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Probabilistic risk assessment of hurricane-induced debris impacts on coastal transportation infrastructure

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A R T I C L E I N F O

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A B S T R A C T

Hurricanes pose a significant challenge to the resilience of coastal communities, causing not only direct physical, social, and economic impacts but also indirect or cascading effects. Among these, debris-related impacts can cause structural damage from debris collisions and disrupt essential services by blocking roadways, thereby slowing the recovery of other infrastructures. As a result, it is essential to better understand and model debris and its uncertain impacts on coastal communities in the face of storm hazards. This paper puts forward a methodology to probabilistically evaluate hurricane-induced debris and its impacts on community-scale transportation infrastructure. Selected features of the proposed methodology are showcased using testbed community data and input models relevant to the Galveston region in Texas, USA. The findings highlight the need to account for debris impacts when assessing transportation network resilience metrics in coastal areas. Without this consideration, the impacts of such events, including equitable access to emergency facilities, could be underestimated. The results reveal that when debris and roadway damages are considered together, connectivity loss to emergency facilities could increase from 2% to 17% under a representative 500-year storm event.

1. Introduction

Climate disasters such as hurricanes and tsunamis significantly impact communities, posing critical challenges to their resilience. For instance, overall costs and damages from weather and climate disasters in the U.S. since 1980 exceed $2.275 trillion [1]. Furthermore, the resilience of coastal communities and their infrastructure is also impacted by cascading consequences of these extreme events [2,3]. Such consequences can range from connectivity loss to critical facilities (e.g., due to debris accumulation) to long-term physical and mental health issues [3,4]. In particular, debris generated during these events results in approximately 27% of the total disaster recovery cost, while, together with the damages to roadway infrastructure, it can also decrease the functionality of the transportation network [5–7]. For example, accessibility to emergency facilities is critical in the aftermath of extreme events, which highly relies on transportation network functionality [8–11]. Although the impact of debris following seismic hazards has been explored in several studies, the complexity of storm events leaves more knowledge gaps yet to be addressed [12–15]. Additionally, the effects of debris can have long-term consequences, highlighting the necessity for preparedness and disaster debris management planning [7, 16]. The heightened potential of these consequences is further exacerbated by the increased frequency of weather-related disasters due to climate change and land-use modification [17–20].

Several studies have focused on predicting debris generated from weather and climate disasters such as hurricanes, tsunamis, and floods. Escobedo et al. [21] proposed a model to predict tree debris using data from seven hurricanes in Florida. Hughes et al. [22] developed a fragility model for tree damage that takes into account wind speed and integrates tree failure impacts into an evaluation of community-level resilience. HAZUS [23] proposed models to predict hurricane-induced debris from the built environment and trees using hazard and structural measures, which is one of the most widespread methods but emphasizes wind alone and has been shown to yield significant errors [24]. Gonzalez-Duenas et al. [24] developed a data-driven model to predict the amount of debris from different sources following a severe storm using machine learning techniques. However, these models only predict the total volume of the debris in specific areas without giving a high resolution distribution of it, which is important for evaluating infrastructure impacts such as connectivity loss of roadway networks. As a result, a few studies have recently addressed debris dispersion and considered the effect of debris on community-level connectivity [22,

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25–27]. Nevertheless, the proposed models and methodologies lack a comprehensive simulation that considers high-resolution probabilistic debris evaluation and its cascading impact at the community-level.

Transportation infrastructure is one of the key systems affected by debris from storm events. Roads could become impassable as a consequence of damage to the roadway infrastructure or debris accumulation due to flooding-related hazards, such as hurricanes and tsunamis [28, 29]. Identifying areas without access to emergency facilities, including emergency medical centers and fire stations, is crucial, without which emergency response can be delayed [9,30,31]. There are few studies that assess the impact of both infrastructure damage and debris on the connectivity to emergency facilities, and a comprehensive approach for capturing the entire process is yet to be developed [27]. To address the aforementioned gaps, this paper proposes a probabilistic debris dispersion model to evaluate the distribution of debris in the aftermath of hurricane events, and couples this model with connectivity analysis of the transportation network for emergency response taking into account both the effects of uncertain debris and damage to roadway infrastructure.

This paper presents a methodology for the probabilistic assessment of the effects of hurricane-induced debris on coastal transportation infrastructure at a community scale. The proposed approach addresses uncertainty in both debris dispersion and connectivity analysis by employing probabilistic models in conjunction with Monte Carlo sampling [32]. Moreover, it offers flexibility as it can be applied at different levels of detail, such as census tracts or blocks. This methodology is showcased by a comprehensive application to Galveston Island, TX, comprising a detailed transportation network, emergency facilities including emergency medical centers and fire stations subject to a hurricane event. Utilizing Monte Carlo simulation, in each sample, a hurricane hazard scenario is used to predict the volume of debris and damage to roadway infrastructure using state-of-the-art models. Then, based on the proposed debris dispersion model outputs and roadway infrastructure damages, the transportation network condition is updated. Here, the uncertainty in the analysis is described using a random field concept and random variables that serve as input to roadway and bridge fragility models [33]. For the first time, this study introduces the use of the random field method for spatially distributing the predicted debris volume on the ground. Finally, connectivity loss to emergency facilities is evaluated for both census blocks and tracts within Galveston Island. Moreover, to evaluate connectivity loss, the ground clearance height of the vehicles is considered as another source of uncertainty, which is an important measure to determine their movement ability in the presence of debris.

In the following sections, the overarching probabilistic methodology is first presented with details of models, which includes the introduction of the newly developed debris dispersion model (Section 2). Then, the proposed methodology is showcased by applying it to Galveston Island, TX (Section 3), testing model integration and demonstrating results visualization and insights gained. Finally, Section 4 concludes the paper with the key contributions, findings, conclusions, and recommendations for future work.

2. Overarching probabilistic methodology

Fig. 1 shows the general methodology to probabilistically evaluate the hurricane impacts on coastal communities, focusing on debris generation and transportation infrastructure. In summary, this methodology requires a set of interacting probabilistic models. These models are classified into three different groups: hazard models including event selection and intensity estimation, which indicate the hazard scenario(s) and their intensity; exposure models encompass debris models, which assess debris volume and distribution of it given the hazard event intensity parameters, and damage models, which evaluate the damage to roadways and bridges using fragilities given the hazard event; and finally impact models, which evaluate the impact of a hurricane on transportation infrastructure and the emergency response given debris distribution and roadway damages. It is emphasized that the proposed methodology is not limited to adoption of the specific models showcased in the application of this study.

Given a hazard scenario, intensity measures are calculated, which are inputs for the subsequent models. Debris models use hazard intensity results first to evaluate debris volume in the area of interest and second to disperse debris on the ground based on the volume of it. In parallel, damage models use hazard intensity results to evaluate damages to the roadways and bridges utilizing damage fragilities. Subsequently, the distribution of the debris and damages to the roadways and bridges are used to update the condition of the transportation network, which inform analysis of the connectivity to emergency facilities in the area of interest. In each sample, realizations of outputs are evaluated in the chain of probabilistic models using a set of random variables. Moreover, the probability distribution of each model's output can be obtained using Monte Carlo sampling. In the following sections, the models are described in detail.

