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Investigations of disaster information representation from a geospatial perspective: Progress, challenges and recommendations

Weilian Li[1,2] | **Jun Zhu**[1] | **Saied Pirasteh**[1] | **Qing Zhu**[1] | **Lin Fu**[1] | **Jianlin Wu**[1] | **Ya Hu**[1] | **Youness Dehbi**[2]

[1]Faculty of Geosciences and Environmental Engineering, Southwest Jiaotong University, Chengdu, China

[2]Institute of Geodesy and Geoinformation, University of Bonn, Bonn, Germany

Correspondence
Jun Zhu, Faculty of Geosciences and Environmental Engineering, Southwest Jiaotong University, Chengdu, China.
Email: zhujun@swjtu.edu.cn

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Abstract

The complexity of disasters creates a significant challenge in the knowledge acquisition of the public. With the development of geospatial technologies, maps, geographic information science, and virtual geographic environments are widely used to represent disaster information and help the public better understand disaster risk. However, the application, design, and specific challenges have not been investigated comprehensively in disaster information representation thus far. This article presents the weaknesses and strengths of the existing methods for representing disaster information in recent decades, and then gives some basic ideas for efficient disaster knowledge communication. The objective of this article is to provide a clear image that improves users' understanding of disaster information and bridge the communication gaps in disaster management.

1 | INTRODUCTION

In recent years, global climate change and rapid economic growth have increased the frequency and intensity of natural and human-made disasters, posing severe challenges to disaster prevention and mitigation (Ao et al., 2020, 2021; Bhatt, Mall, & Banerjee, 2015; Ryan, Johnston, Taylor, & McAndrew, 2020; Li et al., 2020). Knowledge communication plays a central role in improving public awareness and making scientific decisions (Dawson & Johnson, 2014). It can eliminate people's optimistic bias and illusion of safety (Spittal, McClure, Siegert, & Walkey, 2005), change their conceptual approach to mitigation, and enhance their risk awareness, thereby improving their prevention abilities and reducing disaster losses (Burningham, Fielding, & Thrush, 2008; Day, 2011; Smith, Porter & Upham, 2017).

Disaster information representation acts as a bridge between disaster knowledge and public perception, which is a gradual process influenced by social, cultural, and scientific factors (Andrienko, Fabrikant, Griffin, Dykes, & Schiewe, 2014; Bodum, 2005; Glander & Döllner, 2009; Li et al., 2021; MacEachren, 2004). It explains what, where, why, when, and how for a given disaster from the geospatial perspective (Bandrova, Zlatanova, & Konecny, 2012). In primitive times, oral and written records provided information about the nature of disasters. However, with the development of cartography and information science, maps and geographic information science (GIS) make it possible to identify and understand more complex disaster problems, and they have been used to understand the geographic context of disasters for a long time (Cariolet, Vuillet, & Diab, 2019; Dang et al., 2021; Klimešová & Brožová, 2012; Tomaszewski, 2020).

In addition, inspired by Michael Batty's (1997) virtual geography theory, the concept of the virtual geographic environment (VGE) was proposed in 1998 and used in various applications (Dang et al., 2021; Lin et al., 2013; Luo et al., 2021). It has been widely used for disaster phenomenon simulation and multi-dimensional visualization, contributing to a deeper understanding of the real disaster environment (Ding et al., 2015; Guo et al., 2021; Li et al., 2021; Lin et al., 2013; Pirasteh, Shamsipour, Liu, Zhu, & Chengming, 2020). Nevertheless, the current representation of disaster information has remained a challenge and a hot topic among researchers.

Recently, the topic of virtual reality (VR) has become more and more popular (Chen & Lin, 2018; Dang et al., 2021; Hu et al., 2018; Luo et al., 2021). In addition, the rise of augmented reality (AR) and mixed reality (MR) has enriched the way disasters are expressed. There are also enhanced virtual or mixed virtual–real disaster environments that allow users to have a more natural and realistic risk perception and experience (Chen & Lin, 2018; Rydvanskiy & Hedley, 2021; Zhang, Gong, et al., 2020). All of the above achievements have led to a continuous improvement in the representation of disaster information and knowledge communication.

However, to the authors' knowledge, the applications, designs, and specific challenges have not been investigated comprehensively in disaster information representation thus far. Therefore, this article is focused on the following objectives: (1) to review the inventory of the current state of the art for maps, GIS, and VGEs for disaster information representation; and (2) to improve the efficiency of knowledge communication. Some basic ideas for improving the quality and effectiveness of disaster information representation are also proposed.

The remainder of this article is organized as follows. In Sections 2 and 3 a background is given and related works are introduced. In Section 4 some basic ideas are proposed for improving the representation efficiency of disaster information. Finally, Sections 5 and 6 present the discussions, conclusions, and suggestions for going forward.

2 | BACKGROUND

2.1 | What is disaster information representation?

There are various definitions of the term "representation," but they mainly involve two aspects. One definition in the UK dictionary powered by OXFORD LEXICO is as the description or portrayal of someone or something in a particular way or as being of a certain nature. Another definition is the use of signs that stand in for and take the place of something else (Mitchell, 1995). The former is focused on subjective comments made about people or things that influence subsequent opinions or actions, as described in *Merriam-Webster*. In contrast, the latter can be called visual representation, which explores the association of symbols with their referents and how ideas and knowledge can be communicated through symbols (Lurie & Mason, 2007).

In brief, visual representation can be understood as visualization in its various forms. This form of representation is not just a detailed diagram but an accurate description of things and their relationships (Lurie and Mason, 2007). In other words, natural disasters have a strong spatiotemporal component; therefore, maps and virtual geographical scenes can play a decisive role in disaster information representation (Dransch, Rotzoll, & Poser, 2010).

However, disaster information representation is interpreted in this article as taking virtual geographical scenes as the basic carrier and using efficient data management, filtering, and visual representation to enable semantic enhancement and a deep focus on key disaster scene information. This expands the public's understanding of the causes, evolution, and results of disasters and thus improves disaster awareness (Dransch, Etter, & Walz, 2005; Li et al., 2019, 2020, 2021).

2.2 | What is the role of representation in disaster knowledge communication?

Visual representation is a way to visualize knowledge and a bridge for knowledge communication between people. The main visual representations aimed at knowledge communication include heuristic sketches, conceptual diagrams, visual metaphors, knowledge animation, and knowledge maps (Eppler & Burkhard, 2004). Disaster knowledge communication is a process of encoding and decoding disaster-related information. From a geospatial perspective, a conceptual diagram is a structured visual representation that effectively organizes and manages disaster objects and their interrelationships to support and develop dynamic maps and three-dimensional (3D) representations. The use of dynamic representations in the decoding process can enhance the interpretability of disaster information and facilitate mental mapping by the public (Macchione, Costabile, Costanzo, & De Santis, 2019; Qiu, Du, Zhu, & Fan, 2017; Yuan & Hornsby, 2007).

