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An integrated evacuation decision support system framework with social perception analysis and dynamic population estimation

Atsushi Nara[a,*], Xianfeng Yang[c], Sahar Ghanipoor Machiani[b], Ming-Hsiang Tsou[a]

[a] Department of Geography, San Diego State University, 5500 Campanile Drive, San Diego, CA 92182-4493, USA
[b] Department of Civil Engineering, San Diego State University, 5500 Campanile Drive, San Diego, CA 92182-1324, USA
[c] Department of Civil & Environmental Engineering, University of Utah, 110 Central Campus Dr., Salt Lake City, UT 84112, USA

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ABSTRACT

In designing evacuation plans, it is critical for the responsive agencies to consider the dynamic change of human population within impact areas and understand social perception from local residents. Although a large number of evacuation models has been reported in the literature, many used census survey data which represent only the nighttime population distribution. To fill this research gap, this paper introduces a novel data integration framework for developing an evacuation decision support system for wildfire, Integrated Wildfire Evacuation Decision Support System (IWEDSS). IWEDSS integrates multiple data sources including social media, census survey, geographic information systems (GIS) data layers, volunteer suggestions, and remote sensing data. The integration is based on multi-disciplinary theoretical and modeling approaches including Geographic Information Science, civil and transportation engineering, computer science, social media and communication. IWEDSS includes four core modules: dynamic population estimation, stage-based robust evacuation planning, social perception analysis, and web-based geomatical analytic platform. It offers tools for evacuation planers and resource managers to make better decisions that can reduce the evacuation time and potential number of injuries and deaths. This paper also presents a case study to demonstrate the suitability of incorporating social media data to estimate the dynamic change of human population.

1. Introduction

Effective evacuation during disastrous events is one of the most challenging issues for many local government agencies and large city traffic control centers in U.S. To build an effective evacuation model and response plans, the responsive agencies need to consider the dynamic change of human population in impact areas and social perception from local residents when designing traffic assignment plans, evacuation procedures, and shelter locations [1]. Conventionally, population data come from government cross-sectional episodic census surveys. Census data represent only the nighttime population distribution, which hardly reflects dynamic population during a day, on weekdays vs. weekends, or with variations in seasons and holidays. Emerging Big Data from cellphone calls [2], social media [3], volunteered geographic information (VGI) [4], and sensor networks [5] open unprecedented opportunities to analyze and model human dynamics in space and time [6] and furthermore to capitalize on crowdsourcing intelligence for hazard information reporting, sharing, and modeling during disastrous events. This paper introduces a novel data integration framework for developing an evacuation decision support system for wildfire, Integrated Wildfire Evacuation Decision Support System (IWEDSS). IWEDSS integrates multiple data sources including social media, census survey, geographic information systems (GIS) data layers, volunteer suggestions, and remote sensing data. It consists of four core modules: (1) dynamic population estimation, (2) stage-based robust evacuation models, (3) social perception analysis, and (4) a web-based geospatial analytics platform. The system provides key functions for data collection, traffic demand modeling, evacuation operation, and information dissemination. IWEDSS offers scientifically-based and data-driven analytic tools for evacuation planers and resource managers to make better decisions that can reduce the evacuation time and potential number of injuries and deaths. This paper also presents a case study to demonstrate the suitability of incorporating social media data to estimate the dynamic change of human population.

2. Relationship to other research

Focusing on the four core modules of the IWEDSS framework, a review of the literature and discussions for each core module are presented below.

* Corresponding author.
E-mail addresses: anara@mail.sdsu.edu (A. Nara), x.yang@utah.edu (X. Yang), sghanipoor@mail.sdsu.edu (S. Ghanipoor Machiani), mtsou@mail.sdsu.edu (M.-H. Tsou).

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2.1. Population estimation

The prevailing use of social media and mobile phone data provides a great research opportunity for researchers to map and analyze dynamic human behaviors, communications, and movements [7]. People use smart phones, mobile devices, and personal computers to build up their digital life and to leave their digital footprint on the Internet. These human-made digital records provide a foundation for human dynamics research. Human dynamics is a new transdisciplinary research field attracting scientists and researchers from different domains, including complex systems [8], video analysis [9,10], and geography [7]. One key research question of human dynamics is the dynamic change of population distribution in urban areas. Conventionally, the change of population distribution is estimated from census survey with data sampling and forecasting techniques. Recently, scientists started to use satellite images [11], mobile phone data [12,13], or vehicle probe data [14] to estimate the dynamic change of population distribution at small area level. One example is to use mobile phone-based call detail records (CDR) to detect spatial and temporal differences in everyday activities among multiple cities [15]. Another example is to estimate seasonal, weekend, and daily changes in population distribution over multiple timescales with aggregated and anonymized mobile phone data [13]. In GIS and cartographic research, dasymetric mapping methods have been applied to estimate population density using census data and ancillary data sources [16–18]. The integration between vector-based census tracks and raster-based land cover data and satellite images for dasymetric mapping is a challenging problem. Mennis [19] introduced raster surface representation of population density framework to combine categorical ancillary data and population density. To improve the traditional problems of binary value in categorical data and areal weighting, Mennis and Hultgren [20] introduced an intelligent dasymetric mapping technique (IDM) with a data-driven methodology to calculate the ratio of class densities. Applying the concept of IDM, IWEDSS calculates population density utilizing social media data (geotagged and check-ins data) combined with other GIS data sources to estimate the dynamic distribution of human population at different times. There are several advantages of using social media for population estimation. The real-time updates of social media messages can reflect dynamic changes of population better than expensive remote sensing imagery, which requires time-consuming data collection and data processing procedures [21]. Alternatively, mobile phone data, such as CDR, are also very expensive. Another drawback of CDR is the missing of actual communication content in each phone record. In contrast, social media data are easy-to-collect, free (using public access methods), content-rich, and real-time updated [7].

2.2. Stage-based evacuation planning

Developing an effective evacuation plan is an important task during disaster events. Relocating people within the affected areas to safe places or shelters can reduce the impact of disaster events significantly. For evacuation planning and operations, the system input shall include both zoning of impact areas and estimation of evacuation demands [22]. To model the traffic demand at the aggregate level, dividing the impact area into a set of geographic zones is always critical [23]. However, the size of zones along with their total amount shall vary by the evacuation location and type of emergency event. For example, in evacuation of natural disasters such as wildfire [24] and hurricane [25], the evacuation zones shall have a larger size compared with the ones in downtown evacuation [26]. Modeling of evacuation demand usually provides the number of evacuees and their departure time choice within each zone. For mandatory evacuation, the number of evacuees is directly obtained from population size while non-mandatory evacuation often requires the estimation of people's evacuate/stay decisions. In practice, many factors, such as the influence of neighbors [27] and strength of social network [28], may affect the evacuation decisions. A comprehensive review of this issue could be found in [22]. With the total evacuation demand, estimation of evacuees' departure time would distribute the demand into transportation network over time. Based on the empirical evidence, stated intention surveys, planner judgment, and simulation of the warning message diffusion [29], studies often assumed an S-curve in various evacuation operations (e.g., wildfire [30–32]:; hurricane [33,34]:).

Given the zoning and traffic demand information, planning of evacuation shall address two critical issues: selection of traffic routes and determination of evacuation strategies [22]. With simulation based optimization technique, a category of studies adopted microscopic and mesoscopic models to design evacuation routings. Representative tools for such applications include VISSIM [35], CORSIM [36], DYNASMART [37], DynusT [38], and DynaMIT [39]. In addition to those traditional methods, recent studies also implement agent-based simulation models for evacuation planning [40,41]. Instead of using simulation based models, another research category intended to formulate the evacuation process by linear or nonlinear programming models. Those models often have an objective function such as minimization of evacuation time [42] and a certain set of constraints which formulated with CTM [43] or other network optimization techniques [44]. Recognizing that severe congestion may occur on transportation networks during evacuation, existing studies have introduced various strategies to reduce the evacuation time. From the supply side, effective strategies include contraflow operations [45], crossing elimination [46], intersection signal optimization [47], and ramp closure [48], among others. Among existing demand side strategies, the effectiveness of stage-based operations has been demonstrated by many existing studies [41,43,44,49]. By ranking the disaster impact in different zones, this strategy optimizes evacuation sequences with the purpose of reducing traffic demand on roadways. However, such staging operations often require the collaboration of evacuee social networks to disseminate evacuation information.

2.3. Social perception analysis and feedback based evacuation plans

The insights provided by social media data have been applied to various scientific fields; some examples include: disease outbreaks [50], travel related information through social media [51], social tie strength evaluation [52], relationship between happiness and life patterns [53], and political power of social media [54]. Social media applications are also rapidly growing in interest among disaster research, such as studies of time sensitive waiting times in information propagation [55], mechanisms of information production and distribution during flooding of the Red River Valley [56], identifying information contributing to enhancing situational awareness during Oklahoma Grassfires and the Red River Floods [57], online information exchange behaviors of the public organizations during the Deepwater Horizon oil spill disaster [58], and mapping of natural disasters using geo parsed real time tweet data streams [59]. Guan and Chen [60], instead of characterizing social media in the context of a disaster, characterized a disaster using social media. They introduced a "degree of disaster" measured using social media data to understand the evolution of a disaster [60]. More related to behavioral studies, Liu and colleagues studied disaster behaviors by introducing a social mediated crisis communication model (SMCC) model [61–63]. They examined how publics communicate about crises [63], and how they consume crisis information considering different origins (initiated from an internal organizational issue or from an issue external of the organization), and how it affects preferred information form and source [61]. Although considerable research has been done relating social media and disaster, no research utilizing real time utilization of the social media information in the transportation planning process could be identified. IWEDSS employs the power of social media in evacuation planning in a real time manner by introducing a feedback based evacuation planning system.