2.1. Hazard modeling

Hazard models consist of event selection and intensity estimation models. Multiple scenarios with various return periods can be considered along with hindcasts of previous historical events or scenarios of

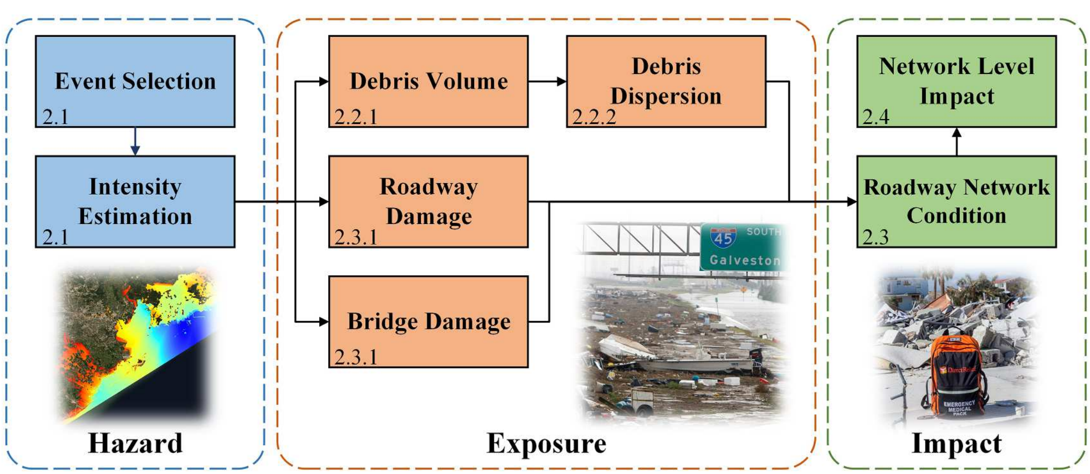

Fig. 1. Overview of the methodology. Inputs and outputs are shown in each step along with the relation between them and section of the paper that presents the proposed or adopted models. Images derived from [34,35].

interest to stakeholders of a region. In the present study, output from the current state-of-the-art dynamically coupled versions of Advanced Circulation (ADCIRC) and Simulating Waves Nearshore (SWAN) simulation model is used to evaluate the intensity measures needed for debris and damage models [36,37]. As mentioned before, the proposed methodology is not limited to the particular model classes in the application of this study. Any model or scenario that has the ability to evaluate the required intensity measures for the next steps can be used in the current methodology. For instance, transportation infrastructure damage models use fragilities, which require maximum wave height, relative surge elevation, and inundation duration as their input.

2.2. Debris modeling

2.2.1. Debris volume prediction model

This model receives the event intensity measures evaluated by hazard models and then predicts the volume of the debris in the interested area. There are different debris volume prediction models in the literature that require a particular set of input and give the results in various levels of refinement. For example, Gonzalez-Duenas et al. [38] developed a data-driven model that predicts waterborne debris using machine learning methods. While this model offers one viable option for use in the proposed framework, it requires eleven storm variables and nine land cover variables, and provides a deterministic estimate. As an alternative, the state-of-the-art probabilistic model developed by Gonzalez-Duenas et al. [24] is adopted, which was developed using Gaussian process regression to predict uncertain debris volume. Moreover, it uses a wide range of variables related to the storm, built environment, demographics of the region, and natural environment, which makes it an advantageous choice compared to other available models.

Incorporating a comprehensive set of parameters, the model reflects the complexity of factors influencing debris volume. Storm parameters, including wind field intensities, storm surge, and momentum flux, are evaluated at the cell level [24]. Built-environment variables encapsulate urban landscape patterns and vulnerability, using measures such as developed area percentages, urban lag, and road density [24,39,40]. Crucially, a weighted probability of structural failure in each grid cell, based on data from a housing unit inventory for Galveston Island [41], is integrated into the model. Human systems aspects are taken into account with demographic and socioeconomic variables, analyzed at the census block group resolution [42]. This inclusion represents an acknowledgement of the human impact of natural disasters on debris generation, which includes parameters such as population density, median household income, and percentage renters. The natural environment is also given consideration, with spatial coverage and diversity measurements for each grid cell, including land-cover classes, shoreline proximity, and elevation data [41]. The model operates at three distinct resolutions (500 m, 250 m, and 125 m grid cells) aligning with the approach outlined by Gonzalez-Duenas [24]. Model training was undertaken with data from the Hurricane Ike debris removal database, leveraging nearly 25,000 unique debris pick-up locations [24,43,44]. To guarantee high data quality, the geospatial data was processed using a dedicated workflow integrating Google APIs, Jupyter notebooks, and the Design-Safe CI platform [24]. The model's comprehensive approach and high-resolution capability present a robust tool for debris prediction, thus enabling effective disaster management planning and interventions. The results of this model (debris volume in each cell) are used as an input for the debris dispersion model, which is proposed in the next section.

2.2.2. Debris dispersion model

Existing models can estimate the volume of debris within an area (or cell), but fail to indicate the spatial distribution of it at a resolution required for subsequent analyses of infrastructure impacts. For instance, considering debris impacts on the transportation network, we are interested in knowing not only the volume of debris within a specific area but also if the debris is accumulated on roadways and whether it hinders the functionality of the network. This process is uncertain, which necessitates the use of probabilistic models with high resolutions. Although some studies have recently begun to address the question of debris dispersion experimentally and numerically, they are either limited to other hazard events, such as a tsunami, or disperse debris in a deterministic way that can result in a bias in the predictions [27]. Hence, to address the knowledge gap, a probabilistic debris dispersion model is developed in the current study.

The debris dispersion model is developed using the concept of random fields. A random field is a random function over an arbitrary domain that takes a random value at each point in that domain [33]. In fact, a random field is the representation of the joint probability distribution for a set of random variables. While it has many applications in physics, biology, data science, and even civil engineering, this is the first time that it has been used for debris dispersion [45–47]. Given the total volume of debris, the distribution of it can be evaluated using a spatial random field in a way that the sum of the debris volume is equal to the total volume of the debris in a specific area (or cell). To generate a random field over a certain field, a semi-variogram can be used. A semi-variogram is a function describing the spatial dependencies between every two points of a random field using their distance. Normally in physical problems, points far apart will vary more than points close to each other. For the purposes of this study, the following semi-variogram is adopted [48,49]:

$$\gamma(r) = \sigma^2 \cdot \left(1 - \mathrm{cor}\left(s \cdot \frac{r}{l}\right)\right) + n \tag{1}$$

where r = the lag distance; l = the main correlation length; s = scaling factor for unit conversion or normalization; σ^2 = variance; n = nugget (subscale variance used to generate noise in the model); and $cor(h)$ = the normalized correlation function depending on the non-dimensional distance ($h = s \cdot \frac{r}{l}$). The characteristics of the semi-variogram can be described using the mentioned parameters and the covariance model that has been considered. The covariance model describes how much two random variables can change together with varying spatial locations (i.e., their covariance). The Gaussian covariance model ($\exp(-h^2)$) has been adopted in this study since it is the most widely used model in generating random fields that can properly characterize the physical behaviors of common natural problems. Using the Gaussian covariance model, Eq. (2) can be written as below [49]:

$$\gamma(r) = \sigma^2 \cdot \left(1 - \exp\left(-\left(s \cdot \frac{r}{l}\right)^2\right)\right) + n \tag{2}$$

Using the above formulation and the help of GSTools python package, the random field can be generated for all the areas with debris, which are separated by grids [50,51]. To illustrate the functionality of this method, Fig. 2(a) shows a one-dimensional random field as a stochastic process. In fact, a random field is a generalization of a stochastic process, in which the underlying parameter can instead take values that are multi-dimensional [52]. As it can be seen, 100 realizations of a Gaussian-distributed random stochastic process are displayed, with values in each realization highly correlated through the Gaussian covariance model, making the process almost continuous. Moreover, the aggregation of all realizations would result in a Gaussian distribution with the prior mean and variance that has been used for the generation of the semi-variogram function. By generalizing the concept in two-dimensions, Fig. 2(b) illustrates a realization of a random field in two-dimensional Euclidean space.

