Probabilistic Modeling of Hurricane-Induced Debris Impacts for Coastal Community Resilience Analysis

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ABSTRACT: Climate disasters such as hurricanes significantly impact coastal communities, posing critical challenges to their resilience. Besides direct economic and social losses, coastal communities suffer from indirect cascading consequences of these extreme events. In particular, debris-related impacts pose significant economic burdens, while also resulting in cascading consequences. These consequences include, for example, structural damage due to debris impact, functionality impairment to transportation networks affecting access to emergency facilities, and delayed recovery of other systems. As a result, there is a need to better understand and model debris and its uncertain impacts on coastal communities in the face of storm events. This paper puts forward a probabilistic framework to evaluate hurricane-induced debris and its impacts at the community scale, which is essential in conducting a comprehensive resilience analysis of coastal communities. This framework poses interdependent probabilistic models spanning from the spatial estimation of debris presence and volume for hurricane events, to debris-induced physical damages and network level performance impacts (considering transportation infrastructure as an illustration). Moreover, this study use Monte Carlo approach to conduct simulations, which is accelerated by utilizing a deep neural network surrogate model in transportation network connectivity analysis. Select features of the proposed framework are illustrated using testbed community data and existing or approximated input models relevant to the Galveston region in Texas, USA. The results indicate the importance of capturing debris impacts when considering community-scale resilience metrics in coastal regions, without which the consequences of these events and equity of access to emergency facilities in the aftermath of them can be underestimated.

1. INTRODUCTION

Climate-induced events, such as hurricanes and tsunamis, exert a pronounced impact on communities, thereby creating critical impediments to their capacity for recovery and adaptation. As an example, the overall costs and damages from weather and climate disasters in the United States since 1980 exceed $2.275 trillion (Smith 2020). Additionally, the ability of coastal communities and their infrastructure to withstand and recover from extreme events is affected by the chain reaction of consequences that follow (Almutairi et al. 2020; Dong and Li 2016). These consequences can range from connectivity loss to critical facilities (e.g., due to debris accumulation) to long-term physical and mental health issues (Almutairi et al. 2020; Lowe et al. 2015). Debris generated during extreme climate events accounts for a significant proportion of disaster recovery costs, estimated at approximately 27%. Additionally, the damages to roadway infrastructure in conjunction with debris can impede the functionality of transportation networks (FEMA 2007; Tuzun Aksu and Ozdamar 2014). For example, accessibility to emergency facilities is critical in the aftermath of extreme events, which highly relies on transportation networks (Cui et al. 2016; Green et al. 2017). Concerns regarding the annual risks of such consequences associated withstorm induced debris are expected to rise given projections of climate change and land-use modification (Field 2012; Highfield et al. 2014; Masozera et al. 2007; Winsemius et al. 2016).

Several studies have focused on predicting debris generated from weather and climate disasters such as hurricanes, tsunamis, and floods. Escobedo et al. (2009) proposed a model to predict tree debris using data from seven hurricanes in Florida. HAZUS (FEMA 2012) 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. More recently, Gonzalez-Duenas et al. (2022) developed a data-driven model to predict the amount of waterborne debris following a severe storm using machine learning techniques. However, these models focus on predicting the total volume of debris in specific areas, rather than providing insight into its distribution at a resolution sufficient for inferring infrastructure impacts. This lack of information hampers decision-making regarding the impact of debris on connectivity loss in roadway infrastructure, for example. To address this gap, recent studies have begun to focus on debris dispersion and its effect on community-level connectivity (Kameshwar et al. 2021; Nistor et al. 2017; Park and Cox 2019). Despite recent advancements in debris dispersion modeling, current models are limited in their ability to predict the distribution of debris, particularly in regards to its impact on community-level connectivity in roadway infrastructure. This study aims to address this limitation by proposing a probabilistic debris dispersion model that incorporates uncertainty in order to more accurately evaluate the distribution of debris and its impact on community-level connectivity.

Identifying areas without access to emergency facilities, including medical centers and fire stations, is crucial to support emergency response (Green et al. 2017; Albano et al. 2014). This is important since the prompt emergency response is pivotal for the safety of residents within communities (Kocatepe et al. 2019). While few studies evaluated connectivity to emergency facilities considering debris presence, a comprehensive probabilistic methodology that captures the range of uncertainties in the problem is also lacking (Kameshwar et al. 2021). To address the mentioned knowledge gaps, this study presents a probabilistic methodology to evaluate connectivity loss to emergency facilities in the aftermath of hurricane events considering debris presence.