However, the role of representation in disaster knowledge communication varies in several ways. They include: (1) reporting disaster facts in the media—including social networks and story maps (Scholz & Jeznik, 2020)—and transmitting disaster situations to the public; (2) dynamically visualizing the entire disaster process and communicating knowledge to the public, thus improving their disaster awareness about the hazard itself and warning signals; (3) providing concrete information about a hazard, such as location or time; and (4) making information about suitable protection measures available (Dransch, Rotzoll, & Poser, 2010; Palttala, Boano, Lund, & Vos, 2012).

3 | RELATED WORK: PROGRESS AND CHALLENGES

3.1 | Oral and written communication

People have experienced various kinds of disasters since early human history, and disasters have been explored over a relatively long historical period. In primitive times, people mainly relied on word of mouth to transmit disaster information. Oral communication is the oldest method of disaster knowledge communication and remains prevalent today (Cai & Yao, 2012). Hopkins (1999) believed that knowledge based on experience was far more reliable, so that disaster knowledge acquired by word of mouth was more influential than information conveyed by the written word. Zhang, Zhu, et al. (2014) stated that oral communication plays an important role in disaster pre-warning information dissemination when all electronic networks are paralyzed, and the Monte Carlo method was used to simulate the pre-warning information dissemination process and tornado risk. The experimental results showed that population density is the most important influencing factor. O'Brien and Federici (2019) highlighted that oral and written communication channels could be used at different stages of a crisis with different audiences. Moreover, an individual may act as a translator of oral or written content in one crisis instance. Sjoraida and Anwar (2018) pointed out that there is a sharp distinction between oral, written, and electronic media in risk communication. Electronic media are near-instantaneous

TABLE 1 Summary of papers on oral and written communication

No.	Reference	Method	Strength	Weakness	Authors' opinion
1	Fujii, Tamano, and Hattori (2021)	General communication	Vividness	Lack of accuracy	A hybrid approach by combining traditional and modern disaster prevention knowledge
2	Sjoraida and Anwar (2018)	Literature overview	Oral communication can influence mutual expectations among individuals to adjust their behavior	Slow propagation and bound by time and place	Trying to combine oral, written, and electronic media
3	O'Brien and Federici (2019)	Literature overview	Individuals can translate and transmit oral or written content to others	Communication is not optimal in information dissemination speed	They can be used for communication in early disaster preparation
4	Zhang, Zhu, et al. (2014)	Comparative analysis and evaluation	Oral communication can be used in some serious disaster cases	Disaster information can be disseminated only within a limited distance	Using different communication media according to different disaster situations
5	Hopkins (1999)	General communication	Disaster knowledge acquired by word of mouth was more influential than the written word	Limited by time and space	The combination of oral and written communication

and not bound by time and place. Thus, it can broadcast more widely than oral and written communication. Furthermore, Fujii, Tamano, and Hattori (2021) argued that oral communication conveys the experience of past disasters, possesses vividness, and can induce rapid evacuation of people during disasters by acting on their emotions, such as fear or anxiety. In fact, when a disaster occurs, victims exchange information regarding what they saw, heard, and felt, and members of their audience become new communicators and spread information to others. This approach can vividly convey the "fear" of a disaster to influence people's emotions (Fujii, Tamano, & Hattori, 2021). However, oral communication requires communicators to store information in their minds and respond verbally. Moreover, written communication allows one to manipulate, edit, and change the text and then redistribute risk messages to others (Sjoraida & Anwar, 2018). Such communications have limitations, such as the lack of accuracy from the perspective of modern disaster prevention research. Table 1 illustrates the strengths and weaknesses of oral and written communication. In addition, disaster knowledge can be disseminated and communicated only within a limited distance. With the emergence of text and paper and social media, the representation of disaster information has gradually overcome time and geographical limitations. The combination of oral and written communication greatly enhances the dissemination of disaster knowledge (Allen, Stanton, Di Pietro, & Moseley, 2013; Uchida, Takahata, Shibata, & Shiratori, 2011). However, due to the lack of positioning, measurement, and visual modeling functions in text and paper media, it is difficult to convey abundant information and accurate knowledge to the public (Chen, Lin, Kolditz, & Chen, 2015; Lin et al., 2013).

The following subsection describes the role of social media and story maps in disaster mapping and GIS representation.

3.2 | Disaster mapping and GIS

We have seen progress in artificial intelligence (AI) techniques, particularly in geospatial applications and the large-scale availability of high-quality data, high-definition (HD) maps and 3D models (Dehbi, Hadiji, Gröger, Kersting, & Plümer, 2017; Liu, Wang, & Zhang, 2020). Advances in both hardware and software to efficiently process these data can transform a range of fields from computer vision, including AR, MR, VR, and 3D dynamic representation, and natural language processing to mapping and disaster management (Scholz & Jeznik, 2020). For example, the availability of high-resolution geographic data and high-performance computing techniques incorporating deep learning technology in a fast and accurate manner can be exploited for object detection and mapping after an earthquake to support the rescue and relief team.

In recent years, due to the potential of social networks and AI techniques, particularly in geospatial areas, and the large-scale availability of high-quality data for representation, researchers have used them more often in crisis management studies (Dang et al., 2021; Scholz & Jeznik, 2020; Zhu et al., 2020). Social networks are rich sources of event information. For example, there are two GeoThings (https://geothings.tw/, http://appx.georvs.cn/; https://app.georvs.ca) and social platforms to support disasters and resilience. This information includes text and images shared by eyewitnesses, which can be used in disaster simulation and damage assessment. With the development of wireless networks and mobile technologies, people can play an important role in news distribution following natural disasters such as earthquakes. Because social networks provide the ability to exchange personally created content, the information extracted by these networks can include temporal and spatial data associated with different events. One of the benefits of social network data is its online nature: data are immediately available. The other attribute is its *in situ* nature: it can be gathered in the case of local conditions, such as street accessibility, blocked streets, injured people, damage to buildings and other infrastructure (Wu & Cui, 2018). These data can be used in post-disaster assessments to provide information layers that are less time-consuming than those based on remote sensing methods and geospatial artificial intelligence (GeoAI) techniques.

Moreover, the opportunities in open-source and cloud-based sharing open geospatial training data sets have improved disaster services and GIS mapping (https://www.radiant.earth/mlhub/). Therefore, it has been shown that users tend to share their status during a disaster on social networks, indicating the potential of such networks for a quick damage assessment. Furthermore, previous research has shown that the severity of damage in a region has a direct correlation with the amount of disaster-related social media content generated from the same region (Scholz & Jeznik, 2020; Wu & Cui, 2018).

Some of the most active social networking sites, such as Twitter, WhatsApp, WeChat, Instagram, Youku, and YouTube, provide people free access to personal information, including text messages, location, and social relationships. All of these features have resulted in the inclusion of Twitter/WeChat and other social media in crisis management studies (Zhang, Wu, Wang, & Su, 2017). Therefore, creating visualization and representation platforms for partnering people and various sectors to support the disaster management process can improve the understandability of rescue and relief assessment plans. For example, Li and Rao (2010) explored the role of Twitter in providing rapid response news during the Sichuan earthquake of 2008. The Sichuan earthquake was China's largest natural disaster in 30 years. Here, we note that a broader use of social media has proliferated the spread of fake news and misinformation during a natural disaster or catastrophe (Allcott, Gentzkow, & Yu, 2019; Torpan et al., 2021). Therefore, it is necessary for social media data to be filtered and cleaned before further visual representation.

