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An on-demand construction method of disaster scenes for multilevel users

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Abstract

Disaster scenes can effectively transmit disaster information and help people make sensible decisions. However, the current 3D scenes of disasters still have certain limitations. First, related studies have focused on the construction of 3D scene technology itself and lacked a detailed semantic description of the disaster scene, which is not conducive to standardizing the process of scene construction and supporting efficient analysis. Second, the 3D scene is generally fixed, preventing full consideration of the different needs of multilevel users involved in disaster management. This paper proposes an on-demand construction method of disaster scenes for multilevel users. The creation of a knowledge graph for disasters, calculation of semantic relevance and optimal selection of scene contents are discussed in detail. Finally, taking a debris flow disaster as an example, a prototype system is developed to implement experimental analysis. The experimental results show that the constructed knowledge graph can normalize the semantic relationships among multilevel users, scene objects and visualization methods in a formal way and accurately describe the different needs of multilevel users. The 3D scenes of debris flow disasters driven by the knowledge graph can reduce the complexity and difficulty of the modeling process while satisfying the diverse needs of multilevel users.

Keywords Disasters · Multilevel users · Knowledge graph · 3D scenes · On-demand construction

1 Introduction

Global climate change and rapid economic growth have increased the frequency and intensity of natural and manmade disasters (Bhatt et al. 2015; Cui 2014). Over the past decade, global catastrophes (e.g., the Haiti Earthquake, Hurricane Katrina, the Wenchuan

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Earthquake, etc.) have seriously threatened human lives and property (Fan and Zlatanova 2011; Bergholt and Lujala 2012). UNISDR (United Nations Office for Disaster Risk Reduction) and the international community have highly valued the significance of disaster mitigation and the sustainable development of the environment (UNISDR 2015). Many major disaster prevention and mitigation measures have been issued, such as "The International Framework for Action," "The International Strategy for Disaster Reduction," "The Hyogo Framework for Action" and "The Sendai Framework for Disaster Risk Reduction." Therefore, disaster prevention and mitigation have become urgent tasks that need to be addressed worldwide.

The primary objective of disaster mitigation is to understand the relevant disaster risks. The Sendai Framework for Disaster Risk Reduction 2015–2030 (SFDRR) emphasized that the policies and practices for disaster risk management should be based on an overall understanding of disaster risk, and the corresponding disaster management scheme should periodically formulate disaster schemes, update location-based disaster risk information and disseminate the risk information to stakeholders (Kelman 2015; Aitsi-Selmi et al. 2015). To build public awareness regarding disaster mitigation and encourage people to become involved in related tasks, the Chinese government issued "The Disaster Prevention and Mitigation Plan of China." This plan highlighted the necessity of improving propaganda and education mechanisms for disaster prevention and reduction goals, increasing the popularization of disaster knowledge in different social groups and enhancing disaster risk awareness (Shi 2016). Therefore, it is of great theoretical and practical significance to strengthen research on the scientific issues related to disasters to enhance the capacity for disaster prevention and risk communication.

As an effective tool for understanding and communicating disaster risk, risk maps can illustrate the range and degree of disasters and thus improve the overall understanding of disaster risk (Burningham et al. 2008; Hagemeier-Klose and Wagner 2009; Henstra et al. 2019; Dransch et al. 2010; Peng et al. 2018). However, a risk map can transmit only static information, and modeling and dynamic visualization are restricted to other methods (Costabile et al. 2015). Compared with risk maps, virtual geographic environments (VGEs) emphasize the integration and sharing of multisource data and can provide high-level analyses of geographic problems, simulations of geographic phenomena and predictions of environmental changes via geographic analysis models and multi-perception technologies (Lü 2011; Lin et al. 2013; Avagyan et al. 2018). Based on the framework of VGEs, many scholars have constructed virtual disaster scenes by coupling simulations of disaster evolution processes and integrating risk assessment methods. On this basis, many systems of disaster emergency simulation and analysis have been developed and applied to floods, debris flows and landslides, among other disaster emergencies (Denolle et al. 2014; D'Aniello et al. 2015; Li et al. 2015; Liu et al. 2017; Yin et al. 2017). VGEs have unique advantages in disaster emergency decision making and enhance disaster risk awareness (Lin et al. 2013; Chen et al. 2015; Chen and Lin 2018; Havenith et al. 2019). However, the above disaster systems focus on the visualization of disaster scenes and lack a guidance mechanism and a specific semantic description of objects during scene construction, which makes it difficult for these systems to support formal scene construction and efficient analysis.

One of the key priorities in disaster risk reduction is ensuring that stakeholders understand their exposure to disaster risks and that they can take protective actions (Henstra et al. 2019; Kellens et al. 2009; Khan et al. 2017). To this end, scholars have performed corresponding research on risk communication. For example, Meyer et al. (2012) acquired user knowledge through questionnaires and used that knowledge to improve the quality of flood risk maps. Macchione et al. (2018) constructed a 3D map of floods and discussed how the map enhanced public risk awareness in detail. White and Kingston (2010) developed a participatory geographic information system and enabled the public to participate in flood risk management. Zhang et al. (2019) realized the optimal organization and dynamic scheduling of debris flow disaster data for different user terminals by analyzing different visualization tasks, thereby improving the efficiency of scene rendering and providing disaster information to users. Although there has been some progress in improving the efficiency of risk communication and user awareness regarding disaster reduction, most risk maps and disaster scenes are still oriented toward a risk expert perspective, without considering multilevel user needs, and they lack quantitative descriptions of different user needs; therefore, many products cannot be directly applied in the on-demand construction of disaster scenes for multilevel users (Strathie et al. 2017).

Disaster scenes involve a large number of objects, and the relationships among objects are complicated, so establishing the semantic associations among multilevel users, scene objects and visualizations from a conceptual perspective and achieving a consistent understanding of disaster scenes at the semantic level are critical for disaster scene modeling and disaster information sharing (Li et al. 2019). An ontology is a formal specification of a shared conceptual model that enables knowledge sharing in different domains (Studer et al. 1998; Fensel 2001). A knowledge graph is a structured semantic knowledge database that describes entity relationships and attributes. Moreover, an ontology is the conceptual template of a knowledge graph, while the latter is the instance filling of the former (Pujara et al. 2013). Many scholars have applied ontologies in the disaster domain. For example, ontologies have been used for flood risk assessment, earthquake emergency response knowledge modeling and representation, the aggregation of spatiotemporal data for natural disaster emergency tasks and knowledge reasoning in the emergency response to sudden geological disasters (Scheuer et al. 2013; Xu et al. 2014; Joshi et al. 2007; Qiu et al. 2017). However, most of the current research focuses on the storage and management of disaster knowledge. Further research on the construction and application of ontologies and knowledge graphs based on virtual disaster modeling is needed.