While infrastructure system reliability and resilience simulations are becoming more complex and popular in decision-making, there is high demand for more efficient ways to conduct these analyses. One of the most popular approaches to quantify the uncertain impact of natural hazards on communities and infrastructures is through the use of Monte Carlo simulation for sampling and uncertainty propagation. However, this method suffers from high computational costs, especially when used for complex systems (Nabian and Meidani 2018). One of the ways to accelerate these types of simulations is using surrogate models. Surrogates can approximately describe the relationship between inputs and outputs of the system and become a substitute for heavy simulations (Nabian and Meidani 2018). While there are several surrogate modeling techniques, each one suitable for different problems and available data, a deep neural network (DNN) is used for this study. In fact, DNN surrogate has been constructed and used to speed up the connectivity analysis, which is the most time-consuming parts of the simulation.

The remainder of this paper is structured as follows: First, the overarching probabilistic methodology is presented with details of models, which includes the introduction of a developed debris dispersion model along with the use of deep neural network surrogate model for network impact computation (section 2). Then, the proposed methodology is showcased by applying it to Galveston Island, TX (section 3). Section 4 concludes the paper with the key contribution, findings, conclusions, and recommendations for future work.

2. METHODOLOGY

The proposed methodology in this study requires a set of interacting probabilistic models, which are explained separately in the following sections. It is emphasized that the proposed methodology is not limited to the specific models showcased in the application of this study.

2.1. Hazard Modeling

Hazard group 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 interest to stakeholders of a region. In the present study, output from the current state-of-the-art ADCIRC+SWAN simulation model (ADCIRC; SWAN) is used to evaluate the intensity measures needed for debris and damage models.

2.2. Debris Modeling

This model receives the event intensity measures evaluated by hazard models and then predicts the volume of the debris in the interested area. In the current study, the state-of-the-art probabilistic model developed by Gonzalez-Duenas et al. (2022b) 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. For example, considered storm and hazard-related parameters include surge depth, bathymetry, wave height, wave period, wave direction, water velocity, among others. Furthermore, this model evaluates the debris volume in three different low, intermediate, and high resolutions that are square grid cells of 500, 250, and 125 m. 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.

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 transportation network, we are interested in knowing not only the volume of debris within an interested area but also if the debris is accumulated on roadways and whether it hinders functionality of the network. This process is uncertain, which necessitates use of probabilistic models with high resolutions. Although some studies have recently begun to addressed 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 (Kameshwar et al. 2021). Hence, to address the knowledge gap, a 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 the domain. In fact, a random field is the representation of the joint probability distribution for a set of random variables (Adler and Taylor 2007). While it has many applications in physics, biology, ecology, and data science, this is the first time that it has been used for debris dispersion (Hernández-Lemus 2021). Given the volume of debris, the distribution of the debris can be evaluated using a random field function. For the purpose of this study, a conditional random field function is used to account for locations that debris tends to get stuck there. For instance, there is a higher chance for debris to accumulate near the buildings' locations.

2.3. Transportation Network Performance

Debris accumulation on the roadways can prevent emergency vehicles from having a complete access to the transportation network. While most of the studies only consider damages to the roadway infrastructures, this study aims to evaluate debris impacts on the transportation network, without which the connectivity loss in the aftermath of hurricane events can be underestimated.

Given the distribution of debris on ground, accumulated debris on the roads can make them impassable. One vehicle can pass through one road, while the road is considered impassable for the other due to differences in the ground clearance height. In the current study, emergency vehicles are considered for transportation network analysis, such as ambulances and fire trucks. Lognormal distribution with a mean of 25 cm and a coefficient of variation of 0.2 is considered for the ground clearance height of the emergency vehicles (Sobanjo 2006). In each sample, one realization of ground clearance is compared to the height of the debris in each road to determine whether the road links are impassable for the particular group of emergency vehicles or not. Therefore, the updated transportation network and available roads are different in each sample. Eventually, using Monte Carlo sampling, the probability of each road becoming impassible is evaluated for different types of emergency 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 medical centers and fire stations. These facilities have a critical role in reducing 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 medical center or fire station, a connectivity loss ratio (CLR) is used (Panakkal et al. 2022). 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., medical centers) under normal situations and D^f is the shortest distance for the same pair of nodes after roads condition became updated due to the hurricane event. CLR can vary between 0 and 1 with zero denoting no impact from hurricane event on the network accessibility and one denoting complete loss of connectivity to the nearest emergency facility of a certain type. 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.

Connectivity analysis is the most time-consuming part of the Monte Carlo simulation. As a result, DNN has been used to make a surrogate model for accelerating connectivity analysis. DNN is a type of artificial neural network with multiple layers of nodes (also known as artificial neurons) that perform computations and transformations on the input data to produce output. It is designed to automatically learn and extract complex features from input data through the use of backpropagation and gradient descent optimization algorithms. Part of the samples has been simulated without any surrogate model. Then, the results have been used to train a DNN model for the connectivity analysis part, which is then used to accelerate the next simulations. The configuration of DNN is set based on Nabian and Meidani (2018).

