International Journal of
Geo-Information

MDPI

Article

GeoGraphVis: A Knowledge Graph and Geovisualization Empowered Cyberinfrastructure to Support Disaster Response and Humanitarian Aid

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Abstract: The past decade has witnessed an increasing frequency and intensity of disasters, from extreme weather, drought, and wildfires to hurricanes, floods, and wars. Providing timely disaster response and humanitarian aid to these events is a critical topic for decision makers and relief experts in order to mitigate impacts and save lives. When a disaster occurs, it is important to acquire first-hand, real-time information about the potentially affected area, its infrastructure, and its people in order to develop situational awareness and plan a response to address the health needs of the affected population. This requires rapid assembly of multi-source geospatial data that need to be organized and visualized in a way to support disaster-relief efforts. In this paper, we introduce a new cyberinfrastructure solution—GeoGraphVis—that is empowered by knowledge graph technology and advanced visualization to enable intelligent decision making and problem solving. There are three innovative features of this solution. First, a location-aware knowledge graph is created to link and integrate cross-domain data to make the graph analytics-ready. Second, expert-driven disaster response workflows are analyzed and modeled as machine-understandable decision paths to guide knowledge exploration via the graph. Third, a scene-based visualization strategy is developed to enable interactive and heuristic visual analytics to better comprehend disaster impact situations and develop action plans for humanitarian aid.

Keywords: knowledge graph; visualization; cyberinfrastructure; semantics; visual analytics; humanitarian aid; disaster response; spatial decision support; storytelling; big data

Citation: Li, W.; Wang, S.; Chen, X.; Tian, Y.; Gu, Z.; Lopez-Carr, A.; Schroeder, A.; Currier, K.; Schildhauer, M.; Zhu, R. GeoGraphVis: A Knowledge Graph and Geovisualization Empowered Cyberinfrastructure to Support Disaster Response and Humanitarian Aid. *ISPRS Int. J. Geo-Inf.* **2023**, *12*, 112. https://doi.org/10.3390/ijgi12030112

Academic Editors: Florian Hruby and Wolfgang Kainz

Received: 29 December 2022
Revised: 16 February 2023
Accepted: 24 February 2023
Published: 7 March 2023

1. Introduction

The 21st century has witnessed an increasing frequency and intensity of disasters, including extreme temperatures, drought, wildfires, landslides, hurricanes, floods, and wars, resulting in significant economic losses and devastating impacts to peoples' lives. As one of the most populous and geographically expansive countries, the United States (US) is exposed to a variety of natural disasters. According to a recent statistic by the National Oceanic and Atmospheric Administration (NOAA), the US has encountered 89 weather- and climate-related disasters, causing damage valued at $1 billion or higher in the last five years (2017–2021). These disasters have caused a death toll of 4557 people and displaced over 6 million people [1,2] (NOAA 2022; IDMC 2022). To improve the resiliency outcomes of a community and strengthen both preparedness and response effectiveness for various disaster types, it is important to quickly gather critical disaster related information to make informed decisions.

Several challenges remain, however, when attempting to achieve effective disaster management and mitigation. First, in order to gain a comprehensive view of a disaster situation and its potential impacts, rapid assembly of geospatial data from multiple sources is often required. For instance, as Hurricane Ian gathered strength and moved towards Florida in September 2022, it was critically important to collect related geophysical information, such as its projected trajectory, speed, and strength. After the hurricane made landfall, responders had to gain situational awareness of the affected area, including critical damage, cascading aftereffects, the location of vulnerable populations, and the medical needs of residents. From the perspective of humanitarian aid and public health, it is also crucial to identify experts who have local knowledge about the medical systems, potential disaster-induced health issues, and the need for medical supplies. These multi-disciplinary datasets—ranging from geophysical observations and model simulation results to socioeconomic and public-health profiles of local populations—are not only heterogeneous in content but also in their respective sources, locations, and formatting. Thus, their integration and interoperability present great challenges [3–5]. Second, the diversity, amount, and complexity of the data, known as the "big data" problem, inevitably hinder effective analysis and decision making [6,7]. For instance, many of these datasets are maintained by various organizations and documented in different geographical units (e.g., counties, ZIP codes, and weather-forecasting zones), with little cross-walk (i.e., definitions of semantic and spatial attributes and their relationships) between the datasets, resulting in an analysis that requires large amounts of data pre-processing, making the semantic and integrated analysis difficult to achieve [8,9]. Third, decision making in a disaster scenario requires collaboration and coordination across multiple disciplines, sectors, and borders. An information platform that is available only to a small subset of people in this decision chain will limit the ability to share relevant information among organizations and hinder coordinated responses. A decision-making workflow that is accessible only to specific analysts will make its re-use difficult to achieve, limiting its applicability beyond a particular situation [10–12]. In addition, the geospatial data and analytical results need to be presented and communicated in a way that is easy to comprehend and interact with [13].

The emergence of cyberinfrastructure, which is defined by the National Science Foundation (NSF) as the next generation data and computing infrastructure built upon distributed computers and information communication technology, has the potential to accelerate decision making and support critical real-world problem solving [14]. It achieves this through the integration of four key components in a scientific analysis workflow: data, computing, visualization, and community. Since the term was coined, cyberinfrastructure platforms have been developed across many science and engineering domains, such as biology [15], hydrology [16], environmental sciences [17], plant science [18], geoscience [19], and geography [20]. Many of these solutions address one or more aspects of cyberinfrastructure research. For instance, CyberGIS is a platform aiming to use cloud and high-performance computing to conduct rapid computation-intensive spatial analysis [21]. PolarHub is a cyberinfrastructure solution focusing on large-scale crawling to support automated discovery and ready access to distributed geospatial data [22]. Li et al. [4] developed it as a cyberinfrastructure portal for disaster management, which adopts a server-side compression and client-side decompression to improve data transmission speed over the Internet to allow near real-time analysis of big data [23].

In the past decade, exciting progress has been made in cyberinfrastructure research, especially in the areas of service-oriented analysis and computing, resulting in dramatic increases in systems-level interoperability across multi-source data [22,24]. However, the semantic-level annotation and linkages among disparate datasets, essential to support semantic interoperability and intelligent analysis of multi-source data in a disaster response scenario, are far less well studied. Although research in developing ontologies and large-scale knowledge graphs to model natural disasters has been increasing in recent years, information inside these knowledge bases is mostly at the conceptual level (e.g., defining key concepts or ontological schema) instead of the real data level. Furthermore, locational information is rarely built into knowledge graphs. Finally, few cyberinfrastructure systems exist that employ knowledge graphs, particularly those with an advanced visualization interface to facilitate interaction with the graph.

In this paper, we describe such a graph-powered visualization application, specifically developed to guide situational awareness during natural disasters and to support relief experts and decision makers as they develop plans for disaster relief, such as the distribution of medical and other humanitarian supplies. Our research focuses on making contributions to spatial data infrastructure and cyberinfrastructure research in three aspects: (1) building an integrated semantic schema and corresponding knowledge graph to model spatiotemporal big data; (2) ensuring the re-use and interoperability of our knowledge graph with existing standards, such as those from W3C and Open Geospatial Consortium (OGC); and (3) developing a user-friendly visualization interface to allow interactive exploration and visual analytics of graph data to support disaster response and humanitarian aid. The next section provides a review of relevant research.