This paper proposes an on-demand construction method of disaster scenes for multilevel users. The proposed method highlights the creation of a knowledge graph based on mapping semantic information, calculations of semantic relevance and the optimal selection of scene objects. The remainder of this paper is organized as follows. Section 2 describes the core method of the on-demand construction of disaster scenes for multilevel users. Section 3 describes the development of a prototype system and the experimental analysis. Section 4 presents the conclusions of this study and provides a brief discussion of future works.

2 Methodology

2.1 Creation of knowledge graphs for multilevel users

2.1.1 Analysis of multilevel users

As stated previously, different users have different needs in terms of disaster information, and the construction of disaster scenes should consider end-user needs (Alphen et al. 2010; Kellens et al. 2009). This paper classifies users as decision makers, rescuers and the general public according to their characteristics and functions in disaster management.

(1) Decision makers
Decision makers are the staff members who work in governmental emergency management departments. These individuals usually need to make quick decisions within a short emergency time with limited disaster information (Zhou et al. 2018; Zhang et al. 2018). Decision makers approach disasters from a macro perspective, so they are most concerned with the disaster range and the number of affected people. Because experts provide disaster services to decision makers, these individuals have the ability to process high densities of information.

(2) Rescuers
Disaster rescuers are members of professional rescue teams. In contrast to decision makers, these individuals do not have special expertise and knowledge in disasters, 3D visualization, or emergency mapping. The timeliness of rescue is the key to the disaster emergency response, so a 3D scene of disasters for rescuers should be simple and easy to interpret.

(3) General public
The general public lacks disaster risk awareness, and most people believe that disasters will not occur in the area where they live. Therefore, it is particularly important to raise public awareness regarding disaster prevention and reduction (Burningham et al. 2008). A 3D scene of disasters can reproduce the disaster environment and the spatiotemporal evolution process, thereby enhancing the public perception of debris flow disasters and providing reasonable protection measures (Todd et al. 2014).

2.1.2 Conceptual hierarchy analysis of a scene and ontology construction

In this paper, the concept of geographic ontology is introduced in the domain of disasters. By analyzing the conceptual hierarchy structure and relationships between disaster scenes, different concepts are classified and defined. These concepts are connected through semantic relationships, which are used as a knowledge template to guide the subsequent creation of knowledge graphs.

(1) The contents of disaster scenes
Bandrova et al. (2012) noted that the contents of a 3D map can be subdivided into three types: main content, secondary content and additional content. This paper divides disaster scenes into four components, namely basic geographic objects, disaster objects, disaster information objects and emergency management objects, as shown in Fig. 1 and Table 1.

(2) The construction of a disaster ontology
An ontological structure is mainly expressed in the form of a tuple. While a typical ontology structure is a triple, which consists of concepts, relationships and individuals. In this paper, we define the structure of a disaster ontology, and a quintuple is adopted to describe the disaster ontology model, as shown in Formula (1):

$$O_d = \langle \mathrm{MU}, \mathrm{SO}, \mathrm{VM} | \mathrm{RC}, \mathrm{RI} \rangle \tag{1}$$

A disaster ontology model consists of M(ultilevel)U(ser), S(cene)O(bject), V(isualization)M(ethod), R(elationship of)C(oncept) and R(elationship of)I(ndividual).

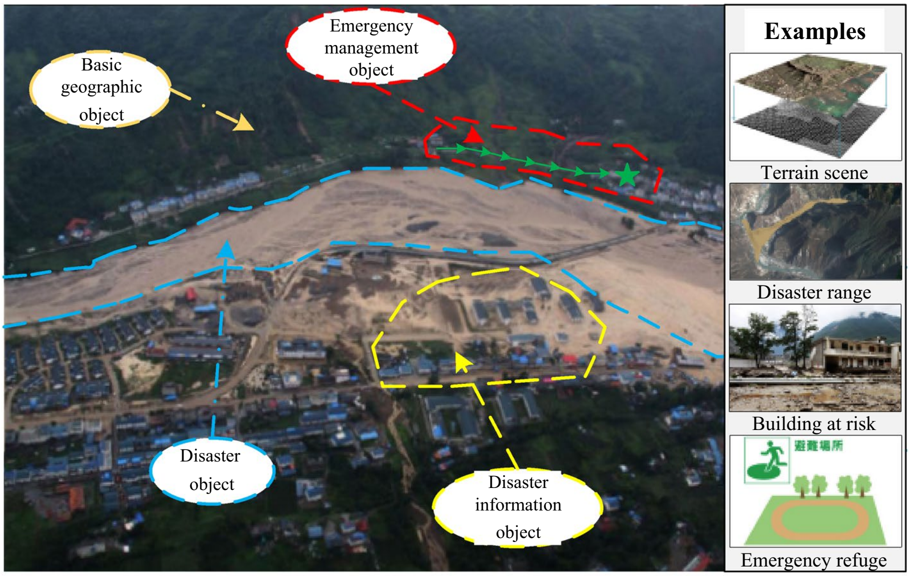


Fig. 1 Conceptual hierarchy analysis of objects in disaster scenes

The construction of disasters for multilevel users mainly includes four stages: (1) domain specification, (2) conceptualization, (3) ontology construction and (4) formalization. Figure 2 shows the process of constructing the disaster ontology.

2.1.3 Multilevel semantic mapping among multilevel users, scene objects and visualization methods

Given the lack of necessary relevance among multilevel users, scene objects and visualization methods, this paper proposes a multilevel semantic mapping method, as shown in Fig. 3.

The multilevel semantic mapping relationship can be expressed as follows:

$$U\{\text{user1},\ldots\} \xrightarrow{f(s1,s2)} O\{\text{object1},\ldots\} \xrightarrow{f(s3,s4)} V\{\text{visualization1},\ldots\}, \tag{2}$$

where U denotes the multilevel users, O denotes the scene objects, and V denotes the visualization methods. Furthermore, $f(s1, s2)$ indicates the first level of semantic mapping, where $s1$ is the semantic constraint for scene integrity, $s2$ denotes multilevel user preferences, and the scene objects for multilevel users can be obtained by filtering with the first-level semantic constraint. Additionally, $f(s3, s4)$ indicates the second level of semantic mapping, where $s3$ is the influence of scene objects on the visualization efficiency, $s4$ is the necessity of augmented expression, and the visualization methods of scene objects can be determined by the second-level semantic constraint, which makes disaster scenes easy to read and understand.

