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ABSTRACT

With the increased frequency of natural hazards and disasters and consequent losses, it is imperative to develop efficient and timely strategies for emergency response and relief operations. In this paper, we propose a cyberGIS-enabled multi-criteria spatial decision support system for supporting rapid decision making during emergency management. It combines a high-performance computing environment (cyberGIS-Jupyter) and multi-criteria decision analysis models (Weighted Sum Model (WSM) and Technique for Order Preference by Similarity to Ideal Solution Model (TOPSIS)) with various types of social vulnerability indicators to solve decision problems that contain conflicting evaluation criteria in a flood emergency situation. Social media data (e.g. Twitter data) was used as an additional tool to support the decision-making process. Our case study involves two decision goals generated based on a past flood event in the city of Austin, Texas, U.S.A. As our result shows, WSM produces more diverse values and higher output category estimations than the TOPSIS model. Finally, the model was validated using an innovative questionnaire. This cyberGIS- enabled spatial decision support system allows collaborative problem solving and efficient knowledge transformation between decision makers, where different emergency responders can formulate their decision objectives, select relevant evaluation criteria, and perform interactive weighting and sensitivity analyses.

1. Introduction

A highly responsive decision-making process based on comprehensive and timely information is critical for emergency managers, planners, first responders, voluntary agency coordinators, and other professionals in the event of hazards and disasters. For example, a well-formed decision-support system can help a community better respond to and recover from a hazard event. Conversely, poor decision making may potentially result in unexpectedly severe casualties and mounting costs (FEMA n.d.a). Therefore, a decision support system plays an essential role in emergency management.

Facilitating the decision-making process during an emergency response can, however, be a challenging task. Disaster responders often need to make quick decisions in complex situations that involve multiple and even conflicting objectives under time stress. The decision goal is usually achieved through an inquiry into a series of spatial questions closely tied to decision objectives and their associated evaluation criteria based on diverse socioeconomic and demographic conditions. In general, the primary goal of emergency management is to protect the health and safety of people (FEMA n.d.a). If a limited amount of rescue resources is available, rescue personnel need to prioritize interventions at the most vulnerable locations ahead of other locations to save more lives and property, which raises the question: where are vulnerable groups of people in a disaster? The second goal of emergency management is to protect property and the environment, as well as to minimize the disruption of community activities (FEMA n.d.a). To meet this goal, governmental organizations would be interested in knowing which area had the greatest economic loss and needs the most significant financial support after a disaster event. Here, risk is defined as the interaction between hazard and vulnerability (Blaikie et al. 2004), where vulnerability is the potential to suffer loss or harm (Cutter 1996).

Geographical Information Systems (GIS) provides the technical capability to help a decision maker in understanding interdependencies between spatial, socioeconomic, and cultural factors in decision-making processes (Sugumaran and Degroote 2011). However, most conventional GIS approaches lack support for taken into account domain experts' knowledge and decision-making capabilities, which weakens their ability to enable decision processes dealing with conflicting objectives (Hendriks and Vriens 2000). Advances in decision-making theories and GIS capabilities have provided opportunities for the development of Multi-Criteria Spatial Decision Support Systems (MCSDSS). Additionally, GIS can provide capabilities for storing, managing, analyzing, and visualizing geospatial data. Multi-criteria analyses offer a rich collection of decision techniques for structuring problems that contain conflicting objectives and enabling the prioritization of decision alternatives and sensitivity analyses.

Various types of MCSDSS has been developed to support decision making in environmental hazard and emergency management. Malczewski (2006) classified GIS-based multiple-criteria decision-making analyses (GIS-MCDM) into two categories: decisions under conditions of certainty and those under uncertainty. Brito and Evers (2016) conducted a literature survey on using MCDM for flood risk management. From 1995 to 2015, there were 180 articles published on this topic, among which 22% of the articles focused on ranking alternatives for flood mitigation, 15% on vulnerability assessment, and 3% on emergency management. The rest of the articles are related to the topics of risk and hazard assessment, susceptibility assessment, coping capacity, and reservoir flood control. Wang et al. (2011) proposed a spatial multi-criteria approach for flood risk assessment in the Dongting Lake region. Karnatak et al. (2007) developed a web-based multicriteria spatial decision analysis application. Mitra et al. (2017) proposed a multi-criteria decision support system that was based on a Bayesian network approach for analysing landslide risk assessment. Zhang et al. (2014) developed a fuzzy multiple-attribute decision-making model to identify the vulnerability of an urban area based on population information. In their model, expert knowledge was collected using a questionnaire combined with a fuzzy modeling approach.

However, most of the aforementioned studies are subject to several limitations. First, decision criteria as well as their weights are often difficult to identify and quantify. Despite the uncertain nature of decision processes, some MCSDSSs do not allow a sensitivity analysis to quantify output uncertainties, and weights are often collected from engineers or system developers rather than domain experts. Second, current MCSDSSs are incapable of facilitating knowledge sharing and communication among different decision makers. In MCSDSS, decisions are often made by a group of decision makers such as domain experts, engineers, system developers, and users with diverse backgrounds, skills, and different preferred terminologies (Turban, Aronson, and Liang 2000). These various users contribute to a synergistic and complex decision space. Thus, how the knowledge can be collected, represented, and transferred between different decision makers promptly under time stress is

extremely important to emergency management. Third, knowledge, often derived from geospatial data, comes from various data sources with different formats and scales, leading to tremendous computational challenges (Yang et al. 2017). Therefore, cyberGIS is needed in a MCSDSS to provide high-performance computation support during an emergency, for tasks such as fast data queries and information visualization (Lin et al. 2015).