2. Literature Review

2.1. Disaster Ontologies and Knowledge Graphs

There is a growing amount of research focusing on constructing ontologies and knowledge graphs for disaster preparedness and resilience [25]. An ontology is a formal representation of world entities and their interrelationships, reflected in well-formed schema and rules that constrain the semantic relationships [26–28]. Due to its advantage in allowing flexible knowledge sharing, exchange, and integration through standardization, ontology modeling has been broadly adopted to support different phases of disaster and emergency management [29–31]. For instance, Wu et al. [32] evaluated flood risk and predicted flood likelihood by leveraging semantic concepts defined in a disaster ontology that contains elements of extreme weather, disaster conditions and surroundings, and human and social properties. Murgante et al. [28] built a multilingual ontology for seismic risk prevention and management. It is constructed to reduce conceptual and terminological ambiguity by comparing existing ontologies and formulating seismic risk concepts and their relationships. To support disaster response and recovery, Dhakal et al. [29] created a knowledge-based system to support disaster resilient construction practices, in which a document classification technique was used to facilitate information retrieval, knowledge classification, and transferral. Ge et al. [33] developed a knowledge graph that integrates remote sensing images and other spatiotemporal data for predicting the occurrence of natural disasters, such as forest fires and landslides. Wang et al. [34] built a general GeoKG (KG—Knowledge Graph) framework to capture the spatio-temporal changes of a geo-object. The authors compare their GeoKG definition with another popular YAGO (Yet Another Great Ontology) framework to discuss the strengths and weaknesses in modeling administrative regions (e.g., state). Jung et al. [35] developed an ontology-driven slope modeling tool based on information gathered from users' mobile devices, the environment, and local authorities. This tool was developed to support risk assessment and rapid disaster response. Other than building an ontology to model a specific disaster, Bouyerbou et al. [36] developed an ontology for multiple major disasters, containing surface, disaster, and damage sub-ontologies, as well as sub-ontologies for land-cover and land-use classification, man-made disasters, and natural disasters. Their ontology is compliant with GeoSPARQL and OWL-Time to support spatiotemporal information modeling and retrieval, and it was used in a post-earthquake disaster management scenario to support the semantic retrieval of information extracted from remotely sensed imagery.

These ontologies serve as important building blocks for constructing a knowledge graph for disaster management at a broad scale. As an instantiation of ontologies, a knowledge graph maps real-world data into a formal ontological representation by integrating and inter-linking cross domain, heterogeneous datasets [11,34]. Instead of solely focusing on the physical properties of disasters, our knowledge graph, called KnowWhereGraph [8], links data from a variety of domains to render a comprehensive picture of the disaster-affected area for better developing situational awareness and actionable plans for disaster relief and humanitarian aid.

2.2. Cyberinfrastructure as an Empowering Technology for Disaster Management and Decision Support

As a high performance advanced computing platform, cyberinfrastructure connects "computational systems, data and information management, advanced instruments, visualization environments, and people" to address data- and computation-intensive problems [37]. Geospatial cyberinfrastructure is an expansion of cyberinfrastructure research into the geo-domains that support location-based analysis and knowledge discovery [38]. Compared to traditional information systems, cyberinfrastructure emphasizes the effective management of data, utilizing service-oriented computing and advanced visual analytics to enable data-driven decision making.

Cyberinfrastructure technology has been adopted to develop integrated decision-support systems for decision-making and disaster management. For example, Patrisina et al. [39] designed an information system that combines a waterfall model with an object-oriented programming approach and a relational database to support disaster response operations. The authors aimed to develop an integrated system from back-end data management to front-end user interaction to allow dynamic data exchange, thus providing decision makers, stakeholders, and volunteers with efficient and effective information support. Kijewski-Correa et al. [40] developed NJcoast, a secure, web-based platform visualizing the latest coastal risk information gathered from authorities at different levels, to give policy makers and practitioners access to information on coastal hazards and related topics. Hong et al. [41] designed a geospatial information system to visualize a flood and tsunami situation with a 3D building model. This strategy was developed to render disaster inundation scenes and provide rich details about factors such as buildings, floors, and households. The system also provided disaster-loss analysis displayed using statistical charts. Sermet and Demir [42] developed an intelligent question-answering system based on a flood ontology. It presents a visualization and knowledge generation platform to help answer questions about floods. The system focuses on the generation and development of knowledge engines, as well as an integration with a public-facing communication platform, to visualize the flood-affected areas on a map.

In our research, we leverage the collective power of knowledge graphs and cyberinfrastructure by utilizing the rich knowledge built into KnowWhereGraph to help decision makers quickly gain insights about a disaster impacted area. Much previous research modeled disaster ontology at the terminology level; in comparison, our knowledge graph combines multi-source, thematically connected big datasets together to provide comprehensive support for disaster management and response. In addition, the data and knowledge are organized and visualized in a way that enables heuristic-based knowledge exploitation, alleviating the technical burden on relief experts and decision makers in discovering, processing, and interpreting heterogeneous data. The next sections describe in detail our graph and visualization strategy.

3. A Disaster Relief Use Case for Hurricane Preparedness and Response

Tropical cyclones, or hurricanes, are recurring seasonal storms that threaten the lives and property of millions of Americans living across the Southeastern Seaboard and Gulf Coast. For instance, in August 2017, Category 4 Hurricane Harvey struck Texas and Louisiana, causing over $125 billion in damage. Many humanitarian aid organizations are in need of critical data to support rapid and effective emergency relief response to such impending or ongoing disasters. For instance, when a disaster occurs, it is critical to develop situational awareness to understand the following aspects:

Q1: What is happening now in the disaster area?
Q2: What happened here in the past?

Q3: What are the consequences? What damage has this caused due directly to the disaster or the cascading aftereffects?
Q4: To whom is this happening? Specifically, how many people are affected? Where are the most vulnerable populations located?
Q5: What are the health risks in the region?
Q6: What are the immediate medical needs of the population and what is the capacity of the local health infrastructure to meet those needs?

The next section describes how KnowWhereGraph and the GeoGraphVis platform help address these questions for better hurricane preparedness and response.

4. Knowledge Graph Construction

4.1. An Integrated Ontological Schema

Figure 1 presents KnowWhereGraph's integrated ontological schema for disaster management of hurricanes and their cascading aftereffects, such as flooding. An ontological schema provides the semantic definitions of a dataset, including classes and properties. We also call it an ontology for short. After a scientific dataset is converted into the graph format defined by an ontology, it becomes a subgraph. All the semantically and spatiotemporally connected subgraphs compose the comprehensive knowledge graph that we call KnowWhereGraph. Specifically, the **Storm Track Ontology** represents a storm system's movement and physical properties, like wind speed. The **Disaster Impact Ontology** models information from NOAA hazard impact reports about damage to property, injuries, and loss of life. The **Health Index Ontology** provides data on public health–related conditions nationwide, and it can be quickly linked to the disaster-impacted area through our spatial-semantic relationship modeling (explained in detail in Section 4.2). The **Disaster Expert Ontology** depicts researchers who have expertise in one or more topics related to a natural disaster. To link these datasets spatially, the **Location Ontology** contains information about administrative boundaries (e.g., county, state) as well as other geographical units (e.g., weather forecast zones). The entire knowledge graph is built around public datasets. Some are provided by federal agencies such as NOAA [43], while others are provided by private organizations, including GADM (Global Administrative Areas) [44] and Semantic Scholar [45]. Detailed descriptions and sources of each dataset are listed in Table 1.