The decision making process during evacuation is a complex task that is made by the authorities and individuals/households [64]. In current evacuation plans usually the latter is dependent on the former, but our framework incorporates the interdependency between the two decision making entities. This interdependency is expected by society. According to the American Red Cross survey, 69% of adults believe that emergency responders should be monitoring social media sites to quickly send help [61]. Building this connection will result in capturing more compliant response from the public regarding disaster warnings. Disaster warnings are deemed to be a social process [22]. Interpretation of the message and subsequent actions varies among individuals. Individuals' decision making process includes several stages and processes [22] including (1) receiving an initial message, (2) interpreting the message, (3) assessing personal risk, (4) determining whether protection is attainable, (5) determining whether protective action can be handled, (6) determining whether the action will significantly reduce the consequences, (7) assessing options, and (8) choosing an action [65]. Any information related to these stages that is obtained through the analysis of the social media will allow for more efficient evacuation planning. Sutton et al. [66] conducted a survey about disaster information and communications technology, which showed a majority of participants sought information online. Some part of their search effort was to fill gaps in official news sources. Feedback based evacuation planning allows for recognizing these gaps and filling them in with complementary messages.

2.4. Web-GIS and spatial decision support systems

GIS play a crucial role in disaster management by supporting geographical decision making in mitigation, preparedness, response, and recovery [67,68]. GIS is capable of helping decision makers to conduct risk mapping, emergency planning, emergency plan activation, and damage assessment by: the multi-layer geographical data integration composed of physical, social, demographic, and/or economic information [69]; spatial and spatiotemporal data analytics [70]; simulation models [71–73]; social media [74]; cartographic visualizations [75]; and crowdsourcing geographic information [76,77]. In past years, great efforts have been made to develop GIS software, toolkits, and spatial decision support systems for disaster management in both public and private sectors [78,79]. Hazus-Multi-Hazard (Hazus-MH) is an example developed by Federal Emergency Management (FEMA). Hazus-MH is a commonly used, standardized, and standalone desktop decision support software designed to assess physical, economic and social impacts of earthquakes, hurricanes, flood, and tsunami emergencies in the U.S [80]. It is an add-on extension to commercial GIS software, ESRI ArcGIS, and uses mapping and spatial analysis functions to produce loss estimates of the total cost of damages and casualties based on plausible disaster scenarios.

The capability of existing decision support tools like Hazus-MH, however, is often limited by underlying assumptions and system design. First, most existing tools are often based on incomplete offline information. For example, the loss estimation in Hazus-MH does not consider dynamics of human activities, or social interactions in both physical and virtual space. In fact, human dynamics vary by time of day, day of the week, month of the year, and establish congruent and incongruent mobility patterns [6,81]. Furthermore, such human dynamics can be affected by accessible dynamic information, such as live traffic information, place/event recommendations, and emergency alerts and evacuation orders, which are conveyed through physical and online social interactions (e.g., meeting with friends, mobile phone applications, and social media) [82]. These dynamic human activities, mobility patterns, and their interactions are crucial factors for decision making in emergency evacuation.

Second, the sum of the hardware, software, and training requirements needed for full GIS implementation is an obstacle to local and state emergency management personnel [83]. Desktop GIS mapping and analysis tools require sophisticated knowledge in software, hardware, and databases with a steep learning curve and a substantial time commitment [84]. Many local communities lack the resources to fully support the implementation of traditional decision support tools [85]. Closed, standalone desktop disaster management systems can be a major barrier to data and information sharing, participatory decision making, and timely situational awareness. Web-GIS, an alternative approach, offers the potential to reduce these limitations. Web-GIS is a collection of network based geographic information services using the Internet to access geographic information, spatial analytical tools, and GIS web services [86,87]. By extending traditional desktop GIS functionality to the web, applications can be developed that are dynamic, accessible, interactive, and interoperable [83]. As compared to desktop GIS, web-GIS offers improved spatial data access and dissemination, spatial data exploration and geovisualization, spatial data processing, analysis, and modeling [88,89]. These web-based geospatial information technologies and services are built upon the principles of Web 2.0; namely, individual production and user generated content, crowdsourcing, big data, architecture of participation, network effects, and openness [90,91]. Nevertheless, designing and implementing a spatial decision support system over the web presents challenges such as performance, technology integration, interoperability, security and privacy, and quality of service [92].

3. Framework of integrated wildfire evacuation decision support system (IWEDSS)

The IWEDSS framework incorporates a novel dynamic population estimation, evacuation models, social perception analysis, and web-GIS techniques to build a robust evacuation plan. IWEDSS provides key functions for data collection, traffic demand modeling, evacuation operation, and information dissemination and offers scientifically based and data driven analytic tools. IWEDSS aims to support decision makings for evacuation planers and resource managers that ultimately helps to reduce the evacuation time and potential number of injuries and deaths. It integrates multiple data sources including social media, census survey, GIS data layers, volunteer suggestions, and remote sensing data. Fig. 1 shows four core modules of IWEDSS: dynamic population estimation, stage-based robust evacuation models, social perception analysis, and a web-based geospatial analytics platform.

Using the Big Data driven techniques, the first module of IWEDSS estimates hourly based population density distribution in small urban areas. Dynamic population distribution information will serve as the demand input for designing evacuation models. Adopting the disaster impact models to predict the temporal spatial impact of the wildfire events, the second system module performs a risk assessment of the urban area and determine the evacuation risk zones. Then a stage-based robust plan, accounting for the uncertainty of traffic demand estimated with population density, will be initialized for evacuation operation. The third module analyzes the public opinions and feedback from local residents based on social media text analysis and volunteer suggestions. IWEDSS utilizes social media analytic research testbed (SMART) dashboard 2.0 [93,94] and a mobile app (ReadySD-Social) [95,96] for collecting suggestions from registered local volunteers to monitor public opinions and suggestions from local residents nearby disastrous events. By integrating the hourly based dynamic population model from the first module and the social perception analysis from the third module, IWEDSS estimates the movement of people during disasters and makes adjustment of the evacuation plan and shelter locations in a real time manner. Implemented as a web-based geospatial analytics platform, it provides an integrated computational modeling environment and web-based user friendly analysis tools for disaster mitigation planning and emergency responses. With scientifically based estimation, visualization, and analysis tools, IWEDSS delivers suggestions for decision makers, resource managers, and public officers actionable knowledge by fostering the understanding of the impacts of hazards on their communities of interest and measuring the effectiveness of mitigation

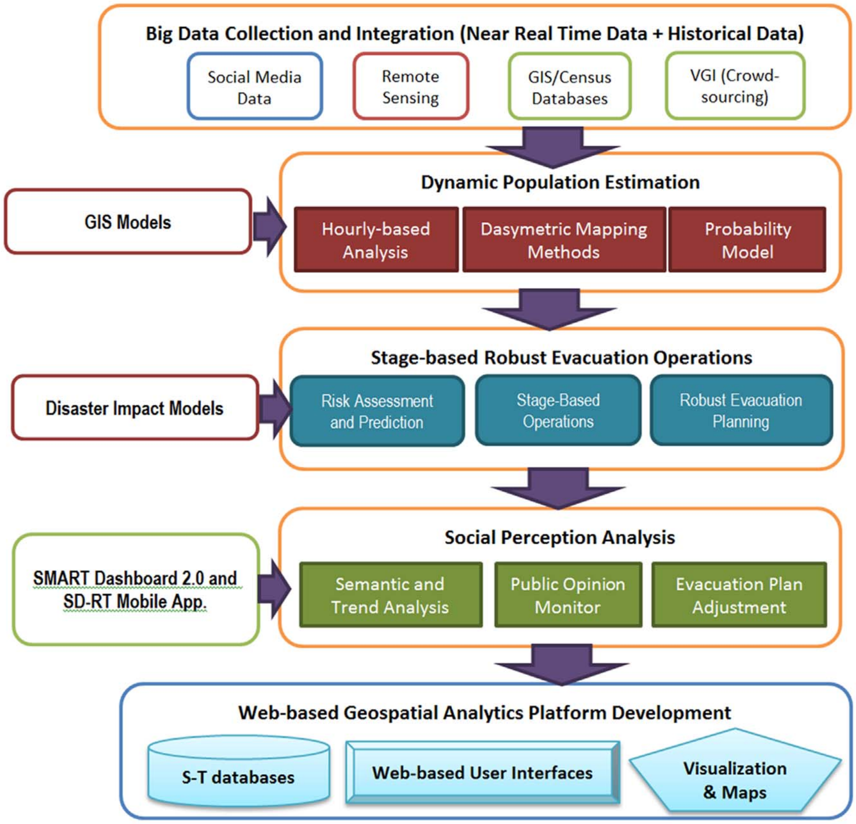

Fig. 1. The design framework of IWEDSS.

strategies before, during, and after a wildfire event.

3.1. Dynamic population distribution (density) estimation model

The first module, which plays a key role in IWEDSS, estimates the hourly based population density distribution in small urban areas by utilizing big data collected from historical and near real time information including social media data, remote sensing imageries, existing GIS data, Census demographic data, and volunteer crowdsource based geographic information.