Table 1 Describes the contents of disaster scene objects in detail

Category	Term description	Contents
Basic geographic objects	Basic geographic information of the disaster area before a disaster	Terrain, buildings, roads, etc.
Disaster objects	Describe the disaster itself	Disaster location, range, evolution process, etc.
Disaster information objects	Describe the impact of a disaster on disaster-bearing bodies	Affected buildings, roads, towns, and population, etc.
Emergency management objects	Describe the agencies, people, and measures involved in the emergency management process	Emergency agencies, shelters, evacuation routes, etc.

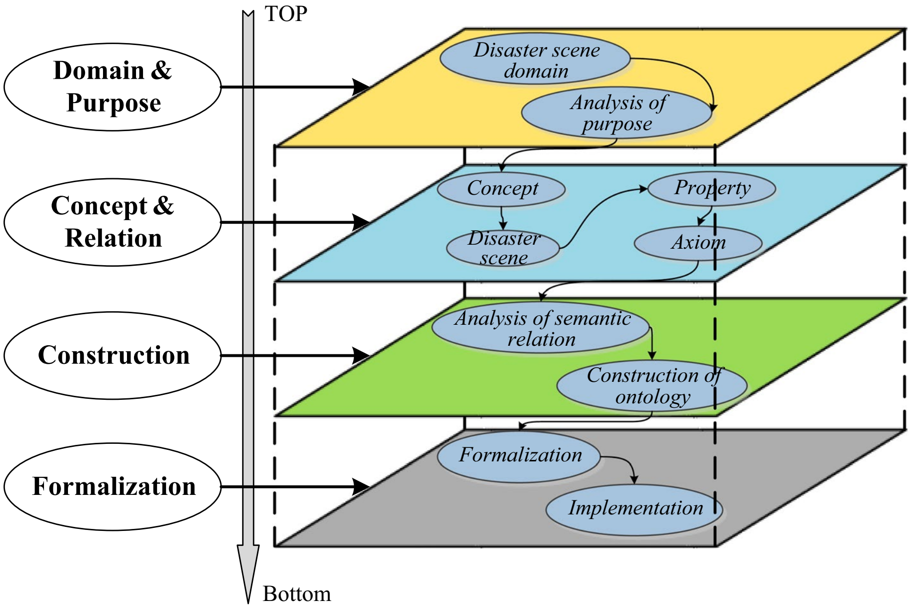


Fig. 2 The process of constructing the disaster ontology

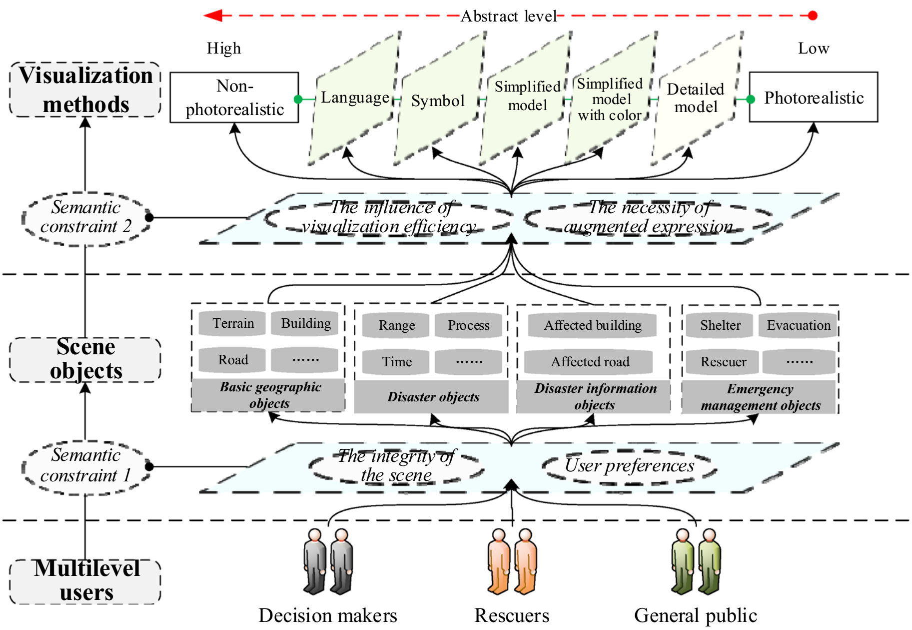


Fig. 3 Multilevel semantic mapping among multilevel users, scene objects and visualization methods

2.1.4 Creation of a scene knowledge graph based on semantic mapping

A knowledge graph is a structured knowledge base that describes the relevant concepts and their relationships in the physical world using symbols. Entities are connected through relationships that form a network of knowledge structures (Paulheim 2017). Domain knowledge about disasters exists in the data layer of a knowledge graph in the form of an "entity object-semantic relationship" and exhibits a "node-edge" graph structure. Moreover, a knowledge graph for disasters can describe the semantic relationships among multilevel users, scene objects and visualization methods clearly, thus guiding disaster scene construction and reducing modeling complexity.

G (a graph) consists of set V (vertices) and set E (edges), as shown in Formula (3):

$$\begin{cases} G = (V, E) \\ V = V(G) \\ E = E(G) \end{cases}, \tag{3}$$

where G denotes the knowledge graph, V denotes the finite set of nodes, E is the finite set of edges connecting the nodes in V, and both E and V contain attributes.

Taking the disaster ontology described in Sect. 2.1.2 as a conceptual template, a knowledge graph for disasters can be designed by using multilevel semantic mapping, as described in Sect. 2.1.3. In addition to storing disaster knowledge, the knowledge graph can also be used for subsequent calculations of semantic relevance and scene modeling. Figure 4 shows the process of mapping a disaster ontology to a graph structure.