3. CASE STUDY: GALVESTON ISLAND

In this section, a testbed community is used to demonstrate the proposed methodology.

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. 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 (FEMA 2007). Figure 1 shows Galveston Island and its location in the Gulf of Mexico.

3.2. Hazard Scenario

While the proposed methodology is compatible with various sets of hazard models, dynamically coupled versions of Advanced Circulation (ADCIRC) and Simulating Waves Nearshore (SWAN) simulation

Figure 1: The study area showing the location of Galveston Island in the hurricane-prone Gulf of Mexico.

results of FEMA 36 storm were used to estimate needed parameters in the following models. FEMA 36 is a probabilistic 500-year return period storm event in the Houston-Galveston area, which is widely used in research studies (Fereshtehnejad et al. 2021). Some of the parameters that have been estimated using the mentioned simulation are the surge depth, wave height and direction, flow velocity, and wind field characteristics.

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 recommendation by Gonzalez-Duenas et al. (2022a). Figure shows the output of the debris volume prediction model in Galveston Island for one sample. 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

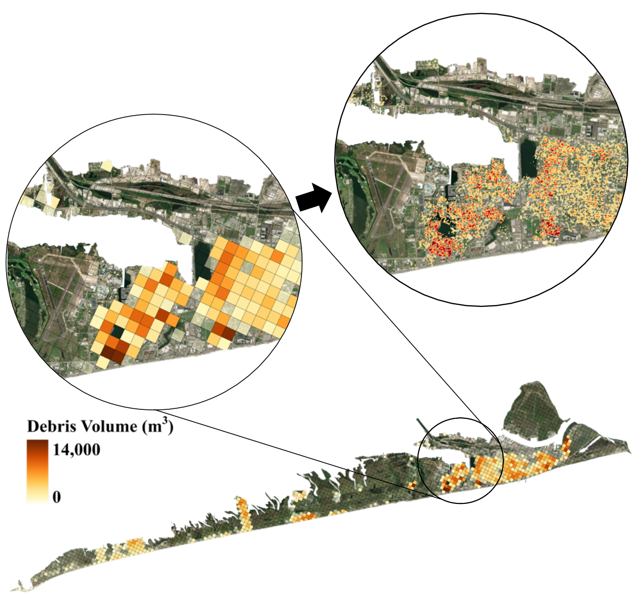

Figure 2: A realization result of debris volume prediction model; and debris dispersion model.

the volume of debris were higher at those parts of the island. Moreover, Figure demonstrates the distribution of debris using the debris dispersion model introduced in the methodology section for the same sample. It can be seen that debris dispersion is completely consistent with the debris volume results.

3.4. Transportation Network Condition

As mentioned before, different types of vehicles can be considered in this study. Although access to emergency facilities for normal vehicles can play an incontrovertible role in the aftermath of a hurricane event, connectivity for emergency vehicles is considered the main shape of emergency response in the analyses. Figure illustrates the probability of road closure for emergency vehicles due to debris presence in the aftermath of the hurricane event. Debris tends to accumulate in the island's most populated area, mainly in its central parts. 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.

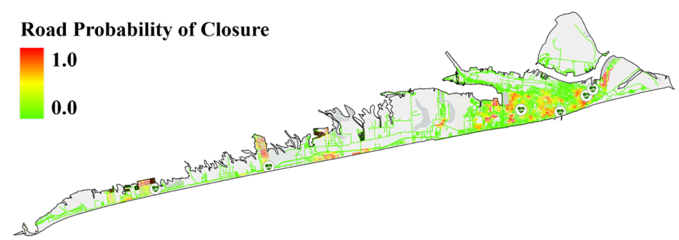

Figure 3: Probability of road links closure in the aftermath of hurricane event.

3.5. Network Level Impact

Given that the majority of computational expenses in the analysis pertain to network connectivity analysis, it has been deemed appropriate to model it utilizing a DNN with two hidden layers. The input data is a set of binary values showing whether the road links of the network are closed due to debris presence or not. The outputs are the CLR of 23 different census tracts, which are used to measure the quality of connection from those census tracts to emergency medical centers. Moreover, 30 percent of the data has been used to validate the surrogate model.

Since the dimension of input data is high (number of links in the network), the computation burden of the neural network and its accuracy may be affected. Hence, Principal Component Analysis (PCA) has been conducted to reduce the dimensionality of the input first. Figure shows the result of PCA on the data. As shown, the same accuracy can be achieved by using only half of the data in the new dimension. As a result, the first 400 principal components of the input data are used to train the DNN model.