This module includes four processes to integrate and clean heterogeneous geotagged or check in social media data (including Twitter, Instagram, Foursquare, and Flickr) for the population density estimation. The first process is collecting geographically referenced social media data by social media APIs (Application Programming Interfaces). The social media APIs allow accessing various types of geographic information tied with social media posts such as geographic coordinates (i.e., longitude and latitude), street address, city name, and state name. To analyze them for dynamic population estimates, it is necessary to conduct geocoding, a process to convert from nongeographic coordinates to geographic coordinates, i.e., latitudes and longitudes. However, different types of social media data require different geocoding procedures. Thus, this module implements multi-level geocoding methods for Twitter, Instagram, Foursquare, and Flickr data by using their geotagged coordinates and bounding boxes of check in places. Specifically, the geocoding module utilizes five types of geocoding sources at multiple spatial scales: (1) geotagged coordinates at a point of interest level, (2) place check in location at a point of interest level or a defined bounding box, (3) user profile location at often a city or state level, (4) time zones, and (5) texts containing locational information (explicit or implicit information) at a point of interest level using a text location centroid. After the geocoding procedure, the second process is data cleaning to reduce and/or remove sources of noise and errors in these social media data. Examples of noise and error

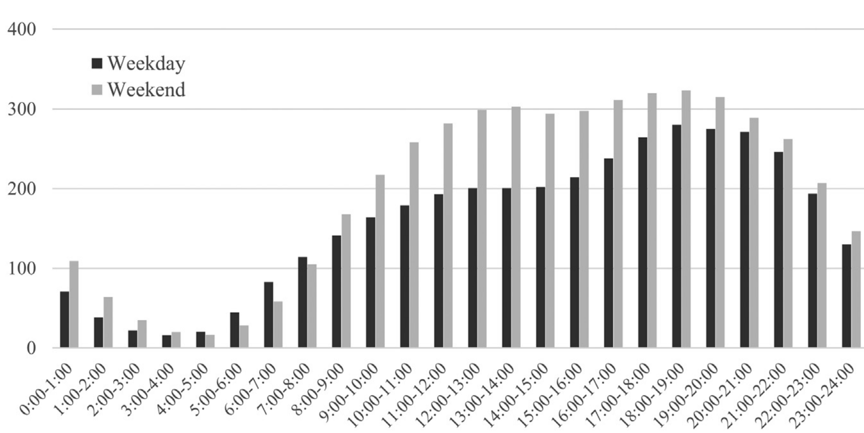

Fig. 2. Average count of unique Twitter user in San Diego, 2015 (n = 1571 TAZs).

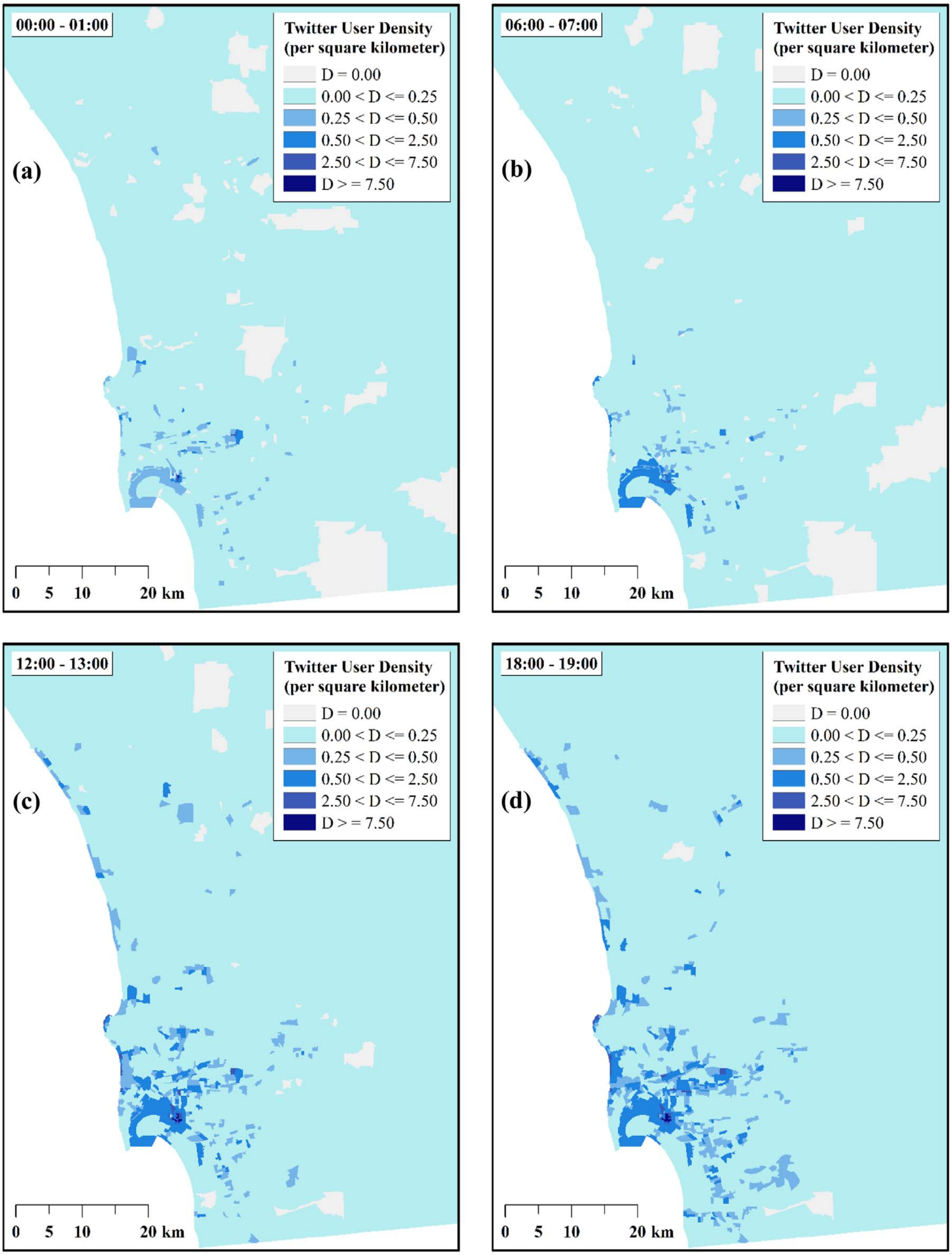

Fig. 3. Weekday hourly average Twitter user density distribution in San Diego in four time periods; (a) 0:00 – 1:00, (b) 6:00 – 7:00, (c) 12:00 – 13:00, and (d) 18:00 – 19:00.

data include advertisements and marketing messages.

The third process calculates the hourly average density of unique social media users at a certain spatial unit. In the IWEDSS framework, Traffic Analysis Zones (TAZs), commonly used for transportation planners and modelers, are chosen as basic spatial units of analysis. Since social media users may post multiple messages within an hour at multiple locations [97], we count only one geotagged message for every unique user for a certain hour at a TAZ. Then the hourly average density of social media users for each TAZ is calculated by the total counts of unique users in an hour divided by the area of each TAZ and the number of days for the data collection period.

To demonstrate the calculation of the hourly average density of social media users, we conducted a case study based on Twitter data, which were collected throughout the year of 2015 (from 2015/1/1 to 2015/12/31) within the bounding box of San Diego County. The collected geotagged Twitter posts, or tweets, consist of 7833,449 originally and 2494,011 after the data cleaning procedure. Fig. 2 draws the weekday (Monday to Friday) and weekend (Saturday and Sunday) average hourly count of unique Twitter users in San Diego County. Both weekday's and weekend's temporal trends on the average count of unique Twitter users show a similar pattern with two peaks around 13:00 and 19:00 and low counts in the early morning. However, values on the weekend daytime hours are higher than those on weekday. These population variations over time between weekday and weekend suggest that it is necessary to adjust the population density estimation using social media data by taking the temporal variation factor into account. Fig. 3 displays spatial distributions of the average hourly Twitter user density in San Diego County within TAZs during weekday in four time periods; (a) 0:00–1:00, (b) 6:00–7:00, (c) 12:00–13:00, and (d) 18:00–19:00. These maps depict realistic dynamic population changes by capturing higher Twitter user densities in TAZs, which have very few population according to the Census survey data. Those areas include popular points of interest such as Balboa Park, San Diego Zoo, shopping malls, and San Diego International Airport.

Finally, based on the hourly average density of unique social media users, we propose to calculate the social media based hourly population density estimate by applying temporal and spatial variation models defined as below [98].

$$\rho_{(t,s)} = D_{(t,s)}\varphi_{(t)}\phi_{(s)}$$

where, $\rho_{(t,s)}$ represents the population density estimate in a temporal unit t (i.e., a certain hour) at a spatial unit s (i.e., a TAZ), $D_{(t,s)}$ is the average density of unique social media users in t at s, and $\varphi_{(t)}$ and $\phi_{(s)}$ are scaling factors to adjust the population density estimate based on temporal and spatial variations respectively. $\varphi_{(t)}$ is defined as a value of factor multiples with the frequency number of hourly average social media user in each TAZ. $\phi_{(s)}$ is defined by utilizing a dasymetric mapping method [19,99,100], which is a geospatial technique to more accurately distribute data using ancillary information such as land use and land cover. We specifically employs the basic concept of intelligent dasymetric mapping technique (IDM) [20] to refine the population density estimate based on different types of land use data (residential areas, commercial areas, etc.) and census data.