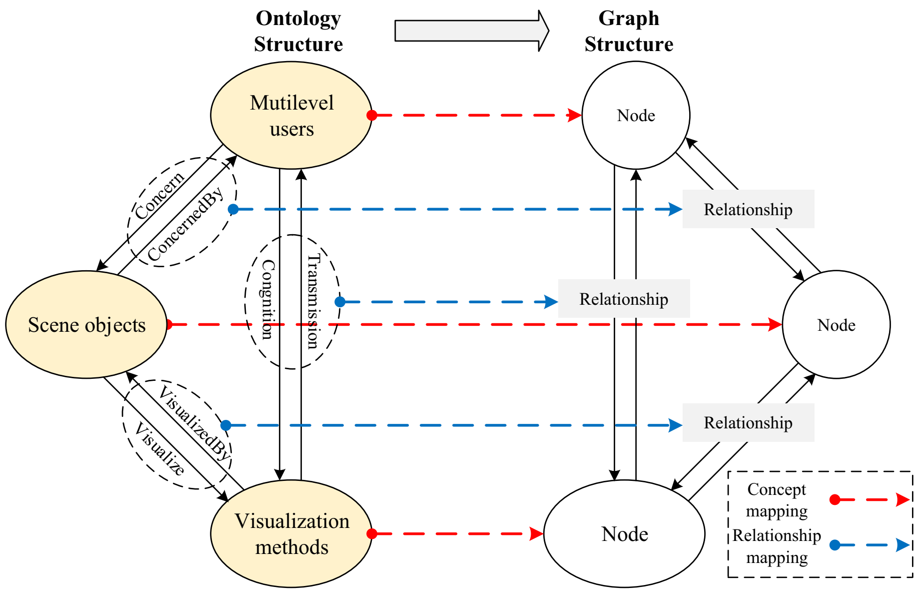


Fig. 4 Mapping a disaster ontology to a graph structure

2.2 On-demand construction of debris flow disaster scenes

2.2.1 Calculation and ranking of semantic relevance

Although a knowledge graph of disaster scenes can explicitly represent the relationships among multilevel users, scene objects and visualization methods, it is difficult to quantify each user's needs for scene objects due to the lack of a further calculation of semantic relevance. The weight of each node is recursively calculated by the personalized PageRank algorithm using the graph structure (Pirouz and Zhan 2017). In the algorithm, we consider the subjectivity of the multilevel users, and no jump can be made to any node in a random walk process. A random walk is a mathematical object, known as a random process. Based on this concept, central node jumps can occur only to specific nodes representing a user need; thus, a high access probability can be obtained based on the nodes representing user needs and some related nodes. This probability is defined as semantic relevance.

A strongly connected graph is formed based on the demand mapping relationships among user nodes, scene object nodes and visualization nodes, and a knowledge graph of disasters is generated with rich semantic features to facilitate logical reasoning. Based on this approach, the semantic relevance among multilevel users and scene objects can be calculated by adopting the personalized PageRank algorithm and obtaining the Top-N recommendation set by ranking the importance of each relation. The algorithm is shown in Formula (4):

$$\mathrm{PR}(i) = (1-\alpha)r_i + \alpha \sum_{j\in \mathrm{in}(i)} \frac{\mathrm{PR}(j)}{|\mathrm{out}(i)|} \quad r_i = \begin{cases} 1 & i = u \\ 0 & i \neq u \end{cases}. \tag{4}$$

This paper uses the above formula to calculate the semantic relevance of all scene object nodes relative to the user nodes u. PR(i) denotes the PR value of node i, that is, the access probability; r_i denotes the initial vector of user preferences; in(i) represents the in degree, that is, the set of nodes pointing to node i; out(i) represents the out degree, that is, the set of nodes that node i points to; and α is a damping factor, which is usually equal to 0.85 and can prevent decreases in semantic relevance accuracy caused by the clustering of some nodes due to the existence of isolated nodes (Brin and Page 1998; Becchetti and Castillo 2006). The semantic relevance of all scene object nodes relative to user node u can be iteratively calculated, and the recommendation set of the Top-N scene objects that meet the relevant user needs can be obtained by ranking the PR values.

2.2.2 Construction of disaster scenes based on recommendation sets

Scientific and appropriate visualization can increase the effectiveness and interpretability of disaster information. When the Top-N set is obtained, we update the knowledge graph and adopt the fusion visualization method with the spatial semantic constraints proposed by Li et al. (2019) to construct a disaster scene. Semantic constraint rules, which include the spatial location, attribute category, and spatial topology, are designed to ensure the seamless integration of scene objects. Finally, self-explanatory symbols and photorealistic scene cooperation are used to construct and visualize disaster scenes that meet user needs and efficiently transmit disaster information.

3 Experimental analysis

3.1 Study area description

Affected by the "5·12" Wenchuan Earthquake, Wenchuan County in Sichuan Province has become a debris flow-prone area in China. In recent years, many debris flow disasters have occurred in Wenchuan County, and the losses caused by the disasters in Sanjiang town, Shuimo town and Yinxing village were the most serious. This paper selects a debris flow disaster that occurred in Shuimo town as a case study for experimental analysis. Figure 5 shows the case study area.

3.2 The ontology of a debris flow disaster

To describe the process of debris flow disasters from top to bottom, this paper uses Protégé to aggregate concepts into classes and present them in a hierarchical structure. Protégé was developed by Stanford University, and it is a free and open-source ontology editor. Figure 6 shows the hierarchical relationships among the classes involved in a debris flow disaster.

3.3 Prototype system implementation and on-demand construction of disaster scenes

Based on the above research results, a knowledge graph and 3D scene of a prototype system for constructing debris flow disasters was implemented using JavaScript, Java, Node.js, the Neo4j graph database, and the Cesium and D3 open-source libraries. Figure 7 shows the interface of the prototype system. This system was mainly used to create knowledge