The presented formulation is fully random, taking into account only the mean value and the variance when generating the random field. To model debris dispersion with higher accumulation chances at certain locations, the conditional random field concept is used. This method combines given observations with a random field generated according to a covariance model, using the Kriging or Gaussian process regression

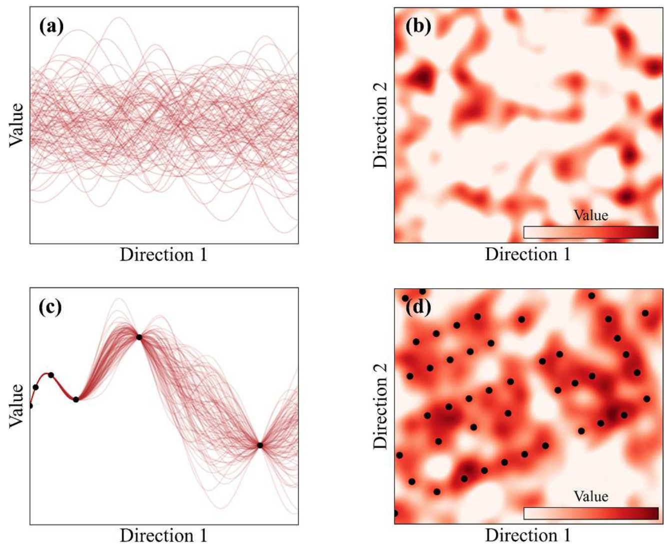

Fig. 2. (a) Random field in one dimension; (b) Random field in two dimensions; (c) Conditional random field in one dimension; (d) Conditional random field in two dimension.

method for data interpolation [53]. Kriging tries to estimate the value of a field at some point x_0, when there are some fixed observed values $z(x_1)\ldots z(x_n)$ at given points x_i. The estimation of z_0 can be calculated as below [50]:

$$z_0 = \sum \omega_i \cdot z_i \tag{3}$$

where $W = (\omega_1, \ \ldots, \ \omega_n)$ are weights that depend on the given covariance model and the location of the target points. Fig. 2(c) shows the Kriging model in the one-dimensional field for 100 realizations. It can be seen that while the model captures all the observation points, the process is still random between the points. The generalized form of the Kriging model in a two-dimensional field is illustrated in Fig. 2(d). Here, the points are set to have higher values compared to the mean value of the random field. In the proposed method for debris dispersion, this feature has been used to address the higher chance of debris accumulation in some points, such as building locations [27].

The debris dispersion model presented in this section has limited input (i.e., debris volume) along with conditioning parameters. In this study, the conditioning parameters hinge solely on the locations of buildings. However, should future studies introduce more sophisticated, weighted conditional random fields, there would inevitably be a need to expand the range of required input data. Such additional inputs could span various parameters influencing debris location and accumulation, including factors like hazard intensity measures, land use and land cover, socio-demographic data, and more. The current model enables conversion of debris volume per grid cell into a high-resolution distribution, taking into account the locations with a higher propensity for debris accumulation. By distributing the debris volume within each grid cell, the resulting conditional random field value signifies the debris height at each point. This information can be used to assess the potential impact of debris on transportation infrastructure, including whether roadways are becoming blocked due to debris accumulation. The subsequent sections of the methodology will delve deeper into how these impacts are considered.

2.3. Transportation network performance

In this section, the performance of the transportation network is evaluated, given the damages to the roadway infrastructures and debris accumulated on the network. Coastal roadways are susceptible to damage because of wave attacks, overtopping, bluff erosion, shoreline recession, wave-induced structural loads, and wave runup [54]. Moreover, coastal bridges have been shown to have a significant vulnerability to damage during hurricane-induced waves and surge events [55]. Furthermore, debris accumulation on the roadways can prevent normal and emergency vehicles from having access to different parts of the transportation network. While most of the studies only consider damages to the roadway infrastructures, this study aims to combine roadway infrastructure damages with debris impacts on the transportation network, without which the connectivity loss in the aftermath of hurricane events can be underestimated. A detailed explanation of the methods is described in the following sections.

2.3.1. Roadway infrastructure damage

For coastal roadways, a data-driven fragility model proposed by Darestani et al. [54] is adopted, which is based on logistic regression. The probability of failure for each road segment is as follows:

$$P_{f_{\text{roadsegment}}}(D_W, I_d) = \frac{1}{1 + \exp(a_0 + a_1 \times \ln(D_W) + a_2 \times \ln(I_d))} \tag{4}$$

where D_W = distance from the shoreline (m); and I_d = inundation duration (hr). a_0, a_1, and a_2 are the coefficients of the logistic regression. A value of 200 m is recommended for the length of each road segment. As a result, roads should first be divided into 200-m segments. Therefore, the probability of failure for each road link is calculated using the probability of the union of failure events of its 200-m segments as follows:

$$P_{f_{\text{road}}} = 1 - \prod_{i=1}^{n} \left(1 - P_{f_{\text{roadsegment}_i}}\right) \tag{5}$$

where $P_{f_{road\ segment_i}}$ = probability of failure of segment i obtained from Eq. (4). In each sample, a set of realizations of a uniform random variable between zero and one are compared with the failure probability of roads to determine whether each of the road links has failed in that particular sample or not. Therefore, using Monte Carlo sampling, different sets of road links fail in each sample of the analysis.

To evaluate the probability of failure for the bridges, the fragility model developed by Ataei and Padgett [55] is adopted. The probability of failure is conditioned on maximum wave height, relative storm surge elevation, and unit mass of spans. The bridge failure that is considered in this study is deck unseating, which is one of the most common severe modes of failure for bridges in the face of hurricanes [55]. Like roadways, in each sample, uniform random variables are compared with the failure probability of bridges to determine whether each of the bridges has failed in that specific sample or not. The fragility model for evaluating the probability of failure is as follows:

$$P_{f_{bridge}} = a + b \cdot H_{\max} + cZ_c \tag{6}$$

where a, b, and c are known parameters based on the length of the bridge; H_{max} is the maximum wave height in meters; and Z_c is relative surge elevation.