Since disasters have a strong spatiotemporal component, maps can play a decisive role in knowledge communication (Dransch, Rotzoll, & Poser, 2010). Disaster maps include hazard maps and risk maps. The former are also called damage maps, and are used to show the consequences of a specific disaster event; the latter reflect the possibility of a disaster event occurring. These two concepts are mixed in many cases (Meyer et al., 2012). Disaster maps are most widely used in flood information representation (Henstra, Minano, & Thistlethwaite, 2019). Flood simulation software, such as MIKE (https://www.mikepoweredbydhi.com/), HEC (Hydrologic Engineering Center, https://www.hec.usace.army.mil/), FLO-2D (https://flo-2d.com/), and Delft 3D (https://oss.deltares.nl/web/delft3d/), can be used to calculate the extent, flow velocity, and water depth. This information is overlaid with capacity/resource maps and social maps on GIS platforms to analyze the risk level of houses and roads, and then the final spatial distribution and accessibility are presented through map symbols and colors (Liu & Wu, 2018; Meyer et al., 2012; Ntajal, Lamptey, Mahamadou, & Nyarko, 2017; Symonds et al., 2016; Thakur, Parajuli, Kalra, Ahmad, & Gupta, 2017; Waldman et al., 2017; Wu, Liu, & Chen, 2013). However, cartographers and disaster management professionals guide the investigation and design of disaster maps and their thematic focus, which can often lead to the contents of disaster maps not matching the requirements of the public, and the representation methods cannot be easily understood (Holub & Fuchs, 2009; Meyer et al., 2012).

In addition, Mark, Freksa, Hirtle, Lloyd, and Tversky (1999) believed that the first stage of human geospatial cognition is to obtain direct and straightforward spatial information. In other words, the first question that needs to be answered in a disaster information representation and mapping is "where is the disaster?" (Bandrova, Zlatanova, & Konecny, 2012; Martin & James, 1993). GIS and story maps through social media turn out to be useful tools for visualization and mapping of disaster risks (e.g., debris flows, earthquakes, floods, tornadoes, and landslides) and emergency management in most parts of the world. For example, Figure 1 shows the spatial distribution of maximum debris flow depths under different grid cell sizes. Moreover, research has shown that outputs are efficient and valuable in disaster management (Bednarik, Yilmaz, Martin & James, 1993; Dang et al., 2021; Luo et al., 2021; Marschalko, 2012; Ntajal et al., 2017; Tate et al., 2011). Thus, the combination of social media, GeoAI, GIS spatial analysis, and visualization of maps can effectively tell us where buildings are damaged, where roads are open for evacuation, and where supplies should be stationed for planning purposes (Andrienko et al., 2014; Tomaszewski, 2020).

Furthermore, to reduce the professionalism of disaster maps and make them more accessible to the public, the use of social media, such as WeChat and Open GIS, story maps, and open sources is advised. Moreover, panel discussions and questionnaires have been conducted in some studies to enable users to participate in the mapping process (Gaillard & Pangilinan, 2010; Liu & Wu, 2018; White, Kingston, & Barker, 2010). For example, a participatory GIS

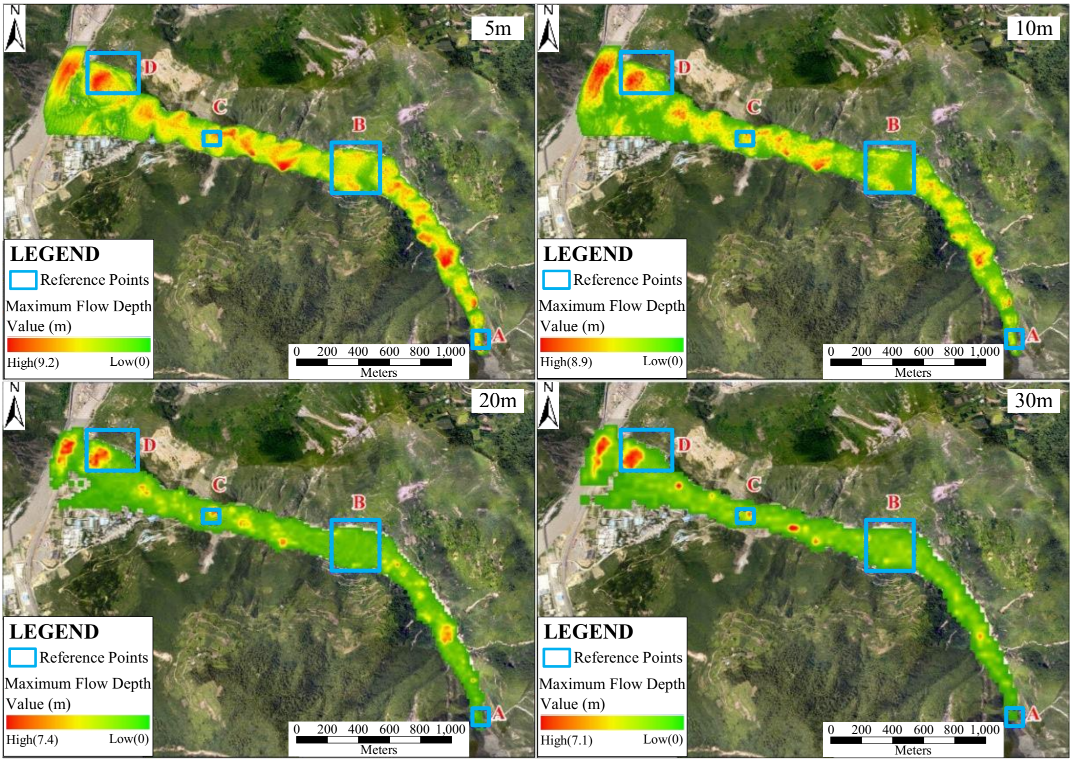

FIGURE 1 Example for visualization and mapping disaster risks: Spatial analysis of debris flow depths under different grid cell sizes (Yin et al., 2017)

has been developed to engage the public in flood risk management and used participatory mapping to raise disaster risk awareness among youth in the Philippines. Furthermore, participatory and collaborative risk mapping have been incorporated to enhance disaster resilience. However, although a disaster map can present the public with basic disaster information, such as the inundation area, water depth, and affected buildings, the capacity of a 2D map to carry information is limited. Therefore, it is difficult to support the dynamic visualization of the whole process of disaster evolution (Li et al., 2020). Nevertheless, Table 2 gives a summary of papers on disaster mapping and GIS.