The ontologies cover definitions of main classes and spatiotemporal and other properties attached to them. Boxes are color coded in the ontology diagram (Figure 1). Orange boxes refer to classes defined in and unique to KnowWhereGraph; pink boxes refer to classes defining location related concepts; blue boxes are classes related to time; and gray boxes contain instances of a class that are drawn from the various source datasets. Edges with black arrowheads represent properties; those with white arrowheads indicate subclass relations; and edges with white arrowheads with a line through them indicate instance-class relationships. Our graph representation adheres to W3C standards for Semantic Web construction, including RDF (Resource Description Framework; [46]) and OWL (Ontology Web Language; [47]). To ensure interoperability between KnowWhereGraph and other graphs, the class definitions in the graph aim to maximize re-use and inheritance from existing standards, in particular the W3C's SOSA (Semantic Sensor Network Ontology; [48]), indicated by the green boxes. SOSA is an ontology designed for observation-driven graph engineering; hence, it has become a valuable upper-level ontology for modeling disaster-related observations, such as storm paths, disaster impacts, and public health-related data. Four SOSA classes are adopted here: (1) *sosa:FeatureOfInterest*, indicating the target of interest; (2) *sosa:Observation*, specifying an act to estimate the value of some property of *sosa:FeatureOfInterest*; (3) *sosa:ObservationCollection*, referring to a set of *sosa:Observations*; and (4) *sosa:ObservableProperty*, describing a property of a target that can be measured. Three properties—*observedProperty*, *hasMember*, *hasFeatureOfInterest*—are also SOSA definitions adopted to connect the four classes in our knowledge graph. Finally, *sosa:phenomenonTime* is another SOSA property used to annotate the observation timestamp of a phenomenon.

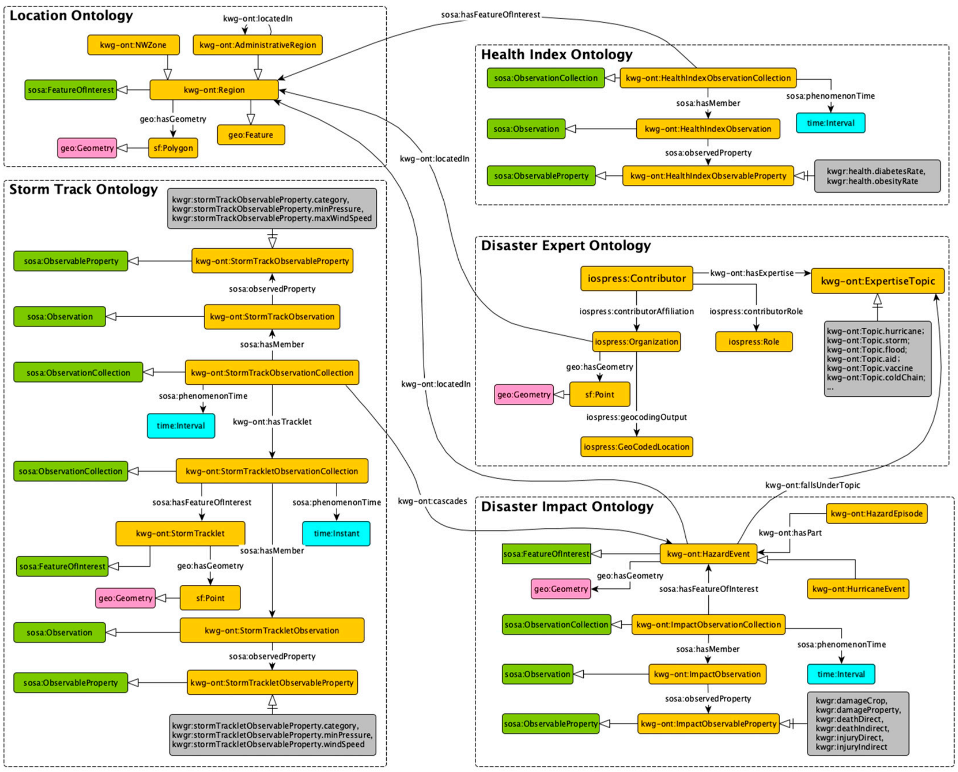


Figure 1. An integrated ontological schema for disaster management of hurricanes in KnowWhere-Graph. Classes and relationships belonging to the same ontology are shown in dashed boxes. Black arrows across the dashed boxes show the semantic linkages among different ontologies.

Table 1. Datasets for disaster management of hurricanes. All URIs were accessed on 26 February 2023.

Ontology	Dataset	Publisher	Description	URI
Storm Track	Atlantic hurricane database	National Oceanic and Atmospheric Administration (NOAA)	A dataset with data collected every six hours, containing information on location, maximum winds, central pressure, and size of known tropical cyclones and subtropical cyclones.	https://www.nhc.noaa.gov/data/#hurdat (accessed on 16 Janurary 2023)
Disaster Impact	Storm event database	National Oceanic and Atmospheric Administration (NOAA)	A dataset covering storm and other significant weather event reports with statistics on personal injuries and damage estimates.	https://www.ncdc.noaa.gov/stormevents/ (accessed on 16 Janurary 2023)
Health Index	Public health data	University of Wisconsin Population Health Institute	A database containing public health factors, such as a food environment index based on counties.	https://www.countyhealthrankings.org/explore-health-rankings (accessed on 16 Janurary 2023)
		Centers for Disease Control and Prevention	A database containing public health factors, such as diabetes rates and obesity rates	https://nccd.cdc.gov/DHDSPAtlas/ (accessed on 16 Janurary 2023)
Disaster Expert	Expert data	Semantic Scholar	A dataset on experts' areas of expertise, work affiliations, and locations.	https://www.semanticscholar.org/product/api (accessed on 16 Janurary 2023)
Location	Global administrative areas	Database of Global Administrative Areas (GADM)	Boundaries of the world's administrative regions.	https://gadm.org/data.html (accessed on 16 Janurary 2023)
	Weather forecast zones	National Weather Service (NWS)	Boundaries of areas used by NWS for forecasts and warnings as well as map backgrounds.	https://www.weather.gov/gis/PublicZones (accessed on 16 Janurary 2023)

The Location Ontology focuses on the formalization of space and place. *Location-Boundary* is defined as a subclass of geo:*Feature*, which is compliant with the GeoSPARQL standard [49]. A *LocationBoundary* can have the predicate geo: *hasGeometry* and an object such as a Polygon to store its geometric information, e.g., as a series of points delineating the boundary of an area. Two subclasses of *Region* are used for data analysis in this work. *NWZone* refers to a National Weather Service Public Forecast Zone, which is a geographic unit sometimes used to submit a disaster impact report. *AdministrativeRegion* is a hierarchical definition of administrative boundaries, including country, state, and county, which are linked through a spatial relationship named *locatedIn*.

