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ORIGINAL PAPER

Measuring the accessibility of critical facilities in the presence of hurricane-related roadway closures and an approach for predicting future roadway disruptions

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Abstract

Roadway closures magnify the adverse effects of disasters on people since any type of such disruption increases the emergency response travel time (ERTT), which is of central importance for the safety and survival of the affected people. Especially in the State of Florida, high winds due to hurricanes, such as the Hurricane Hermine, lead to notable roadway disruptions and closures that compel special attention. As such, in this paper, the accessibility of emergency response facilities, such as police stations, fire stations and hospitals in the City of Tallahassee, the capital of Florida, was extensively studied using real-life data on roadway closures during Hurricane Hermine. A new metric, namely Accessibility Decrease Index, was proposed, which measures the change in ERTT before and in the aftermath of a hurricane such as Hermine. Results clearly show those regions with reduced emergency response facility accessibility and roadways under a disruption risk in the 1-week window after Hermine hit Tallahassee. City officials can pinpoint these critical locations for future improvements and identify those critical roadways, which are under a risk of disruption due to the impact of the hurricane. This information can be utilized to improve emergency response plans by improving the roadway infrastructure and providing alternative routes to public.

Keywords Accessibility of critical facilities · Roadway closures during disaster · Roadway disruption prediction · Tree classification by CNN

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1 Introduction

Roadway closures magnify the adverse effects of disasters on people since any type of such disruption increases the emergency response travel time (ERTT), which is of central importance for the safety and survival of the affected people. An emergency response plan, therefore, should include strategies to evaluate the conditions of existing roadway networks during and in the aftermath of disasters such as hurricanes (e.g., many strategies have been developed to alleviate the suffering of public after the infamous Hurricane Katrina). Within such plans, the available transportation network should be evaluated with respect to disasters using historical data and/or predictions in order to assess the roadway conditions and identify the critical locations. Especially in the State of Florida, high winds due to hurricanes, such as the Hurricane Hermine, lead to notable roadway disruptions and closures. Even the lower strength storms may still be strong enough to adversely affect the transportation network (i.e., roadway disruptions and closures due to fallen trees, which might cripple the emergency response operations). Focusing on this accessibility-based analysis is especially critical since providing necessary aid to hurricane victims in a timely manner can alleviate possible adverse consequences of hurricanes.

The previous research shows that transportation accessibility has been a special interest, especially given the advances in computational power that has enabled the analysis of more computationally complex problems. Numerous studies have focused on the accessibility of critical facilities such as supermarkets (Widener et al. 2015), nursing homes (Saliba et al. 2004), health care facilities (Islam and Aktar 2011; Ulak et al. 2017), multimodal facilities (Ozel et al. 2016) and shelters (Kocatepe et al. 2016). These studies take advantage of geographical information systems (GIS)-based tools to perform accessibility analysis. However, to the authors' knowledge, there has not been a study that is focused on both emergency facility accessibility based on real-life disaster data and prediction of future roadway disruptions. As such, the objective of this study was twofold. First, accessibility of emergency response facilities such as police stations, fire stations and hospitals in the City of Tallahassee, the capital of Florida, was extensively studied using real-life data on roadway closures due to Hermine. This was achieved by the temporal reconstruction of the reported roadway closures on the Tallahassee roadway network in the 1-week window after Hermine hit Tallahassee. Furthermore, new metric, namely Accessibility Decrease Index (ADI), was proposed, which measures the change in ERTT before and in the aftermath of a hurricane such as Hermine. That is, ADI value is equal to the ratio between ERTT before and after a hurricane. As a result of this approach, regions with reduced emergency response facility accessibility were identified. In order to calculate the ADI values, 8-min threshold value was selected for after-hurricane ERTT based on the existing literature (Blackwell and Kaufman 2002; Pons and Markovchick 2002; Pons et al. 2005; Ulak et al. 2017). For those regions with after-hurricane ERTT values higher than this threshold, ADI scores were calculated and illustrated since these regions are critical for emergency response. To calculate travel time between two locations, there are different available costs such as distance, and static and dynamic congested travel time. However, in this study, it is assumed that actual travel time for emergency vehicles such as police, fire and rescue and emergency medical services (EMS) is very close to the free flow time (FFT), considering that all vehicles should yield to emergency vehicles by law.

Second, hurricane-related roadway disruption probabilities were estimated for major roadways, which are usually utilized as evacuation or emergency response routes. Note that the recent improvements in the technology increased the availability of the satellite images.

This fact along with the development of image recognition techniques led to many studies in the literature in the context of satellite images data extraction (Castelluccio et al. 2015; Albert et al. 2017). The concept of convolutional neural network (CNN) was introduced in 1997 (Lawrence et al. 1997). Unfortunately, the computational power of computers was not sufficient at the time, and it took 20 more years for the CNN to become one of the most popular techniques in the machine learning field. Please see (Simard et al. 2003) for more information on CNN. Recent studies have also showed the incredibly high accuracy of CNN for a high number of classifiers (Krizhevsky et al. 2012). Lately, CNN was also used to extract data from satellite images for land usage classification (Zhu and Newsam 2015), updating road data information (Costea and Leordeanu 2016), and for high wind risk analysis (Powell et al. 1998; Vickery et al. 2000; Amirinia and Jung 2017; Kakareko et al. 2017). In the current research, we used CNN and satellite images to investigate the hurricane-related roadway disruption probabilities by recognizing and classifying tree types along major roadways, calculating their fragility to wind speeds. Those results can be used for analyzing critical roadways, which can be disrupted by tree failures. City officials can pinpoint these critical locations for future improvements and enhancing emergency response plans.

2 Study area, Hurricane Hermine and data

The City of Tallahassee, the capital of Florida, being the most populated city in the Leon County, hosts 286,272 people and is home to two major universities and a community college. The urbanized area of Tallahassee has a population of 190,894 according to the US Census estimate (Census 2016). The City of Tallahassee is a full service municipality providing essential services to the region: electric, gas, water solid waste, sewer, public works, airport, mass transit, etc. During emergency situations and disasters, the City of Tallahassee recognizes that a transportation system functions as a whole, and requires that each piece works together at all levels (i.e., institutional and operational) so that the system runs safely and efficiently.

Tallahassee was hit by Hurricane Hermine in September, 2016. Hermine provoked disruptions in all services in Tallahassee from 10:00 p.m. of September 1, 2016, to 4:00 a.m. of the next day September 2, 2016, affecting thousands of customers. Tallahassee radar images (AccuWeather 2017; NDAA 2017) show the time and path of Hermine as shown in Fig. 1. Please refer to the Hermine report by NHC at (Berg 2016) for detailed information. Maximum speeds reached during Hurricane Hermine varied for different parts of the city (Fig. 2a). These high wind speeds resulted in fallen trees and roadway disruptions in Leon County (Fig. 2a). The roadway closure data are provided by the City of Tallahassee, through a mobile app called DigiTally (2017). It is a tool that connects residences directly with City of Tallahassee staff in order to resolve issues more effectively and efficiently. Users can file requests for any issues and monitor others. During Hurricane Hermine, 776 roadway closures were reported due to fallen trees in a 1-week window (Fig. 2b). Note that 7th day closures shown in Fig. 2b do not indicate that those closures occurred on 7th day, but correspond to closures which exist until 7th day. In case of an emergency, police (law enforcement), fire and hospital response teams are dispatched to locations of the emergency. In Tallahassee, five hospitals, thirteen fire stations and fourteen police stations are ready to serve the public (Fig. 2c) (U.S. Census Bureau 2015).