3.3 | Virtual disaster scenes in three dimensions

Three-dimensional dynamic visualization increases the efficiency of interpreting data. It helps people to understand the connotations of data quickly and improves spatial information cognition (Bülthoff, Campos, & Meilinger, 2008; Li et al., 2020). Virtual disaster scenes in three dimensions break through the deficiencies of 2D maps in the representation of spatial dimensions and provide a more intuitive option for understanding and analyzing the real world. Some researchers have applied the smoothed particle hydrodynamics (SPH) method (Lin et al., 2020) and virtual reality platforms (Winkler, Zischg, & Rauch, 2018) to simulate free surface motion and 3D flood dynamics in large- and small-scale urban scenes through computer graphics. Moreover, the natural environment has been analyzed by the volume of fluid (VOF) method (Munoz & Constantinescu, 2018). However, disaster situations in the 3D dynamic visualization of the environment and VGE require more in-depth studies. More details can be found, for example, in Renschler and Wang (2017), Lü et al. (2019), Lin et al. (2020), and Luo et al. (2021).

TABLE 2 Summary of the papers on disaster mapping and GIS

No.	Author & year	Method	Strength	Weakness	Authors' opinion
1	Peng, Yue, and Li (2017); Kuveždić Divjak, Đapo, and Pribičević (2020)	Designing cartographic symbols to represent disaster information	Rich in semantics and self-explanatory	Difficulty in representing dynamic phenomena	Self-explanatory symbols and photorealistic scene cooperation
2	Meyer et al. (2012); Henstra, Minano, and Thistlethwaite (2019)	Hazard/risk maps	A powerful and convenient tool to help people understand a disaster situation	The design and visualization approach is too professional	Considering the public cognition needs
3	Gaillard and Pangilinan (2010); Liu and Wu (2018)	Participatory mapping	Disaster maps can be improved by considering the public's suggestions	A large number of samples are required to analyze public preferences	Deep learning for analyzing the public's cognitive patterns
4	Carver (2001), White, Kingston, and Barker (2010)	Participatory GIS	Incorporating local knowledge into GIS is beneficial for disaster risk management policy formulation	Interactive and attractive interfaces for convenient participation are insufficient	Providing a flexible parameter configuration and a user-friendly interface

A VGE is derived from 3D GIS and geography and is described as a computer-based digital geographic environment for geographic assessment and problem-solving (Lin et al., 2015). It aims to provide an open, digital window for the real physical world, allowing people to understand beyond reality through geographic simulations and immersive experiences (Chen & Lin, 2018; Lü et al., 2019; Lin et al., 2013). In addition, disaster information representation based on VGE can support disaster process simulation, multi-dimensional dynamic visualization, and public participation, which constitutes a great leap forward in disaster information representation and risk knowledge communication.

Many researchers have constructed virtual disaster scenes by integrating VGE with geographic models to support diverse disaster prevention and mitigation applications (Denolle, Dunham, Prieto, & Beroza, 2014; Li et al., 2021; Wang et al., 2016; Yu et al., 2021), which mainly includes three aspects: (1) 3D numerical simulation representation; (2) photorealistic 3D visualization; and (3) non-photorealistic 3D visualization. For example, Lai et al. (2011) used a verified 3D flow numerical model as input data to build an interactive 3D virtual environment, which increased interactivity between stakeholders and improved communication efficiency from public participation in a 3D virtual environment flood representation. Wang et al. (2016) realized 3D numerical simulation of debris flow motion using the SPH method by incorporating non-Newtonian fluid behavior, which reproduces well the debris-flow process and benefits the analysis of flow characteristics and affected areas for risk assessment and mitigation design. Later, a workflow was developed for the representation of 2D hydraulic simulations within a 3D virtual environment (Macchione et al., 2019). It was used to support scientists, technicians, and the public for emergency management in flood risk communications.

Regarding the photorealistic 3D visualization of disasters, Yang et al. (2008) extended the traditional SPH method to realize the interaction between the solid phase and liquid phase, which successfully simulates floods, landslides, and debris flows with different mixtures and vividly demonstrates the process of multiphase flow destroying buildings. Later, Evans et al. (2014) created a realistic 3D visualization of flooding in Exeter, UK. They demonstrated that a 3D virtual environment is a powerful tool in changing flood risk perceptions and raising awareness of residuals.

Furthermore, non-photorealistic 3D visualization turns out to be an enabling technology for designing and implementing effective visualization systems and overcoming the traditional mindset established by photorealistic computer graphics (Döllner, 2007; Jahnke, Meng, Kyprianidis, & Döllner, 2008). It is used to represent disaster information and transmit disaster knowledge to the public. For example, numerical simulation, risk analysis, and non-photorealistic 3D visualization of debris flow disasters have been integrated into a VGE system to provide an efficient tool to support risk analysis, real-time interaction, and geographic knowledge sharing (Yin et al., 2017). Later, Li et al. (2019) proposed a fusion visualization method for disaster information based on self-explanatory symbols and photorealistic scene cooperation. They found that the combination of non-photorealistic visualizations (such as language, symbols, and color) and photorealistic visualizations can reveal more disaster semantic information while ensuring a certain degree of realism. Moreover, the literature has shown that the vivid representation of disaster information plays a crucial role in practical knowledge and risk communication because vivid information may improve memorability and the construction of mental representations (Dransch, Rotzoll, & Poser, 2010). For example, Figure 2 shows a rapid 3D reproduction of dam-break floods. Previous studies on virtual disaster scenes in three dimensions are summarized in Table 3.

3.4 | Challenges and gaps in current disaster information representation

Based on the previous sections and the literature, the authors highlight the five major challenges for disaster information representation.

1. Social engagement and participation in data sharing and reliable information are lacking in developing disaster GIS maps and 3D representation. However, data privacy requires a compendium on licensing

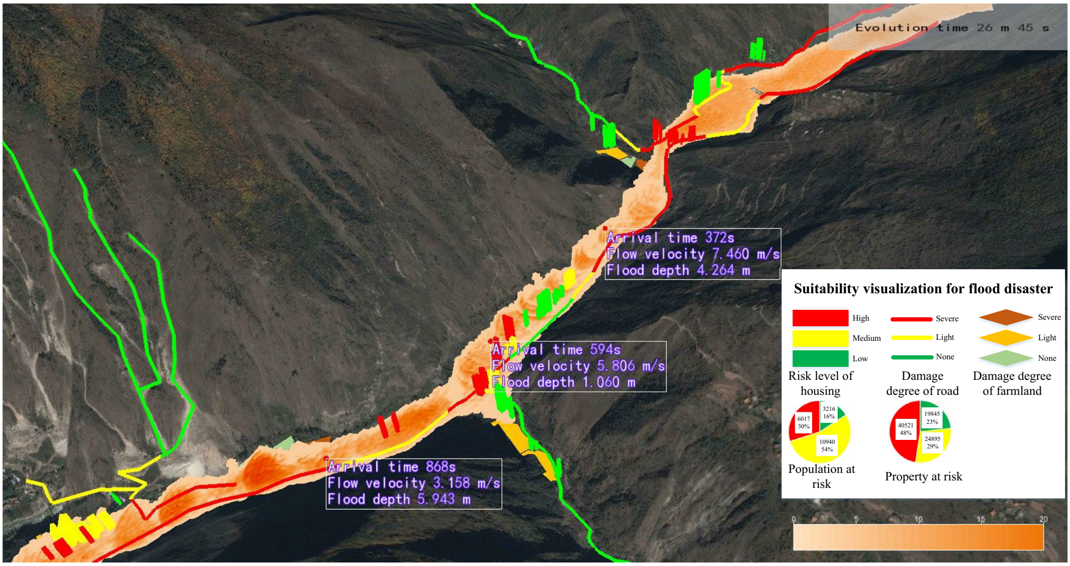

FIGURE 2 A rapid 3D reproduction of dam-break floods supporting communication and improving memorability (Luo et al., 2021)

of geospatial information, which was developed 2018 by the United Nations Committee of Experts on Global Geospatial Information Management (UN-GGIM) (https://ggim.un.org/documents/E-C20-2018-9-Add_2-Compendium-on-Licensing-of-Geospatial-Information.pdf)