In this article, we demonstrate a cyberGIS-enabled MCSDSS that can be used to model two decision goals in emergency management mentioned above (FEMA n.d.a). This research considers a flooding case in Austin that happened on 31 October 2013, and combines several data sources such as census data, social media data, and a flood hazard map. In our MCSDSS, domain experts are also users, and a Simple Multi Attribute Rating Techniques (SMART) form is implemented in the user interface to help the domain experts select relevant criteria and generate weights. Weighted Sum Model (WSM) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) models are used to combine the relevant criteria along with the criteria weights, and analysis results are interactively visualized on a map. Finally, a sensitivity analysis is performed to evaluate the sensitivity of selected criteria, and a questionnaire was developed to validate the results of the decision analysis. In order to address the above mentioned first and second challenges, our decision support system can facilitate knowledge transformation between different decision makers efficiently, since domain experts (users) can formulate their decision objectives, select relevant evaluation criteria, and perform weighting and sensitivity analysis by using an interactive user interface. The weight of the criteria can be directly generated by a group of domain experts through the user interface. Furthermore, our decision support system is implemented on a cyberGIS-Jupyter platform, which leverages a Jupyter notebook, Docker containers, cloud-based infrastructure provisioning, and high-performance computing. Furthermore, it allows diverse data sources (e.g. census data and social media data) to be integrated into the system and visualized onto an actionable vulnerability map to support spatial decision making. The current implementation of the spatial decision support system, as described in the remainder of this paper, can produce a near real-time vulnerability map depicting the highest overall vulnerability value within a study area during the flooding event.

2. Background and theory

This section provides a theoretical background of key concepts used in this research. It includes various types of vulnerability indicators, spatial decision support systems, multi-criteria decision-making techniques, and decision-making sensitivity analyses.

2.1. Social vulnerability indicators for emergency management

In the context of social sciences, vulnerability often refers to a condition of people as opposed to physical structures, economies, or regions of the earth (Wisner et al. 2004; Juntunen 2006). Inhabitants with higher social vulnerability seem to suffer more significantly from a disaster compared to those with lower vulnerability (Brouwer et al. 2007). In this respect, social vulnerability can be used as an important indicator/tool to evaluate the disaster preparedness of local communities, dispatch emergency responses, and allocate limited resources for disaster relief. Federal agencies, such as Centers for Disease Control and Prevention (CDC) and National Oceanic and Atmospheric Administration (NOAA), have adopted social vulnerability indices to map and identify vulnerable communities that may need support before, during, and after a hazard event. Commonly, an index system, based on a weighted linear combination of relevant variables, is used to develop social vulnerability indicators. For example, the pioneering work by Cutter, Boruff, and Shirley (2003) defines the Social Vulnerability Index (SoVI) using 11 independent factors derived from 42 variables based on a factor analytic approach. Flanagan et al. (2011) developed another social vulnerability index (SVI) based on the percentile ranks of 15 census variables at the census tract level with the

goal of improving all 4 phases of the disaster management, including preparedness, response, recovery, and mitigation. Bjarnadottir, Li, and Stewart (2011) proposed a Coastal Community Social Vulnerability Index (CCSVI) to project the social vulnerability of hurricane-prone areas under climate change scenarios by combining both intensities of climate-induced hazard factors and various social characteristics. Various types of social vulnerability indicators for disaster management have been developed in literature, such as family structures (Cutter, Boruff, and Shirley 2003), education (Morrow 1999; Cutter, Boruff, and Shirley 2003), socioeconomic status (Rygel, O'sullivan, and Yarnal 2006; Collins and Bolin 2009), employment (Cutter, Boruff, and Shirley 2003), age (Morrow 1999; Cutter, Boruff, and Shirley 2003; Rygel, O'sullivan, and Yarnal 2006), race and ethnicity (Cutter, Boruff, and Shirley 2003; Rygel, O'sullivan, and Yarnal 2006), and gender (Rygel, O'sullivan, and Yarnal 2006). In addition to the social vulnerability indicators, the availability of motor vehicles will affect the rescue route planning. People with motor vehicles can quickly drive away from the risk area during certain disasters. Social indicators can be developed based on several aspects for disaster management. Fenton and MacGregor (1999) identified five classes of social indicators: informative indicators, predictive indicators, problem-oriented indicators, program evaluation indicators, and target delineation indicators. King and MacGregor (2000) claimed that social vulnerability indicators could be developed based on the aspects of vulnerability and resilience of communities that affected by a disaster. For instance, low income households can be an indicator of vulnerability and high-income households can be an indicator of resilience, and rank trades occupations are more important for resilience than highly paid ones. Community vulnerability and resilience can be further divided into social, economic and demographic characteristics and attributes, behavior and values, which become a separate construct that is indicated by the set of social vulnerability indicators. A review of relevant literature indicates that the commonly used methods for constructing social vulnerability include Analytical Hierarchy Process (AHP), Principal Component Analysis (PCA), and Geographic Information Systems (GIS), which help to identify, manage, and visualize social vulnerability indices in specific geographical areas (Tate 2012; Frigerio et al. 2016; Frigerio and De Amicis 2016).

However, social vulnerability assessment in emergency management currently faces several challenges due to its uncertain and complex nature. First, the social vulnerability index system is difficult to construct, since it is often based on emergency responders' subjective experiences. Emergency management can be considered as a set of collaboration processes among various types of emergency responders, such as fire and rescue departments, emergency medical crew, transportation agencies, and insurance companies, with varying decision criteria and foci. Emergency management requires effective collaboration and coordination among multiple parties and objectives, that may lead to overlapping disaster response efforts, ineffective communication, and poor coordination. The second challenge is to assign weights to the social vulnerability indices for evaluating the vulnerability of an area in a case of any disaster. Emergency responders should create their own decision objectives and assign weights to the indicators according to their professional responsibilities. However, this raises the question of how emergency responders' knowledge can be collected and represented in geospatial modeling processes to efficiently support spatial decisions. Human knowledge exists in a compiled format while computers require information to be represented in a structured way (Turban, Aronson, and Liang 2000).

2.2. Use of social media in emergency management

In addition to social vulnerability indicators, social media data (e.g. Twitter) has been often used to model communication behaviors of disaster responders to improve situational awareness in emergency management. Social media channels allow for quick dissemination of information during a crisis, as well as two-way communication between members of the public and emergency management organizations (Goodchild and Alan Glennon 2010). Chatfield, Scholl, and Brajawidagda (2013) used Twitter as a warning tool in natural disasters. Kryvasheyeu et al. (2016) found that

there was a correlation between the number of tweets mentioning hurricane Sandy and the time when the hurricane landed in the continental United States. Schnebele and Cervone (2013) found that the magnitude of the Calgary flood had a similar pattern to the location of flood related tweets. Li et al. (2018) developed a kernel-based flood mapping model to map the flooding possibility for the study area based on the water height points derived from tweets and stream gauges. Kongthon et al. (2012) classified the flood-related tweets into four major categories: situation announcements and alerts, support announcements, requests for assistance, and requests for information. Most of these situational tweets were tweeted by local citizens who knew what had been happening during a disaster situation. This raises the question of how social media could help to improve communications between emergency management organizations and citizens. Therefore, there is a need to establish a disaster-related social media channel and mapping application, so citizens can provide more detailed or accurate information to assist authorized agencies during emergency incidents.