While the proposed approach can produce realistic hourly dynamic population density estimates, a key challenge is to evaluate the outcome. Particularly, the model validation, involving the goodness-of-fit of the model to real data, is challenging since such fine temporal scale dynamic population data from real world covering a large area are extremely difficult to obtain. As an alternative approach, this paper attempts to validate the IWEDSS framework by comparing two population densities, nighttime and daytime, derived from Census survey data with weekday and weekend average hourly unique Twitter user densities.

First of all, we compute the nighttime "residential" population density at TAZs by aggregating Census 2010 Decennial population data at Census blocks. The daytime population refers to the number of people who are present in an area during typical business hours. It can be estimated by the commuter-adjusted population estimate method defined as below [101].

$$\begin{aligned} Commuteradjustedpopulation = {} & Totalareapopulation \\ & + Totalworkersworkinginarea \\ & - Toatlworkerslivinginarea \end{aligned}$$

To obtain the number of workers working or living in TAZs, we use the U.S. Census Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES). LODES data are available at Census blocks, and thus they are aggregated to TAZs to calculate the commuter adjusted population density representing the daytime population. Fig. 4(a) and (b) represent Census based population density estimates for nighttime and daytime respectively.

We employ Spearman's rank correlation coefficients to test the relationship between the weekday and weekend hourly unique Twitter user densities and census-based nighttime and daytime population densities. Table 1 illustrates the result indicating that the hourly unique Twitter user densities are more strongly related to the daytime population density rather than the nighttime "residential" population density for all hours in both weekday and weekend. In addition, the hourly unique Twitter user densities are more strongly correlated with the

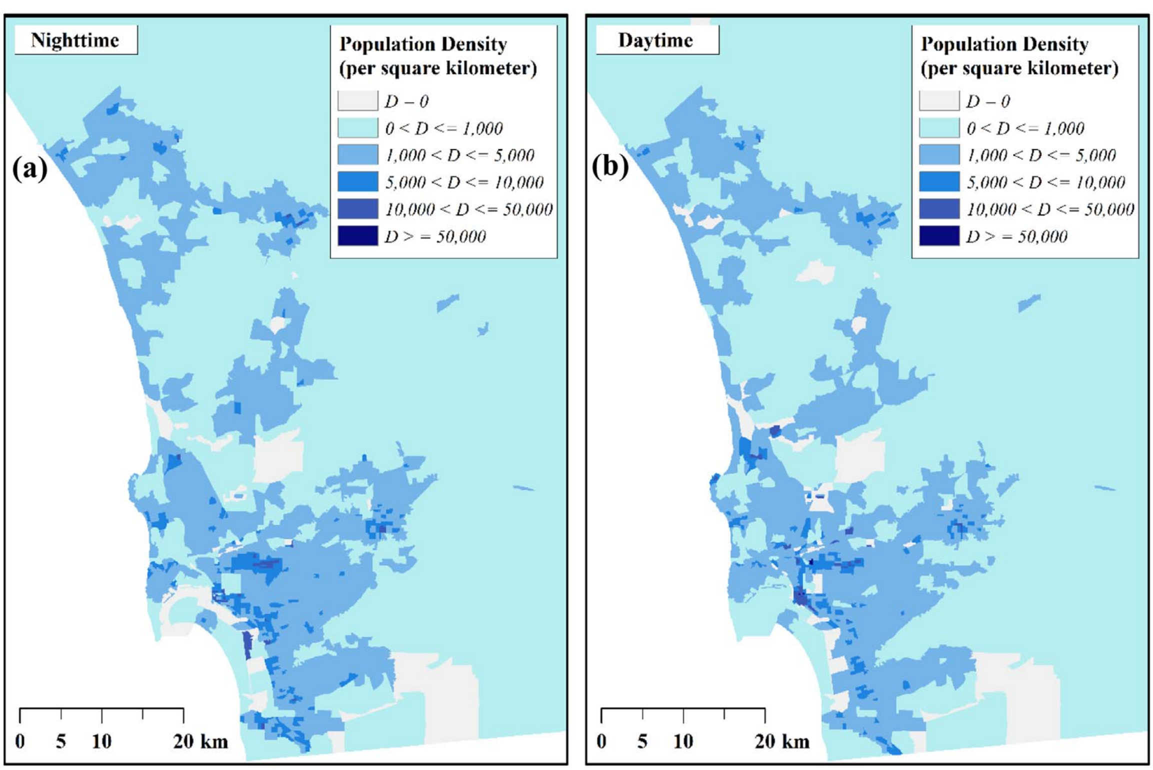

Fig. 4. Census based nighttime (a) and daytime (b) population density distributions.

Table 1
Spearman's rank correlation coefficients between the hourly unique Twitter user densities and the nighttime and daytime population densities estimated based on census surveys.

Time	Weekday		Weekend	
	Night Time	Day Time	Night Time	Day Time
0:00–1:00	0.615***	0.640***	0.572***	0.604***
1:00–2:00	0.564***	0.597***	0.498***	0.537***
2:00–3:00	0.451***	0.496***	0.442***	0.471***
3:00–4:00	0.399***	0.468***	0.311***	0.344***
4:00–5:00	0.317***	0.429***	0.222***	0.294***
5:00–6:00	0.453***	0.560***	0.231***	0.348***
6:00–7:00	0.473***	0.601***	0.351***	0.464***
7:00–8:00	0.446***	0.611***	0.462***	0.554***
8:00–9:00	0.428***	0.606***	0.488***	0.595***
9:00–10:00	0.427***	0.616***	0.485***	0.608***
10:00–11:00	0.423***	0.619***	0.504***	0.637***
11:00–12:00	0.431***	0.634***	0.470***	0.615***
12:00–13:00	0.435***	0.637***	0.500***	0.643***
13:00–14:00	0.450***	0.645***	0.497***	0.642***
14:00–15:00	0.473***	0.661***	0.493***	0.636***
15:00–16:00	0.496***	0.673***	0.488***	0.628***
16:00–17:00	0.501***	0.667***	0.515***	0.651***
17:00–18:00	0.529***	0.672***	0.521***	0.639***
18:00–19:00	0.555***	0.684***	0.524***	0.639***
19:00–20:00	0.576***	0.685***	0.551***	0.652***
20:00–21:00	0.608***	0.690***	0.584***	0.659***
21:00–22:00	0.619***	0.682***	0.600***	0.665***
22:00–23:00	0.653***	0.695***	0.617***	0.665***
23:00–24:00	0.646***	0.684***	0.602***	0.648***

(n = 1571).
*** $p < 0.001$.

nighttime population during evening hours (17:00 to 0:00) than the morning to afternoon hours (4:00 to 16:00). These results indicate that more geotagged Twitter messages are posted from "work-oriented" locations supporting our assumption that geotagged social media data are suitable for estimating dynamic human activities. Furthermore, we found that correlation coefficients are generally lower for weekend densities. This suggests that distributions of Twitter users during weekend are relatively different from "residential" and "work-oriented" population distributions as compared to weekday.

3.2. Stage-based robust evacuation operation model

The second module is a stage-based robust evacuation operation model using the estimated population density derived from the first module. By dividing the entire city into a set of TAZs, where a zone of under 3000 people is in common, the module determines the evacuation sequence for each TAZ along with suggested routings. In addition, to fully recognize the potential estimation errors of population density, the module design the evacuation plan with a robust optimization framework which considers the population input as uncertainty.

After identifying the location of the occurred disaster (i.e., wildfire), IWEDSS first determines the impact areas which need to be evacuated. For example, the 2007 San Diego wildfire had over 1 million of evacuees and Fig. 5 shows a map of 2007 San Diego County wildfire evacuation plan (red color: burning area; orang color: fire perimeters; purple color: mandatory evacuation area; green color: reopened area). To predict the spread of wildfire over time (hourly based extent and intensity estimation), IWEDSS employs a well-established commercial software, Wildfire Analyst™, which utilizes real time weather information (wind speed and direction), land cover, terrain data, and other related factors.