2. Social media have improved the efficiency and scope of disaster information communication, but at the same time, they also bring some misinformation. Filtering and cleaning social media information is an important part of the disaster information and representation process.
3. Lack of efficient data management. Disaster data have become increasingly abundant with the continuous development of Earth observation and sensor networks and Internet of Things (IoT) technologies. Therefore, how to efficiently manage disaster data and their relationships is a problem that needs to be solved.
4. The content of a 3D scene is overloaded. In 3D scene construction, all disaster data put into the virtual scene will lead to information overload. Thus, it is necessary to select data with different needs in mind.
5. Scarcity of semantic information. The existing scene representation focuses on visualization and does not consider the cognitive needs of the public, which leads to scarcity of semantic information and inefficient public perception.

4 | BASIC IDEAS FOR IMPROVING REPRESENTATION EFFICIENCY

This article proposes some basic ideas to comprehensively represent disaster information and to improve the representation efficiency of disaster information; these mainly include a disaster knowledge graph, optimal selection of scene data, and augmented representation, as shown in Figure 3.

Before detailing the three core modules, it is necessary to briefly describe the processing and cleaningof data. Because disaster data have differences (e.g., in source, format, and multimodality), data processing and cleaning (e.g., format conversion, space-time unification, and filtering) are consequently required before disaster data organization and management.

TABLE 3 Summary of previous research on virtual disaster scenes in three dimensions

No.	Author & year	Method	Strength	Weakness	Authors' opinion
1	Lai et al. (2011), Wang et al. (2016), Symonds et al. (2016), Macchione et al. (2019), Shin et al. (2019)	3D numerical simulation representation	High-precision simulation and representation of disasters	Many complex parameters are required and representation too professional	Simplifying input parameters and trying to make the representation easy to understand
2	Yang et al. (2008), Evans et al. (2014), Zibrek, Martin, and McDonnell (2019)	Photorealistic 3D visualization	Good and vivid visual effect	Scarcity of semantic information and sufficient detail	Highlighting disaster semantic information in realistic scenes
3	Döllner (2007); Jahnke et al. (2008); Yin et al. (2017); Li et al. (2019)	Non-photorealistic 3D visualization	More effective at conveying disaster information and more expressive	Difficulty in reproducing the real disaster process	Non-photorealistic visualization cooperates with photorealistic ones

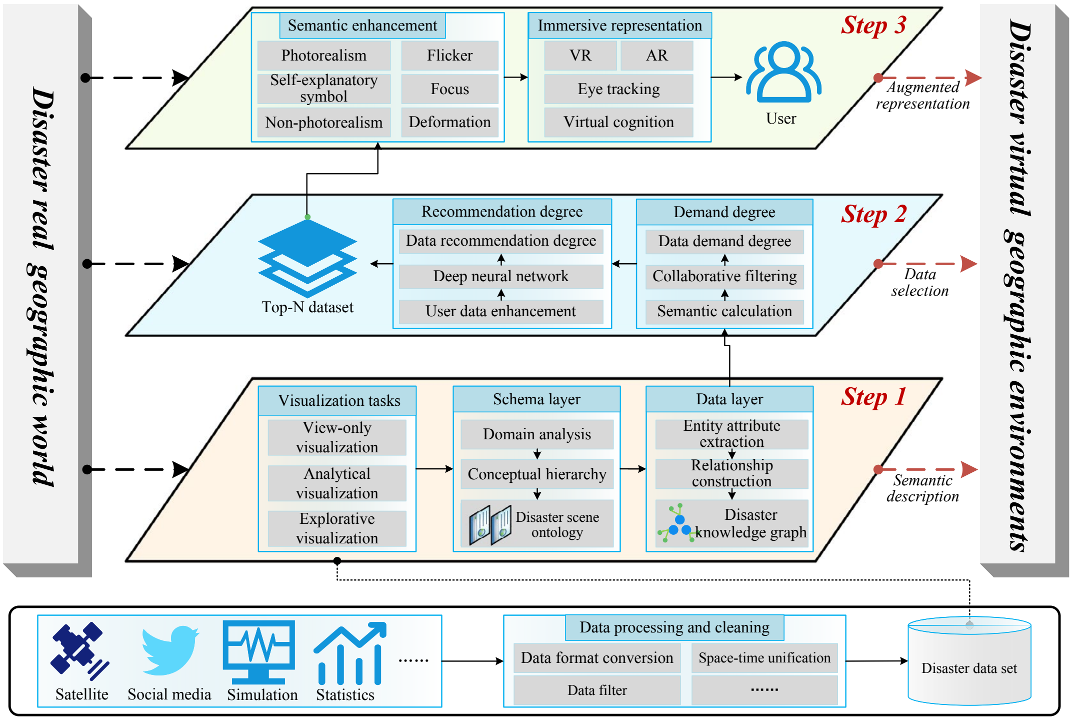

FIGURE 3 Overall framework of improving the representation efficiency of disaster information

Here, we would like to emphasize the importance of the data filter. Social media continuously generate a large amount of information, which will inevitably include some misinformation and false information. This may have extremely negative impacts during a disaster or a social event. In this context, many approaches deal with this increasingly important topic. For instance, Torpan et al. (2021) proposed some strategies to handle misinformation, such as the level of organization in tackling false information, emphasis on spreading truthful information, semi-official management mechanisms, and campaigns to enhance awareness of false information. From a geospatial perspective, machine learning, deep learning, and spatial analysis can be used to filter out misinformation and false information from social media.

For example, public awareness of Covid-19 has been adversely affected by misinformation on social media. In terms of misinformation handling, a set of pandemic misinformation keywords (e.g., do not stay at home, city lockdown) can be developed, and then deep approaches, such as convolutional or recurrent neural network models, can be designed for automatically identifying and filtering misinformation from social media (Ajao, Bhowmik, & Zargari, 2018; Liu & Wu, 2018). Moreover, it is also meaningful to analyze the patterns and factors influencing misinformation dissemination from a geospatial analysis perspective (Forati & Ghose, 2021; Wang, Zhang, Fan, & Zhao, 2021).

This section explains the three core components of our framework to improve the representation efficiency of disaster information.

4.1 | Disaster knowledge graph for multilevel visualization tasks (step 1)

The development of space–air–ground integrated Earth observation images and sensor network technologies has greatly improved the ability to obtain disaster data (Dehbi, Klingbeil, & Plümer, 2020; Li, 2016). These advancements have provided a good opportunity for people to understand disasters and create challenges for disaster information management, analysis, and representation (Qiu et al., 2017).