ATXfloods is an online application for collecting real-time flood information and mapping emergency road closures in Austin. Austin city has also Twitter channel, which displays the content of tweets that are related to Austin flood events (@ATXfloods)(Twitter 2018a). Similarly, Federal Emergency Management Agency (FEMA) also provides a Twitter channel, which supports communication between citizens and first responders before, during, and after an emergency (Twitter 2018b). Here, Twitter data is used as a communication tool in applications where the spatial context is ignored. For instance, it is not obvious as to where people might request assistance.

2.3. Spatial decision support systems

Decision support systems (DSSs) have many definitions. Turban, Aronson, and Liang (2000) identified four key components of DSSs: a data management system (e.g. a database management system), a management subsystem (quantitative models that provide the system with analytical capabilities and software management), a knowledge-based management subsystem (an intelligent knowledge base that stores knowledge that can be used to make decision), and an interface subsystem (the user communicates with the DSS through this subsystem). According to above mentioned definitions of DSSs, a spatial decision support system (SDSS) can be defined as a framework for integrating analytical and spatial decision modeling capabilities (management subsystem), spatial and non-spatial data management (data management system), domain knowledge (knowledge acquisition and knowledge-based management system), spatial display capabilities and reporting capabilities (user interface) (Sugumaran and Degroote 2011). The next section introduces two types of decision-making models that were used in our MCSDSS management subsystem.

2.4. Multi-criteria decision making (MCDM)

A variety of GIS analytical methods have been developed to help decision-makers solve spatial decision-making problems with multiple criteria. The WSM is the earliest and probably the most widely used method (Fishburn 1967). The weighted product model (WPM) can be considered a modification of the WSM and has been proposed in order to overcome some of its weaknesses. The analytic hierarchy process (AHP), as proposed by Saaty (Saaty 1980, 2008), is a later development that has recently become increasingly popular. Belton and Gear (1983) suggested a modification to the AHP (which we will call the revised AHP) that appears (as it is demonstrated in later chapters) to be more consistent than the original approach. Some other widely used methods are the ELECTRE and the TOPSIS methods (Hwang and Yoon 1981).

MCDM analysis is a mathematical decision-making framework where many decision criteria are combined to meet one or several objectives to give support for decision making. Given a set of m

alternatives, denoted as $A_1, A_2, A_3, \ldots, A_m$, and a set of n decision criteria, denoted as $C_1, C_2, C_3, \ldots, Cn$, it is assumed that the decision maker (DM) has to determine the performance value a_{ij} (for $i = 1, 2, 3, \ldots, m$ and $j = 1, 2, 3, \ldots, n$) of each alternative in terms of each criterion. A matrix A with a_{ij} values is defined, along with the criteria weight W_j (the weight of the relative performance of the decision criteria). Usually, these weights are normalized to add up to one. Finally, the alternatives are ranked.

2.4.1. Weighted sum model

If there are m alternatives and n criteria, the best alternative is the one that satisfies (in a maximization case) the following expression:

$$A = \max \sum_{j=1}^{n} a_{ij}w_j, \text{ for } i = 1, \ldots, m \text{ and } j = 1, \ldots, n \tag{1}$$

Where A is the WSM score of the best alternative, n is the number of decision criteria, a_{ij} is the actual value of ith alternative in terms of the jth criterion, and w_j is the weight or importance of the jth criterion.

2.4.2. Technique for order preference by similarity to ideal solution (TOPSIS)

The TOPSIS technique is based on the concept that the best alternative is the one that is closest to its ideal solution and farthest from the negative ideal solution (Behzadian et al. 2012). The formal TOPSIS procedure is defined as follows:

Step 1: Calculate normalized rating for each element in the decision matrix.
Step 2: Calculate weighted normalized ratings. The weighted normalized value v_{ij} is calculated through this formula

$$v_{ij} = w_j a_{ij}, \quad i = 1, \ldots m; \ j = 1, \ldots, n. \tag{2}$$

Step 3: Identify the positive ideal A^* and negative ideal A^- solutions. The A^* and A^- are defined in terms of the weighted normalized values, as shown bellow

$$A^* = \{v_1^*, v_2^*, \ldots, v_j^*, \ldots, v_n^*\} = \{(\max_i v_{ij} | j \in J_2) | i = 1, \ldots m\} \tag{3}$$

$$A^- = \{v_1^-, v_2^-, \ldots, v_j^-, \ldots, v_n^-\} = \{(\min_i v_{ij} | j \in J_2) | i = 1, \ldots m\} \tag{4}$$

Where J_1 is a set of benefit attributes and J_2 is a set of cost attributes.

Step 4: Calculate separation measures. The separation between alternatives can be measured by n dimensional Euclidean distance. The separation of each alternative from the positive idea solution is given by

$$S_i^* = \sqrt{\sum_{j=1}^{n} ((v_{ij} - v_j^*)^2}, \ i = 1, \ldots, m \tag{5}$$

Similarly, the separation from the negative ideal solution is given by

$$S_i^- = \sqrt{\sum_{j=1}^{n} ((v_{ij} - v_j^-)^2}, \ i = 1, \ldots, m \tag{6}$$

Step 5: Calculate similarities to ideal solution.

$$C_i^* = \frac{S_i^-}{S_i^* + S_i^-} \quad i = 1, \ldots m \qquad (7)$$

$0 \leq C_i^* \leq 1$ where $C_i^* = 0$ when $A^* = A^-$ and $C_i^* = 1$ when $A_i = A^*$

Step 6: Rank preference order. Choose an alternative with maximum C_i^* or rank alternatives according to C_i^* in descending order.