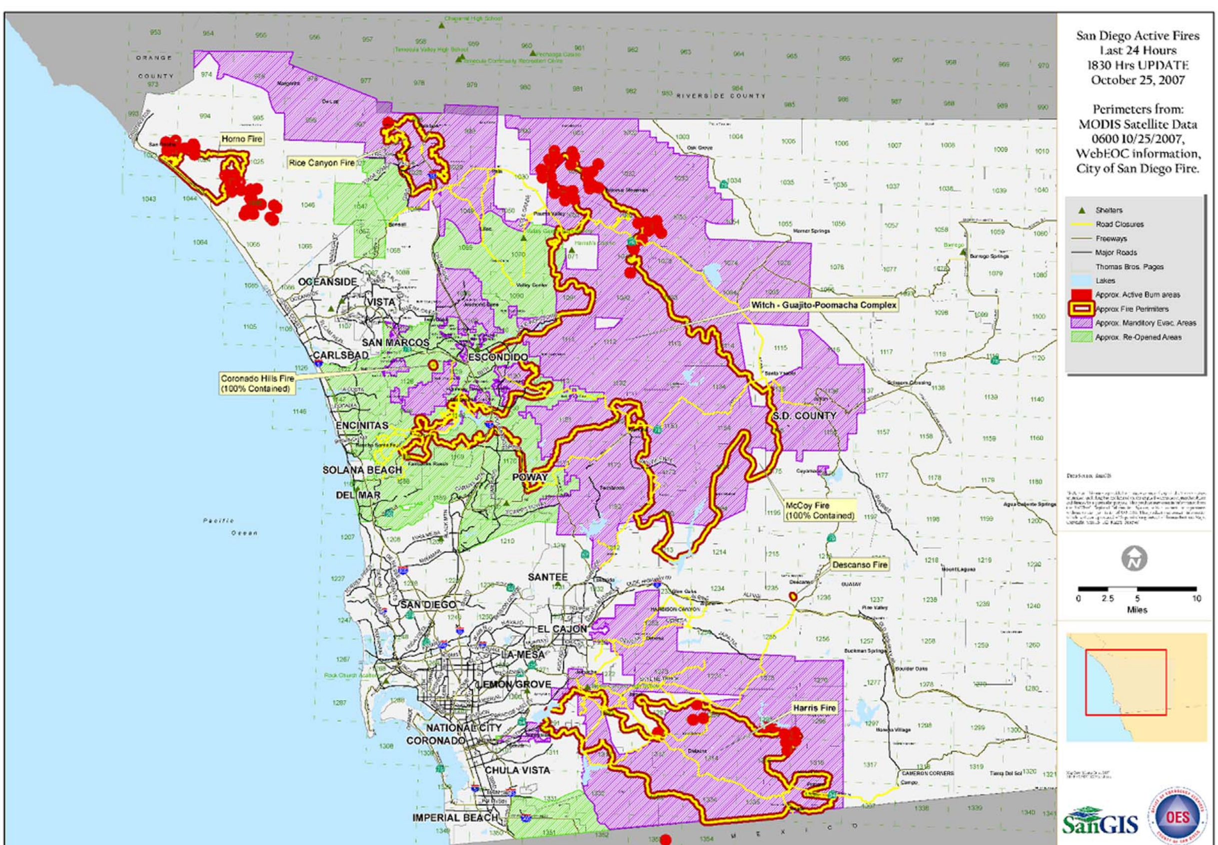

Fig. 5. A map of San Diego County wildfire evacuation plan at 3:30 a.m., October 25, 2007 [102].

Then, the predicted wildfire spread areas over time are used to determine the evacuation risk zones (ERZ) in the region threatened by the disaster. The ERZ is defined as the zone containing population with highest evacuation risk which is measured by whether they can be safely evacuated before the reach of disaster impact. With time dependent assessment of the risk rate in all ERZs, this module optimizes their evacuation time according to the location of shelters, roadway capacities, and potential traffic demand generated. In review of literature, evacuation demand modeling is always a challenging issue due to the traffic flows under evacuation conditions differ from those in regular days. Conventional methods usually use the historical survey information for estimations. However, due to the difficulty in collecting up to date data, such models may fall short of accuracy due to the dynamic nature of population distributions. Therefore, the hourly based population density estimation derived in the first module serves as a key input of evacuation demand modeling.

Similar to most existing studies in this subject, the demand model includes two primary steps: determination of number of evacuating vehicles, and prediction of evacuee departure time. The first step will involve an estimation of average vehicle occupancy rate in each zone. Then the rate multiplied by the zone's population produces the total traffic demand. After assigning an evacuation sequence to each ERZ, the next step is to distribute the evacuees over time according to the prediction of their departure time choices. Many existing studies employed the cumulative departure S-curves [103]. IWEDSS follows the same line but recalibrates the curve based on people's perception of the disaster collected by social media information acquired in the third module.

One feature that many disasters have in common is their uncertain nature, in which exact data are unlikely to be available combined with a high likelihood of social disruption. Under such conditions, use of unreliable estimated data as the input of an evacuation planning system may require much more effort for plan changes in real time operations. To overcome this issue, a robust optimization function in this module, along with the state based evacuation strategy, accounts for the input data uncertainties. Specifically, such uncertainty is contributed by the estimated traffic demand generated in each zone and departure time choices of evacuees.

For designing the evacuation routings of ERZs, this module first develops a base model, which is in the deterministic form and formulated as a mesoscopic simulation model in order to optimize computational efficiency. Given the defined uncertain input set, the module formulates the so called robust counterpart, that is, an extension of the base model, which takes the uncertainties into account. In strict robustness, the objective is to find a solution that is feasible for all possible cases and is able to provide best performance in the worst case scenario. For this evacuation problem, such a worst case in terms of time dependent traffic demand is the one that can cause the largest delay on roadway network, for which some vehicles will need to be guided to a farther route. However, due to the tradeoff between efficiency and robustness, the strict robustness definition may lead to an overly conservative plan. Thus, this module redefines a set of open balls in Cartesian space for the uncertain inputs so as to limit their variations. This robust optimization model brings an innovative solution to overcome the impact of traffic demand estimation errors.

3.3. Social perception analysis

The third module is composed of public opinion monitoring, semantic and trend analysis, and evacuation adjustment plan based on social perception. People behave differently in times of crisis based on their perception of risk and danger. Therefore, efficient wildfire evacuation planning and developing mitigation strategies require both technical transportation network analysis as well as understanding of social perception from local residents. Social opinion and information dissemination of such opinion among individuals could facilitate or constrain the successful implementation of an evacuation plan. Thus, understanding social perception can be used as a powerful decision support tool to respond effectively to wildfire evacuation.

IWEDSS embeds a public opinion monitor, which is based on the existing system, the Social Media Analytics Research Testbed (SMART) dashboard [93,94]. The SMART Dashboard has been applied to many public opinion monitoring tasks, including flu outbreaks, vaccine exemptions, flooding, and wildfires. Fig. 6 illustrates the screenshot of the SMART dashboard for monitoring California Wildfire events daily by using predefined keywords. IWEDSS implements an improved SMART Dashboard (SMART Dashboard 2.0) by adding new hourly based data updating and dynamic keyword searching functions for real time and near real time analysis. In addition, it implements a social perception analysis model that applies semantic and trend analysis techniques to extract knowledge from social media texts to understand evacuees' general perception, sentiments, and attitude toward evacuation related subjects as well as the extent of social confirmation of the official warnings and recommendations. Multilevel Model of Meme Diffusion (M3D) is employed as a theoretical guideline in developing the semantic analysis model. M3D is a new framework designed for describing online communication and the diffusion of memes (social media messages) via different social networks [104]. In real time applications, social perception analysis model is adjusted and updated using two approaches, (1) social media data from the SMART dashboard 2.0 and (2) the volunteers' direct feedback using the ReadySD-Social mobile application.

The social perception analysis model is updated and improved by analyzing direct feedback and comments from registered volunteers directly using a mobile application, ReadySD-Social a mobile app for broadcasting emergency information specifically applying for the San Diego region available for Android and iOS (Fig. 7) [95,96]. Registered local volunteers in San Diego can use the ReadySD-Social app to retweet emergency announcements and evacuation messages from the San Diego County Office of Emergency. The mobile app can be downloaded in both iOS and Android smartphones. ReadySD-Social also allows the registered volunteers to send out their feedback and suggestions related to the evacuation orders and shelter locations directly into an online forum managed inside the IWEDSS. These feedback texts are analyzed and integrated into the social perception model to monitor the course of the evacuation plan implementation and determine attitude evolution over time.

Information obtained through the ReadySD-Social mobile app and the SMART dashboard 2.0 (public opinion monitor) serve as a supporting tool to assist with the evacuation planning. This information allows for greater clarity in the evaluation of the messages. Furthermore, it assists in evaluating which channel gets more notice from people in disseminating important messages, and whether people follow recommendations from authorities. Another example is to provide guides on the frequency of the warnings and recognizing the boundary between adequate warnings and over warning situations or excessive fear appeals. Excessive warning frequencies could lead to disregarding (cry wolf effect). Extracted information is incorporated in real time manner to tailor the evacuation planning toward more efficient and socially acceptable strategies. The results are integrated in wildfire evacuation strategies and logistics by recalibrating the developed plan in the second module.

3.4. A web-based geospatial analytics platform

Implemented as a web-based geospatial analytics platform, IWEDSS offers an integrated computational modeling environment and an interactive decision support system for disaster mitigation planning. There are three core components on the integrated computational modeling environment: (1) spatiotemporal databases; (2) analytical models; and (3) high performance computing (HPC). Spatiotemporal databases allow to store, update, manage, and efficiently query multiple layers of geospatial information necessary to predict the extent and

Fig. 6. The SMART Dashboard for "Wildfires in California" topic.

intensity of disaster impacts over time and determine ERZs. Multi layered geospatial information includes Census based socio demographic data, transportation networks, land use/land cover data, dynamic population estimates, dynamic evacuation demand estimates, and evacuees' perception of disasters. As a second component, a set of server side modules on Linux servers are implemented for the evacuation demand model and the semantic analysis model. In addition, IWEDSS implements data integration modules (described in 3.1) in the spatiotemporal databases to spatially and temporally integrate multiple geospatial data sources, which are heterogeneous in scale, format, structure, and quality. These implementations are achieved through the object relational database framework, Structured Query Language (SQL), and database functions. The third core component is the HPC solution to expedite data preparation, database query, and analytical computations by implementing algorithms that utilize database partitioning, multiple central processing units (CPUs) and graphics processing units (GPUs).