People's demand for disasters extend from viewing to analyzing and the acquisition of disaster knowledge, which is closely related to multilevel visualization tasks, such as view-only visualization, analytical visualization, explorative visualization, and geospatial analysis (Zhu & Fu, 2017). Therefore, clarifying the correlation between multilevel visualization tasks and disaster data and establishing a unified semantic description allows disaster knowledge to be shared at a semantic level (Couclelis, 2010) and knowledge graphs to be drawn.

A knowledge graph describes relevant concepts and their relationships in the real physical world using an entity–relation–entity triple to provide a structured knowledge base (Jiang et al., 2018; Li et al., 2020, 2021). Based on the knowledge graph, semantic associations between multilevel visualization tasks and disaster data are established to solve problems related to isolation and the lack of associations among disaster data. The construction of a disaster knowledge graph can be divided into a schema layer and a data layer (Scheuer, Haase, & Meyer, 2013). In addition, ontology can be used as a schema layer to define public concepts and relationships for the knowledge graph nodes; for example, public $\xrightarrow{\text{Concern}}$ view-only visualization $\xrightarrow{\text{HasPartOf}}$ basic geographic data $\xrightarrow{\text{HasInstance}}$ digital elevation model (DEM) with 0.5 m resolution. Ontology stores are highly abstract and condensed disaster knowledge gained via a literature review, expert research, and reference to national or industry standards (Clemens, 2014).

In addition, as the basic unit of the knowledge graph, entity and relationship extraction is the core technology of knowledge graph construction. Disaster domain knowledge is mainly derived from disaster emergency management departments' disaster databases, including disaster spatiotemporal databases, such as basic geographic data, thematic data, monitoring data, and simulation analysis data of each disaster area, and disaster assessment databases. In addition, the main methods of entity extraction are statistical models (e.g., support vector machines, conditional random fields), deep learning (e.g., long short-term memory conditional random fields), and text mining (e.g., DBPedia, TextRunner) (Lample, Ballesteros, Subramanian, Kawakami, & Dyer, 2016; Sundheim, 1995). These methods allow us to define the relationships between objects and create topology. In other words, disaster domain knowledge extraction establishes the correlation between entities and their attributes. Therefore, semantic similarity calculation becomes the key to relationship discovery and knowledge fusion (Lord et al., 2003; Kim, Vasardani, & Winter, 2017; Toch, Reinhartz-Berger, & Dori, 2011). Thus, the main calculation methods are string similarity, distance-based similarity, and content-based similarity. Based on the above, the resource description framework and attribute graph models can be used for disaster knowledge storage and formal representation.

To illustrate the feasibility of the above-mentioned ideas, we demonstrate a use case combining a knowledge graph and disaster visualization (Li et al., 2020; Zhang et al., 2020), as shown in Figure 4. First, an ontology is constructed to manage the concepts and relationships between multitype users (e.g., ordinary people, victims, rescuers, experts) and disaster data (e.g., DEM, evolution process, impact range). Based on the acquired ontology, a disaster knowledge graph can be designed using multilevel semantic mapping, as shown on the right of Figure 4. Then a user instance is designated as the central node. The top-N recommendation set of disaster data for different user preferences is inferred by calculating the semantic relevance of the central node to other nodes and ranking them accordingly. Finally, a 3D disaster scene that meets the needs of multiple types of users is constructed with the guidance of the top-N set and the new sub-knowledge graphs.

4.2 | Optimal selection of scene data guided by knowledge graph (step 2)

In the process of disaster scene construction, it is difficult to describe the complex geographical process and evolution pattern of disasters if the scene data are insufficient. On the other hand, too much data will lead to scene information overload and inefficient disaster cognition; therefore, selecting disaster scene data needs to be adaptive for different visualization tasks and people's needs (Zhu et al., 2019). The disaster knowledge graph

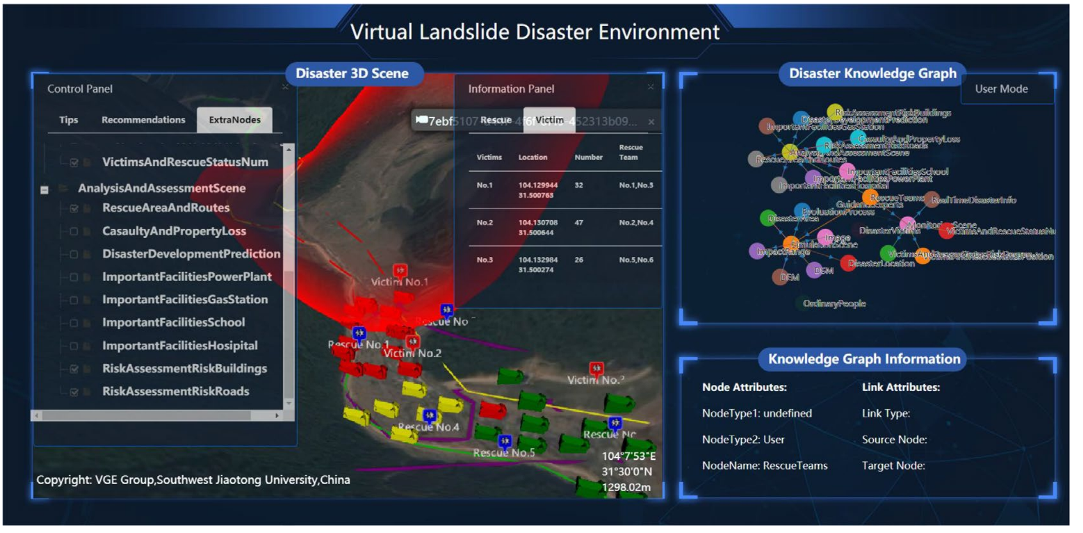

FIGURE 4 An example of the construction of personalized virtual landslide disaster environments based on knowledge graphs (Zhang et al., 2020)

effectively organizes and manages the complex relationships between visualization tasks and disaster data and forms a semantic knowledge network. Nevertheless, it is difficult to quantify each task's needs for scene data due to the lack of a further calculation of semantic relevance (Paulheim, 2017).

There are some recommendation algorithms based on calculating node relevance. For example, Aggarwal et al. (1999) proposed a new collaborative filtering approach based on graph theory in which the nodes represent users, the edges represent the similarity of the two users, and the information is recommended by combining the ratings of nearest neighbor nodes. Zhou et al. (2007) proposed a collaborative filtering method based on network inference, and the item recommendation is made by calculating the association degree between user nodes and item nodes. However, the commonly used algorithms for semantic relevance calculation are PageRank and personalized PageRank (Page, Brin, Motwani, & Winograd, 1999). The personalized PageRank algorithm in particular first needs to specify a central node, and the central node cannot jump to any node randomly during the random walk process but only to the node that has an association with the central node, which reflects the task's need (Pirouz & Zhan, 2017). A hybrid collaborative filtering approach with the joint graph model and semantic relevance is potentially advantageous for achieving visualization task-driven disaster data selection (Zhang et al., 2020).