2.5. Sensitivity analysis

Sensitivity analysis is a critical component of MCDM, which evaluates how changes in the entire vector of a decision matrix (or changes in the current weights of the decision criteria) may change the ranking of the alternatives. One important step of sensitivity analysis is to identify critical criteria and then, if needed, to re-evaluate the weights for the criteria. For the current study, we consider critical criteria to be the criterion whose weight change may change the ranking of any alternative. In this case, the *criticality degree of criteria* is the smallest percent amount by which the current value of w_k (weight of criteria C_k) must change, such that the existing ranking of the alternatives will change. An illustrative example of this calculation is available in Triantaphyllou (2000).

3. Methods

This section introduces data collection and processing techniques and methods used in this research. Various types of data have been used in this research such as Austin city census data, a flood hazard map, and Twitter data collected using the Twitter API. MCDM WSM and TOPSIS models are used as core methodologies in the MCSDSS management subsystem to combine different criteria to produce an overall vulnerability map.

3.1. Data collection and processing

The data used in this research comes from three data sources. Austin city census data was downloaded from the TIGER Geodatabase and American Fact Finder from United States Census Bureau (United States Census Bureau 2017). Census data was collected at the block group level for attributes on the age, sex, educational attainment, poverty, income, housing characteristics, and health insurance status. In this study, the following criteria are used to evaluate the vulnerability of people affected by the flood hazard: total population in an area, number of people over 75 years old, number of people without health insurance, number of people in poverty, number of people in a minority group, area median house value, population education attainment, number of children, people without a vehicle, and the number of tweets that are relevant for the flooding event. While most social vulnerability research (as discussed earlier) includes more vulnerability indicators, in this study we considered a smaller set of indicators to demonstrate our MCSDSS. Our proposed system is also flexible enough to incorporate more vulnerability indicators as considered important for particular hazard or geographic context. In addition to census data, a flood hazard map layer was downloaded from FEMA's flood map service center portal (FEMA n.d.b).

We collected Twitter data through the Twitter API over five years (2012–2017) for the continental United States, and the data has been used for many research projects. The collected Twitter data contains 2 billion tweets (about 4TB), which poses significant computational intensive challenges for traditional GIS computing environments. To resolve this challenge, we used the cyberGIS-Jupyter environment that deployed on the first cyberGIS supercomputer ROGER (Wang 2016; Yin et al.

2017). Geographical and geospatial information sciences have been undergoing dramatic digital transformations, which has fueled the development of cyberGIS as a new generation of geospatial information sciences and systems (GIS) based on advanced cyberinfrastructure during the recent decade (Wang 2016). CyberGIS-Jupyter is a new type of cyberGIS gateway platform that provides interactive, flexible, and reproducible GIS interfaces to advanced cyberinfrastructure. It organically synthesized Jupyter notebooks, containerization, cloud computing, data-intensive computing, and high-performance computing, which grants easy access to the power of advanced cyber-infrastructure inside the user-friendly notebook interfaces. To process the Twitter data, we used the Hadoop functionality of cyberGIS-Jupyter to first filter all tweets within the bounding box of Austin (–98.230, –97.279, 29.986, 30.678) from the whole set of US tweets and retrieve 23,802,637 tweets (about 14GB) inside the Austin area. The next step is to develop a strategy in finding suitable keywords that can be used to filter the Twitter data and identify tweets that are related to flooding events, such as reporting the flooding situation of a location or asking for rescue help during flooding events.

First, we selected Tweets tweeted during flooding events that occurred between October 30th and November 6th in 2013 and 2015, and August 25th through 1 September 2017, which contain the key word 'flood'. This query resulted in 806 tweets, a large number of tweets with a variety of relevant and non-relevant content. For instance, the filtered data contained many false flooding related tweets (e.g. 'Can the flood warnings be any more annoying on the iPhones', 'I'm getting really annoyed of these flash flood warnings on my tv and phone … I get it already'), which are not useful for our case. Therefore, 'flood' may not be the best keyword for filtering the data. After that, we combined the keywords 'flood' to filter the data. For the 'flood rescue' keywords, this resulted in 18 filtered tweets where 6 of them are relevant. Many of other tweets that are related to flooding events were taken from a local news channel's Twitter feed (http://www.topix.com/austin), and so are not tweets from local residents.

In the next step, we selected all Tweets in Austin that happened during the same flooding events and sorted words according to their frequency of appearance in the selected Tweets. By doing so, we are able to see which words are most often used during flooding events. The analysis result is illustrated in Figure 1, where the numbers represent number of tweets that contain the corresponding key word. These results indicate most of the frequently appearing key words (with more than 2118 tweets) are not related to flooding. During this time period, some career channels had been

18382 I	5330 on	2775 have
16581 to	5166 this	2697 Austin
15493 the	5019 TX	2680 #job
13626 a	4859 me	2654 was
11868 in	4403 be	2511 #CareerArc
8893 and	4231 #Hiring	2505 are
8499 my	4209 with	2495 &
8486 you	3976 #Austin	2481 #Jobs
8404 @	3715 it	2471 out
8399 for	3599 that	2430 up
8384 at	3314 so	2252 #Job
6776 I'm	3183 just	2250 Texas
6725 of	2981 Austin	2207 get
6666 is	2827 The	2134 all
6592 😩	2827 like	2134 about
6266	2799 our	2118 This
5854 -	2789 TX)	

Figure 1. Frequency of keywords in tweets during the flooding events.

actively using Twitter for advertising. Therefore, the key words 'Hiring', '#Jobs', and 'CareerArc' have received high ranks.

The NOAA storm events database contains comprehensive and detailed information on major climatic events from January 1950 to November 2017, as entered by NOAA's National Weather Service (NWS). This database was used to search for flood events that occurred between January 2012 and December 2017 in Travis County (NOAA 2018). Search results indicate 88 flood events were recorded with $122.1 million in total property damages. The City of Austin has created a Twitter channel @ATXflood to support communication before, during and after a flood emergency. Therefore, the keyword @ATXflood might be more reasonable to use for filtering the data than using the above-mentioned methods (e.g. using the keyword 'flood' or 'flood rescue'). The tweets that exactly contained the '@ATXflood' keyword were selected, 305 tweets in total. Each tweet contains geospatial coordinates and a timestamp, which is treated as a user's activity at that point. After that, the normalized number of flood events data were plotted together with the normalized number of tweets to observe the spatiotemporal correlation between them (Figure 2). A positive relationship occurs during 2013 except from June to August, in 2014 from April to December, in 2015 from April to May and from September to November, and most of the time in 2016. After that, we computed the correlation coefficient between number of the @ATXflood tweets and number of flood events. The overall correlation coefficient is 0.52, which indicates a moderate positive correlation, meaning people use @ATXflood channel to tweet more frequently during flooding events than other times. Therefore, it is reasonable to include @ATXflood Twitter data in the flood emergency decision process as we have implemented in our proposed MCSDSS.