The Storm Track Ontology is constructed for the semantic representation of storm activities in space and time. Two classes, *StormTrack* and *StormTracklet*, are used to describe the path of a storm. Both of them are modeled as subclasses of sosa:*ObservationCollection*. A *StormTracklet* is a sample point on a track, associated with a specific time, location, and set of geophysical attributes (e.g., wind speed). Each tracklet's observed timestamp is modeled in time:*instant*, which follows the W3C OWL-Time standard [50]. This timestamp information is linked to the tracklet class through a SOSA property sosa: *pheonomenonTime*. For location modeling, the location of each *StormTracklet* is modeled as a geo:*Point* in the Location Ontology. Three attributes are modeled as observed properties of a tracklet, such as its minimum pressure and wind speed. For a track that is composed of multiple tracklets, its temporal information is a time interval that covers all corresponding tracklets' timestamps, and the geospatial information for a track is a set of point locations of the tracklets that compose a storm's full trajectory.

In the Disaster Impact Ontology, different categories of hazard events are defined as subclasses of *HazardEvent* (e.g., *HurricaneEvent*). A *HazardEpisode* is a series of interconnected hazards, such as a storm and its cascading aftereffects (e.g., storm surge and flood), defined as a type of *HazardEvent*. Impacts are modeled as *impactObservationCollection*, which provides hazard impact information, such as property damage and total deaths. Generally the impact of each documented hazard spans a period of time, ranging from hours to days, which is modeled as time:*Interval*. There are six damage types logged in NOAA's Storm Event damage report, including crop damage, property damage, direct death, indirect death, direct injury, and indirect injury. All of these are modeled as a type of *observedProperty* under SOSA.

The Health Index Ontology characterizes the health of a population of a specific area, such as its diabetes rate, obesity rate, and mental health conditions, which are modeled as part of the *HealthIndexObservationCollection* class. As these observational data are provided at the county level, which is a type of *AdministrativeRegion*, a semantic connection is built between the Health Ontology and the Location Ontology based on this shared location information. The property time:*Interval* is used to describe the time—typically year—during which these health-related attributes were collected. The boundary of each county is captured in a polygon to support spatial analysis and visualization.

The Disaster Expert Ontology characterizes experts in terms of their areas of expertise related to disasters. The IOS Press scholar ontology [51] is reused for modeling disaster experts. Each expert is an instance of a *Contributor*. The location of each expert is assigned as the location of the expert's affiliated organization. Each expert's areas of expertise are listed as instances of *ExpertiseTopic*. The experts and expertise topics were automatically extracted by analyzing thousands of scientific publications and reports collected from Semantic Scholar and other online sources.

4.2. Semantic- and Spatial-Relationship Building to Link Cross-Domain Datasets

Understanding complex scenarios often requires the integration of multiple datasets to create a knowledge graph. Here we use three themes: space, time, and entity/attribute semantics to connect relevant datasets. Our modular ontologies become subgraphs of the integrated knowledge graph when they are populated with instance data. All thematic subgraphs, such as the expert subgraph, the hazard impact subgraph, and storm event subgraph, also reference spatial features. This way, they can be easily linked by location to build a comprehensive place-based profile for understanding a disaster.

More comprehensive semantic linkages are built by combining spatial, temporal, and semantic constraints. For instance, although the NOAA hazard impact data includes information on damage caused by different types of disasters, the specific "named" event that caused the damage, such as Hurricane Harvey, is not explicitly provided. To make this semantic linkage and identify which damage reports are directly and indirectly caused by a hurricane event, we used spatial and temporal constraints to find overlaps between the time and location associated with a storm event and the time and location associated with impact reports. In addition, to further improve the accuracy of the results, we performed a textual matching between the event's name (e.g., Hurricane Harvey) and its appearance in the narrative of the impact report [52].

5. Visualization-Based Semantic Exploration

This section introduces the motivation behind the scene-based visualization to organize critical disaster-related data and visual analytical modules into different visual scenes. The end user's role (i.e., disaster relief expert) throughout the development process is discussed. We then use a hurricane response use case to describe the decomposition of the comprehensive decision tasks into multiple scenes to enable visual analytics and situational awareness in the disaster-affected region. Finally, we describe the technical framework to build such a knowledge graph-empowered visualization system to achieve an efficient disaster response.

5.1. Rationale for Scene-Based Visualization

In this era of big data, the information and knowledge contained in massive datasets could contribute greatly towards better understanding and informed decision making. However, many of these vast data resources are highly heterogeneous in format and content, making them difficult to effectively access and explore, much less integrate and synthesize. What is needed are better ways of acquiring and organizing the information in more usable and useful formats that are ready for analysis and storytelling. Within a knowledge graph, such as the KnowWhereGraph, isolated datasets are connected and linkages are built, creating a large and diverse information resource, but exploration of the data remains a challenge. Well-connected knowledge graphs allow for information exploration in potentially any direction, possibly leading end users astray within the vast knowledge base. Hence, here we develop a cyberinfrastructure system that focuses on providing a scene-based visualization to demonstrate the underlying logic and causality among different datasets in a storytelling manner. This visualization strategy reduces the difficulty in comprehending information implied by the data and alleviates confusion caused by an information explosion from the many available datasets. The scene-by-scene and step-by-step visualizations enable an ordered way to explore the knowledge graph by presenting needed information intuitively and heuristically, so that it helps everyone from knowledge-graph specialists, decision makers, and the general public to rapidly develop situational awareness about a disaster, and helps relief experts to develop action plans for humanitarian aid. In essence, the challenge is to build a thematized, scene-based user interface customizable to highly specific needs, while also being readily re-adaptable to a diverse range of other usages of the graph.

To realize the scene-based visualization strategy, we first identify relevant datasets (subgraphs in the knowledge graph) based on a humanitarian relief use case, and then map them to scenes in a visualization workflow, presented in Figure 2. Notably, connections between datasets have no specific directionality in the knowledge graph. According to human cognitive processing and the formalization of popular decision paths adopted by relief experts, we map elements of datasets to scenes and connect different scenes in the visualization workflow. This follows a storytelling process, which we call a visually inspired exploration workflow (VIEW). A benefit of a VIEW's storytelling aspect is that users are able to more easily gain a complete picture of the humanitarian response use case, rather than being presented with a set of disconnected functions for analyzing scattered datasets. Additionally, our visualization system both selects subgraphs with pre-built connections from the knowledge graph and dynamically pulls out and integrates relevant datasets into a visualization scene to meet the decision needs. For example, in Figure 2, the pink sub-graph can be selected along with the green and blue ones through an extended SPARQL query, and each will be used to support visualization in a scene. Moreover, the visual scenes are not necessarily organized as a single decision path. The VIEW can be split into multiple branches based on decision needs to form a decision tree. In such complex cases, users will be guided and can decide which branch to explore next in the visualization system.