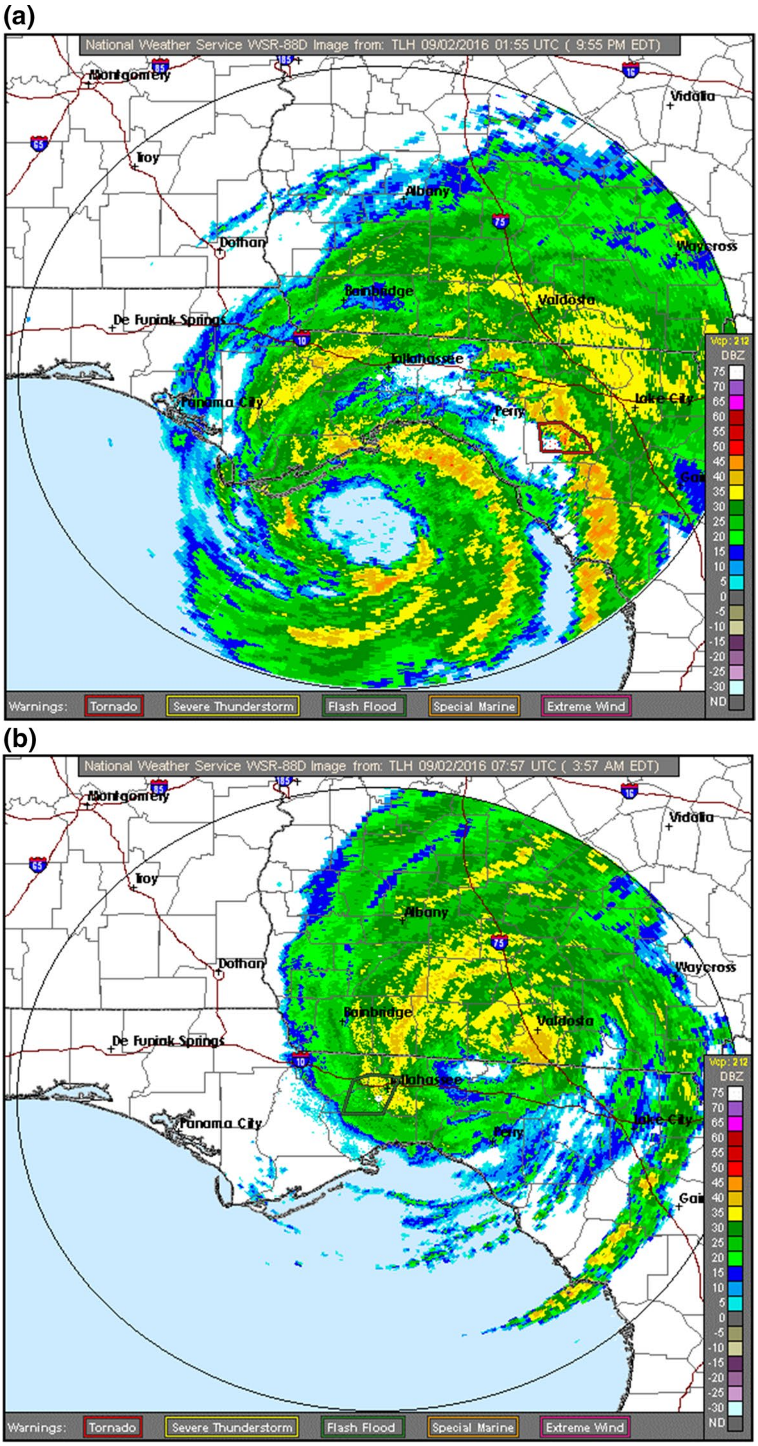

Fig. 1 Hurricane Hermine path over Tallahassee, FL from 09/01/16 to 09/02/16

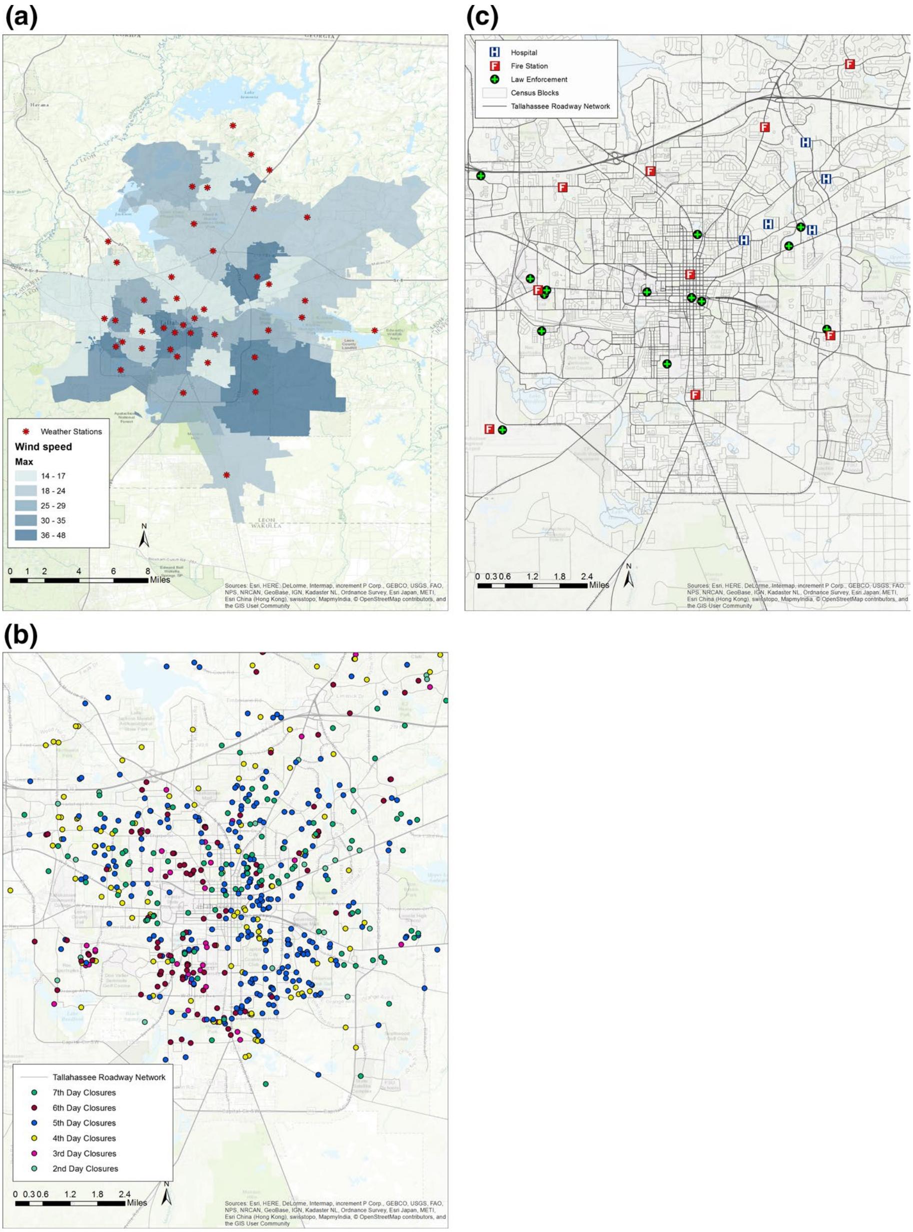

Fig. 2 Study area **a** wind speeds by US Census blocks during Hermine, **b** roadway closures, **c** US Census blocks and emergency response facilities