3.2. Case study

Austin city has experienced serious flooding problems throughout its history. Since the late 1970s, the federal government has paid out $54 million for flood claims in Austin and $43 million more in the rest of Travis County (Price 2016). To present the MCSDSS, this research considers a flooding case in Austin that happed on 31 October 2013. The neighborhoods near Austin-Bergstrom International Airport were overwhelmed when water from the nearby Onion Creek surged past its banks and rolled into their streets, filling homes within minutes. The flood killed four people and damaged
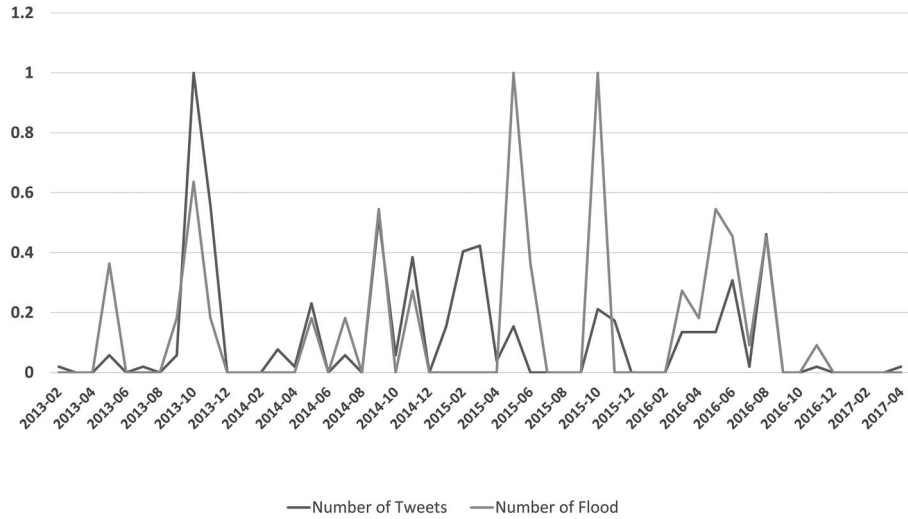

Figure 2. Relationship between the number of Tweets from the @ATXflood channel and the number of flood events in Travis County.

more than 1,200 homes (Jervis 2013). During this flooding event, there were 52 @ATXflood tweets, 178 tweets containing the 'flood' keyword, and 11 tweets with both the 'flood' and 'rescue' keywords captured. In the introduction section, we introduced two decision goals based on FEMA's literature from the perspectives of emergency response and recovery (FEMA n.d.a).

Decision goal 1: which area should rescue personnel go to first in order to save more lives? If the disaster occurs over a large area and the government has limited resources, rescue personnel need to prioritize interventions at the most vulnerable locations ahead of other locations in order to save more lives.

Decision goal 2: which area had the most significant economic loss and needs the greatest financial support to recover from a flooding event?

The structure of our cyberGIS-enabled MCSDSS is presented in Figure 3. In this framework, knowledge for making decisions is collected through interactions between domain experts (users) and the user interface. The collected expert knowledge and geospatial data are stored in the knowledge base, which can be used as input for the model management system. The model management system includes two decision-making models that are used to combine multiple criteria values (social vulnerability indicators) for creating an overall vulnerability score for the decision goals. Each census block is considered as one alternative. For instance, the value for the a_{ij} variable in Equations (1) and (2) were generated using normalized social vulnerability indicator values attached to each block. A weight was simulated using the Simple Multi Attribute Rating Techniques (SMART), which assigned an importance of 100 points to the most important criterion and the next-most-important criteria is assigned a number of points reflecting the ratio of relative importance to the most important dimension (Olson 1996). Furthermore, our decision support system application is designed to enable group decision-making capabilities, so that a group of decision-makers (DMs) can participate in the decision-making process and assign weights to the criteria simultaneously. In this research work, six GIS experts participated in simulating the weight for each criterion based on two decision goals. A weight matrix W was generated where d refers to the number of DMs and n refers to the number of evaluation criteria (Figure 3). The final weights were calculated by averaging the value from each row in matrix W. Simulated weighting results are illustrated in Table 1. The weights were normalized to represent variable w_j in Equations (1) and (2). The area that has the highest (or maximum) overall value is considered as the recommended place for earliest intervention.
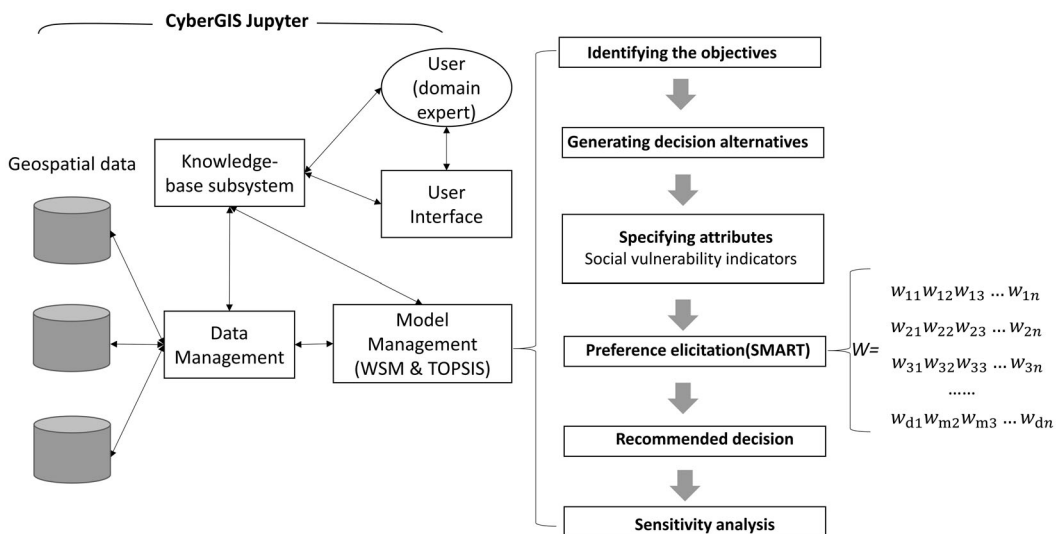

Figure 3. An overview of cyberGIS-enabled MCSDSS.