From the previous description, it can be concluded that the hybrid collaborative filtering approach with the joint graph model and semantic relevance can be used to calculate the degree of demand for disaster data for specific visualization tasks and users. However, the calculation process is only based on the association relationship between entities in the knowledge graph without considering the historical preference data. This approach has improved the intelligence of disaster data selection to some extent, but they still have some subjectivity guided by experts. Exploratory visualization allows a large number of users to interact with virtual disaster scenes in three dimensions. In the interaction process, their interaction behaviors and data preferences can be recorded, such as users' selection results for different spatial data, users' viewing time for specific data, and their browsing methods for different data. These data reflect users' preferences. Then we can take full advantage of the learning and predictive power of deep learning models, a specific deep neural network can be used for multiple rounds of training to mine and quantify the user's preference for the disaster data. For example, RippleNet is an end-to-end framework that naturally incorporates the knowledge graph into recommender systems (Wang et al., 2018). Similar to actual ripples propagating on water, RippleNet can depict the spreading process of each user's preference in the entire knowledge graph of disasters, and then the user's preference index for the disaster data is calculated.

Finally, the recommendation degree is ranked, and the result of a calculation based on a knowledge graph and deep learning is considered to be a high-precision disaster data recommendation set (Zhang et al., 2020).

4.3 | Augmented representation of scenes considering public perception (step 3)

With the development of computer graphics and the gradual upgrading of software and hardware, photorealistic representation has been carried out many applications in the fields of 3D GIS, VGE, and digital cities (Nebiker, Cavegn, & Loesch, 2015). For example, reproducing the disaster process in a photorealistic way enriches the content and quantity of visual information and can facilitate mental mapping (Döllner & Kyprianidis, 2009). However, at the same time, the following problems need to be addressed. First, fine geometry and textures will increase the amount of scene data. Second, a photorealistic scene exposes the user to a high cognitive workload of information processing. Third, users' attention may be entirely captured by appearances and thus ignore the information under the surface (Bunch & Lloyd, 2006; Glander & Döllner, 2009; Jahnke et al., 2008).

In expressing the disaster information process, the key problem is how to use as little information as possible to obtain greater efficiency in disaster knowledge transmission for diverse application needs. Thus, rich semantic information is better than photorealistic visualization (Li et al., 2019). Generally, there are two ways to enhance the semantic representation of disaster information. From the cartography perspective, combining text, symbols, colors, and simple level-of-detail (LOD) models can reveal more disaster semantic information while ensuring a certain degree of realism. According to the degree of abstraction of the real world, text has the highest level of abstract representation, and can be used for labeling and promoting information. Following disaster symbols, which are self-explanatory and have the ability to convey semantic information, they can be adopted to represent the location and accessibility of important facilities and dangerous facilities. Moreover, simple LOD models maintain the original 3D characteristics but reduce the amount of data. Therefore, with the use of simple LOD models with emergency colors to visualize disaster data, the effective and augmented representation of disaster information can be realized with a guarantee of a certain realism (Jahnke et al., 2008; Li et al., 2019). In a similar context, Kolbe, Gröger, and Plümer (2008) stated that 3D city models are a suitable tool with high potential for emergency response. Lee, Park, Park, and Jang (2016) showed how 3D city models can also serve as a basis for decision-making in the context of urban flooding. In addition, static and dynamic visual variables can be combined to emphasize important disaster scene information through visual effects, such as flickering and highlighting (Garlandini & Fabrikant, 2009; Li et al., 2021; MacEachren, 2004). The purpose is to enhance the focus of key information, attract public attention and improve people's risk perception.

Furthermore, with the development of VR, AR, and MR technologies and the increasing popularity of consumer-grade devices, the representation environment and interaction of virtual disaster scenes have been enriched. In addition, immersive disaster scenes have the advantages of strong user experience, natural human–computer interaction, and user active perception (Chen & Lin, 2018; Lai et al., 2011; Zhang et al., 2020). Moreover, applying eye tracking to virtual disaster cognition can record information, such as gaze direction, area of interest, and fixed time. They can quantify the ability of disaster scene objects to convey disaster information and then further refine the visual representation (Dong et al., 2018; Popelka & Brychtova, 2013). Thus, immersive experience and interaction for disaster publicity and education can help transform the dissemination of disaster information from one-way communication guided by experts to two-way communication with public participation. Therefore, it can significantly improve the efficiency of the public perception of disaster scenes. Figure 5 shows an efficient flood dynamic visualization based on 3D printing and AR, which is useful for assisting participants in understanding flood hazards and providing a more intuitive and realistic visual experience.

In addition, the conceptual framework for improving the representation of efficiency comprises additional aspects such as semantic relevance calculation, self-explanatory symbols and photorealistic scene cooperation, and immersive 3D representation For more details accompanied by further flow diagrams, the interested reader is referred to Li et al. (2019, 2020), Hu et al. (2018), and Zhang et al. (2020).

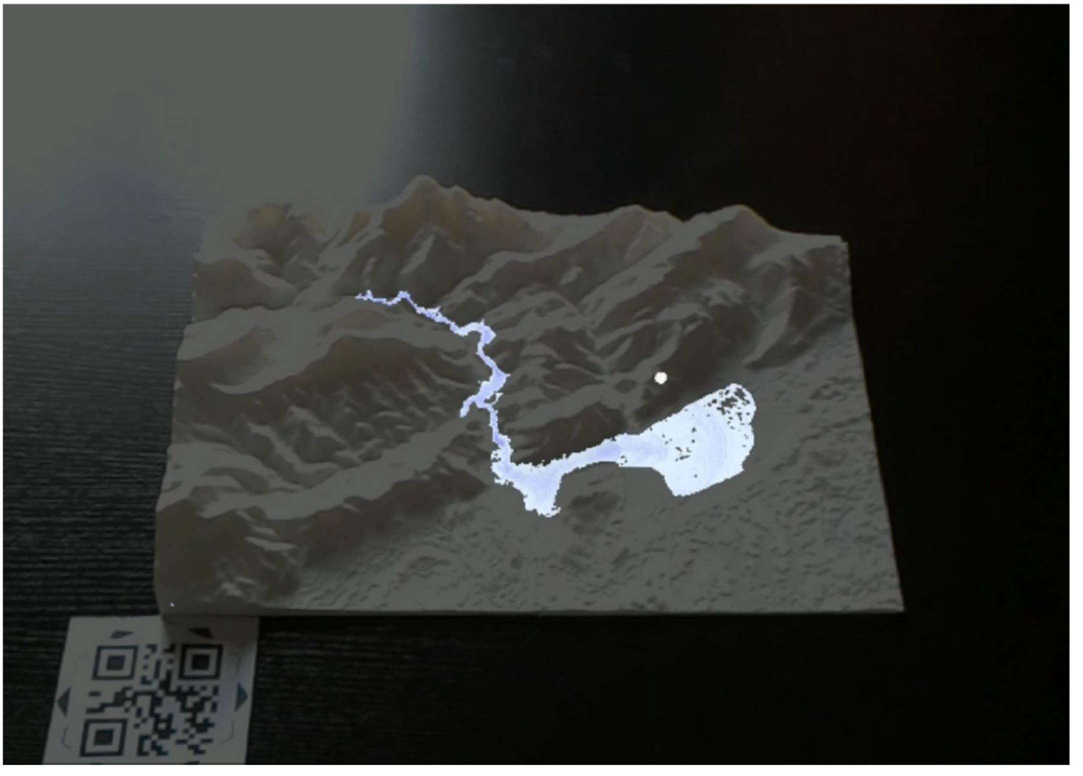

FIGURE 5 Flood dynamic visualization approach based on 3D printing and AR (Zhang, Gong, et al., 2020)

5 | DISCUSSION

In this article, we have put forward basic ideas for improving the representation efficiency of disaster information. However, there is still room for further discussion, and we hope that our work can inspire readers to apply further creative thinking to address the challenges raised here.

