019**, *9*, 2661. [CrossRef]
212. Xiang, H.; Yi, J.; Zhou, B.; Wu, H.; Mou, J. A Study of Autonomous Landing of UAV for Mobile Platform. In Proceedings of the 2021 International Conference on Intelligent Computing, Automation and Systems (ICICAS), Chongqing, China, 29–31 December 2021; pp. 455–461.
213. Ivancevic, V.; Yue, Y. Hamiltonian Dynamics and Control of a Joint Autonomous Land–Air Operation. *Nonlinear Dyn.* **2016**, *84*, 1853–1865. [CrossRef]
214. Moore, J.; Wolfe, K.C.; Johannes, M.S.; Katyal, K.D.; Para, M.P.; Murphy, R.J.; Hatch, J.; Taylor, C.J.; Bamberger, R.J.; Tunstel, E. Nested Marsupial Robotic System for Search and Sampling in Increasingly Constrained Environments. In Proceedings of the 2016 IEEE International Conference on Systems, Man, and Cybernetics (SMC), Budapest, Hungary, 9–12 October 2016; pp. 002279–002286.
215. Ozkan, M.F.; Carrillo, L.R.G.; King, S.A. Rescue Boat Path Planning in Flooded Urban Environments. In Proceedings of the 2019 IEEE International Symposium on Measurement and Control in Robotics (ISMCR), Houston, TX, USA, 19–21 September 2019; pp. B2-2-1–B2-2-9.
216. Kiribayashi, S.; Yakushigawa, K.; Nagatani, K. Position Estimation of Tethered Micro Unmanned Aerial Vehicle by Observing the Slack Tether. In Proceedings of the 2017 IEEE International Symposium on Safety, Security and Rescue Robotics (SSRR), Shanghai, China, 11–13 October 2017; pp. 159–165.
217. Wang, N.; Zheng, J.; Tong, J.; Zhang, K. Joint Location Selection and Supply Allocation for UAV Aided Disaster Response System. In Proceedings of the Intelligent Robotics and Applications, Shenyang, China, 8–11 August 2019; Yu, H., Liu, J., Liu, L., Ju, Z., Liu, Y., Zhou, D., Eds.; Springer: Cham, Switzerland, 2019; pp. 14–26.
218. Gómez, N.; Peña, N.; Rincón, S.; Amaya, S.; Calderon, J. Leader-Follower Behavior in Multi-Agent Systems for Search and Rescue Based on PSO Approach. In Proceedings of the SoutheastCon 2022, Mobile, AL, USA, 26 March–3 April 2022; pp. 413–420.
219. Xing, R.; Su, Z.; Luan, T.H.; Xu, Q.; Wang, Y.; Li, R. UAVs-Aided Delay-Tolerant Blockchain Secure Offline Transactions in Post-Disaster Vehicular Networks. *IEEE Trans. Veh. Technol.* **2022**, *71*, 12030–12043. [CrossRef]
220. Hassija, V.; Chamola, V.; Krishna, D.N.G.; Guizani, M. A Distributed Framework for Energy Trading Between UAVs and Charging Stations for Critical Applications. *IEEE Trans. Veh. Technol.* **2020**, *69*, 5391–5402. [CrossRef]
221. Li, J.; Shang, F. Investigation into the Reliability and Encryption Performance of Wireless Signal Transmission by Network Coding Combined with Blockchain in Natural Disaster Scenarios. *Wirel. Commun. Mob. Comput.* **2022**, *2022*, e4188436. [CrossRef]
222. Betancourt, J.; Wojtkowski, B.; Castillo, P.; Thouvenin, I. Exocentric Control Scheme for Robot Applications: An Immersive Virtual Reality Approach. *IEEE Trans. Vis. Comput. Graph.* 2022. [CrossRef]
223. Wang, Y.; Liu, E. Virtual Reality Technology of Multi UAVEarthquake Disaster Path Optimization. *Math. Probl. Eng.* **2021**, *2021*, e5525560. [CrossRef]
224. Ren, X.; Sun, M.; Zhang, X.; Liu, L.; Wang, X.; Zhou, H. An AR Geo-Registration Algorithm for UAV TIR Video Streams Based on Dual-Antenna RTK-GPS. *Remote Sens.* **2022**, *14*, 2205. [CrossRef]

225. Jain, G.; Yadav, G.; Prakash, D.; Shukla, A.; Tiwari, R. MVO-Based Path Planning Scheme with Coordination of UAVs in 3-D Environment. *J. Comput. Sci.* **2019**, *37*, 101016. [CrossRef]
226. Kovacs, G.; Moshtari, M.; Kachali, H.; Polsa, P. Research Methods in Humanitarian Logistics. *J. Humanit. Logist. Supply Chain Manag.* **2019**, *9*, 325–331. [CrossRef]
227. Lewin, R.; Besiou, M.; Lamarche, J.-B.; Cahill, S.; Guerrero-Garcia, S. Delivering in a Moving World . . . looking to Our Supply Chains to Meet the Increasing Scale, Cost and Complexity of Humanitarian Needs. *J. Humanit. Logist. Supply Chain Manag.* **2018**, *8*, 518–532. [CrossRef]