IWEDSS is designed as a web-based geographic information service

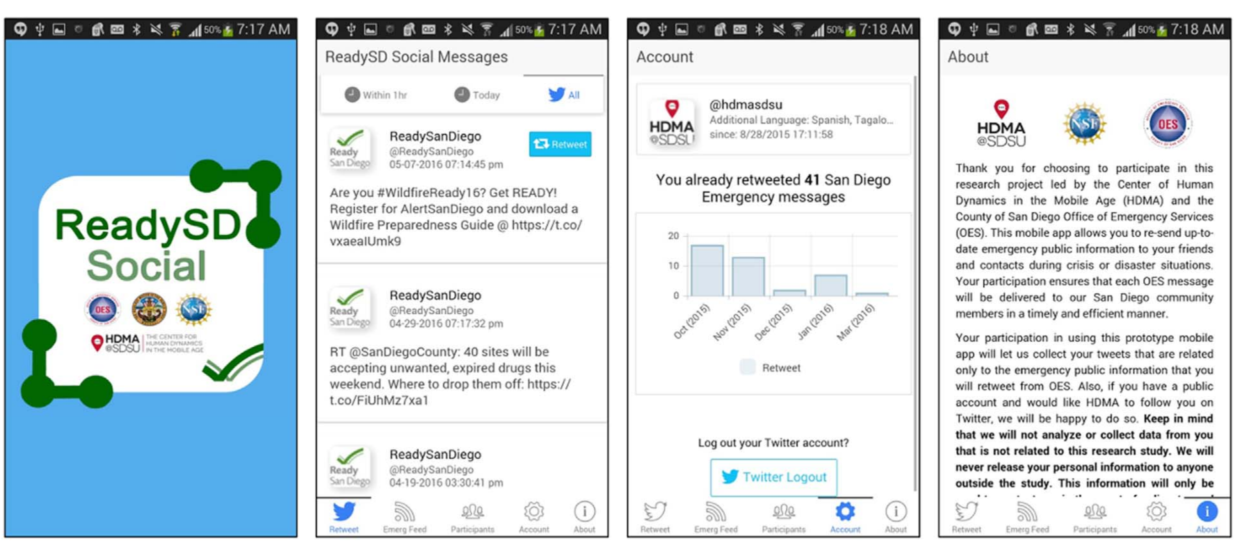

Fig. 7. ReadySD-Social, a mobile app for broadcasting emergency information in San Diego.

as an interactive decision support system for disaster mitigation planning. The web-GIS service provides geospatial tools and user friendly graphical user interfaces (GUIs) that allow users to interactively explore and simulate "what if" scenarios to assess spatial, temporal, and social vulnerabilities before, during, and after a disaster event, particularly focusing on evacuation. The platform is capable of quantifying community functionality, evacuation effectiveness, and system dynamics to evaluate community resilience. The core system is built upon a mixed configuration to take advantages of both open source and proprietary software resources, including ArcGIS, Wildfire Analyst™, PostgreSQL, PostGIS, MongoDB, Open Layers, Node.js, HTML5, JavaScript, and Python.

4. Conclusion

This paper presents an innovative decision support system framework for wildfire evacuation by integrating social media data, GIScience, transportation, and human behavior analysis. As long as the communication grid is available, this framework can be extended to other types of disasters (e.g., tsunami, hurricanes, and technical hazards) with some modifications. The dynamic population density model developed in IWEDSS can be applied in many applications, including urban planning, elections, business marketing, and facility management. The social perception analysis model and public opinion monitors can also help other research domains such as traffic incident detection and public campaigns, as well as other social crises and natural disasters. One of the most valuable components in the IWEDSS framework is to establish a resident feedback network by connecting registered volunteers using a mobile phone application and an online forum. The method of building such community network is replicable for many U.S. cities and it will provide valuable social capital for helping local communities during disaster events and make society more resilient to nature disaster events.

Color artwork

Our preference for color is online only.

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References

[1] R. Chen, R. Sharman, H.R. Rao, S.J. Upadhyaya, Coordination in Emergency Response Management, Commun. ACM 51 (2008) 66–73, http://dx.doi.org/10.1145/1342327.1342340.
[2] T. Pei, S. Sobolevsky, C. Ratti, S.-L. Shaw, T. Li, C. Zhou, A new insight into land use classification based on aggregated mobile phone data, Int J. Geogr. Inf. Sci. 28 (2014) 1988–2007, http://dx.doi.org/10.1080/13658816.2014.913794.
[3] M.-H. Tsou, M. Leitner, Visualization of social media: seeing a mirage or a message? Cartogr. Geogr. Inf. Sci. 40 (2013) 55–60, http://dx.doi.org/10.1080/15230406.2013.776754.
[4] S. Elwood, M.F. Goodchild, D. Sui, Prospects for VGI Research and the Emerging Fourth Paradigm. Crowdsourcing Geogr. Knowl, Springer, Netherlands, 2012, pp. 361–375, http://dx.doi.org/10.1007/978-94-007-4587-2_20.
[5] F. Bonomi, R. Milito, J. Zhu, S. Addepalli Fog Computing and Its Role in the Internet of Things. Proceedings First Ed. MCC Workshop Mob. Cloud Comput., New York, NY, USA: ACM, p. 13–16. http://dx.doi.org/10.1145/2342509.2342513.
[6] M. Yuan, A. Nara, J. Bothwell, Space–time representation and analytics, Ann. GIS 20 (2014) 1–9, http://dx.doi.org/10.1080/19475683.2013.862301.
[7] M.-H. Tsou, Research challenges and opportunities in mapping social media and Big Data, Cartogr. Geogr. Inf. Sci. 42 (2015) 70–74, http://dx.doi.org/10.1080/15230406.2015.1059251.
[8] A.-L. Barabási, The origin of bursts and heavy tails in human dynamics, Nature 435 (2005) 207–211, http://dx.doi.org/10.1038/nature03459.
[9] C. Bregler, Learning and recognizing human dynamics in video sequences, Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (1997) 568–574, http://dx.doi.org/10.1109/CVPR.1997.609382.
[10] J.J. Wang, S. Singh, Video analysis of human dynamics–a survey, Real.-Time Imaging 9 (2003) 321–346, http://dx.doi.org/10.1016/j.rti.2003.08.001.
[11] B. Bhaduri, E. Bright, P. Coleman, M.L. Urban, LandScan USA: a high-resolution geospatial and temporal modeling approach for population distribution and dynamics, Geo J. 69 (2007) 103–117, http://dx.doi.org/10.1007/s10708-007-9105-9.
[12] L. Bengtsson, X. Lu, A. Thorson, R. Garfield, J. von Schreeb, Improved response to disasters and outbreaks by tracking population movements with mobile phone network data: a post-earthquake geospatial study in Haiti, PLoS Med 8 (2011) e1001083, http://dx.doi.org/10.1371/journal.pmed.1001083.
[13] P. Deville, C. Linard, S. Martin, M. Gilbert, F.R. Stevens, A.E. Gaughan, et al., Dynamic population mapping using mobile phone data, Proc. Natl. Acad. Sci. 111 (2014) 15888–15893, http://dx.doi.org/10.1073/pnas.1408439111.
[14] Y. Hara, M. Kuwahara, Traffic Monitoring immediately after a major natural disaster as revealed by probe data – A case in Ishinomaki after the Great East Japan Earthquake, Transp. Res Part Policy Pract. 75 (2015) 1–15, http://dx.doi.org/10.1016/j.tra.2015.03.002.
[15] R. Ahas, A. Aasa, Y. Yuan, M. Raubal, Z. Smoreda, Y. Liu, et al., Everyday space–time geographies: using mobile phone-based sensor data to monitor urban activity in Harbin, Paris, and Tallinn, Int J. Geogr. Inf. Sci. 29 (2015) 2017–2039, http://dx.doi.org/10.1080/13658816.2015.1063151.
[16] C.L. Eicher, C.A. Brewer, Dasymetric mapping and areal interpolation: implementation and evaluation, Cartogr. Geogr. Inf. Sci. 28 (2001) 125–138, http://dx.doi.org/10.1559/152304001782173727.
[17] J.B. Holt, C.P. Lo, T.W. Hodler, Dasymetric estimation of population density and areal interpolation of census data, Cartogr. Geogr. Inf. Sci. 31 (2004) 103–121, http://dx.doi.org/10.1559/1523040041649407.
[18] J.K. Wright, A method of mapping densities of population: with cape cod as an example, Geogr. Rev. (1936) 26, http://dx.doi.org/10.2307/209467.
[19] J. Mennis, Generating surface models of population using dasymetric mapping, Prof. Geogr. 55 (2003) 31–42, http://dx.doi.org/10.1111/0033-0124.10042.
[20] J. Mennis, T. Hultgren, Intelligent dasymetric mapping and its application to areal interpolation, Cartogr. Geogr. Inf. Sci. 33 (2006) 179–194.
[21] P. Dong, S. Ramesh, A. Nepali, Evaluation of small-area population estimation using LiDAR, Landsat TM and parcel data, Int J. Remote Sens 31 (2010) 5571–5586, http://dx.doi.org/10.1080/01431161.2010.496804.
[22] P. Murray-Tuite, B. Wolshon, Evacuation transportation modeling: an overview of research, development, and practice, Transp. Res Part C. Emerg. Technol. 27 (2013) 25–45, http://dx.doi.org/10.1016/j.trc.2012.11.005.
[23] S. Arlikatti, Risk area accuracy and hurricane evacuation expectations of coastal residents, Environ. Behav. 38 (2006) 226–247, http://dx.doi.org/10.1177/0013916505277603.
[24] D. Li, T.J. Cova, P.E. Dennison, A household-level approach to staging wildfire evacuation warnings using trigger modeling, Comput. Environ. Urban Syst. 54 (2015) 56–67, http://dx.doi.org/10.1016/j.compenvurbsys.2015.05.008.
[25] E. Urbina, B. Wolshon, National review of hurricane evacuation plans and policies: a comparison and contrast of state practices, Transp. Res Part Policy Pract. 37 (2003) 257–275, http://dx.doi.org/10.1016/S0965-8564(02)00015-0.
[26] X. Zhang, G. Chang, A dynamic evacuation model for pedestrian–vehicle mixed-flow networks, Transp. Res Part C. Emerg. Technol. 40 (2014) 75–92, http://dx.doi.org/10.1016/j.trc.2014.01.003.
[27] E.J. Baker, Hurricane evacuation behavior', Int. J. Mass Emergencies Disasters 9 (1991) 287–310.
[28] G.O. Rogers, J.H. Sorensen, Diffusion of Emergency Warning: Comparing Empirical and Simulation Results, in: C. Zervos, K. Knox, L. Abramson, R. Coppock (Eds.), Risk Anal. Springer, US, 1991, pp. 117–134, , http://dx.doi.org/10.1007/978-1-4899-0730-1_14.
[29] Southworth F. Regional Evacuation Modeling: A State of the Art Review 1991. doi:10.2172/814579.
[30] Brian Wolshon, Emile Marchive, Emergency planning in the urban-wildland interface: subdivision-level analysis of wildfire evacuations, J. URBAN PLAN DEV.-ASCE - J. URBAN PLAN DEV.-ASCE (2007) 133, http://dx.doi.org/10.1061/(ASCE)0733-9488(2007)133:1(73).
[31] P.E. Dennison, T.J. Cova, M.A. Mortiz, WUIVAC: a wildland-urban interface evacuation trigger model applied in strategic wildfire scenarios, Nat. Hazards 41 (2007) 181–199, http://dx.doi.org/10.1007/s11069-006-9032-y.
[32] Thomas J. Cova, Philip E. Dennison, Frank A. Drews, Modeling evacuate versus shelter-in-place decisions in wildfires, Sustainability 3 (2011) 1662–1687, http://dx.doi.org/10.3390/su3101662.
[33] V. Dixit, T. Montz, B. Wolshon, Validation techniques for region-level microscopic mass evacuation traffic simulations, Transp. Res Rec. J. Transp. Res Board 2229 (2011) 66–74, http://dx.doi.org/10.3141/2229-08.
[34] Michael K. Lindell, Jing-Chein Lu, Carla S. Prater, Household decision making and evacuation in response to Hurricane Lili, Nat. Hazards Rev. 6 (2005) 171–179, http://dx.doi.org/10.1061/(ASCE)1527-6988(2005)6:4(171).
[35] N. Elmitiny, S. Ramasamy, E. Radwan, Emergency evacuation planning and preparedness of transit facilities: traffic simulation modeling, Transp. Res Rec. J. Transp. Res Board 1992 (2007) 121–126, http://dx.doi.org/10.3141/1992-14.
[36] Y. Gu, Integrating a Regional Planning Model (TRANSIMS) With an Operational Model (CORSIM). 〈https://theses.lib.vt.edu/theses/available/etd-02202004-160557/〉 (accessed 4 February 2016), 2004.
[37] P. Murray-Tuite, H. Mahmassani, Transportation network evacuation planning