3 Methodology

3.1 Accessibility of emergency response teams

Following the temporal reconstruction of the events related to the Tallahassee transportation network (e.g., roadway closures due to fallen trees), the ArcGIS "Network Analyst" tool was used to measure the transportation accessibility from police stations (law enforcement), fire stations and hospitals. Three components were identified as part of the approach: (a) origins: police stations, fire stations and hospitals, (b) destinations: US Census block centroids and (c) the roadway network. To find the least cost paths between origins and destinations (O–D pairs), an ArcGIS "OD Matrix" analysis was performed. Travel of the emergency vehicles was assumed to originate at the origin locations and end at the census block centroids, based on the least cost path. It was assumed that actual travel time for emergency vehicles such as police, fire and rescue or emergency medical services (EMS) is very close to the free flow time (FFT), considering that all vehicles should yield to emergency vehicles by law. A threshold value for the response time was selected based on the literature, which states that emergency response time should not exceed approximately 8 min (Blackwell and Kaufman 2002; Pons and Markovchick 2002; Pons et al. 2005; Ulak et al. 2017). For 1-week period, travel times were derived to identify the transportation accessibility metric considering each day' roadway closures in the city. For the census blocks with more than 8-min accessibility and roadway closures due to fallen trees, travel times were compared to daily free flow time. For this purpose, a new metric, namely Accessibility Decrease Index (ADI), was proposed. ADI value is equal to the ratio between emergency response travel time (ERTT) before and after a hurricane event as defined in Eq. 1, which is always bigger than 1. Note that ADI values were not calculated for the locations where ERTT after the hurricane is still lower than the 8-min threshold duration, which indicates that those locations still have acceptable emergency response time. This analysis revealed those regions which have critical emergency response problems due to inaccessibility during and after the Hurricane Hermine.

$$\mathrm{ADI} = f(x) = \begin{cases} \frac{\mathrm{ERTT}_{\mathrm{after}}}{\mathrm{ERTT}_{\mathrm{before}}}, & \mathrm{ERTT}_{\mathrm{after}} > 8\mathrm{minutes} \\ \mathrm{N/A}, & \mathrm{ERTT}_{\mathrm{after}} \leq 8\mathrm{minutes}. \end{cases} \tag{1}$$

3.2 Sensitivity analysis for estimation of roadway disruption probability

The estimation of roadway disruption probability is a multistep problem. The first step was to take satellite image as an input and recognize all trees that can affect roadways during a hurricane (note that Fig. 3a shows a typical satellite image for the analysis used in this study). The CNN methodology was utilized in order to recognize the trees from these satellite images. It was assumed that the trees that should be taken into consideration were in 10 m from the center of the road. To start with, two separate CNNs were trained to identify the number and types of trees around the roadways. The first CNN-1 was used to recognize the trees from the satellite image while the second CNN-2 identified the tree type selection from the pre-selected images identified by CNN-1. The training set was composed of 8000 images for CNN-1 and 2000 for CNN-2. The size of the images was 76×76 RGB pixels. The training pictures were manually selected from the City of Tallahassee satellite images.

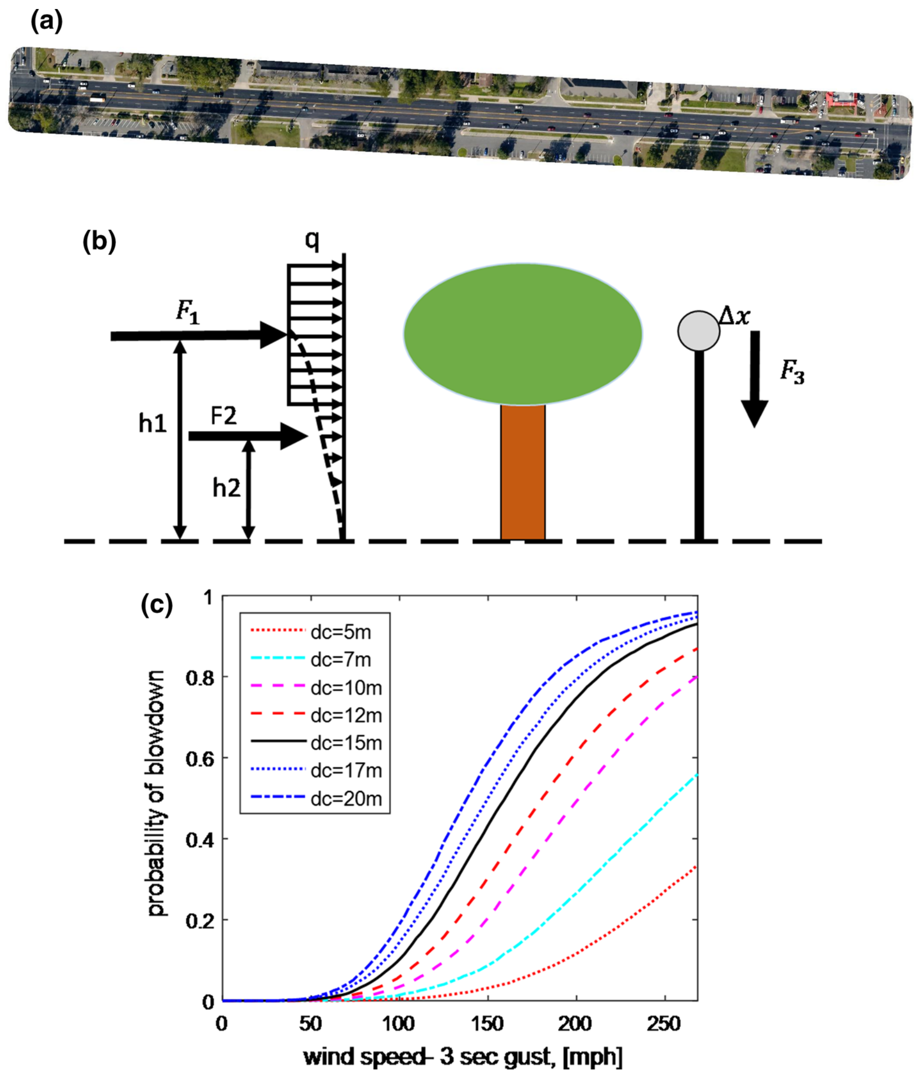

Fig. 3 **a** A satellite image after classifying trees, **b** tree failure model, **c** probability of roadway disruption for shortleaf pine

Two networks were tested on the 10% of the images and exceeded 97% and 93% accuracy for the CNN-1 and CNN-2, respectively.