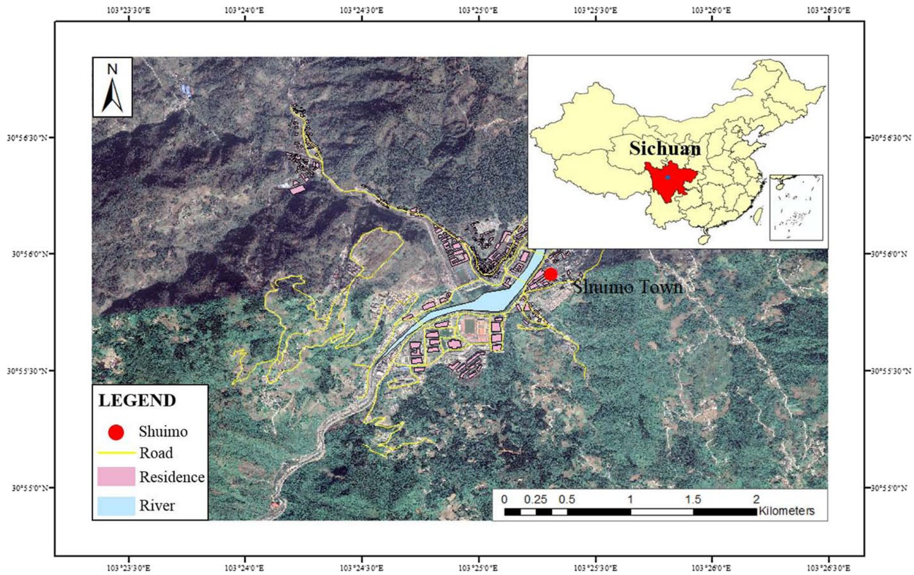


Fig. 5 Study area: a debris flow disaster in Shuimo town, Wenchuan County

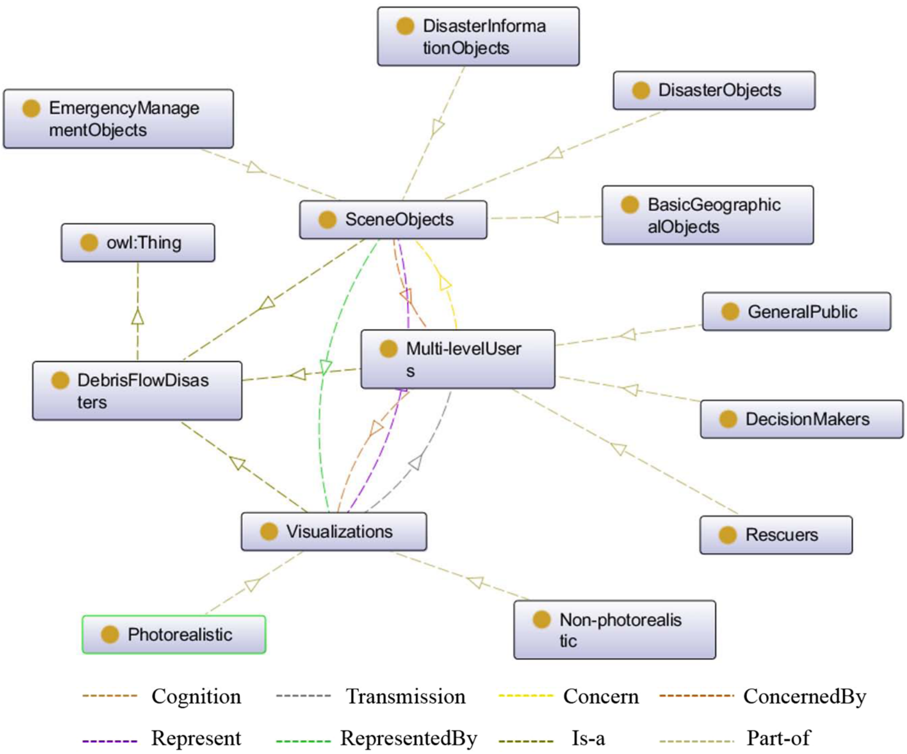


Fig. 6 Conceptual hierarchy of the ontology of a debris flow disaster

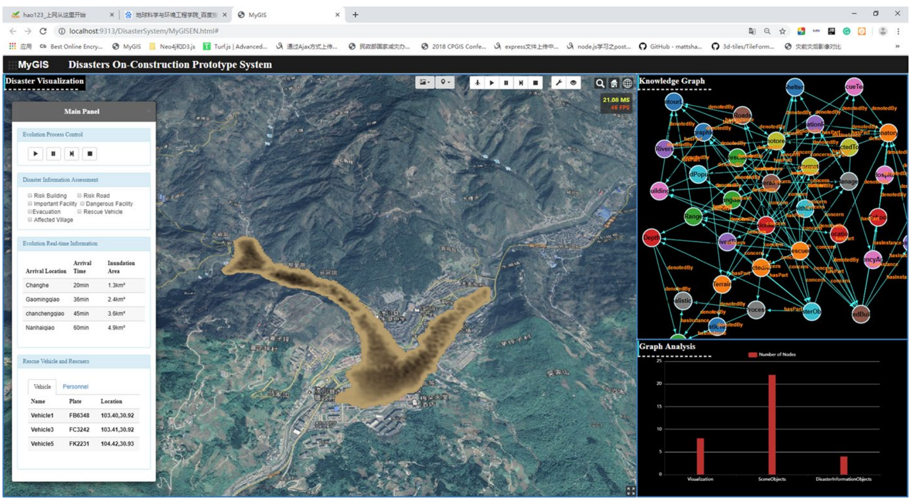


Fig. 7 The interface of the prototype system

graphs for multilevel users, to calculate the semantic relevance among multilevel users and scene objects and to construct a 3D scene of debris flow disasters.

3.3.1 Creation of a knowledge graph for debris flow disasters

By taking the ontology of a debris flow disaster as a conceptual template, the scene objects and corresponding methods for multilevel users can be preliminarily determined based on semantic mapping among multilevel users, scene objects and visualization methods. Based on the above results, a total of 41 entity nodes and 137 relationships were selected, and the Neo4j graph database was used to store these nodes and relationships. Finally, graph data can be visualized, and a knowledge graph of debris flow disasters will be formed in the prototype system.

A knowledge graph of a debris flow disaster scene for multilevel users can express the domain knowledge involved in debris flow disasters, including multilevel user types, disaster scene objects, visualization methods and the corresponding relationships. This approach also supports efficient queries and analyses of semantic disaster information, as shown in Fig. 8.

3.3.2 Calculation of semantic relevance and formation of recommendation sets

To quantify the on-demand relationships between multilevel users and scene objects, with users as the source nodes, the personalized PageRank algorithm described in this paper was used to calculate the semantic relevance between multilevel users and scene objects, as shown in Figs. 9, 10 and 11. A Top-N recommendation set was developed according to the order of semantic relevance.