228. Schiffling, S.; Hannibal, C.; Tickle, M.; Fan, Y. The Implications of Complexity for Humanitarian Logistics: A Complex Adaptive Systems Perspective. *Ann. Oper. Res.* **2022**, *319*, 1379–1410. [CrossRef]
229. Day, J.M.; Melnyk, S.A.; Larson, P.D.; Davis, E.W.; Whybark, D.C. Humanitarian and Disaster Relief Supply Chains: A Matter of Life and Death. *J. Supply Chain Manag.* **2012**, *48*, 21–36. [CrossRef]
230. Kunz, N.; Van Wassenhove, L.N.; Besiou, M.; Hambye, C.; Kovács, G. Relevance of Humanitarian Logistics Research: Best Practices and Way Forward. *Int. J. Oper. Prod. Manag.* **2017**, *37*, 1585–1599. [CrossRef]
231. Kunz, N.; Reiner, G. A Meta-analysis of Humanitarian Logistics Research. *Jrnl Hum Log Sup Chn Mnage* **2012**, *2*, 116–147. [CrossRef]
232. Kovács, G.; Spens, K.M. Humanitarian Logistics in Disaster Relief Operations. *Int. J. Phys. Distrib. Logist. Manag.* **2007**, *37*, 99–114. [CrossRef]
233. Natarajarathinam, M.; Capar, I.; Narayanan, A. Managing Supply Chains in Times of Crisis: A Review of Literature and Insights. *Int. J. Phys. Distrib. Logist. Manag.* **2009**, *39*, 535–573. [CrossRef]
234. Overstreet, R.E.; Hall, D.; Hanna, J.B.; Kelly Rainer, R. Research in Humanitarian Logistics. *J. Humanit. Logist. Supply Chain. Manag.* **2011**, *1*, 114–131. [CrossRef]
235. Kovács, G.; Spens, K.M. Trends and Developments in Humanitarian Logistics—A Gap Analysis. *Int. J. Phys. Distrib. Logist. Manag.* **2011**, *41*, 32–45. [CrossRef]
236. Besiou, M.; Stapleton, O.; Van Wassenhove, L.N. System Dynamics for Humanitarian Operations. *J. Humanit. Logist. Supply Chain Manag.* **2011**, *1*, 78–103. [CrossRef]
237. Majewski, B.; Navangul, K.A.; Heigh, I. A Peek into the Future of Humanitarian Logistics: Forewarned Is Forearmed. *Supply Chain Forum: Int. J.* **2010**, *11*, 4–19. [CrossRef]
238. Polater, A. Dynamic Capabilities in Humanitarian Supply Chain Management: A Systematic Literature Review. *JHLSCM* **2020**, *11*, 46–80. [CrossRef]
239. Agarwal, S.; Kant, R.; Shankar, R. Humanitarian Supply Chain Management Frameworks: A Critical Literature Review and Framework for Future Development. *BIJ* **2019**, *26*, 1749–1780. [CrossRef]
240. Sabbaghtorkan, M.; Batta, R.; He, Q. Prepositioning of Assets and Supplies in Disaster Operations Management: Review and Research Gap Identification. *Eur. J. Oper. Res.* **2020**, *284*, 1–19. [CrossRef]
241. Bealt, J.; Mansouri, S.A. From Disaster to Development: A Systematic Review of Community-Driven Humanitarian Logistics. *Disasters* **2018**, *42*, 124–148. [CrossRef] [PubMed]
242. Santana Robles, F.; Hernández-Gress, E.S.; Hernández-Gress, N.; Granillo Macias, R. Metaheuristics in the Humanitarian Supply Chain. *Algorithms* **2021**, *14*, 364. [CrossRef]
243. Jahre, M. Humanitarian Supply Chain Strategies—A Review of How Actors Mitigate Supply Chain Risks. *JHLSCM* **2017**, *7*, 82–101. [CrossRef]
244. Jiang, Y.; Yuan, Y. Emergency Logistics in a Large-Scale Disaster Context: Achievements and Challenges. *Int. J. Environ. Res. Public Health* **2019**, *16*, 779. [CrossRef] [PubMed]
245. Prakash, C.; Besiou, M.; Charan, P.; Gupta, S. Organization Theory in Humanitarian Operations: A Review and Suggested Research Agenda. *JHLSCM* **2020**, *10*, 261–284. [CrossRef]
246. Anjomshoae, A.; Banomyong, R.; Mohammed, F.; Kunz, N. A Systematic Review of Humanitarian Supply Chains Performance Measurement Literature from 2007 to 2021. *Int. J. Disaster Risk Reduct.* **2022**, *72*, 102852. [CrossRef]
247. Fontainha, T.C.; Leiras, A.; de Bandeira, R.A.M.; Scavarda, L.F. Public-Private-People Relationship Stakeholder Model for Disaster and Humanitarian Operations. *Int. J. Disaster Risk Reduct.* **2017**, *22*, 371–386. [CrossRef]
248. Farahani, R.Z.; Lotfi, M.M.; Baghaian, A.; Ruiz, R.; Rezapour, S. Mass Casualty Management in Disaster Scene: A Systematic Review of OR&MS Research in Humanitarian Operations. *Eur. J. Oper. Res.* **2020**, *287*, 787–819. [CrossRef]