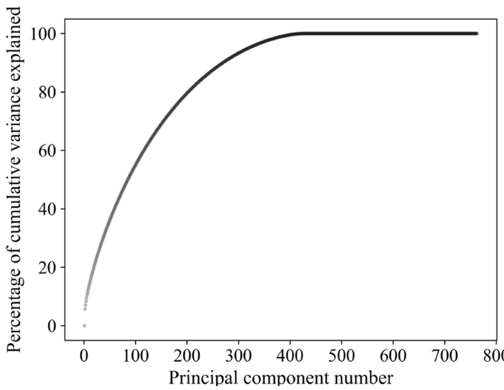

Figure 4: Percentage of cumulative variance explained by the principal components of input data.

Figure 5 shows the results of the DNN model for training and validation. In this study, two hidden layers have been used with Adam optimizer, a replacement optimization algorithm for gradian decent. Furthermore, the mean squared error loss function and R-squared metric are used with having

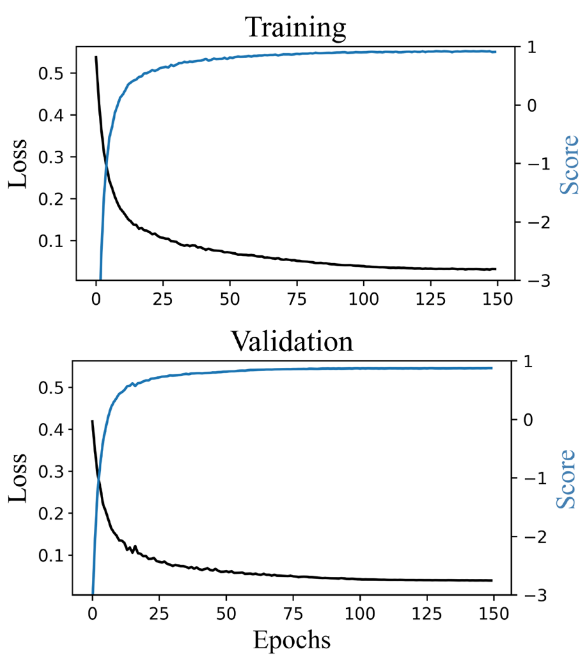

Figure 5: Loss and score change for training and validation data.

30% of the data for validation. As it can be seen, the model is trained very fast and can be used as a substitution for regular and time-consuming connectivity analysis, which takes minutes to complete. The benefits of using the DNN surrogate model are even more when the network is larger and more complex.

Finally, the serviceability of emergency facilities using the CLR, which is defined in the methodology part, is evaluated. The analyses are conducted considering emergency vehicles using transportation network to reach different regions. Figure 6 shows the average CLR for census tracts. Moreover, the distributions of CLRs have been shown for some census tracts, which can give valuable information for risk assessment and decision-making.

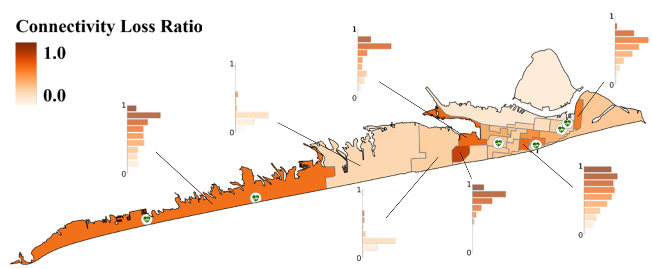

Figure 6: Connectivity loss ratio and its distribution for census tracts to emergency medical centers.

4. CONCLUSION

This study proposed a methodology to evaluate hurricane-induced debris impacts on coastal communities' risk by integrating various models from hazard to cascading consequences and introducing a new model on debris distribution estimation. 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. Furthermore, the proposed methodology gives a quantitative tool to determine the most critical components of infrastructure systems and find the optimal allocation of limited resources to improve coastal communities' functionality in the aftermath of hurricane events.

Despite the advances posed in this paper, there are several lines of future improvement to the model and opportunities to leverage it. 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. Other factors such as the local topography could be considered leveraging the proposed conditional random field approach. Moreover, this framework provides a foundation for evaluating hurricane-induced debris effects on other infrastructures, such as power networks, where debris may similarly pose physical and functional threats to their operation. Conducting a more comprehensive simulation would result in heightened computation costs. Hence, a deep neural network surrogate model is proposed to remedy this. Different scale models for transportation networks besides surrogate models can be used to conduct Multifidelity Monte Carlo estimation that can make the simulation process even more efficient (Peherstorfer et al. 2016). 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.

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