The second step was to classify the selected trees based on their species. According to City of Tallahassee, there are four common tree species in Tallahassee, namely lobby pine, shortleaf pine, sweetgum and live oak. The third step was to approximate the geometric and structural characteristics of these trees. Color thresholding method was used to calculate the crown diameter (Stiles 1959; Deng et al. 1993). The crown diameter was used to approximate the other tree parameters (e.g., weight of the crown, height of the crown) necessary to calculate failure probability, and data from McPherson et al. (2016) were used for this task. The next step was to estimate the tree fragility curves for all recognized trees. Several studies have been published on the probability estimation of tree failure induced by high winds (Baker and Bell 1992; Gardiner 1994; Stacey et al. 1994; Asner and Goldstein 1997). In this study, the model given in Eq. 2 was used for the failure probability estimation. The model involves one failure damage mode which is failure by rupture. Figure 3b and Eqs. 2–4 illustrate the procedure used for failure calculation. The wind model (ASCE 2010) is described by Eq. 2:

$$V_z = b\left(\frac{z}{10}\right)^{\alpha} V \tag{2}$$

where b and α are constants, z is the height of tree measured from the ground and V is the wind speed at 10 m above the ground. The equal wind speed was assumed along the crown of the tree. Equation 3 characterizes the maximum force moment caused by the wind speed, where the forces F_1 and F_2 are caused by wind speed V_z, and F_3 represents the force produced by the weight of the crown, Δx is a initial deflection produced by forces F_1 and F_2.

$$M = F_1 \cdot h_1 + F_2 \cdot h_2 + F_3 \cdot \Delta x \tag{3}$$

The failure is considered when Eq. 4 is satisfied:

$$\sigma_{\mathrm{r}} < \sigma \tag{4}$$

where σ is the maximum stress in the cross section of the tree caused by the moment M and σ_{r} is the modulus of rupture, which depends on the species of the tree. The Monte Carlo simulation was applied in order to calculate the fragility curves for each tree. Figure 3c shows examples of fragility curves for the shortleaf pine. The final step was to calculate the probability of roadway disruption. Based on the fragility curves developed for each particular tree, the overall probability of roadway disruption, P_{r}, was calculated, where P_{r} is the occurrence probability of at least one of the N events $P(E_i)$, and each event represents a failure of a tree along the roadway segment (Eq. 5). Note that the calculated probability corresponds to probability of at least one tree failure along a roadway segment, and this probability was referred as the roadway disruption probability. However, failure of a tree does not necessarily indicate a roadway closure since the fallen tree may or may not block the roadway. Therefore, the calculated probability was called the "disruption probability" rather than "closure probability."

$$P_{\mathrm{r}} = 1 - \prod_{i=1}^{N} \left(1 - P(E_i)\right) \tag{5}$$

where P_{r} is the roadway segment's disruption probability, $i = 1, \ldots, N$ and N is the total number of trees along that roadway segment, and $P(E_i)$ is the probability of failure of tree i.

4 Results

4.1 Accessibility of emergency response teams

Figure 4a shows the free flow travel times from fire stations to census blocks. Major portions of the Southeast Tallahassee and Eastern Tallahassee appear to experience

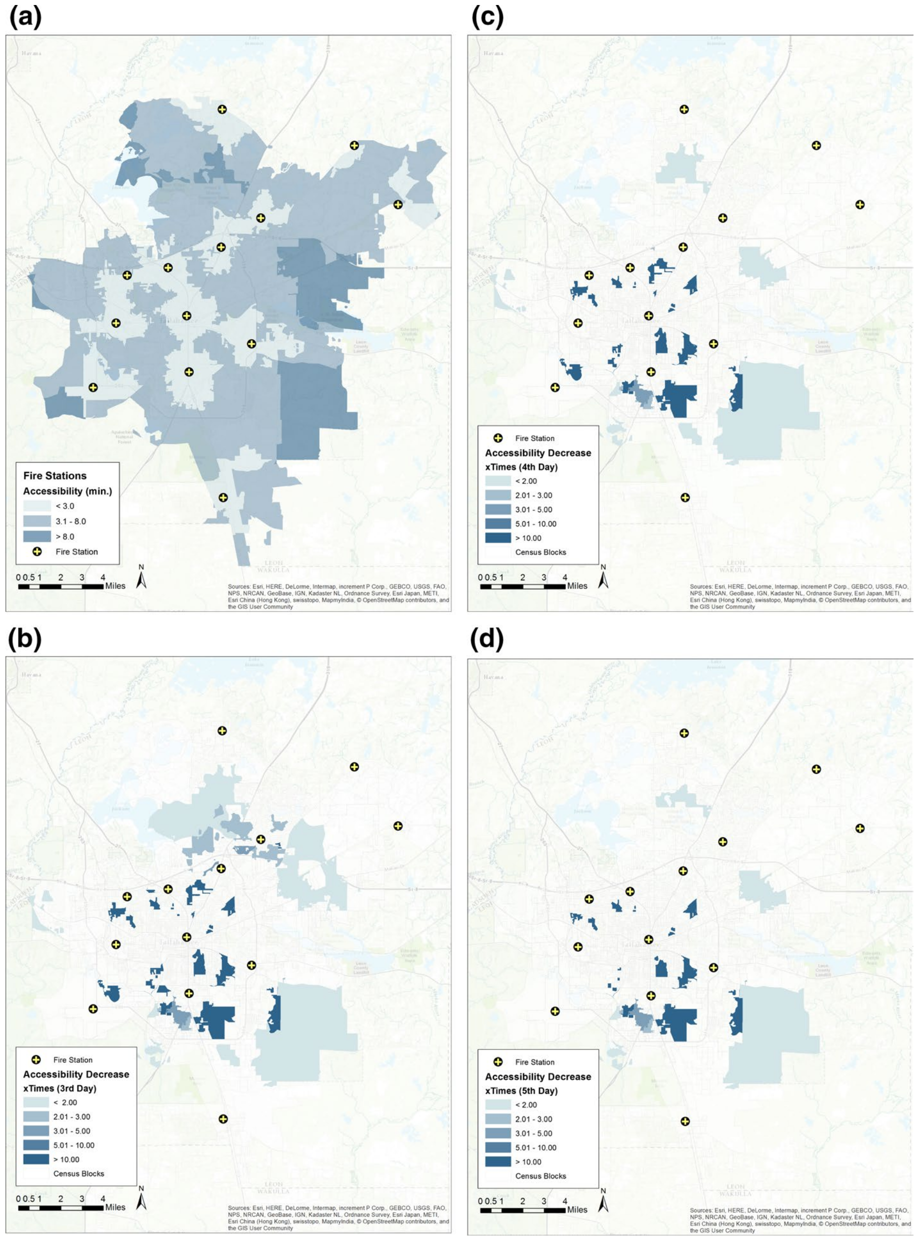

Fig. 4 Accessibility for fire stations

emergency response travel times (ERTT) greater than 8 min. Note that these locations are "major" geographically speaking, but not as "major" demographically speaking. Southeast Tallahassee is a growing residential zoning area, available for future developments, drawing high attention for investors. Even without the focus on emergency response planning, those regions might be considered for future improvements