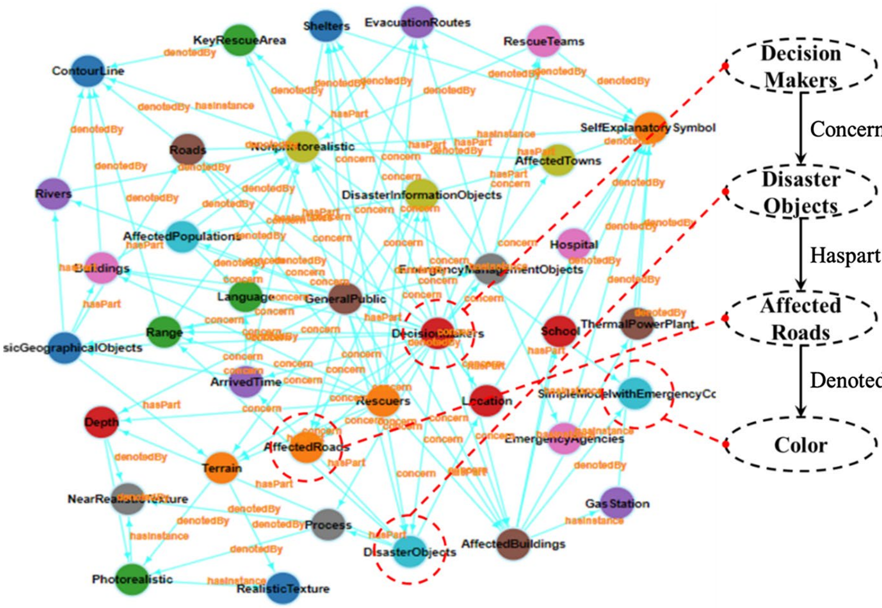


Fig. 8 Construction and analysis of a knowledge graph for debris flow disasters

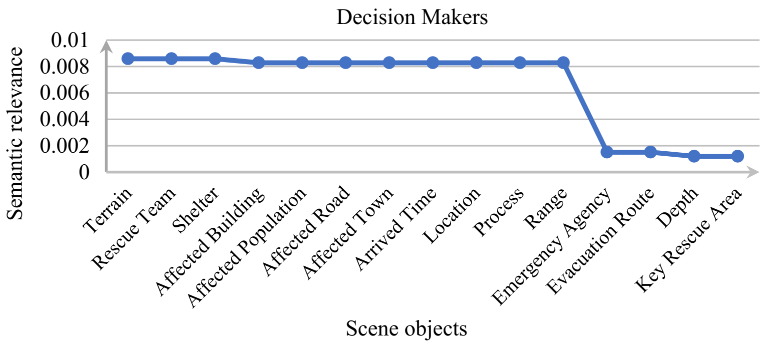


Fig. 9 The semantic relevance between decision makers and scene objects

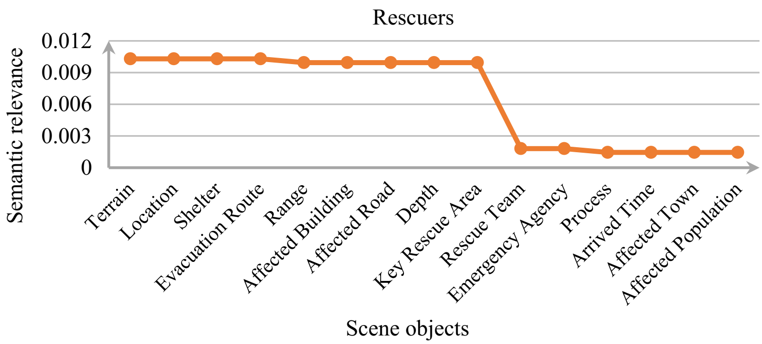


Fig. 10 The semantic relevance between rescuers and scene objects

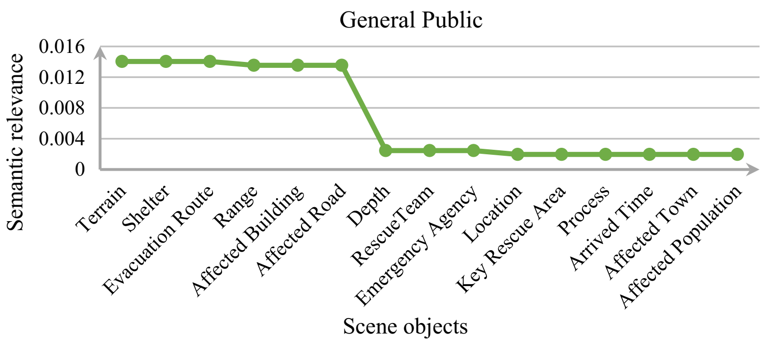
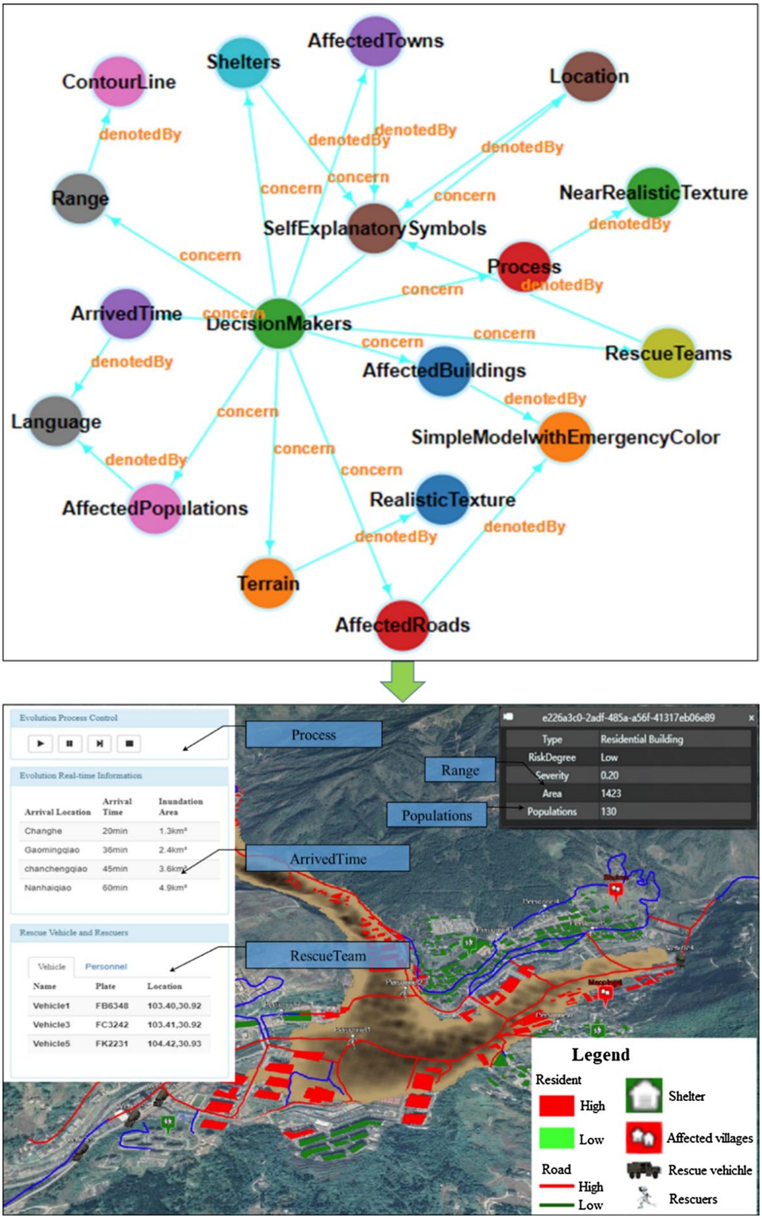


Fig. 11 The semantic relevance between the general public and scene objects

Each of the above three figures has an obvious inflection point, after which the semantic relevance between multilevel users and scene objects drops dramatically. Therefore, it is reasonable to add scene objects before this point to the Top-N recommendation set, and then, the knowledge graph can be reconstructed to guide subsequent scene modeling.