Table 1. Simulated weights for the evaluation criteria in perspectives of two decision goals.

Evaluation Criteria	Decision goal 1	Decision goal 2
Total population	74	83
People over 75 years old	87	70
People without health insurance	60	82
People in poverty	63	83
People in a minority group	60	68
Area median house value	47	66
Population education attainment	41	56
Number of children	93	79
People without a vehicle	78	58

4. Results

This section presents the results of the case study. Our cyberGIS-enabled MCSDSS user interface was implemented using the cyberGIS Jupyter computing platform. Figure 4 illustrates the user interface of the implemented system. It contains several layers, such as a flood hazard layer and a Twitter layer that the DM can switch on or off. In this article, the Twitter layer is used as an additional decision
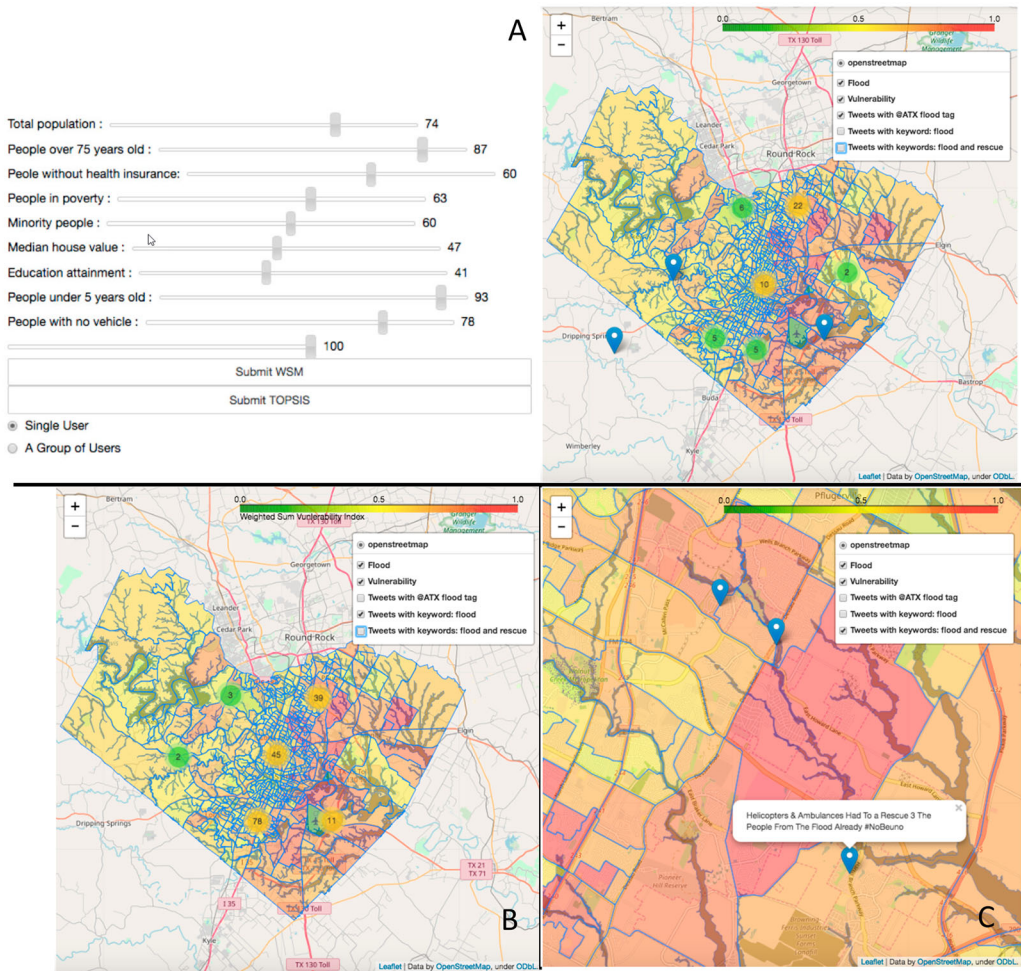

Figure 4. The cyberGIS-enabled MCSDSS user interface.

support tool added on the top of the decision model. The decision maker can use this tool to filter the Twitter data using different keywords. In this article we used three keywords sets: '@ATXflood', 'flood', and 'flood' combined with the keyword 'rescue'. The filtered results are illustrated in Figure 4(A–C) respectively. In the future, this decision support tool can be developed further so the decision maker can enter any keyword of interest and interactively observe the filtered results on the map. In Figure 4(C), the blue pinpoint on the map represents a single tweet with content mentioning 'flood' and 'rescue' during the flooding event. If multiple tweets are geographically close to each other, they are grouped and visualized as clusters on the map with the number indicating the count of tweets in that region (see Figures 4(A and B)). The user can zoom in and out on the map and click on the blue pinpoint to see the tweet contents. This application is capable of visualizing flood-related tweets in real time, and thus help emergency management organizations identify areas and locations of people that are at risk.

The left side of the Figure 4(A) illustrates the weighting slider, which can be used to assign weights to the criteria that are relevant to the decision goals. If the DM selects the option 'using weight from a single user', the vulnerability map will be generated based on the single submitted list of weights. If the DM selects the option 'using weight from a group of users', the assigned weights will be first combined with a weight matrix stored in a common accessible file managed by the CyberGIS-Jupyter notebook. This weight matrix has the weight information previously submitted by other DMs in the same group, and it will be updated based on the latest submitted weight. After that, the weight will be averaged and normalized to generate the final weight to produce an overall vulnerability map.