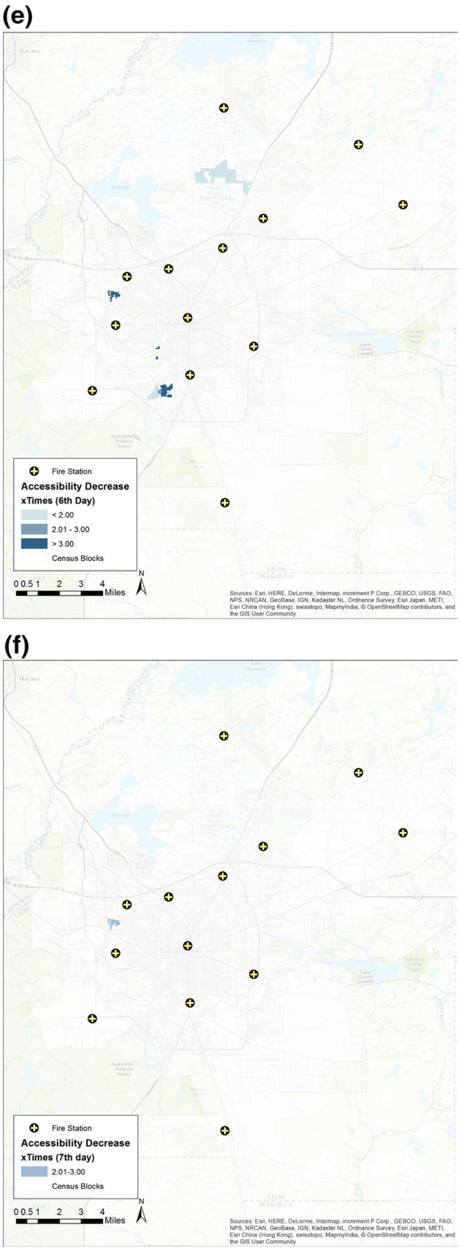

Fig. 4 (continued)

(e.g., building a new fire station) to decrease the emergency response time. Rest of the maps in Fig. 4 displays the change in the ERTTs. Note that all the highlighted census blocks are the ones that have 8 min or more travel times from fire stations. Accessibility Decrease Index (ADI) in these maps shows the amount of change in the emergency response travel time before and after the hurricane event. For instance, if the free flow

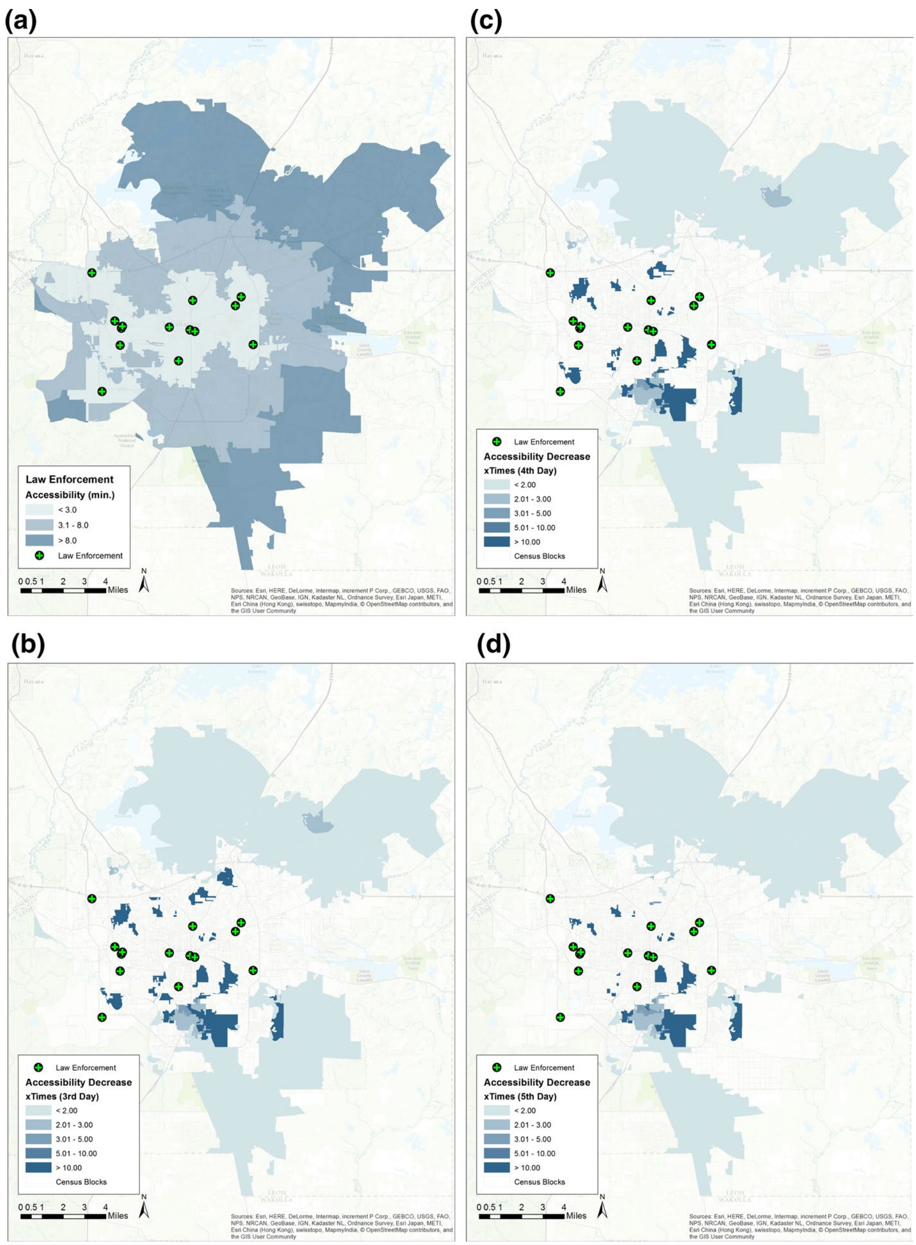

Fig. 5 Accessibility for law enforcement (police stations)

travel time from one station to a census block was 5 min before hurricane and 15 min after the hurricane (due to roadway closures), the ADI equals to three (15/5 = 3). Note that there were no road closures in Day 1 since the hurricane hit the city later in the evening of Day 1. Also note that since Day 2 and Day 3 roadway conditions were almost identical, the analysis results were shown from Day 3 (Figs. 4, 5, 6).

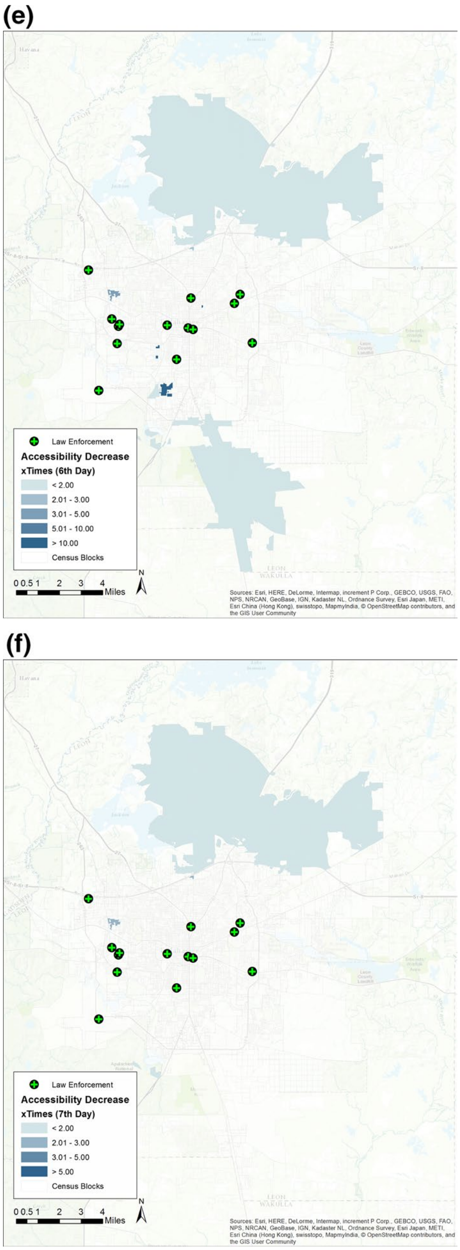

Fig. 5 (continued)