2.3.2. Debris impact on transportation network

Given the spatial distribution of debris, accumulations on the roadways can render them impassable. This impassability is significantly influenced by the ground clearance height associated with the specific vehicle type. In the current study, two different scenarios have been considered: normal vehicles and emergency vehicles. Normal vehicles are the usual passenger cars, while emergency vehicles are those used by emergency services, such as ambulances and fire trucks. Lognormal distributions with means of 15 and 25 cm and a coefficient of variation of 0.2 are considered for the ground clearance height of the normal and emergency vehicles, respectively [56]. Therefore, the updated transportation network and available road links are different for various vehicle groups in each sample. In each sample, one realization of ground clearance height is compared to the height of the debris on each road to determine whether the road links are impassable for the particular group of vehicles or not. Essentially, for every road segment, the peak debris height within that specific segment - ascertained from the conditional random field created by the debris dispersion model - is juxtaposed with the uncertain ground clearance height of the vehicle. Eventually, using Monte Carlo sampling, the probability of each road becoming impassible is evaluated for different types of vehicles.

2.4. Serviceability of emergency facilities

While having updated transportation network condition is crucial for emergency response, it is not sufficient for identifying isolated regions with limited access to critical facilities such as emergency medical centers and fire stations. These facilities play a critical role in reducing life-threatening impacts in the aftermath of hurricane events, which emphasizes the importance of having access to different parts of the affected region. To evaluate the access of different parts of the region to the nearest emergency medical center or fire station, the Connectivity Loss Ratio (CLR) is used as a performance measure [54,57]. CLR is defined as $1 - D^n/D^f$ where D^n is the shortest distance between the considering node to the nearest particular type of emergency facilities (e.g., fire stations) under normal situations and D^f is the shortest distance for the same pair of nodes after road links condition became updated due to the hurricane event. CLR can vary between 0 and 1, with zero denoting no impact from the hurricane event on the network accessibility and one denoting complete loss of connectivity to the nearest emergency facility of a certain type [57]. Eventually, the node results can be aggregated at certain geographic levels, such as census blocks or census tracts, to visualize the impacts of hurricane events on the accessibility of different parts of the community to emergency facilities. This way, decision-makers can identify the most vulnerable regions and priorities risk-reduction activities based on the results.

3. Case study: Galveston island

In this section, a testbed community is used to demonstrate the proposed methodology. First, an overview of the testbed is presented, followed by choosing a hazard scenario and intensity measures that have been used as inputs to subsequent models. Afterward, the proposed debris dispersion model is applied to showcase the distribution of debris in the aftermath of a hurricane event. Subsequently, transportation network condition is updated based on the presence of debris and damages due to the hurricane event. Finally, network-level impacts are evaluated with a focus on connectivity to emergency facilities, which is crucial in the immediate response after hurricanes.

3.1. Overview of Galveston island

Galveston Island, TX, is used to demonstrate the methodology presented in the previous section. Galveston is a coastal town in Texas with a total population of more than 53,000 that forms about 22,000 households [58]. Galveston is primarily adopted for this study due to its susceptibility to hurricane hazards since it is located in the hurricane-prone Gulf of Mexico region. This island has experienced several major hurricane events, such as Ike (2008) and Harvey (2017) with $752 million and $345 million cost respectively for debris removal activities, which make it an ideal testbed for considering debris impacts on coastal communities [59]. Consequently, several studies have highlighted vulnerability of Galveston Island to hurricane events [60]. As an instance, Darestani et al. [54] developed a fragility analysis to assess the performance of coastal roadways subjected to storm hazards; and Fereshtehnejad et al. [41] conducted a probabilistic risk assessment of hurricanes on coupled physical and social systems. Fig. 3 shows Galveston Island and its location in the Gulf of Mexico.

Fig. 3. The study area showing the location of Galveston Island in the hurricane-prone Gulf of Mexico.

The current study focuses on the impacts of hurricane-induced debris on the transportation network and its cascading effects on emergency response. Consequently, a detailed transportation network and emergency facilities including fire stations and emergency medical centers were considered to assess debris impacts along with damages to roadway infrastructures. Fig. 4 shows the transportation network of Galveston Island and the locations of fire stations and emergency medical centers. The network includes 13,410 roadway segments and 10 bridges that provide connectivity to emergency facilities including seven fire stations and six emergency medical centers. Furthermore, Galveston Island is divided into 23 census tracts and 2071 census blocks, whose connectivity to emergency facilities has been evaluated in the next sections.

3.2. Hazard scenario

While the proposed methodology is compatible with various sets of hazard models, dynamically coupled versions of ADCIRC and SWAN simulation results of a storm references as ″FEMA 36″ were used to estimate needed storm hazard parameters to assess the damage inflicted on roadways and bridges and to estimate the volume of debris in the subsequent models [36,37]. FEMA 36 approximately corresponds to a 500-year return period storm surge event in the Houston-Galveston area, and has been widely used in past research studies [61,62]. Some of the storm parameters estimated are the surge depth, wave height and direction, flow velocity, and wind field characteristics. Moreover, wind steadiness was evaluated using the hourly wind velocity estimates from the simulation of the storm following the procedure proposed by Berkovic [63]. These parameters are taken as inputs for the debris estimation and damage fragilities for roadways and bridges.

3.3. Debris dispersion

Having the outputs of the hazard model, debris volume can be predicted probabilistically for each grid in the area of interest. In this study, 250 m grids are used to predict the volume of the debris based on the recommendations by Gonzalez-Duenas [24]. Fig. 5(a) shows the output of the debris volume prediction model in Galveston Island for one realization. It can be seen that most of the debris has concentrated in the populated area, where buildings and infrastructures are located. Furthermore, the southern part of the island is more impacted by the debris since the storm hit the island from the south, and measurements that are directly correlated with the volume of debris were more impactful at those parts of the island. Fig. 5(b) demonstrates the distribution of debris using the debris dispersion model introduced in Section

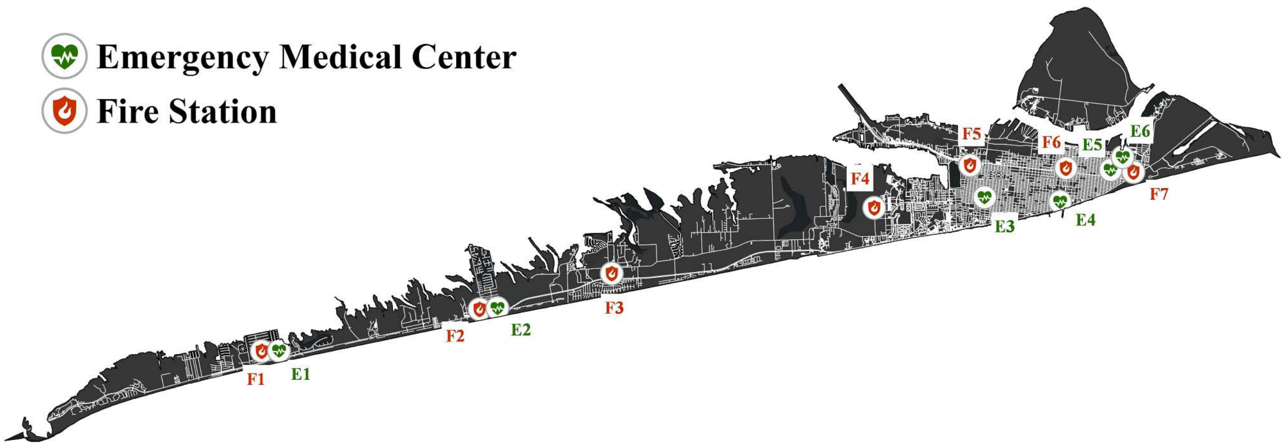

Fig. 4. Transportation network and the locations of emergency facilities in Galveston Island.