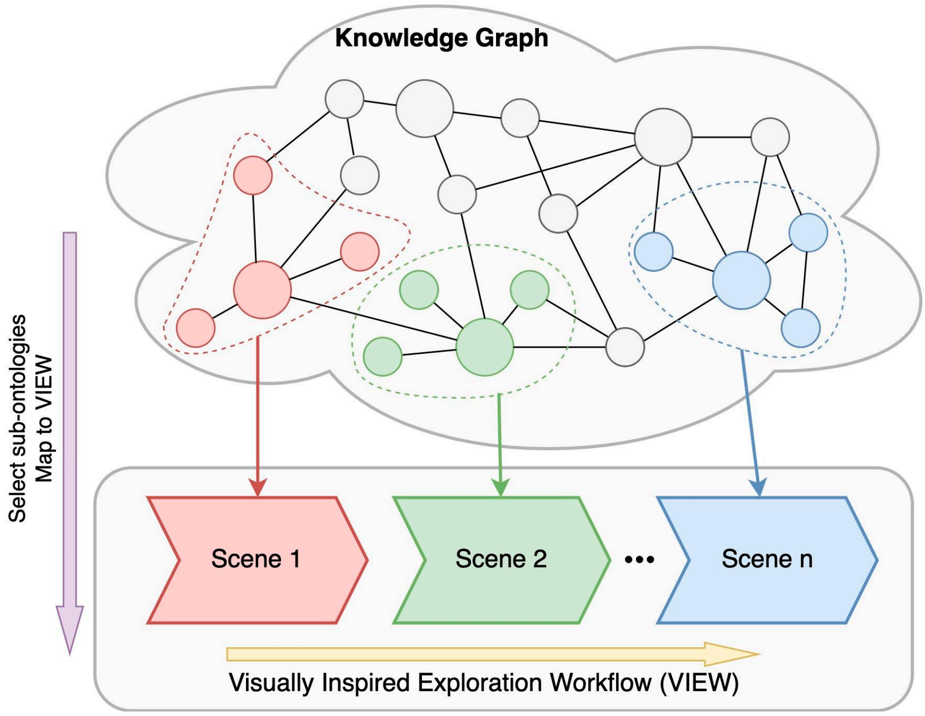


Figure 2. Mapping the datasets from the knowledge graph to support directed visual exploration.

5.2. The Role of Users (i.e., Disaster-Relief Experts)

Disaster-relief experts have been closely involved in the development process of our visualization system—from defining the competency questions to describing the typical workflows they use in order to understand a disaster situation and its related impacts all the way to and testing our visualization platform and providing feedback on its usability and user friendliness. One important partner and collaborator on this project is Direct Relief (https://www.directrelief.org/, accessed on 26 February 2023), a non-profit humanitarian organization dedicated to providing medical assistance to vulnerable populations and communities in emergency situations. A significant challenge relief experts face during a disaster is to rapidly assemble geospatial data from diverse sources for integrated analysis. To further improve the efficiency in data-driven decision making and develop timely and more precise action plans, our development team, composed of knowledge graph, cyberinfrastructure, and visualization researchers, has collaborated closely with Direct Relief experts to document and translate expert knowledge into machine-processable workflows. We have adopted the Agile iterative development model [53] in the design, implementation, and evaluation of the GeoGraphViz system. The procedure of use-inspired research and development is similar to that presented in [54].

We first gained an understanding through conversations with Direct Relief experts on which datasets and data variables are critical in the analysis of a disaster situation. These datasets, from diverse, publicly available sources, were retrieved and semantically and spatially linked by our ontology experts to make them part of our growing knowledge graph. Instead of trying to derive every analytical workflow used by relief experts in different emergency situations, we identified a feasible "decision path" for one disaster type (i.e., hurricane), and then decomposed the decision path into multiple tasks based on iterative discussions with the experts. These decision tasks were eventually expanded and generalized to fit different decision needs. Datasets and visual analytical functions belonging to the same task become a scene in our visualization system. Once a task-based module was developed, the system was tested by disaster relief and other domain experts (e.g., in environmental informatics), who provided feedback on both the usability and the comprehensiveness of the system's functionality. Our software development team has relied on feedback to make continuous, iterative improvements to the system. The usability of the visualization system was also tested in a real-world disaster case to support our Direct Relief collaborators to develop humanitarian aid actions for Hurricane Ian, which made landfall in Florida in October 2022.

5.3. Capturing a Disaster-Response/Relief Workflow

In this section, the detailed implementation of the aforementioned scene-based visualization will be discussed via the hurricane disaster response use case. To start with, users may target a past or an ongoing tropical cyclone or hurricane. The first scene is implemented for this purpose—querying the knowledge graph and allowing all the historical hurricanes to be presented in the user interface and made searchable by a hurricane's name or year. The hurricane events that caused the most severe socio-economic damage are selected and visualized on the map to allow interested users to easily explore these events by interacting with the visualization system. Based on a user's selection of a hurricane event, the geophysical properties of the hurricane, including its trajectory and the corresponding temporal information, as well as its observed properties, such as wind speed, air pressure, and category at different locations and times, are retrieved by querying the knowledge graph. Note that for an ongoing hurricane, part of its trajectory might be available only through model simulation, so instead of pinpointing a hurricane's actual location, part of the trajectory would come from prediction.

With the hurricane track and intensity information pictured, the affected area can be identified, and, hence, the second scene presents the on-the-ground damage caused by the hurricane activity. NOAA's hazard-report data are semantically linked with the hurricane track information for this purpose. All reports are indexed by place. Here, both statistical and map-based visualization are enabled to understand the severity of impact. A scatter plot with brush and link capabilities [55] is displayed to allow exploration of areas that suffer serious damage of multiple kinds (e.g., death and property damage). This allows vulnerable communities to be detected. The scatter plot visualization is linked to the map visualization in such a way that a user can easily identify the geographic location represented by the dots on the scatter plot. The damage reports are also categorized by the disaster type, providing an in-depth view of loss caused by a hurricane and its cascading aftereffects, such as tidal surges, floods, and heavy rainfall.

The third scene is designed to contextualize the socio-economic and health profile of the impacted area so that within an administrative boundary, such as a county, the proportion of vulnerable people—e.g., the elderly, chronically ill, or disabled persons—can be quickly determined. This information can further support the decision-making processes of the disaster responders. In this scene, nodes within the knowledge graph that contain relevant themes, and whose spatial footprints fall within or overlap with the impacted area, are retrieved. For instance, when a hurricane is forming and moving toward the mainland, historical damage information near the areas projected to be affected can be visualized so that communities that often suffer severe impacts from hurricane disasters can be located. Meanwhile, important socioeconomic variables, such as a social vulnerability index, demographic information, income, and health profile (e.g., diabetes rates, obesity rates, mental health status) of the targeted areas can also be derived from the knowledge graph. This information can be visualized on both maps and statistical charts, and can be used for joint analysis with damage report data.

The first three scenes help to contextualize the disaster event as well as the potential risks it will cause. Once awareness around a disaster-impacted area is developed, it is important to find experts who have specialized knowledge about the type of disaster and topics that can facilitate an effective response (fourth scene). For example, experts with a local understanding of the current capacity of non-profit community health clinics would be especially helpful in many contexts, as these facilities provide healthcare for low-income patients who tend to be more vulnerable in a disaster situation. Through a faceted-search interface, multiple expertise areas can be selected as search criteria, and results containing local and non-local experts are displayed in both text and on the map. These experts may become important sources of information in the disaster relief and humanitarian aid response.

Currently, the disaster-response workflow and visual scenes are organized in JavaScript code and configuration files that are lightweight to ensure efficient implementation.

5.4. Interactive Visualization Framework

The scene-based visualization not only allows chaining and ordering of semantically related datasets but also intuitively guides end users step-by-step to understand disaster situations with the interactive visualization system—GeoGraphVis (http://cici.lab.asu.edu/kwg/vis/, accessed on 26 February 2023). Its system-level design is presented in Figure 3. The system framework is built upon React.js, a front-end JavaScript library for building web-based user interfaces. React.js enables a modular design of the system components, separating the functionality and user interaction logic of each component from the others. This design pattern helps reduce the interdependence among system modules, thereby increasing the re-usability and generalizability of existing components. Taking this advantage, each visualization module in Figure 3 is implemented as a React component. User interaction and visualization behaviors with a certain module are maintained internally in the corresponding React component. This way, each visual analytics module is capable of working in standalone mode and becomes easily reusable. The communication among different modules is achieved through a message broker at the global system level to ensure efficient message passing and data exchange.