with household activity interactions, Transp. Res Rec. J. Transp. Res Board 1894 (2004) 150–159, http://dx.doi.org/10.3141/1894-16.
[38] Y.-.C. Chiu, P. Korada, P.B. Mirchandani, Dynamic traffic management for evacuation. 84th Annu Meet Transp Res Board Wash DC, 2005.
[39] R. Balakrishna, Y. Wen, M. Ben-Akiva, C. Antoniou, Simulation-based framework for transportation network management in emergencies, Transp. Res Rec. J. Transp. Res Board 2041 (2008) 80–88, http://dx.doi.org/10.3141/2041-09.
[40] X. Chen, J.W. Meaker, F.B. Zhan, Agent-based modeling and analysis of hurricane evacuation procedures for the Florida keys, Nat. Hazards 38 (2006) 321–338, http://dx.doi.org/10.1007/s11069-005-0263-0.
[41] X. Chen, F.B. Zhan, Agent-based modelling and simulation of urban evacuation: relative effectiveness of simultaneous and staged evacuation strategies, J. Oper. Res Soc. J. Oper. Res Soc. (2008) 59, http://dx.doi.org/10.1057/palgrave.jors.2602321.
[42] H.D. Sherali, T.B. Carter, A.G. Hobeika, A location-allocation model and algorithm for evacuation planning under hurricane/flood conditions, Transp. Res Part B Methodol. 25 (1991) 439–452, http://dx.doi.org/10.1016/0191-2615(91)90037-J.
[43] Y. Liu, X. Lai, G.-L. Chang, Cell-based network optimization model for staged evacuation planning under emergencies, Transp. Res Rec. J. Transp. Res Board 1964 (2006) 127–135, http://dx.doi.org/10.3141/1964-14.
[44] Y.-T. Hsu, S. Peeta, Risk-based spatial zone determination problem for stage-based evacuation operations, Transp. Res Part C. Emerg. Technol. 41 (2014) 73–89, http://dx.doi.org/10.1016/j.trc.2014.01.013.
[45] B. Wolshon, Empirical characterization of mass evacuation traffic flow, Transp. Res Rec. J. Transp. Res Board 2041 (2008) 38–48, http://dx.doi.org/10.3141/2041-05.
[46] T.J. Cova, J.P. Johnson, A network flow model for lane-based evacuation routing, Transp. Res Part Policy Pract. 37 (2003) 579–604.
[47] M. Chen, L. Chen, E. Miller-Hooks, Traffic signal timing for urban evacuation, J. Urban Plan Dev. 133 (2007) 30–42, http://dx.doi.org/10.1061/(ASCE)0733-9488(2007)133:1(30).
[48] S. Ghanipoor Machiani, P. Murray-Tuite, A. Jahangiri, S. Liu, B. Park, Y.-C. Chiu, et al., No-notice evacuation management: ramp closures under varying budgets and demand scenarios, Transp. Res Rec. J. Transp. Res Board 2376 (2013) 27–37, http://dx.doi.org/10.3141/2376-04.
[49] H. Sbayti, H. Mahmassani, Optimal scheduling of evacuation operations, Transp. Res Rec. J. Transp. Res Board 1964 (2006) 238–246, http://dx.doi.org/10.3141/1964-26.
[50] R. Chunara, J.R. Andrews, J.S. Brownstein, Social and news media enable estimation of epidemiological patterns early in the 2010 Haitian cholera outbreak, Am. J. Trop. Med Hyg. 86 (2012) 39–45, http://dx.doi.org/10.4269/ajtmh.2012.11-0597.
[51] Z. Xiang, U. Gretzel, Role of social media in online travel information search, Tour. Manag 31 (2010) 179–188, http://dx.doi.org/10.1016/j.tourman.2009.02.016.
[52] E. Gilbert, K. Karahalios Predicting Tie Strength with Social Media. Proceedings SIGCHI Conference Hum. Factors Comput. Syst., New York, NY, USA: ACM, p. 211–220. http://dx.doi.org/10.1145/1518701.1518736.
[53] M.R. Frank, L. Mitchell, P.S. Dodds, C.M. Danforth, Happiness and the patterns of Life: a study of geolocated tweets, Sci. Rep. (2013) 3, http://dx.doi.org/10.1038/srep02625.
[54] C. Shirky, The political power of social media, Foreign Aff. 90 (2011) 28–41.
[55] E. Spiro, C. Irvine, C. DuBois, C. Butts, Waiting for a retweet: modeling waiting times in information propagation. 2012 NIPS Workshop Soc. Netw. Soc. Media Conference Httpsnap Stanf. Edusocial2012paperssspiro-Dubois-Butts Pdf Accessed, vol. 12, 2012.
[56] K. Starbird, L. Palen, A.L. Hughes, S. Vieweg Chatter on the red: what hazards threat reveals about the social life of microblogged information. Proceedings 2010 ACM Conference Comput. Support. Coop. Work, ACM, p. 241–250.
[57] S. Vieweg, A.L. Hughes, K. Starbird, L. Palen Microblogging during two natural hazards events: what twitter may contribute to situational awareness. Proceedings SIGCHI Conference Hum. Factors Comput. Syst., ACM, p. 1079–1088.
[58] J. Sutton, E. Spiro, C. Butts, S. Fitzhugh, B. Johnson, M. Greczek, Tweeting the spill: online informal communications, social networks, and conversational microstructures during the deepwater horizon oilspill, Int J. Inf. Syst. Crisis Response Manag 5 (2013) 58–76, http://dx.doi.org/10.4018/jiscrm.2013010104.
[59] S.E. Middleton, L. Middleton, S. Modafferi, Real-time crisis mapping of natural disasters using social media, IEEE Intell. Syst. 29 (2014) 9–17, http://dx.doi.org/10.1109/MIS.2013.126.
[60] X. Guan, C. Chen, Using social media data to understand and assess disasters, Nat. Hazards 74 (2014) 837–850, http://dx.doi.org/10.1007/s11069-014-1217-1.
[61] Y. Jin, B.F. Liu, L.L. Austin, Examining the role of social media in effective crisis management: the effects of crisis origin, information form, and source on publics' crisis responses, Commun. Res 41 (2014) 74–94.
[62] B.F. Liu, J.D. Fraustino, Y. Jin, Social media use during disasters how information form and source influence intended behavioral responses, Commun. Res 43 (2016) 626–646.
[63] B.F. Liu, Y. Jin, L.L. Austin, The tendency to tell: understanding publics' communicative responses to crisis information form and source, J. Public Relat. Res 25 (2013) 51–67, http://dx.doi.org/10.1080/1062726X.2013.739101.
[64] H. Lim, M.B. Lim, M. Piantanakulchai, A review of recent studies on flood evacuation planning, J. East Asia Soc. Transp. Stud. 10 (2013) 147–162.
[65] R.W. Perry, Comprehensive emergency management: evacuating threatened populations (Jai Pr), (Contemp. Stud. Appl. Behav. Sci. 3 (1985) (Jai Pr).
[66] J. Sutton, L. Palen, I. Shklovski Backchannels on the front lines: Emergent uses of social media in the 2007 southern California wildfires. Proceedings of the 5th International ISCRAM Conference, Washington, DC, p. 624–632.
[67] T.J. Cova, GIS in emergency management, Geogr. Inf. Syst. 2 (1999) 845–858.
[68] S.L. Cutter, GI science, disasters, and emergency management, Trans. GIS 7 (2003) 439–446, http://dx.doi.org/10.1111/1467-9671.00157.
[69] S.L. Cutter (Ed.), American Hazardscapes: The Regionalization of Hazards and Disasters, Joseph Henry Press, 2002.
[70] G. Andrienko, N. Andrienko, P. Jankowski, D. Keim, M.-J. Kraak, A. MacEachren, et al., Geovisual analytics for spatial decision support: setting the research agenda, Int J. Geogr. Inf. Sci. 21 (2007) 839–857, http://dx.doi.org/10.1080/13658810701349011.
[71] F.N. de Silva, R.W. Eglese, Integrating simulation modelling and GIS: spatial decision support systems for evacuation planning, J. Oper. Res Soc. 51 (2000) 423–430, http://dx.doi.org/10.2307/254169.
[72] F. Fiedrich, P. Burghardt, Agent-based systems for disaster management, Commun. ACM 50 (2007) 41–42, http://dx.doi.org/10.1145/1226736.1226763.
[73] P.M. Torrens, High-resolution space–time processes for agents at the built–human interface of urban earthquakes, Int J. Geogr. Inf. Sci. 28 (2014) 964–986, http://dx.doi.org/10.1080/13658816.2013.835816.
[74] S. McClendon, A.C. Robinson, Leveraging geospatially-oriented social media communications in disaster response, Int J. Inf. Syst. Crisis Response Manag 5 (2013) 22–40, http://dx.doi.org/10.4018/jiscrm.2013010102.
[75] T. Becker, G. König, Generalized cartographic and simultaneous representation of utility networks for decision-support systems and crisis management in urban environments, ISPRS Ann. Photogramm. Remote Sens Spat. Inf. Sci. 1 (2015) 19–28.
[76] M.F. Goodchild, J.A. Glennon, Crowdsourcing geographic information for disaster response: a research frontier, Int J. Digit Earth 3 (2010) 231–241, http://dx.doi.org/10.1080/17538941003759255.
[77] M. Zook, M. Graham, T. Shelton, S. Gorman, Volunteered geographic information and crowdsourcing disaster relief: a case study of the haitian earthquake, World Med Health Policy 2 (2010) 7–33, http://dx.doi.org/10.2202/1948-4682.1069.
[78] B. Tomaszewski, Geographic Information Systems (GIS) for Disaster Management, CRC Press, 2014.
[79] B. Tomaszewski, M. Judex, J. Szarzynski, C. Radestock, L. Wirkus, Geographic information systems for disaster response: a review, J. Homel. Secur Emerg. Manag 12 (2015) 571–602, http://dx.doi.org/10.1515/jhsem-2014-0082.
[80] Hazus | FEMA.gov n.d. 〈http://www.fema.gov/hazus〉 (accessed 4 February 2016).
[81] M. Yuan, A. Nara, Space-Time Analytics of Tracks for the Understanding of Patterns of Life, in: M.-P. Kwan, D. Richardson, D. Wang, C. Zhou (Eds.), Space-Time Integr. Geogr. GIScience Res. Front. US China, Dordrecht, Springer, Netherlands, 2015, pp. 373–398.
[82] F. Goetzke, R. Gerike, A. Páez, E. Dugundji, Social interactions in transportation: analyzing groups and spatial networks, Transp. N. Y 42 (2015) 723–731, http://dx.doi.org/10.1007/s11116-015-9643-9.
[83] E. Tate, C.G. Burton, M. Berry, C.T. Emrich, S.L. Cutter, Integrated hazards mapping tool, Trans. GIS 15 (2011) 689–706, http://dx.doi.org/10.1111/j.1467-9671.2011.01284.x.
[84] C.T. Emrich, S.L. Cutter, P.J. Weschler, GIS and emergency management, Sage Handb. GIS Soc. Lond. Sage (2011) 321–343.
[85] J.C. Maclachlan, M. Jerrett, T. Abernathy, M. Sears, M.J. Bunch, Mapping health on the Internet: a new tool for environmental justice and public health research, Health Place 13 (2007) 72–86, http://dx.doi.org/10.1016/j.healthplace.2005.09.012.
[86] A. Páez, M. Moniruzzaman, P.-L. Bourbonnais, C. Morency, Developing a web-based accessibility calculator prototype for the Greater Montreal Area, Transp. Res Part Policy Pract. 58 (2013) 103–115, http://dx.doi.org/10.1016/j.tra.2013.10.020.
[87] Z.-R. Peng, M.-H. Tsou, Internet GIS: distributed geographic information services for the internet and wireless networks, John Wiley & Sons, 2003.
[88] Z.C. Aye, T. Sprague, V.J. Cortes, K. Prenger-Berninghoff, M. Jaboyedoff, M.-H. Derron, A collaborative (web-GIS) framework based on empirical data collected from three case studies in Europe for risk management of hydro-meteorological hazards, Int J. Disaster Risk Reduct. 15 (2016) 10–23, http://dx.doi.org/10.1016/j.ijdrr.2015.12.001.
[89] S. Dragićević, The potential of Web-based GIS, J. Geogr. Syst. 6 (2004) 79–81, http://dx.doi.org/10.1007/s10109-004-0133-4.
[90] P. Andersen, What is Web 2.0?: ideas, technologies and implications for education 1 JISC Bristol, UK, 2007.
[91] M. Batty, A. Hudson-Smith, R. Milton, A. Crooks, Map mashups, Web 2.0 and the GIS revolution, Ann. GIS 16 (2010) 1–13, http://dx.doi.org/10.1080/19475681003700831.
[92] V. Sugumaran, R. Sugumaran, Web-based spatial decision support systems (WebSDSS): evolution, architecture, examples and challenges, Commun. Assoc. Inf. Syst. 19 (2007) 40.
[93] M.-.H. Tsou, C.-.T. Jung, C. Allen, J.-.A. Yang, J.-.M. Gawron, B.H. Spitzberg, et al. Social Media Analytics and Research Test-bed (SMART Dashboard). Proceedings 2015 International Conference Soc. Media Soc., New York, NY, USA: ACM, p. 2:1–2:7. http://dx.doi.org/10.1145/2789187.2789196.
[94] J.-A. Yang, M.-H. Tsou, C.-T. Jung, C. Allen, B.H. Spitzberg, J.M. Gawron, et al., Social media analytics and research testbed (SMART): exploring spatiotemporal patterns of human dynamics with geo-targeted social media messages (2053951716652914), Big Data Soc. 3 (2016), http://dx.doi.org/10.1177/2053951716652914.
[95] M.-.H. Tsou, ReadySD Social for Android (1.1) [Mobile Application Software], 2017.