Figure 4b shows that there are pockets of census blocks experiencing significant changes in ERTTs and a significant decrease in accessibility for Day 3, 2 days after the Hermine hit Tallahassee. In the northeastern southeastern sections of the city, ADI was less than two times. Pockets with ADI values larger than ten were observed mostly in local roadways where residential townhouses are located. Note that Tallahassee has regions that heavily

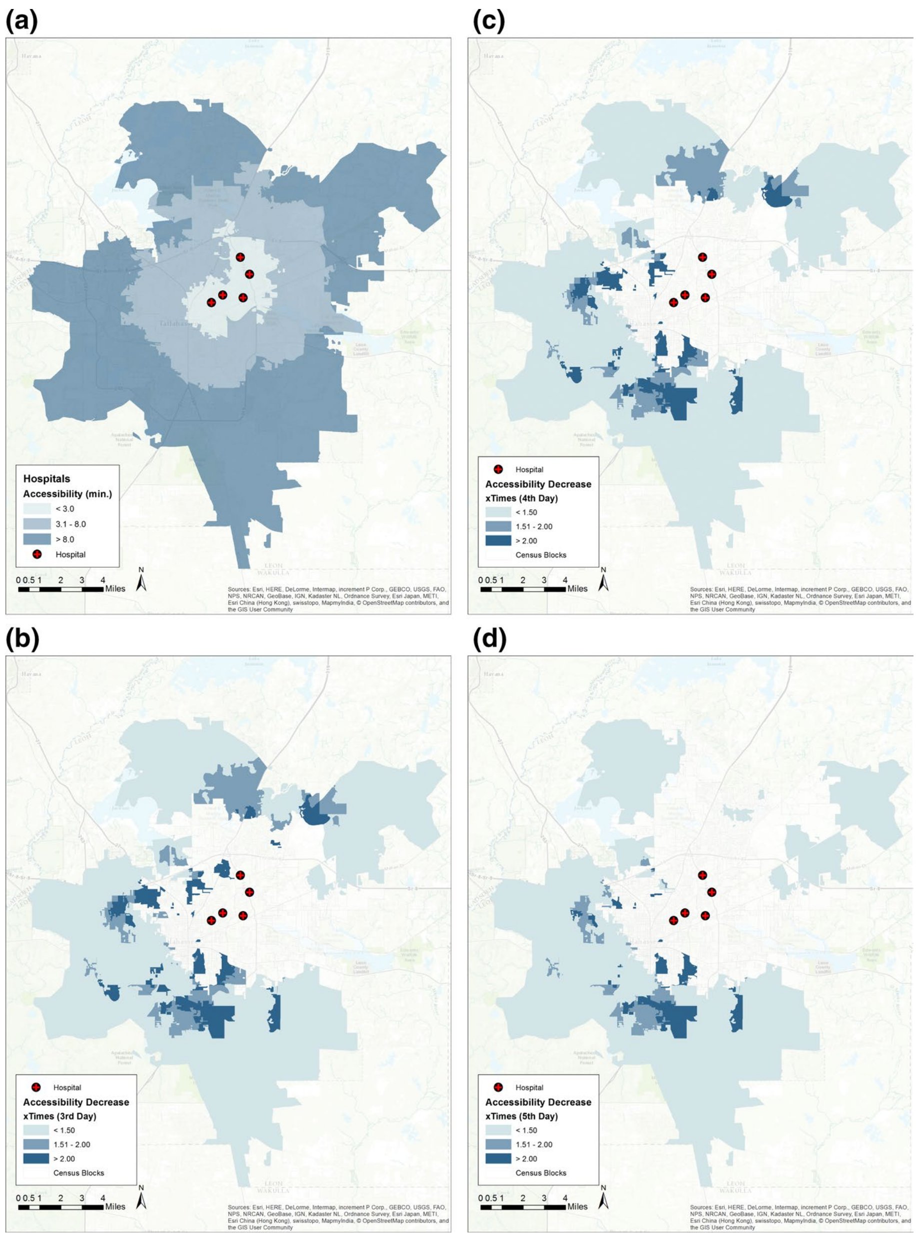

Fig. 6 Accessibility for hospitals

inhabit trees with different types and heights all over the city. Figure 4c shows a clearance in the north and northeastern part in terms of ERTT value on Day 4. This is since the roadways were cleared from trees, ERTTs for fire stations returned to normal in those sections of the city. Pockets with ADI larger than ten have still experienced higher travel times since Day 3. Between Day 4 and Day 5, there was a slight change in ERTT from fire stations

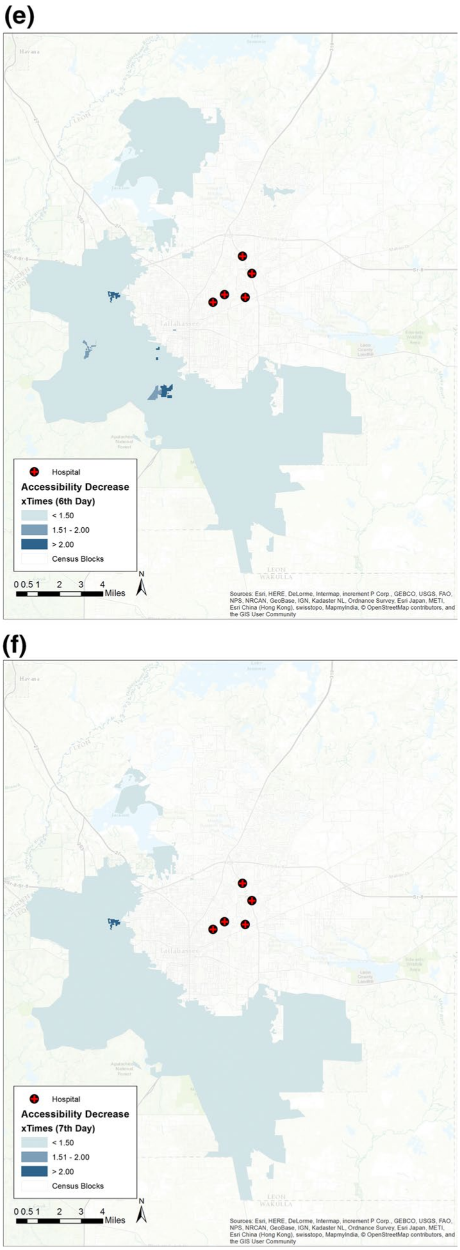

Fig. 6 (continued)

to census blocks. Roadway closures still led to inaccessibility in Day 5 for those pockets with the highest ADI. Recall that those areas are located around neighborhoods with townhouses and local streets (mostly two lanes), which are more prone to roadway closures due to fallen trees than major highways. On Day 6 and Day 7 (Fig. 4e, f), ERTTs for fire stations returned to daily levels as Fig. 4a shows.