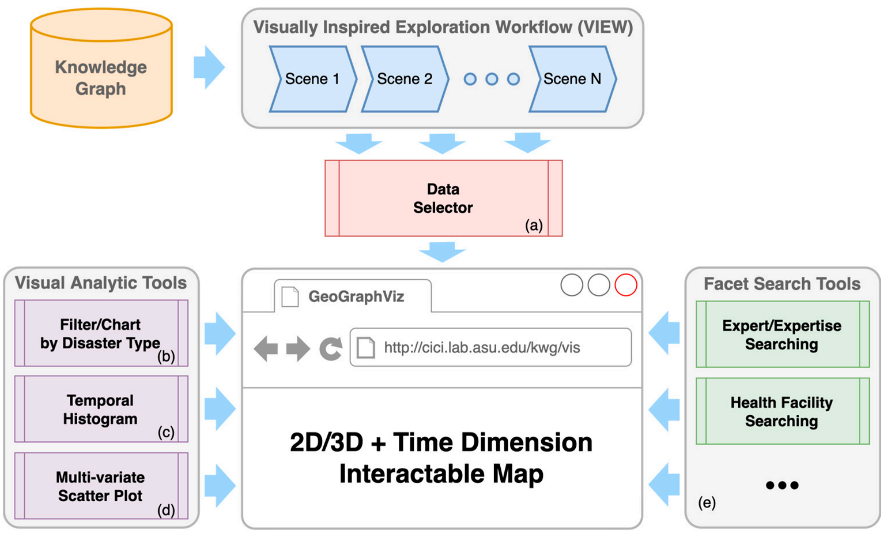
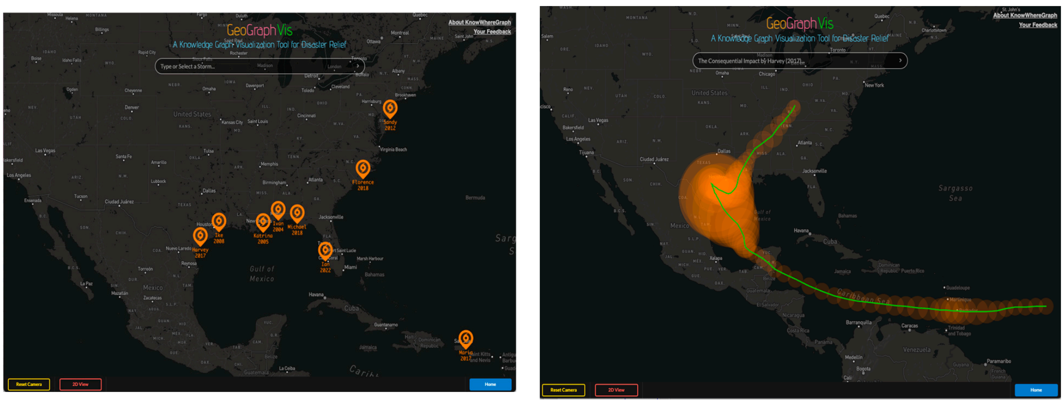


Figure 3. The framework of the GeoGraphVis interactive visualization system.

A base map is available across all scenes, playing a central role in the system. This design fully considers the importance of location and location-based analytics. With the interactive statistical charts or widgets, users can filter the data according to a variety of facets. All the changes will be synchronously reflected on the map and all applicable charts and widgets. The map component is implemented based on DeckGL, a WebGL based map engine allowing for 2D and 3D map visualization with high efficiency. Besides the interactive map, a set of supporting tools have been developed using the D3 library to allow end users to manipulate the data: Tool (a) provides a data selector that allows visualization of selected data variables on the map, and Tool (b) provides a disaster type filter. A hurricane event can lead to a series of cascading aftereffects, such as destructive tidal surges and flooding. This widget provides a multi-selection function to filter the data by cascading disaster type. It also presents statistics of the variable selected using Tool (a) based on the disaster type and displays the results in a bar chart-style widget, and Tool (c) presents a temporal histogram. This widget provides a temporal decomposition of an event's impact, aggregating the value of a chosen variable (e.g., property damage) as it mounted over time across the entire disaster-affected area. This histogram is also interactive, allowing data filtering by a time range of interest. Besides disaster impact data, this widget can be applied to any other variable that has a time dimension. Tool (d) presents a multivariate chart. This is a 2D scatter plot with its two axes representing any two arbitrary variables observed in a particular scene. A third type of information is represented by the shape of the points in the scatter plot. Tool (e) is a faceted search widget for data related to experts and other critical factors, such as medical facilities. This widget searches the knowledge graph by combining multiple topic areas as input parameters and presents the geographical distribution of the results on the map. Detailed information about the experts can also be obtained through interaction with icons on the map.

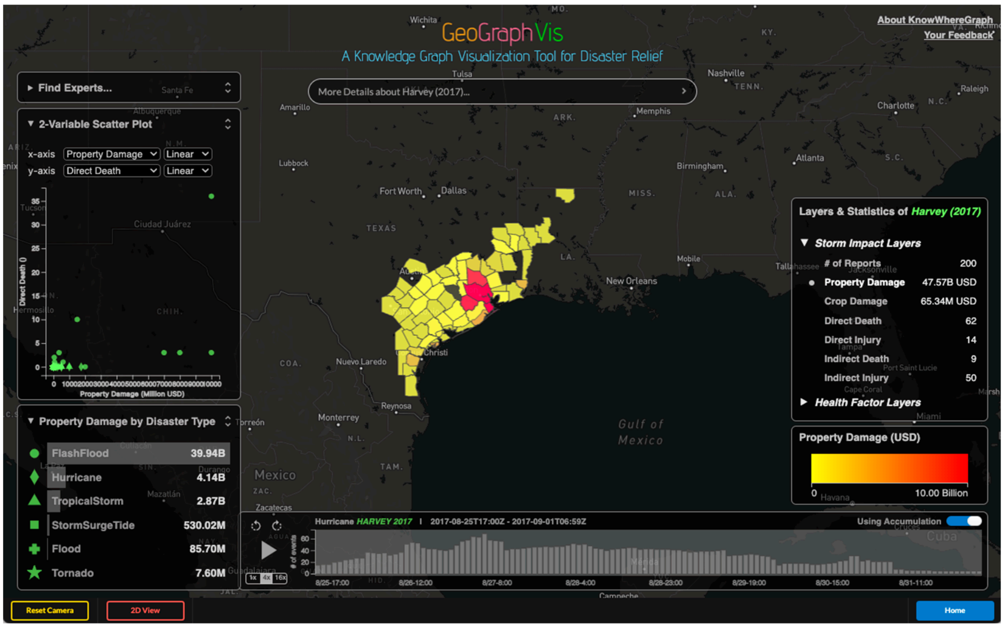
6. Graphical User Interface of GeoGraphVis Customized for the Disaster-Relief Use Case

Figures 4–6 show the graphical user interface of the cyberinfrastructure portal and multiple scenes enabled through the visualization system to serve the needs of humanitarian aid responders. Using the emergency response in the aftermath of Hurricane Harvey as an example, Figure 4a presents Scene One, which displays the costliest hurricane events to have impacted the coastal US in the past 150 years [56]. Clicking on the icon that represents, for example, Hurricane Harvey's landfall location causes its trajectory to be loaded, and the estimated affected area based on the wind speed and category as Harvey moves are drawn as overlapping circles (Figure 4b). The higher the wind speed, the larger the circle. Each circle is associated with a temporal footprint, indicating the time of impact. This spatial and temporal information will be used to locate relevant impact data shown in the next scene. When a new hurricane forms and moves toward the mainland, our portal can also automatically retrieve its real-time and predicted trajectory and display it on the map. This scene helps answer Q1 (What is happening now in the disaster area?) and Q2 (What happened here in the past?) raised in Section 3.