Arrival Location	Arrival Time	Inundation Area
Changhe	20min	1.3km²
Gaomingqiao	36min	2.4km²
chanchengqiao	45min	3.6km²
Nanhaiqiao	60min	4.9km²

Name	Plate	Location
Vehicle1	FB6348	103.40,30.92
Vehicle3	FC3242	103.41,30.92
Vehicle5	FK2231	104.42,30.93

Fig. 12 A debris flow scene for decision makers

3.3.3 Construction of debris flow disaster scenes for multilevel users

With the guidance of the Top-N set and reconstructed knowledge graph, we adopt the fusion visualization method with spatial semantic constraints to construct different debris flow disaster scenes for decision makers, rescuers and the general public, and the complexity and difficulty of the modeling process are reduced while satisfying the diverse needs of multilevel users (Figs. 12, 13, 14).

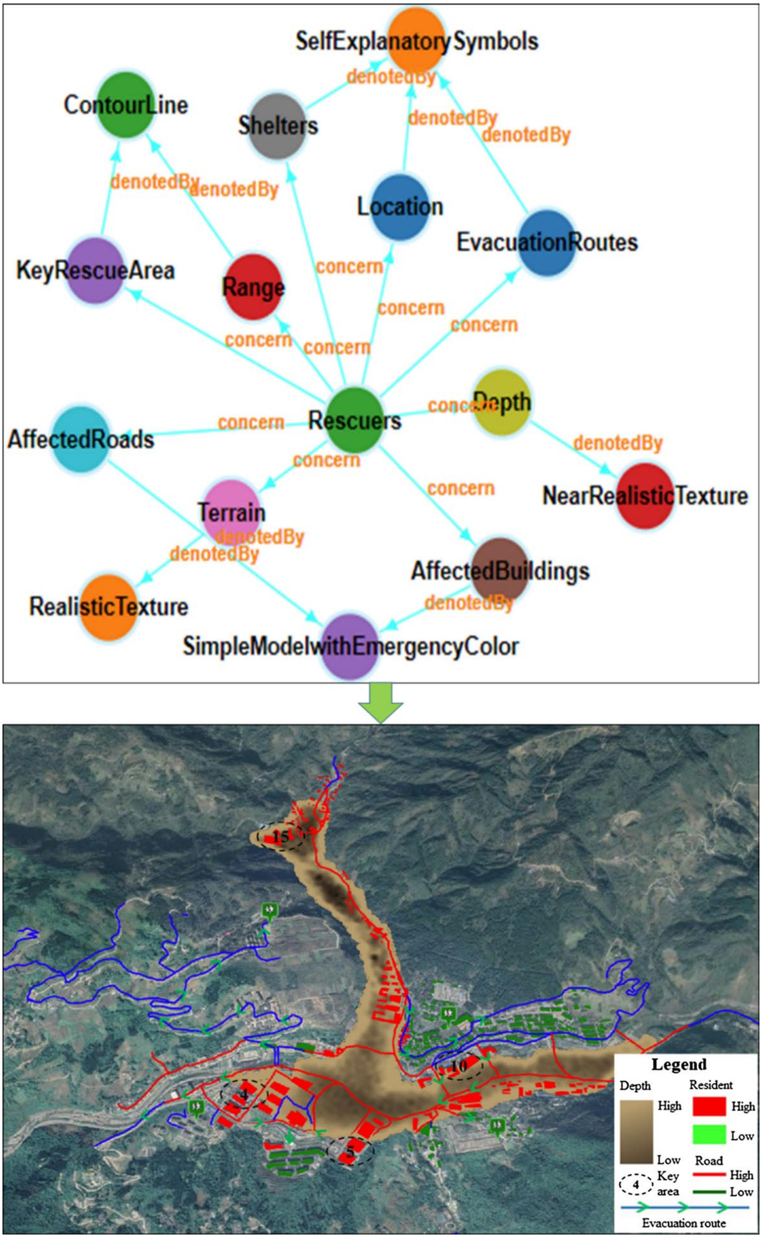


Fig. 13 A debris flow scene for rescuers

3.4 Result analysis and discussion

Driven by the knowledge graph, the proposed method can be used for the on-demand construction of debris flow disaster scenes in 3D for multilevel users. First, the knowledge graph of disasters provides a way to organize and manage the relationships among