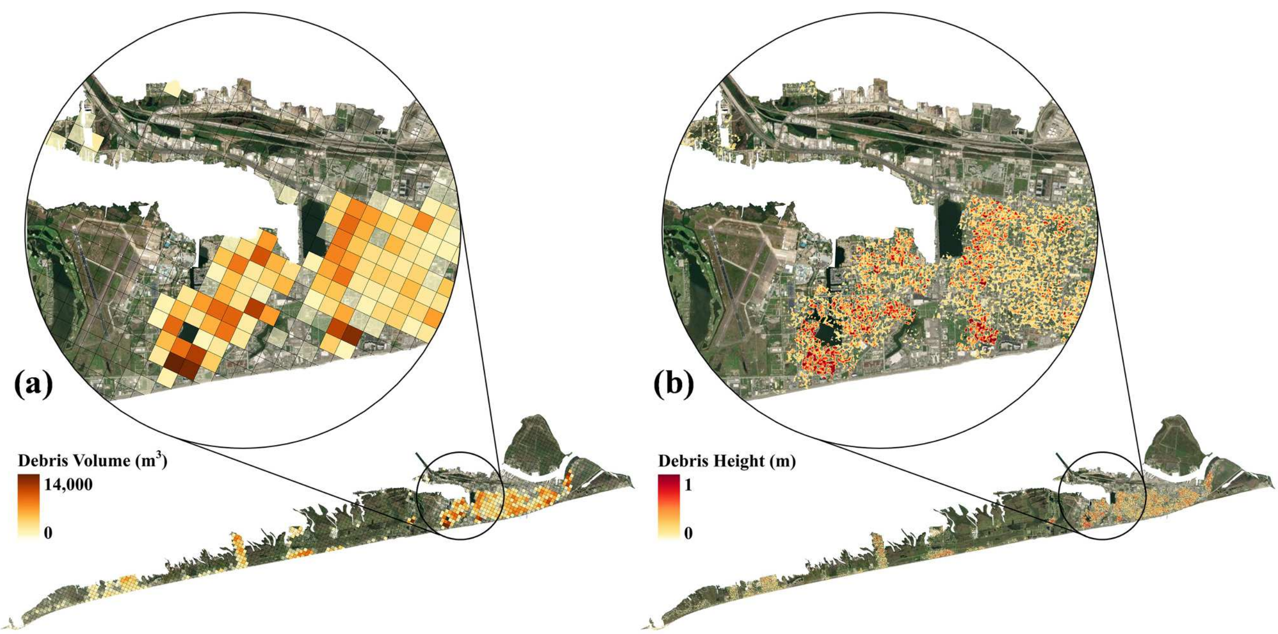

Fig. 5. A realization result of (a) debris volume prediction model; and (b) debris dispersion model.

2.2.2. for the same sample. The debris dispersion is consistent with the debris volume results. Moreover, the debris dispersion model accounts for the correlation and consistency of debris distribution at the grid interfaces, which results in smooth and realistic variation in the spatial domain without any change in the total volume of the debris in each grid. A consistent random field generation for the entire area is achieved by using the same random seed for the Gaussian covariance model in generating random fields within each grid in a sample. The resulting random field in each grid is then normalized so that the total debris in each grid corresponds to the expected debris volume.

As mentioned before, the random field domain generated for each grid is not purely random and here is conditioned to the location of the buildings. Fig. 6 plots the random field domain showing debris height for one sample and aggregated ones for 10 and 100 samples within a specific grid. Considering only one sample, there are some peaks in debris height, while there is no noticeable trend in the generated random field. However, after conducting the conditional random field generation for 10 and 100 samples, the aggregation of the results shows debris presence is most likely to converge to the places where buildings are located confirming the formulation of the debris dispersion model. This capability strengthens the proposed model for debris dispersion to be more realistic, which can be used for considering other effective parameters in predicting the location, accumulation, or deposition of debris in the aftermath of hurricane events. For instance, debris convergence could happen in certain areas due to local topographic characteristics of the area, which can be considered using the proposed model in future work [41].

3.4. Transportation network condition

In this study, both emergency and normal vehicles are considered. However, for simplicity, all subsequent results focus solely on the connectivity of emergency vehicles as the primary form of emergency response, unless a comparison with normal vehicles is being made. Fig. 7 illustrates the probability of road closure for emergency vehicles considering various reasons that can lead roadways to become impassable. The probability of road closure is shown only for damages to roadways and bridges in Fig. 7(a), while Fig. 7(b) demonstrates this probability due to debris presence in the aftermath of the hurricane event. Moreover, the combined probability of road closure for the whole transportation network due to debris presence and damage to roadway infrastructure is shown in Fig. 7(c). The results demonstrate that when

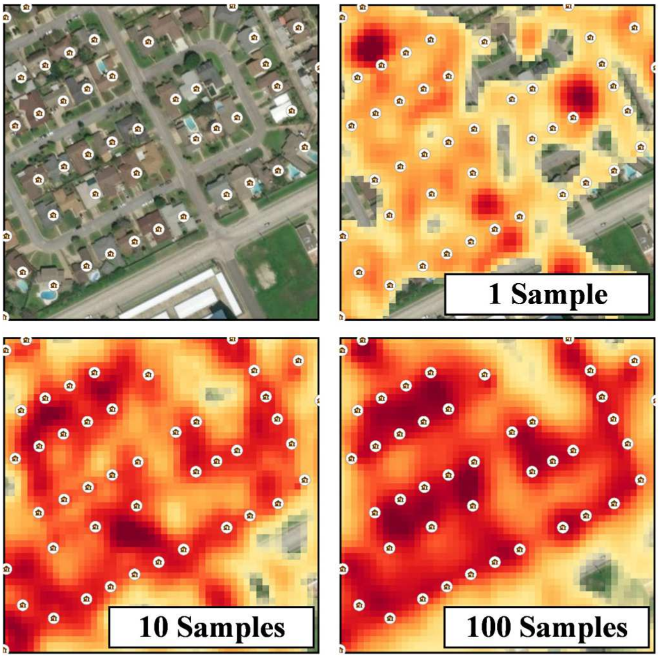

Fig. 6. Aggregated debris distribution (debris height) for various number of samples.

the impact of debris is considered, the mean closure probability of roadways in the transportation network increases from 2% to 19%.

Fig. 7 indicates the importance of considering debris in the risk and resilience analysis of coastal communities facing hurricane events. As demonstrated, roadway infrastructure damage mostly happens near the shoreline, where the intensity of wave attacks and overtopping are higher. However, debris tends to accumulate in the most populated area, mainly in the central parts of the island. Consequently, considering debris impacts is crucial in the coastal community risk and resilience, particularly in the transportation network analysis, without which the impacts of hurricanes would be underestimated. In fact, these roadway infrastructure damages and debris seem to be complementary and affect different locations, which emphasizes the need to consider both of them simultaneously. This is a key feature in the proposed methodology that combines debris impacts with other damage models to comprehensively evaluate transportation network condition immediately after a hurricane event.