The weights illustrated in Table 1 resulted in a vulnerability index map shown in Figure 5. For the first decision goal, both models show block numbers 1, 4, and 5 received high vulnerability values, and rescue personnel should go there first in order to save more lives in an emergency situation. Most of the blocks that received middle-high category overall values in the TOPSIS model received the highest overall values in the WSM. Block numbers 1, 2, 17, and 6 received high overall values in the TOPSIS model but lower vulnerability values in the WSM model. In addition, block number 15 received the low category for both maps. For the second decision goal, block numbers 3, 4, 5, 13 and 14 received the highest overall values for both maps, meaning those blocks may suffer the most economic loss and need the most financial support for post event recovery. Most blocks that received middle-high overall values in the TOPSIS model had high vulnerability value in the WSM. The opposite situation applied to block numbers 1 and 2. Generally speaking, WSM produces a wider range of values and higher output category estimations than the TOPSIS model. Block number 15 represents the Austin-Bergstrom international airport, which received a low vulnerability value for all the decision models. This can be caused by fewer people living in that area compared to the other blocks. However, there are 11 tweets contain 'flood' keyword near block number 15, and most of them are relevant tweets. In this case, the decision maker should not ignore this block due to the low vulnerability score produced by the decision models.

Sensitivity analysis is performed to observe the sensitivity of the criteria, and the results are illustrated in Table 2. The values in Table 2 represent the rank of criticality degrees of the criteria that are explained in section 2.3. For the first decision goal, the number of children and people without vehicles are the most sensitive criteria and median house value is the least sensitive criterion. It means that if the weight of people without vehicles is changed, even by a small value, the census block with the highest vulnerability values will most likely also change. In other words, the weight of people without vehicles should be carefully determined by experts in a real-world decision- making scenario. On the other hand, median house value is the least sensitive criterion so that the census block with the highest vulnerability index is not likely to be changed even if the weight of median house value is significantly increased or decreased. However, a big ranking difference between the two decision models appears for some of the criteria, such as the criteria of people without health insurance and the number of children. For the second decision goal, people without vehicles and insurance are the most sensitive criteria, and population education attainment and the area median house value are the least sensitive criteria. The number of children and people without health
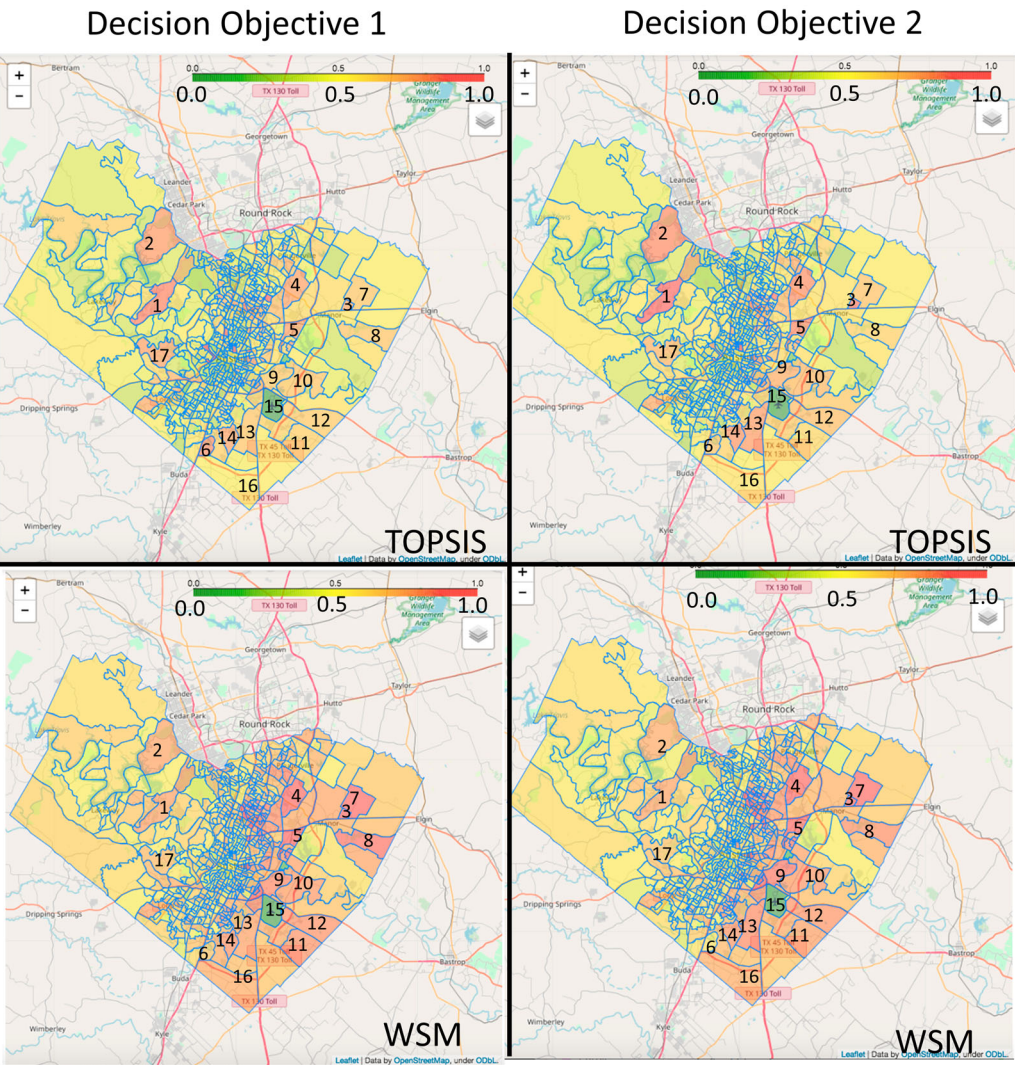
Decision Objective 1

Decision Objective 2

Figure 5. Vulnerability maps based on two decision-making models (WSM and TOPSIS).

Table 2. Sensitivity analysis results.

Criteria	Objective 1 (Rank of Criticality Degrees of the Criteria)		Objective 2 (Rank of Criticality Degrees of the Criteria)	
	TOPSIS	WSM	TOPSIS	WSM
Total population	3	5	2	5
People over 75 years old	2	4	5	6
People without health insurance	7	3	6	1
People in poverty	5	6	3	4
People in a minority group	6	7	4	7
Area median house value	9	9	7	9
Population education attainment	8	8	9	8
Number of children	4	1	8	2
People without a vehicle	1	2	1	3

insurance criteria received the greatest and the second greatest ranking difference between the two decision models.