249. Lettieri, E.; Masella, C.; Radaelli, G. Disaster Management: Findings from a Systematic Review. *Disaster Prev. Manag.* **2009**, *18*, 117–136. [CrossRef]
250. Cooper, B.; Behnke, N.L.; Cronk, R.; Anthonj, C.; Shackelford, B.B.; Tu, R.; Bartram, J. Environmental Health Conditions in the Transitional Stage of Forcible Displacement: A Systematic Scoping Review. *Sci. Total Environ.* **2021**, *762*, 143136. [CrossRef]
251. Shao, J.; Wang, X.; Liang, C.; Holguín-Veras, J. Research Progress on Deprivation Costs in Humanitarian Logistics. *Int. J. Disaster Risk Reduct.* **2020**, *42*, 101343. [CrossRef]
252. Farooq, M.U.; Hussain, A.; Masood, T.; Habib, M.S. Supply Chain Operations Management in Pandemics: A State-of-the-Art Review Inspired by COVID-19. *Sustainability* **2021**, *13*, 2504. [CrossRef]
253. Çelik, M. Network Restoration and Recovery in Humanitarian Operations: Framework, Literature Review, and Research Directions. *Surv. Oper. Res. Manag. Sci.* **2016**, *21*, 47–61. [CrossRef]

254. Nurmala, N.; de Leeuw, S.; Dullaert, W. Humanitarian–Business Partnerships in Managing Humanitarian Logistics. *SCM* **2017**, *22*, 82–94. [CrossRef]
255. Balcik, B.; Bozkir, C.D.C.; Kundakcioglu, O.E. A Literature Review on Inventory Management in Humanitarian Supply Chains. *Surv. Oper. Res. Manag. Sci.* **2016**, *21*, 101–116. [CrossRef]
256. Anuar, W.K.; Lee, L.S.; Pickl, S.; Seow, H.-V. Vehicle Routing Optimisation in Humanitarian Operations: A Survey on Modelling and Optimisation Approaches. *Appl. Sci.* **2021**, *11*, 667. [CrossRef]
257. Johnson, H.L.; Ling, C.G.; McBee, E.C. Multi-Disciplinary Care for the Elderly in Disasters: An Integrative Review. *Prehospital Disaster Med.* **2015**, *30*, 72–79. [CrossRef]
258. Patel, B.S.; Sambasivan, M. A Systematic Review of the Literature on Supply Chain Agility. *Manag. Res. Rev.* **2021**, *45*, 236–260. [CrossRef]
259. Khan, M.; Yong, L.H.; Han, B.J. A Systematic Review of Performance Enhancement of Humanitarian Logistics through Transparency: Current Status and Perspectives. *Int. J. Supply Chain. Manag.* **2019**, *8*, 549.
260. Burkart, C.; Besiou, M.; Wakolbinger, T. The Funding—Humanitarian Supply Chain Interface. *Surv. Oper. Res. Manag. Sci.* **2016**, *21*, 31–45. [CrossRef]
261. Rasouli, M.R. Intelligent Process-Aware Information Systems to Support Agility in Disaster Relief Operations: A Survey of Emerging Approaches. *Int. J. Prod. Res.* **2019**, *57*, 1857–1872. [CrossRef]
262. Banomyong, R.; Varadejsatitwong, P.; Oloruntoba, R. A Systematic Review of Humanitarian Operations, Humanitarian Logistics and Humanitarian Supply Chain Performance Literature 2005 to 2016. *Ann. Oper. Res.* **2019**, *283*, 71–86. [CrossRef]
263. Abidi, H.; de Leeuw, S.; Klumpp, M. Humanitarian Supply Chain Performance Management: A Systematic Literature Review. *Supply Chain Manag. Int. J.* **2014**, *19*, 592–608. [CrossRef]
264. Yáñez-Sandivari, L.; Cortés, C.E.; Rey, P.A. Humanitarian Logistics and Emergencies Management: New Perspectives to a Sociotechnical Problem and Its Optimization Approach Management. *Int. J. Disaster Risk Reduct.* **2021**, *52*, 101952. [CrossRef]
265. Seifert, L.; Kunz, N.; Gold, S. Humanitarian Supply Chain Management Responding to Refugees: A Literature Review. *J. Humanit. Logist. Supply Chain. Manag.* **2018**, *8*, 398–426. [CrossRef]
266. Soosay, C.A.; Hyland, P. A Decade of Supply Chain Collaboration and Directions for Future Research. *Supply Chain Manag. Int. J.* **2015**, *20*, 613–630. [CrossRef]
267. Leiras, A.; de Brito Jr, I.; Queiroz Peres, E.; Rejane Bertazzo, T.; Tsugunobu Yoshida Yoshizaki, H. Literature Review of Humanitarian Logistics Research: Trends and Challenges. *J. Humanit. Logist. Supply Chain Manag.* **2014**, *4*, 95–130. [CrossRef]