[96] M.-.H. Tsou, ReadySD Social for iOS (1.1) [Mobile Application Software], 2017.
[97] K. Leetaru, S. Wang, G. Cao, A. Padmanabhan, E. Shook, Mapping the global Twitter heartbeat: the geography of Twitter, First Monday (2013) 18.
[98] M.H. Tsou, H. Zhang, A. Nara, S.-Y. Han, Estimating hourly population distribution change at high spatiotemporal resolution in urban areas using geo-tagged tweets, land use data, and dasymetic maps, Harvard University, Cambridge, MA, 2017.
[99] Y. Yuan, R.M. Smith, W.F. Limp, Remodeling census population with spatial information from Landsat TM imagery, Comput. Environ. Urban Syst. 21 (1997) 14.
[100] A.F. Tapp, Areal interpolation and dasymetric mapping methods using local ancillary data sources, Cartogr. Geogr. Inf. Sci. 37 (2010) 215–228, http://dx.doi.org/10.1559/152304010792194976.
[101] B. McKenzie, W. Koerber, A. Fields, M. Benetsky, M. Rapino, Commuter-Adjusted Population Estimates: ACS 2006-10, Journey to Work and Migration Statistics Branch, US Census Bureau, Washington, DC, 2010.
[102] SanGIS, Office of Emergency Services. San Diego County Fire Map, 2007.
[103] J.H. Sorensen, Hazard warning systems: review of 20 years of progress, Nat. Hazards Rev. 1 (2000) 119–125, http://dx.doi.org/10.1061/(ASCE)1527-6988(2000)1:2(119).
[104] B.H. Spitzberg, A. Toward, Model of Meme Diffusion (M3D), Commun. Theory 24 (2014) 311–339, http://dx.doi.org/10.1111/comt.12042.