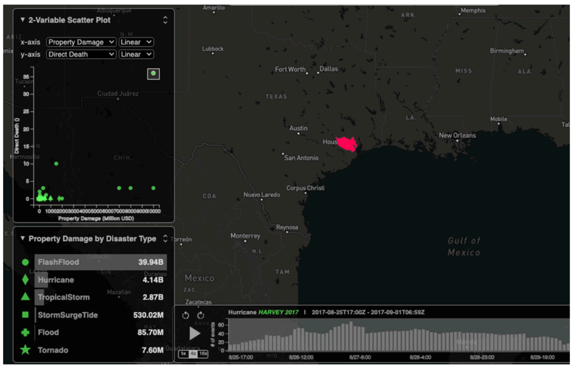


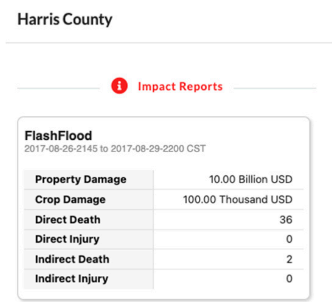
(a) (b)

Figure 4. Graphical user interface of GeoGraphVis and Scene One for investigating historical and ongoing hurricane information. (**a**) Shows the costliest hurricane events and their landfall locations. (**b**) Shows Hurricane Harvey's (2017) trajectory and impact area.



(**a**)





(**b**) (**c**)

Figure 5. Scene Two: (**a**) visualizing data on hazard impacts related to Hurricane Harvey; (**b**) drawing a polygon on the scatterplot to subset impact areas by different levels of damage; (**c**) clicking Harris County on the map to display its detailed impact record in the information panel.

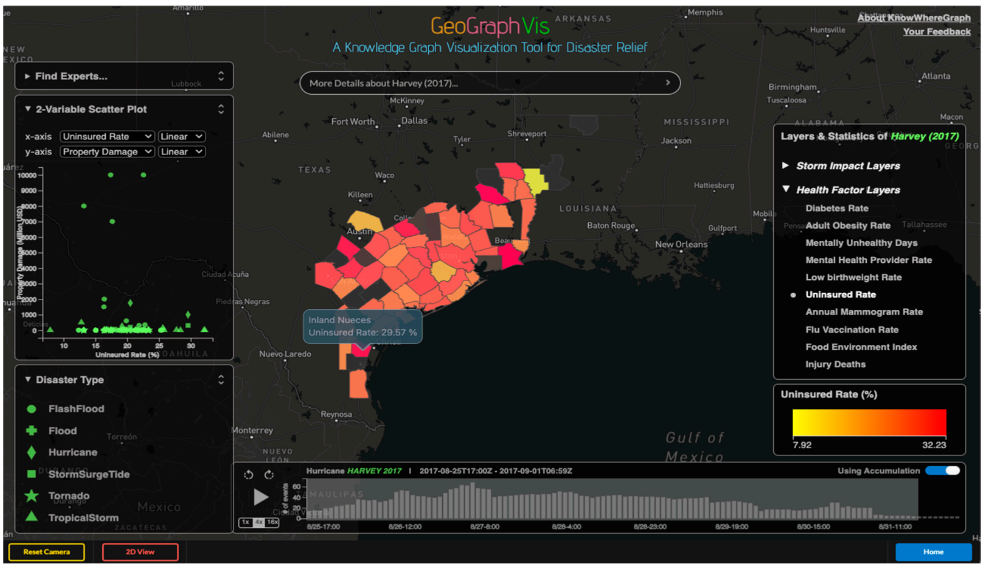


Figure 6. Scene Three: Socio-economic and health profile of the disaster-affected area.

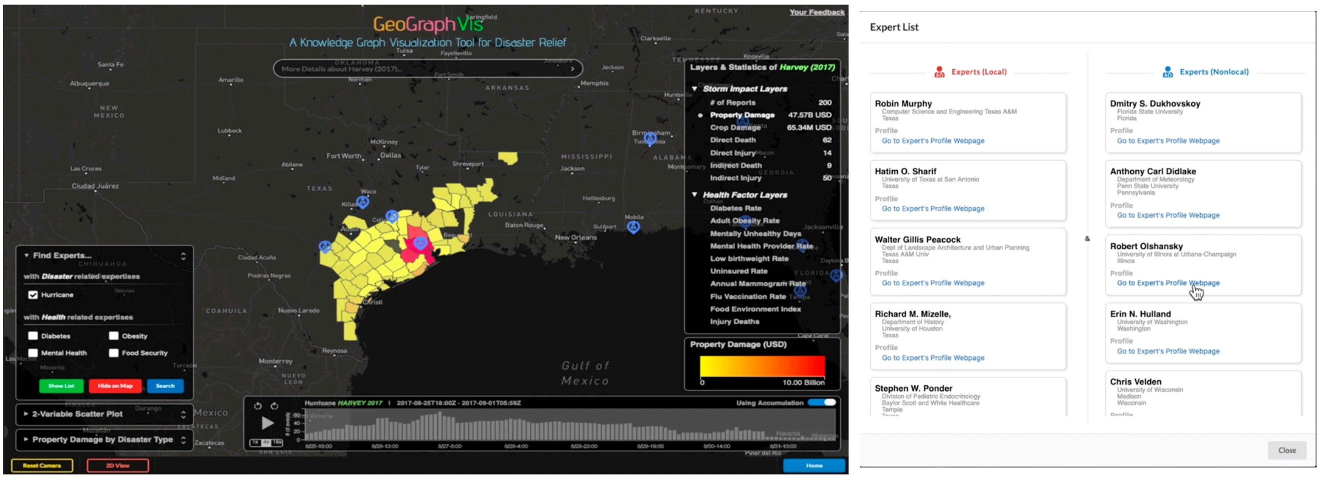
Figure 5 shows Scene Two, which uses multiple visualization methods to present Hurricane Harvey's impact. All features on the map are summarized at county level, with the values (yellow to red: low to high) indicating, for example, the level of property damage. A few counties (e.g., Harris, Fort Bend, Galveston, and Montgomery) suffered severe property damage. The temporal bar at the bottom of Figure 5a can be used to initiate an animation to show the increasing number of impact reports as Hurricane Harvey moves. It can also be used to filter the impact reports based on their submission time. This way, we can gain a temporal view of which areas were affected at what time. More than one impact report can be submitted for the same county, as a place could suffer from multiple cascading aftereffects caused by the hurricane. The Storm Impact Layers tool allows a user to select and view different kinds of damage (e.g., crop damage, direct death) experienced by different regions, and the statistics by different disaster types (total loss in US dollars) are also available in the widget, as shown in the lower left of Figure 5a.