Figure 5a shows that major sections of the north, northeast and southeast of Tallahassee experience ERTTs above 8 min. Similar to the previous analysis, these sections are also open to further development even without considering emergency response. Observing Fig. 5, the northern Tallahassee seems to be struggling in terms of accessibility to police stations in the whole 1-week window. Since there was not a present police station in the southern Tallahassee, residences experienced reduced accessibility compared to accessibility to fire stations (Fig. 4) until Day 7 (Fig. 5f). Note that the accessibility may be better in real life since police vehicles may already be on patrol in the communities. However, under emergency conditions such as hurricanes, roadways may be closed or disrupted, and hence, they may not be able to patrol the area. Northern Tallahassee experienced the same problem, and ERTTs did not return to normal until Day 7. Pockets with the highest ADIs eventually returned to normal conditions on Day 6 (Fig. 6e). Those regions might be considered for infrastructure improvements or new landscape developments in order to manage tree failures.

Unlike fire and police stations, hospitals are heavily clustered in a certain area. This might be disadvantageous for certain regions even under normal conditions. As Fig. 6 shows, a major portion of the City of Tallahassee experiences accessibility problems related to hospitals. Due to this critical inaccessibility, numerous pockets of census blocks were observed to have high ADI values. Day 4 shows that the closest pockets to the northernmost hospital were in a better shape in terms of roadway closures compared to Day 3. On Day 5 (Fig. 6d), a clear improvement was observed in ERTTs from hospitals to census blocks in the northern and northeast sections of Tallahassee. South of Tallahassee still had small pockets of census blocks with high ADIs. Figure 6f shows that even 7 days after hurricane, those parts were still experiencing a lack of accessibility to hospitals.

4.2 Sensitivity analysis for the estimation of roadway disruption probability

As Fig. 2a clearly shows, Hermine hit different section of the town with different wind speeds. Wind speeds were ranging between 14 and 48 mph, which caused 776 roadway closures all over the town (Fig. 2b). Note that wind speed data were collected through 43 weather stations (WeatherSTEM 2017) around the city as shown in Fig. 2a. It should also be noted that a different Hurricane can have different path than Hurricane Hermine. In order to propose a more scalable approach, this section presents a sensitivity analysis for estimating possible roadway disruptions. The analysis was conducted using 435 roadway sections to estimate the roadway disruption probabilities based on the proposed CNN methodology. Note that these sections are demarcated by intersections, and individual satellite image was extracted for each roadway section. In order to show the usefulness of this approach, five major highway corridors were selected: (1) I-10, which starts from the City of Jacksonville in the east, passing through Tallahassee and continuing west toward the City of Pensacola, (2) US-90 which lies parallel to I-10, passing through the downtown Tallahassee, (3) US-319, which extends from Georgia along the Gulf Coast through downtown Tallahassee, (4) US-27, which begins in the southern Florida and extends to the Georgia State border, and (5) SR-263, or Capital Circle SW, which encircles Tallahassee. Note that probability of roadway disruption would increase with the increasing number of trees along the roadway section. Figure 7a shows the disruption probability for a 20 mph wind speed. For all the major highways, probability is below 0.10. Only one roadway has a probability of disruption between 0.20 and 0.30. When wind speed increased to 25 mph, roadways around hospitals started experiencing roadway disruption probabilities

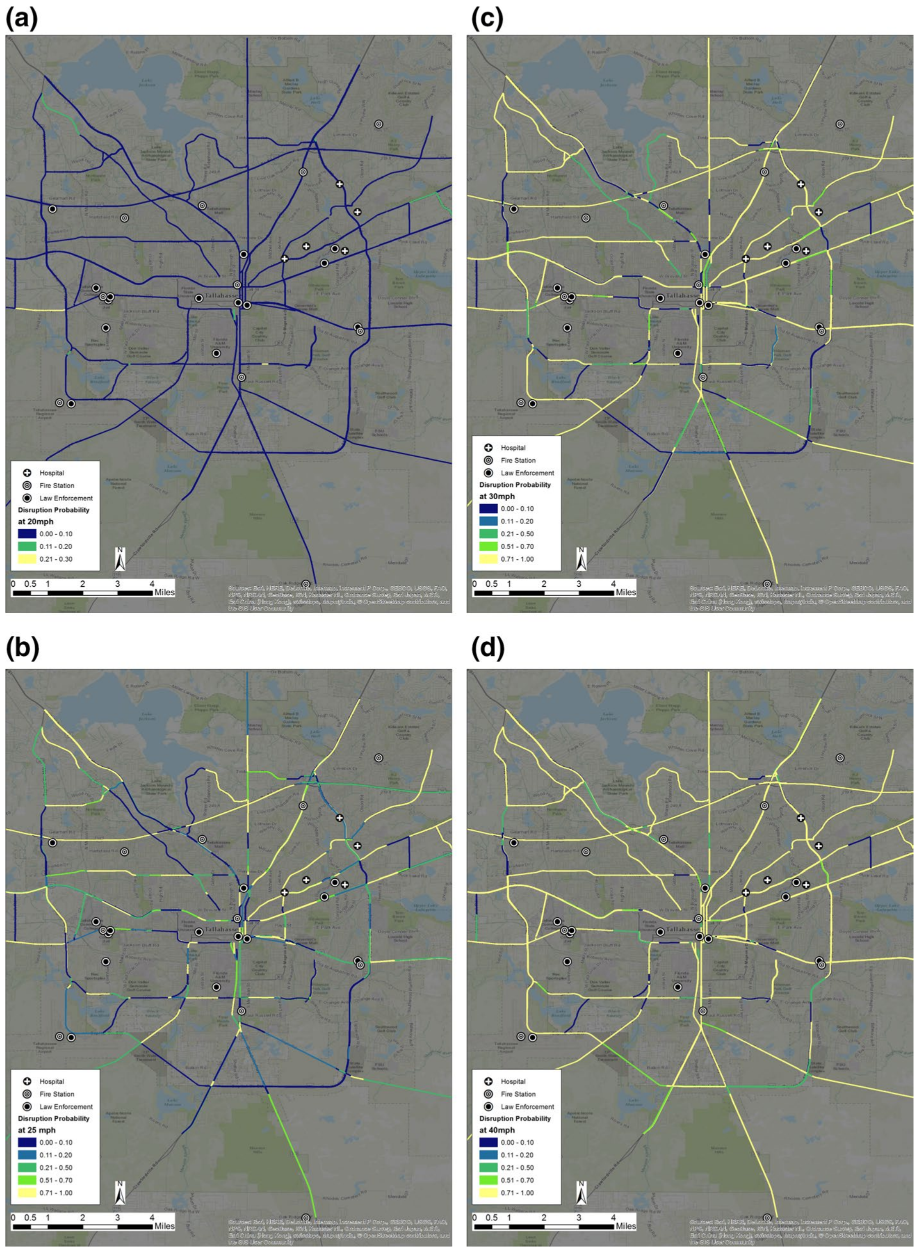

Fig. 7 Roadway disruption probabilities on the major highways of Tallahassee

of 0.70–1.00 (Fig. 7b). With the 30 mph wind speed, 90% of the major roadways around emergency response facilities experienced a probability of roadway disruption of at least 0.70. Capital Circle South, lying from west to east at the bottom of the figures, do not have substantially high roadway disruption probability until 40 mph, which is mostly different than other major roadways. This might be due to the fact that shoulders and sections