Model validation has been challenging task for multicriteria decision analysis (Qureshi, Harrison, and Wegener 1999; Meyer et al. 2014). In this article, we used sensitivity analysis to check the stability of the decision model. Additionally, we developed a questionnaire to evaluate the decision model's results. The questionnaire contains all the attribute information for 10 blocks, such as total population, number of children, people without a vehicle. The participants who have participated in the first questionnaire was asked to fill in the second questionnaire. The decision maker has to give a rank from 1 to 10, based on the given attribute information, where rank number 1 represents the most vulnerable block. This is similar to a real-life emergency situation, in that rescue personnel have to make the decision based on how well they know the area. All the participants said it was hard to rank the 10 blocks based on many given attributes, and there is a need to develop a multicriteria decision support tool to make the ranking easier. After that, these blocks were ranked based on the decision model's vulnerability results and compared with the questionnaire results. By doing so, we can see how well the decision model's results match decision makers' rapid thinking in real life.

The model validation result is illustrated in Table 3. The error rate for each block was calculated using the absolute value of the difference between the decision model's ranking results and the questionnaire's ranking result and divided by the number of 10 (maximum value of the rank). After that the average error rate was calculated. According to the results, both WSM and TOPSIS models produced a over 40% error rate for the decision objective 1, and a smaller error rate (over 20%) for the decision objective 2.

5. Discussion

In this study, MCDM was used to combine different social vulnerability indicators to reach decision goals that are related to emergency management. While we used a limited set of indicators in this case study, more indicators, such as family income status, family structures, housing characteristics, and flood severity (e.g. rainfall intensity), can be included in our proposed MCSDSS in order to make this framework applicable for different kinds of disaster scenarios. The flexible structure and portability of this technology also make it quickly adaptable for any geographic context.

In this article, weights for different evaluation criteria were simulated by six GIS experts. However, the experts who participated in simulating the weights were not emergency management domain experts, therefore the results of the study cannot be used to answer the decision goals correctly in a real-world situation. In the future, real domain experts such as rescue operation officers or public agency professionals should use the application to generate weights in order to make the analysis results more accurate and realistic for an actual disaster scenario.

Table 3. Model validation results.

Blocks	WSM Model		TOPSIS Model	
	Objective 1	Objective 2	Objective 1	Objective 2
1	0.1	0	0	0.2
2	0.8	0.8	0.8	0.8
3	0.2	0.1	0.2	0.1
4	0.4	0.5	0.4	0.5
5	0.6	0	0.5	0.1
6	0.2	0.3	0.4	0.4
7	0.8	0.1	0.9	0
8	0.3	0	0.4	0.1
9	0.4	0.1	0.4	0.1
10	0.6	0.5	0.4	0.3
Average Error	0.44 (44%)	0.24 (24%)	0.48 (48%)	0.26 (26%)

One objective of this work is to develop a software application that enhances the communication between citizens and emergency management organizations. Our application provides fine-grained location (or exact location) information for rescue personnel to evacuate people who need help during the disaster event using a Twitter data layer. For instance, rescue personnel can identify the areas and people at risk by observing the content of a tweet and its corresponding location on the map. Currently, we used three keyword sets to filter the tweets. In the future, text mining techniques can be embedded in the tool to categorize tweets (e.g. according to Kongthon et al. (2012)'s work) in order to support different types of decision problems. For instance, this tool can be developed further so the decision maker can enter any keywords that they think are useful and interactively observe the filtered results on the map. Besides Twitter, this framework can be further expanded by incorporating other social media postings (e.g. Facebook, Instagram, Snapchat/Snap Map, etc.) to make it more useful for emergency responders and more accessible to wider audience.

In this application, our analysis is at the block group level, which is the finest-grained geographic level in U.S. Census where socio-economic data is reported. It would have been better if we could use the parcel level but enumerating data at that granular level will be a separate research project by itself. In this article, we are proposing a computational framework, and it can be implemented later by rescue organizations using more detailed data (e.g. parcel level data or their own rescue data, which might not be publicly available) to provide fine-grained location information.

Other important aspects of this application are ensuring consistent results or facilitating different actors in quickly reaching an agreement. WSM produces more diverse values and a higher output category estimation than the TOPSIS model. Simanaviciene and Ustinovichius (2010) found that if the values of criteria differ by 10% from the average criterion value, the TOPSIS method is more sensitive than the WSM. In our case, for both decision objectives, both models produced consistent answer for some places that have high vulnerability. Both models provide interfaces (through weights) for trials and errors from decision makers. We used sensitivity analysis to check the stability of the decision model. Additionally, we developed a questionnaire to validate decision model's results. As a result, both WSM and TOPSIS produced similar validation results for each decision objective. However, clear error differences appear between the two objectives. For instance, both models produced a higher error rate for the first decision objective, and a lower error rate for the second decision objective. Finally, the parameterization and evaluation of the models should depend on a panel of experts and decision makers following Delphi style approaches. For instance, if there are extremely limited rescue resources available, a decision maker might want to consider using the results that are produced by the TOPSIS model first since it produces fewer hot spots than WSM results.

6. Conclusion

In this article, we described a cyberGIS enabled decision support framework, which combines a high-performance geospatial computing environment (cyberGIS Jupyter), advanced multi-criteria decision analysis models, various types of social vulnerability indicators, and Twitter data to efficiently support spatial decision-making processes in emergency management. The advantages of this MCSDSS come from several perspectives. First, cyberGIS Jupyter enables collaborative big data analytics so various types of data sources can be integrated into the decision-making processes. Second, multiple and conflicting objectives are common decision problems in emergency management. In this study, two types of MCDM models (WSM and TOPSIS) were constructed, where many different criteria can be combined to meet one or several objectives and give support in decision making. Third, this framework supports group decision making and collaborative problem solving, which is important since emergency management requires effective collaboration and coordination among emergency responders. In this framework, emergency responders can work together to formulate decision objectives, select relevant evaluation criteria, and perform interactive weighting and sensitivity analysis. In addition, we developed an innovative way to use Twitter data to enhance

communications between citizen and emergency management organizations, and therefore to improve the awareness of various spatial situations. For instance, this framework can support geo-visualization of near real-time Twitter data and help emergency organizations identify the areas and people that are at risk. Finally, the interactive user interface enables the expert knowledge of decision makers to be collected and incorporated to efficiently support spatial decision making for emergency management.

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