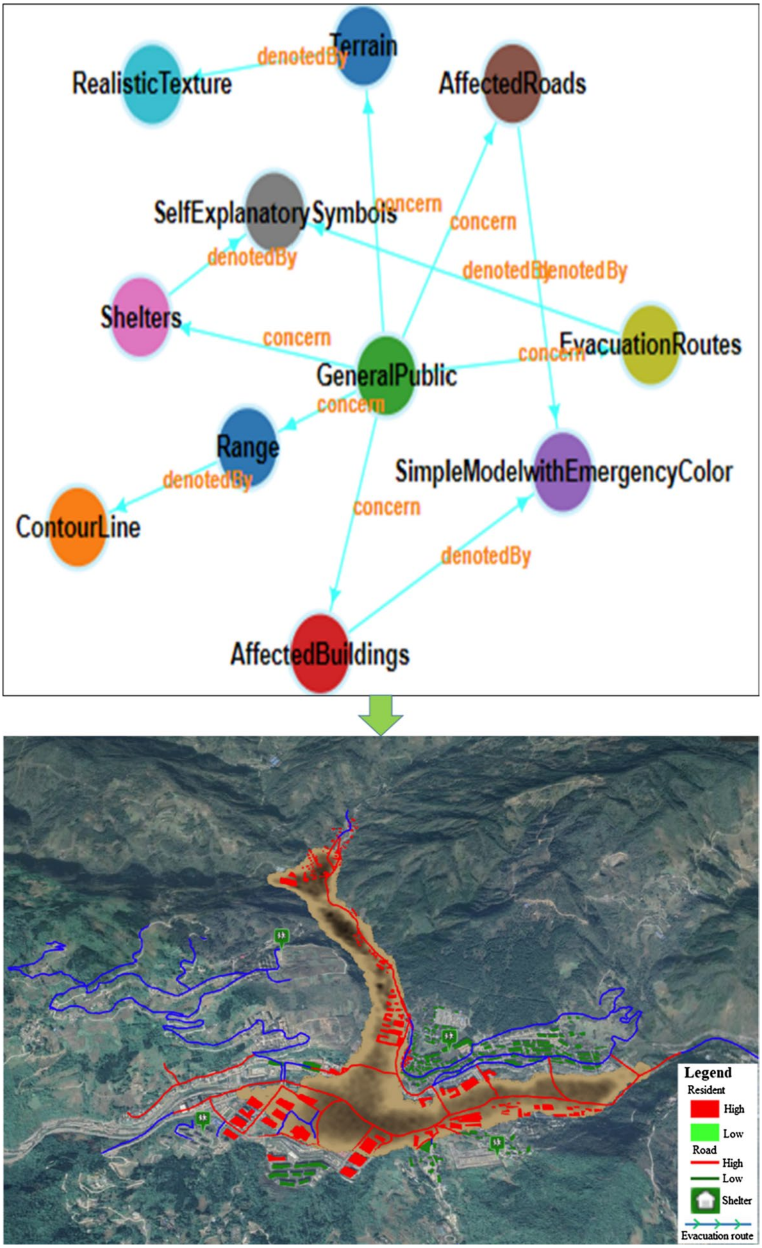


Fig. 14 A debris flow scene for the general public

multilevel users, scene objects and visualization methods; it can also be used to effectively obtain and analyze the corresponding scene objects for different users and then form a guidance graph that can be used to guide the scene construction process, thus reducing the complexity of scene modeling. Second, 3D scenes have the ability to vividly illustrate the spatiotemporal evolution process of disasters, which can attract the attention of users and improve the perceptibility of disaster information. This approach has the potential to propagate disaster knowledge and enhance people's risk awareness based on news media. Third, we constructed different 3D scenes of disasters for multilevel users. The scene for decision makers has the highest information density because decision makers want to have a comprehensive understanding of disasters at the macrolevel; they focus on the disaster location, disaster range, rescue situation and damage situation. The scene for the general public is the simplest because the public has limited expertise and mainly cares about property damage.

An important aspect of disaster risk management is risk communication, which aims to improve the resilience of people in emergencies. Additionally, emergencies not only require people with different knowledge backgrounds but also involve interdisciplinary knowledge integration (Samuels 2011; Maskrey et al. 2016). Compared with traditional methods, the proposed method has the following two advantages.

(1) A knowledge graph is used to guide the process of disaster scene construction, which improves the efficiency of disaster scene modeling in 3D.

    The related studies on disaster scene construction in 3D and disaster information visualization have focused on the technology itself (Hu et al. 2018; Macchione et al. 2018; Zhang et al. 2019; Tsai and Yau 2013), such as photorealistic visualization, the level of detail of model and dynamic data scheduling. Thus, these methods lacked a guidance mechanism and specific semantic descriptions of objects during scene construction. In this paper, we use the knowledge graph to organize and manage the semantic relationships among multilevel users, scene objects and visualization methods. With the guidance of the knowledge graph, semantic heterogeneity issues related to disaster scene objects can be avoided, and the difficulty and complexity of disaster scene modeling can be reduced, thereby enhancing the efficiency of disaster scene modeling in 3D.

(2) Considering the different needs of multilevel users, the disaster scene in 3D is constructed on demand.

    As mentioned in the introduction, the existing risk maps and disaster scenes are still oriented toward a risk expert perspective, without considering multilevel user needs and domain knowledge (Dransch et al. 2010; Strathie et al. 2017; Leskens et al. 2014). In this paper, we calculate the semantic relevance between users and scene objects based on a knowledge graph, which can quantify the different needs of multilevel users. In addition, the optimal selection of disaster scene content based on the ranking of semantic relevance values can be achieved to provide a friendly and understandable 3D disaster scene for multiple users and improve user awareness regarding disaster information.

4 Conclusions and future work

Disaster scenes in 3D can be used to transmit location-based disaster information to users, update information over time, improve the general understanding of disaster risk and enhance public risk awareness and protection. This paper proposed an on-demand construction of disaster scenes for multilevel users. Key technologies, including the creation of a knowledge graph for disasters, calculation of semantic relevance and optimal selection of scene content, were addressed in detail. Finally, taking a debris flow disaster as an example, a prototype system was developed to perform experimental analyses. The experimental results showed that the proposed method is suitable for the on-demand construction of debris flow disaster scenes in 3D. The main contributions of this article are summarized as follows.

First, the knowledge graph is adopted to define the semantic relationships between objects and describe the diverse needs of multilevel users. A knowledge graph of disasters is constructed by analyzing the multilevel users involved in disaster management, the conceptual hierarchy of disaster scenes and semantic mapping relationships. The disaster scene objects and corresponding visualization methods required by multilevel users can be quickly queried and efficiently analyzed.

Second, the on-demand construction of debris flow disaster scenes in 3D for multilevel users is driven by the knowledge graph. We designate user-centered nodes to calculate the semantic relevance between multilevel users and scene objects and quantify the different scene requirements of users. According to the ranking of semantic relevance values, a Top-N recommendation set is formed, and the knowledge graph can be reconstructed. The reconstructed knowledge graph can reduce the complexity and difficulty of the modeling process. Finally, a 3D disaster scene that meets the needs of multilevel users and is easy to understand is constructed.

Despite the achievements described above, this paper has some shortcomings. A certain degree of domain expert knowledge is still needed to construct a knowledge graph. The diverse needs of multilevel users need to be further specified and quantified. Therefore, a questionnaire and eye-tracking experiment will be combined in future work to analyze user needs, and this knowledge will be integrated into a knowledge graph for disaster scene construction. In this way, personalized customizations of debris flow disaster scenes can be achieved to meet various requirements.

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Author's Contributions WL, JZ and YC provided the initial idea for this study; WL, YZ and YH designed and performed the experiments; WL, LF and YG recorded and analyzed the experimental results; WL wrote this paper.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflicts of interest.

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