In the absence or shortage of emergency response, normal vehicles can also be used for emergency purposes. Moreover, having access to different parts of the community for these types of vehicles indicates whether the community can immediately get back to its normal functionality or not. As another insight, Fig. 8 compares the condition of the transportation network for normal and emergency vehicles immediately after the hurricane event. As it can be seen, roadways have less probability of being closed for the use of emergency vehicles compared to normal vehicles since they have higher ground clearance height, making them capable of moving among a broader range of debris height on the roads. The results show that the average roadway link probability of closure is 0.32 for normal vehicles compared to 0.19 for emergency vehicles, which means that emergency vehicles on average have access to 13% more roadway links. However, connectivity to specific locations such as emergency medical centers might be even harder for normal vehicles since the whole path must be passable for a vehicle to reach that location from its origin. This is one of the main reasons that the network level impacts are also considered in this study through connectivity analysis, which is the main focus of the next section.

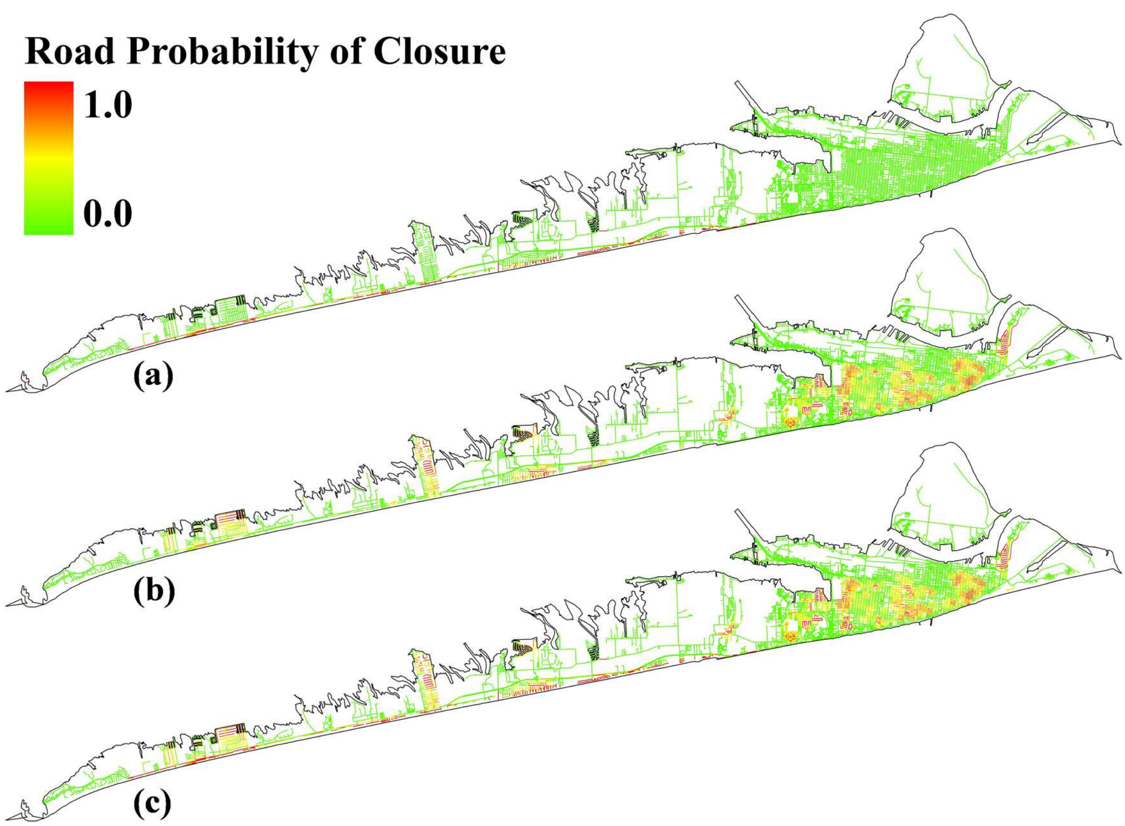

Fig. 7. Probability of road links closure in the aftermath of hurricane event considering (a) only road and bridge infrastructure damage; (b) only debris impact; and (c) both together.

Fig. 8. Probability of road links closure in the aftermath of hurricane event considering both roadway infrastructure and debris impact for (a) normal vehicles; and (b) emergency vehicles.

3.5. Network level impact

This section evaluates the serviceability of emergency services using the CLR performance measure as defined in Section 2.4. Again, the analyses are mainly conducted considering only emergency vehicles in the transportation network. Furthermore, emergency medical centers are assigned to be the main locations of interest in the connectivity analyses and fire stations are only used for comparison. Fig. 9 indicates the connectivity loss ratio for census blocks to emergency medical centers considering the damage to roadway infrastructure, debris, and both together. According to Fig. 9(a), a similar pattern as noted in Section 3.4. is observed; since census blocks near shorelines have a high CLR, that means they have a high probability of losing their connection to emergency medical centers and the possible path for them would be longer

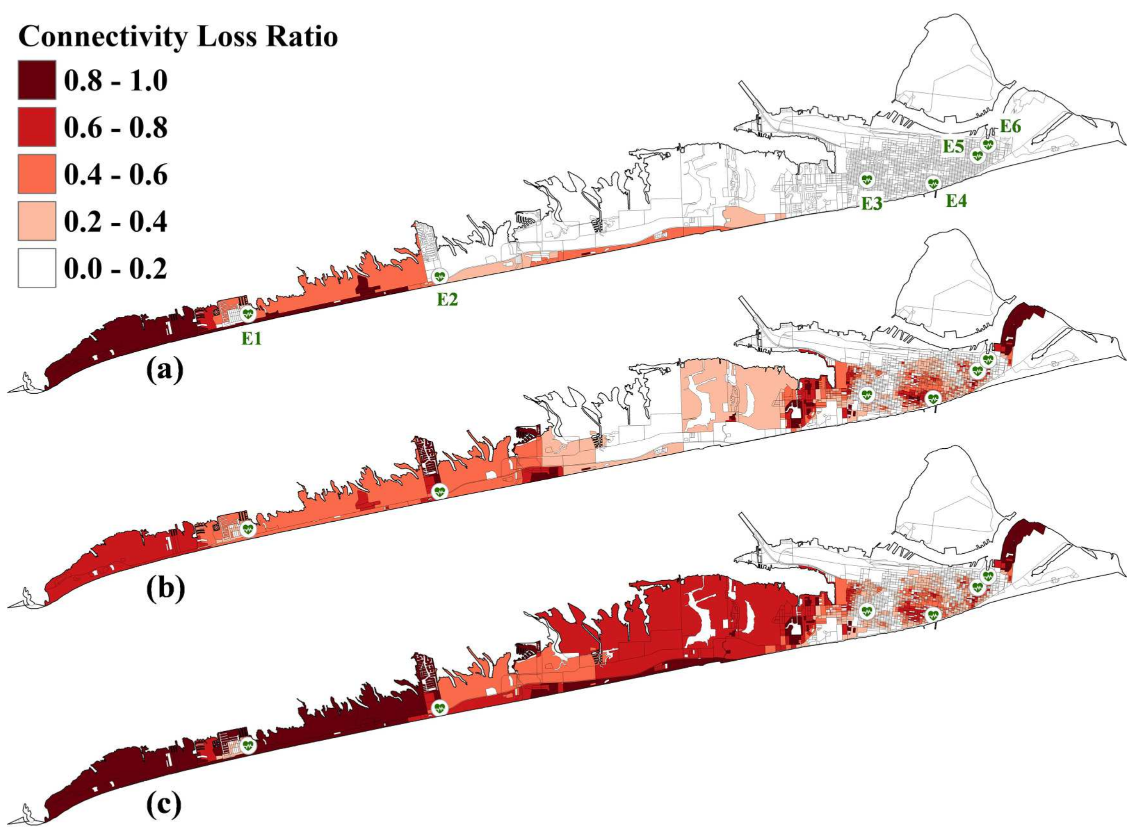

Fig. 9. Connectivity loss ratio to emergency medical centers in the aftermath of hurricane event considerong (a) only road and brideg infrastructure damage; (b) only debris impact; and (c) both toghether.