(e)

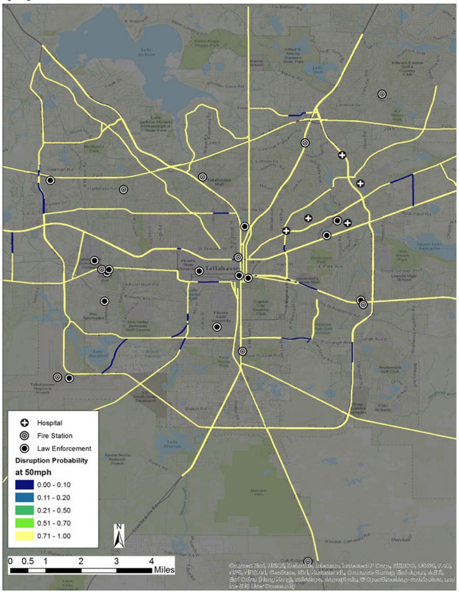

Fig. 7 (continued)

along this roadway do not have substantial number of trees like other major roadways, or shoulders may be more than enough in terms of length so that a fallen tree cannot affect the roadway. Right after the hurricane, this roadway section (Capital Circle South) can be a safe passage for emergency response. In the western sections of the city, where fire stations and police stations are clustered, major roadways have experienced high probabilities of roadway disruption with 40 mph wind speed. City officials might consider providing alternative routes for the emergency response possibilities for future hurricanes in these locations. 50 mph wind speed, as shown in Fig. 7e, causes 95% of the major roadway sections to have probabilities higher than 0.70. This also indicates the need to have emergency plans and strategies to find the safest and fastest routes for efficient emergency response operations.

4.3 Comparison of predicted roadway disruptions and roadway closures reported during Hurricane Hermine

The proposed prediction model was utilized in order to find the roadway disruption probabilities of roadway segments under different wind speeds experienced during hurricane Hermine. To do this, first, each roadway segment was assigned the 95th percentile wind speed measured at the weather station closest to that roadway segment. Based on these wind speeds, roadway disruption probability of each roadway segment was found and roadways were mapped based on this probability (Fig. 8). Following, a kernel density estimation (KDE) (Brunsdon 1995; Ulak et al. 2018) approach was utilized to find the roadway closure density in the City of Tallahassee, which produced a closure density surface. Visual inspection of Fig. 8 indicates that there is a substantially strong spatial relationship between

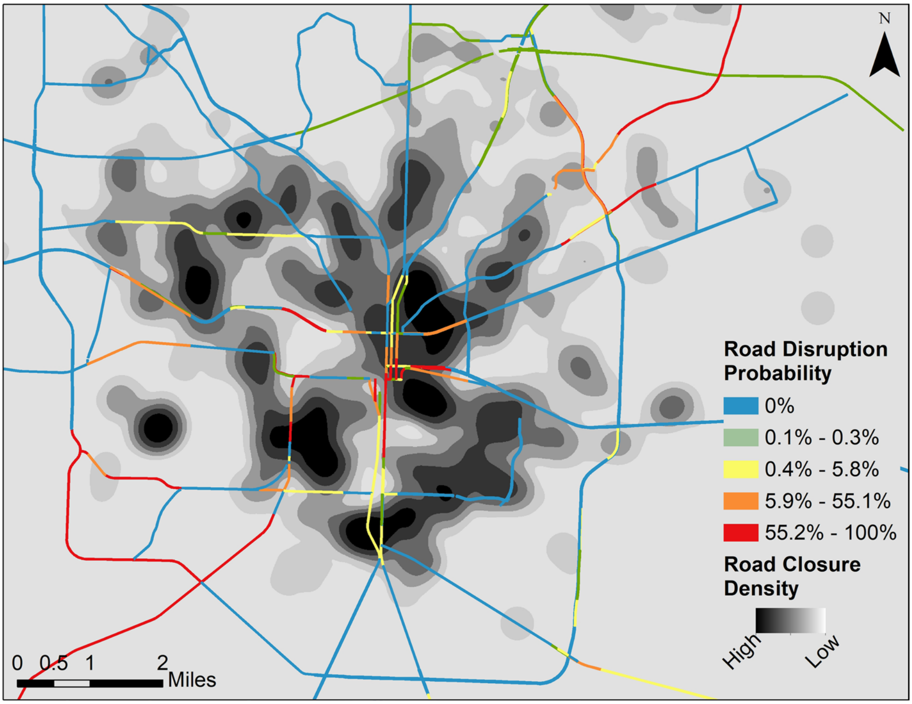

Fig. 8 Comparison between disruption probability and reported closures

high closure density locations and roadway disruption probabilities. That is, the relationship trend implies that the higher the closure density, the higher the disruption probability. It is worth noting that there are roadway segments (a) with high disruption probability where closure density is relatively smaller and (b) with low disruption probability where high closure density is observed. However, note that the roadway closure data are obtained from DigiTally (2017) app which is composed of user reported roadway closures. Therefore, the roadway closure data at hand do not represent all of the closures experienced during the hurricane (particularly local roadways are overrepresented due to the immediate access of the residents to these roadways). Moreover, the predicted probabilities are roadway disruption probabilities rather than closure probabilities. That is, a disruption may or may not lead to a closure which would not be reflected by the closure data. Nevertheless, Fig. 8 still illustrates a significant spatial relationship between closure density and roadway disruption probability.

5 Conclusions

This study presents a GIS-based methodology to assess and analyze the accessibility to critical emergency facilities (e.g., police stations, fire stations and hospitals) in the context of roadway disruptions due to disasters such as hurricanes. A new metric, namely Accessibility Decrease Index (ADI), was proposed, which measures the change in the emergency response travel time (ERTT) before and in the aftermath of a hurricane such as Hermine.

ADIs were used to identify those regions with reduced accessibility to emergency facilities in the aftermath of Hermine. In order to propose a more scalable approach, which can help city officials planning for future hurricanes, a tree failure modeling approach was also presented in order to estimate the probability of hurricane-related roadway disruptions under different hurricane wind speeds based on a convolutional neural network (CNN)—and satellite image-based approach.

City officials can pinpoint the identified critical locations for future improvements (i.e., landscaping modifications to eliminate the threat of fallen trees, and roadway geometry modifications) and enhancing emergency response plans (i.e., providing alternative routes to emergency response crews). Officials might consider having such plans in place for future hurricanes in the critical sections of the city depending on the facility type. There may be other alternatives such as patrolling emergency services or establishing new emergency response facilities in these sections. Note that any suburban location close to the city can also be supported by these activities. However, this study focused only on the City of Tallahassee, and the proposed approach can be extended to other locations. Another caveat of this study is as follows: if roadway sections get longer, the probability of roadway disruption substantially increases with more trees along these sections. Therefore, as a future work, shorter and/or equal length roadway sections can be considered to increase the accuracy and reliability of the proposed approach. Future work also will focus on the effect of tree failures on downed power lines in addition to roadways, which will definitely be a more comprehensive analysis to solve disruption-related problems in the aftermath of a hurricane.

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Compliance with ethical standards

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

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