The scatterplot on the left-hand side of Figure 5a presents reports for areas that experienced both property damage and direct death. The dot(s) at the upper right of the figure indicate(s) areas with both high "property damage" and "direct death". After selecting this area, its corresponding county information (i.e., Harris County) is displayed on the map (Figure 5b). Clicking on the county on the map causes the corresponding damage information to be displayed in a table (Figure 5c). The table also displays the time and cause (i.e., flash flood) of the reported impact.

Through visualization in this scene, we can gain a clearer picture of the consequences and damage caused by the hurricane, addressing Q3 (What are the consequences? What damage has this caused due directly to the disaster or the cascading aftereffects?) and, partially, Q4 (To whom is this happening? Specifically, how many people are affected? Where are the most vulnerable populations located?) of the competency questions posed in Section 3.

Figure 6 further shows Scene Three, which allows exploration of socio-economic and health contexts of the disaster-impacted area. The functions of all the widgets in the previous scene are carried through and remain available in this scene. The scatterplot filter can help end users identify areas (i.e., Inland Nueces County, indicated in the figure by the pop-up balloon) that have relatively high rates of people who lack health insurance and suffered high property damage. Clicking the map on Inland Nueces County brings up an information panel (not shown) that reveals that this county was impacted mainly by a high wind and storm surge caused by the hurricane. Identifying vulnerable communities and populations with medical needs is important to help answer Q5 (What are the health risks in the region?) and part of Q4 (To whom is this happening? Where are the most vulnerable populations located?) presented in the use case.

In addition to gaining situational awareness of disaster-impacted areas, the GeoGraphVis system also provides a faceted search panel as the next scene (Figure 7) to find local and non-local experts with specialized disaster relief knowledge. Once search keywords are selected (Figure 7a), a list of experts with relevant expertise is shown in a results panel (Figure 7b). These experts may serve as important resources to guide the development of plans for distributing medical supplies and establishing shelters to help vulnerable populations in the disaster situation. Q6 (What are the immediate medical needs of a population and what is the capacity of the local health infrastructure to meet those needs?) in the use case will be better answered through the support of experts who have rich local knowledge.



(**a**) (**b**)

Figure 7. Scene Four: Faceted search to locate experts with specialized disaster-response knowledge. (**a**) Search for experts with expertise in "Hurricane." (**b**) The results panel shows a list of local and non-local experts.

7. Conclusions and Discussion

This paper introduces a cyberinfrastructure solution that is empowered by knowledge-graph and scene-based visualization to support interactive disaster-information usage for emergency management and humanitarian aid. The system, GeoGraphVis, builds upon the expressive power of ontologies and a bespoke knowledge graph in semantically connecting multi-faceted datasets to address complex spatial decision-making problems in a data-driven manner. This knowledge graph differs from other knowledge graphs in its spatiotemporally explicit knowledge representation, as all of the geographical datasets are indexed and linked explicitly through space and time. This way, they can be better utilized to answer geospatial questions. In addition, the interconnected knowledge is organized into a novel, visually inspired exploration workflow (VIEW) to enable scene-based visualization, which guides the end users and decision makers to gain situational awareness step by step. This new visualization strategy effectively reduces the burden caused by an information explosion and allows the exploration of densely populated knowledge bases in a heuristic and ordered manner.

This paper demonstrates the modeling, visualization, and spatial decision making enabled by the GeoGraphVis system. Our initial goal is to use and combine advanced technologies to create societal benefits, and to deliver help to people in need during a disaster situation. This platform was adopted by disaster relief experts who responded to Hurricane Ian, which made landfall in Florida in September 2022, to rapidly locate clinics and elderly communities that were most vulnerable and in need of relief support. One challenge in the disaster response process is the collection and integration of real-time information about ongoing situations as the disaster is happening. Our cyberinfrastructure portal has integrated real-time hurricane trajectory information, and we are currently expanding its capabilities to integrate power outage information, infrastructure damage, and public needs processed from multi-source geospatial data. The use of near real-time satellite imagery and GeoAI-based image interpretation [57], as well as social media data [7], will help automatically derive relevant information that will further empower informed decision making. In addition, we are also working on expanding the expert knowledge base to include non-academics who may have on-the-ground information about a disaster-impacted area and could provide valuable local knowledge to better support the development of effective relief plans.

One challenging issue that many spatial data infrastructure and cyberinfrastructure platforms face, including ours, is the semantic interoperability among formalized knowledge frameworks [58,59]. This is especially true in environmental monitoring applications, where discrepancies among semantic definitions of geographical features (e.g., are landslides, mudslides, and debris flows synonyms?) will affect the ability of a system to more accurately and precisely respond to a user's query. In the GeoGraphVis system, we started to enable faceted search functions to help end users find experts (with expertise in disaster resilience, for example) and health facilities (e.g., hospitals). Integrating with and "re-using" terms and patterns from established community ontologies, such as ENVO (The Environment Ontology; [60]), will both enrich the encoded knowledge in our knowledge graph as well as enable query expansion and semantic search capabilities to provide users with a better search experience. Currently, the disaster response workflow and the visual scenes are organized in JavaScript code and configuration files that are lightweight to ensure efficient implementation. We will investigate the feasibility and efficiency of encoding this workflow into potentially more powerful and interoperable representations based on W3C recommendations, such as SPARQL/SHACL(Shapes Constraint Language), to enable workflow-level semantic interoperability [61–63]. These will be important directions for the next phase of our research and development.

In the future, we also plan to scale up the technology to enable exploration of impacts beyond the US to the global level and to assist with emergency responses internationally. This includes ongoing efforts to include additional disaster types; collecting and integrating data on global health infrastructure and health hazards; and enhancing the cyberinfrastrucure's capabilities to process and visualize big data.

Author Contributions: Conceptualization, Wenwen Li; methodology, Sizhe Wang, Wenwen Li and Yuanyuan Tian; software, Sizhe Wang, Xiao Chen and Zhining Gu; validation, Anna Lopez-Carr, Andrew Schroeder, Mark Schildhauer, Kitty Currier and Rui Zhu; formal analysis, Wenwen Li, Sizhe Wang, Xiao Chen, Yuanyuan Tian and Zhining Gu; resources, Wenwen Li, Anna Lopez-Carr and Andrew Schroeder; data curation, Yuanyuan Tian, Kitty Currier and Rui Zhu; writing—original draft preparation, Wenwen Li, Sizhe Wang, Xiao Chen and Yuanyuan Tian; writing—review and editing, all authors; visualization, Sizhe Wang, Yuanyuan Tian and Wenwen Li; supervision, Wenwen Li; project administration, Wenwen Li; funding acquisition, Wenwen Li and Mark Schildhauer All authors have read and agreed to the published version of the manuscript.

Funding: This work is in part supported by the National Science Foundation under award number 2033521.

Data Availability Statement: All datasets used in this research are public datasets.

Acknowledgments: The authors would like to thank the KnowWhereGraph project team (https://knowwheregraph.org/, accessed on 26 February 2023) for input and data support.

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

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