compared to the normal condition. On the other hand, census blocks in the middle parts of the island did not lose their connection to emergency medical centers and have a connection similar to the pre-event condition. To highlight the impacts of debris, Fig. 9(b) illustrates CLR by only considering the effects of debris on the transportation network, which has a higher impact in the populated areas further from the shoreline. Again, damage to roadway infrastructure and debris have a complementary impact on the serviceability of emergency services, which indicates the importance of considering them simultaneously as shown in Fig. 9(c). The importance of leveraging the newly proposed framework that allows incorporation of debris effects when evaluating post-event network performance is underscored by comparing the average CLR of 0.02 considering only roadway infrastructure damage to the CLR of 0.17 that results when debris impact is also considered.

The proposed methodology provides further insights into the evaluation of debris impact by first estimating the probable location and height of debris to capture the impacts on the transportation network, and second considering different emergency facilities and types of vehicles to conduct a comprehensive simulation for various scenarios. Fig. 10 compares various emergency facilities and types of vehicles together in the aftermath of hurricane event. The average CLR for normal vehicles is almost twice that of emergency vehicles, which indicates the importance of emergency facilities and their dispatch services and vehicles being functional immediately after hurricane hazards. Moreover, the average CLR of fire stations for normal vehicles is 0.50 compared to 0.56 for emergency medical centers, which indicates the importance of number and locations of these facilities that can effectively cover the specified area. As it can be seen, not only is there one more fire station on the island, but they are also spread more efficiently to have access to different parts of it. These kinds of analyses can also be used within a risk mitigation process to find the optimum location of emergency facilities, so they can have better access to various parts of the serviceability area.

Since the proposed framework allows estimation of not only the expected value key performance metrics but also their uncertain outcomes, the results can be evaluated in terms of distribution or percentiles of performance metrics like CLR. Such information can support risk-informed decision-making or even be tailored to the risk tendencies of stakeholders. For instance, Fig. 11 shows the exceedance probability having a CLR of 0.9 for emergency vehicles considering their access to emergency medical centers. Censuses blocks having exceedance probability near one are highly vulnerable to losing access to emergency medical centers for the given hurricane event. This information can be used to identify areas with the most susceptibility and plan for risk mitigation solutions in preparation for future hurricane events. As the results indicate, the west side of the island, along with the shoreline and regions near E4 are the most vulnerable areas.

As another insight into the capabilities of the proposed methodology, Fig. 12 shows the average CLR for census tracts, underscoring that the level of resolution or aggregation of results may be varied per user interest. Moreover, this figure highlights that applying the proposed probabilistic method enables new insight into the distributions of CLR, and that different tracts present varying distribution types and characteristics. For instance, census tract A in Fig. 12 has two major probability masses near 1 and 0.5 making them the most probable outcomes for CLR in that specific census tract, but also highlighting that these outcomes are more bimodal in nature than other tracts. This is an artifact of some key links in that census tract that are vital, whose closure can cut the connectivity of the census tract to emergency medical centers. As a result, identifying and reducing the closure probability of those links in the mentioned census tract can dramatically decrease the chance of that census tract losing access to emergency medical centers. On the other hand, CLR distribution for census tract B shows a more even distribution of link importance.

4. Conclusion

This study advances the state-of-the-art in evaluating hurricane-induced debris impacts on coastal community risks by proposing a novel probabilistic methodology that introduces a new model for high resolution debris distribution estimation rooted in conditional random fields, and integrating it within a framework from hazard to cascading consequence analysis. In particular, this paper distinguishes itself from the current state-of-the-art by developing a debris dispersion model that

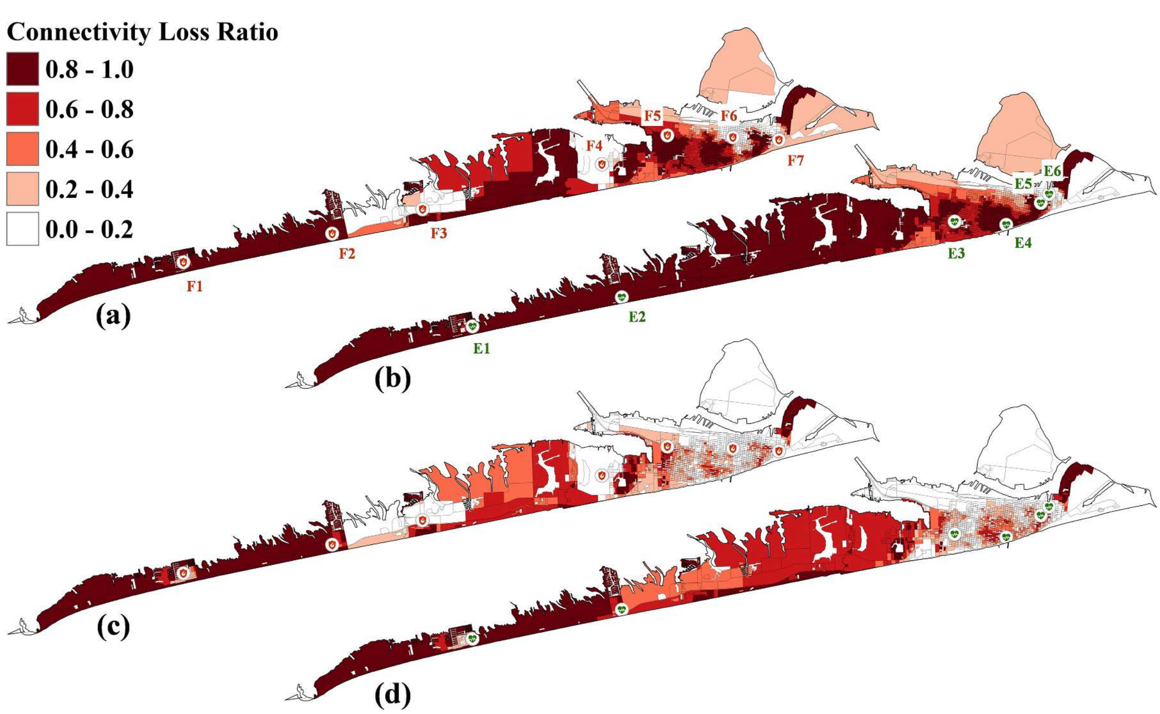

Fig. 10. Connectivity loss ratio in the aftermath of hurricane event considering (a) normal vehicles-fire stations; (b) normal vehicles-emergency medical centers; (c) emergency vehicles-fire stations; and (d) emergency vehicles-emergency medical centers.