Disasters have always been an important threat to human societies. As a result of such crises, many people have been affected, injured, and incurred financial losses. Despite some progress and challenges, as indicated in this article (cf. Tables 1–3), maps and 3D virtual environments and scenes can determine the priorities of relief workers. The identification of affected areas using maps and 3D scenes after critical events can support relief workers in providing emergency services more quickly, and can also make resource allocation more efficient.

One of the main resources in mapping and creating 3D scenes for visualizing and representing disasters and damage is remote sensing incorporating GeoAI, AR, MR, and VGE techniques. However, methods based on remote sensing usually have a time delay of 48–72 hours or atmospheric limitations, such as cloudy weather; therefore, their effectiveness decreases. They are also very costly. In addition, the frequent lack of pre-disaster images makes it difficult to detect the correct changes. However, drone images taken immediately after a disaster can resolve the delay in acquiring remote-sensing satellite data.

Although presenting disaster events via social networks to make maps and 3D images in a short time can provide effective results, the use of various tools, such as sensors and 5G, allows for more accurate results. Therefore, integrating social networking information and other information sources can support the production of reliable and efficient maps and scenes. The authors' findings demonstrate that remote sensing images, social networks and story maps could be good information supplements in GeoAI mapping, 3D scenes and disaster information representation from the geospatial perspective. Integrating user-generated spatial content with other data sources, such as remote sensing and geospatial data, increases the quality of and reduces the time required to generate trusted information, 3D virtual environments and maps. However, social engagement and data sharing privacy have remained a significant challenge in research and for countries; therefore, more sociocultural education is needed in addition to learning technologies.

Moreover, the resilience capacity of a locality can be viewed as its ability to respond to and recover from an event utilizing geospatial maps and 3D virtual environments. For example, to know how much a city resists hazards and what actions are needed to reach the required level, it is first necessary to estimate and measure resilience by defining a framework and utilizing GIS maps and 3D virtual environments. Furthermore, the use of dynamic 3D representation of disasters as opposed to static maps is quite helpful to the public (Li et al., 2021; Macchione et al., 2019). However, the complexity and information density of 3D disaster scenes can increase the public's memory and cognitive burden. In addition, storytelling and geo-narratives can effectively organize the causal logic of disaster events and have potential advantages when communicating disaster knowledge to the public. Additionally, designing a scientific and reasonable cognitive experiment is an important part of the workflow of disaster information representation, knowledge communication, and risk awareness improvement.

Finally, as a means of non-structural mitigation, disaster education can enrich people's disaster perception. However,the main sources of disaster education and awareness are currently books, newspapers, cartoons, and videos, which have played an active role in disseminating disaster knowledge (Kelman, 2015). However, they rely excessively on "publicly available images and texts." The authors hope that open GIS and open sources and data can enrich disaster GIS mapping, 3D visualization and disaster education. Furthermore, social media can contribute to education and develop reliable geospatial disaster information, GIS mapping, and 3D representation. Nevertheless, from the geospatial perspective, integrating a 3D representation of the whole disaster process into disaster education can deepen the public's understanding. This is because it is apparent that the more interactive and public-oriented communication material there is, the better disaster information is understood. Thus, developing algorithms and integrating new immersive technologies, such as VR, AR, and MR, should be a significant research stream in disaster education.

While these new technologies empower the general public to contribute to and engage in disaster management, they also act to marginalize others (Haworth & Bruce, 2015). We must be aware that the digital divide makes it difficult for members of the public with limited socioeconomic circumstances to access the rapidly expanding digital world (Van Dijk & Hacker, 2003), which means that the introduction of new geoinformation technologies in disaster education cannot ignore the conventional text- and image-based means. According to statistics, global 4G population coverage was over 80% at the end of 2020 and is forecast to reach around 95% in 2027, so the role of smartphones in daily disaster management is also becoming increasingly important. Therefore, research on disaster knowledge dissemination, disaster warning systems, and disaster adaptive mapping for smartphones should also be continued.

6 | CONCLUSIONS AND SUGGESTIONS

Given that much attention has been given to GIScience, VGEs, and disaster (Bandrova, Zlatanova, & Konecny, 2012; Cutter, 2003; Lin et al., 2013; Lü et al., 2019), this article has focused on disaster information representation from a geospatial perspective. Therefore, we first reviewed disaster information representation and its role in knowledge communication, and then identified the strengths and weaknesses of disaster mapping and the 3D virtual environment. We also analyzed the weaknesses and strengths of the existing methods for representing disaster information in recent decades, and determined gaps and challenges. Subsequently, we proposed some basic ideas to solve the above challenges (cf. Figure 3). For example, a knowledge graph is adopted to manage the relationship between disaster data and multilevel visualization, optimal selection of disaster data guided by the knowledge graph, and augmented representation of scenes considering public perception. We concluded that disaster information representation should be studied in greater depth and emphasized and applied in disaster education substantially with social participation and data sharing. However, we are aware that our arguments constitute only part of the solutions necessary. Therefore, we hope these arguments will benefit disaster information representation development and further enhance public risk awareness.

The authors understand that technologies play a significant role in disrupting the geospatial segments using IoT, big data, sensors, AI, and digital twins for automation. Therefore, we recommend integrating various technologies incorporating social partnerships, story maps, and data sharing, which may significantly impact short- to medium-term disaster management and the representation of information in GIS mapping and virtual environments. Thus, smartphones, tablets, and other mobile devices can contribute to people's expectations and use of geospatial applications. With the upgrade of HD maps and the emergence of a new-generation rendering engine (such as Unreal Engine), we recommend that researchers study GIS maps and 3D rendering at high definition. We also recommend utilizing every pixel and providing geometry and labels on-screen, constructing a visual disaster scene that is highly similar to the real disaster and encouraging more people to experience the great harm caused by the disaster through virtual experience. Furthermore, with the increasing application of robots and autonomous driving technology in the field of emergency response and disaster management, how to covey information to these non-human devices, better assist them in disaster risk identification, analysis and presentation, and feed the results back to decision-makers is also a new issue worthy of investigation. Finally, we concluded that increasing accuracy and detail information for disasters requires more new devices, open-source platforms, and innovative algorithms for automated data capture, feature detection and extraction, simulation and highly effective representation.

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CONFLICT OF INTEREST

No potential conflict of interest was reported by the author(s).

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