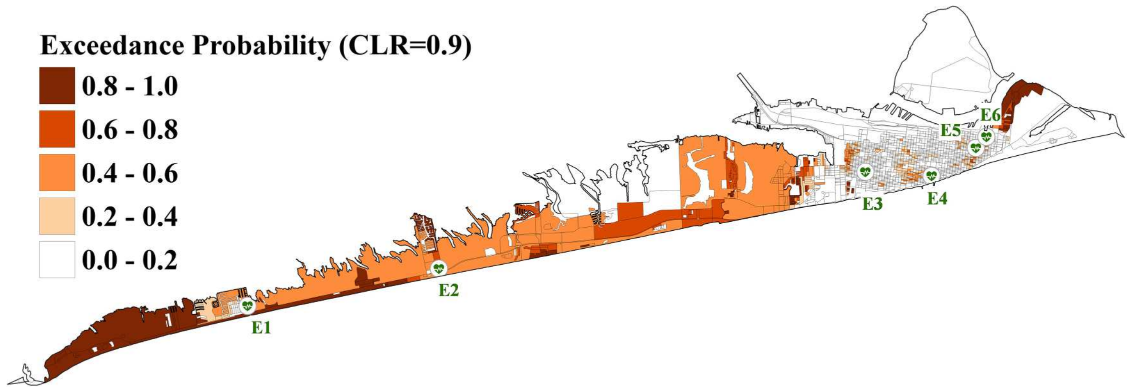

Fig. 11. Probability of exceeding a connectivity loss ratio of 0.9 for census blocks considering access to emergency medical centers via emergency vehicles.

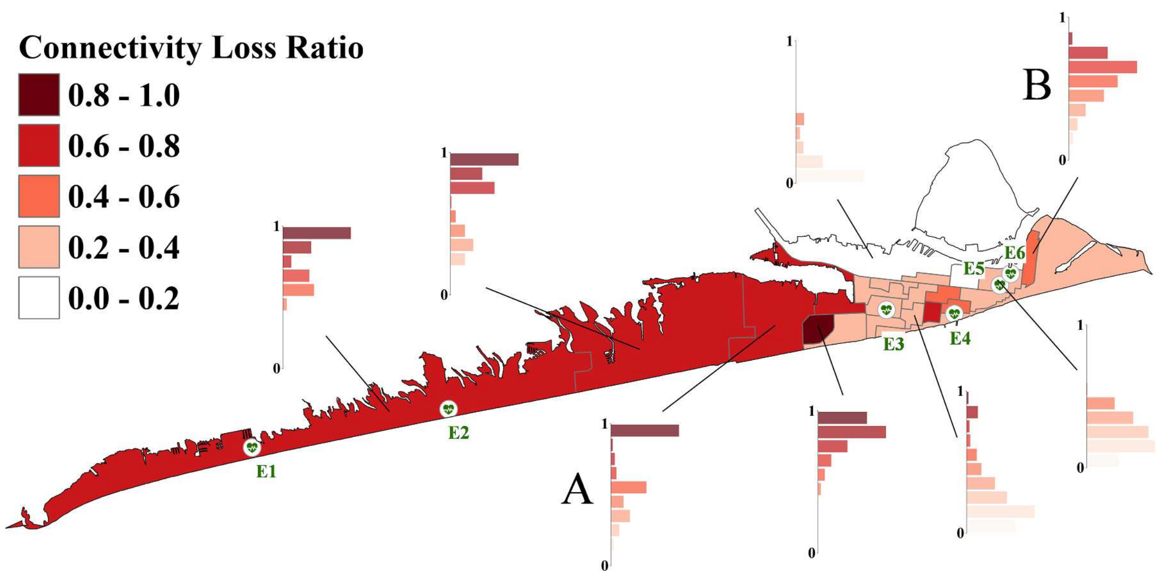

Fig. 12. Connectivity loss ratio and its distribution for census tracts considering emergency vehicles and emergency medical centers.

probabilistically estimates the location and height of debris and facilitates capturing cascading consequences on the transportation network in a fully probabilistic fashion. In this case, analysts can for the first time distinguish the relative importance and impact of capturing functionality inhibition from debris alongside physical damage to bridges and roadways on uncertain metrics of infrastructure performance, like connectivity loss ratio—at different scales (e.g. census tract vs. census block), for different vehicle types, or considering percentiles of the distribution of the performance metric.

The proposed methodology is showcased by its application to Galveston Island community under hurricane hazard, using a realistic and detailed transportation network, socio-demographic units, and spatial distribution of emergency facilities. The results indicate the importance of considering debris impacts along with damages to roadway infrastructure in the risk assessment of coastal transportation networks, without which the impacts of hurricane events would be underestimated. Alternative ways of presenting and analyzing the results can support and range of risk-informed decisions, ranging from identifying critical regions and infrastructure components for which to target pre-event mitigation resources to estimating debris quantities, their distribution, and impact on access to support post-event debris management and recovery efforts.

Despite the advances made in this paper, there are remaining challenges that should be addressed in future work. While the debris dispersion model is able to probabilistically estimate the location and height of debris in each sample and cell, it is conditioned only to the location of buildings in this study. Other factors such as the type of building, local topography, and intensity-correlated variables such as surge flow could be considered leveraging the proposed approach using conditional random field. Additional research should be conducted to investigate how these conditions can influence the local dispersion of debris and inform weighting parameters in the model. This could be informed by further field data collection, processing high resolution areal imagery, remote sensing, or even cutting-edge numerical models [64]. The results presented in this paper leverage the existing debris volume model from Gonzalez-Duenas et al. [24], which was empirically derived with data from the Houston-Galveston area. However, further validation or updating of the model is required with data from other regions in order to generalize its applicability and apply it within the proposed framework to other regions. Alternatively, this network level impact framework is amenable to incorporating next generation debris estimation models as they emerge from future work. Additionally, other cascading consequences of debris could be added to the framework, such as the physical damage due to debris impact, which was neglected in this study. Moreover, this study lays the groundwork for assessing the impacts of hurricane-driven debris on other infrastructures like power networks, taking into account their interdependencies. With future climate projections, debris could likewise pose more physical and operational risks to these systems. Finally, this work can be extended to include models of the recovery dynamics and the process of debris removal which can influence diverse metrics of community resilience.

Author contributions statement

This work was carried out in collaboration between both authors. Kooshan Amini, the primary author, conceived, designed, and executed the study. He developed the initial framework, performed the analysis, and drafted the original manuscript under the guidance and supervision of Jamie E. Padgett.

Jamie E. Padgett, as the second author and supervisor of the project, played an integral role in shaping the research and manuscript. She contributed to the development of the framework, provided crucial guidance for the analysis, and critically reviewed and edited the manuscript for important intellectual content, ensuring the accuracy and integrity of the work.

Both authors have read and approved the final version of the manuscript.

CRediT authorship contribution statement

Kooshan Amini: Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jamie E. Padgett:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

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