14th International Conference on Applications of Statistics and Probability in Civil Engineering, ICASP14
Dublin, Ireland, July 9-13, 2023

A performance-based probabilistic framework to model risk to power systems from hurricanes

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ABSTRACT: Utility companies are often prepared for small-scale blackouts under normal operating conditions. However, they face crucial challenges with extreme weather events, such as hurricanes. Utilities must make risk-informed decisions to prioritize their limited resources (e.g., for grid hardening) in cities expected to experience larger and longer hurricane-induced outages. Probabilistic outage models can capture the uncertainty in power outages and characterize the grid's vulnerabilities to local environmental conditions, such as winds responsible for falling trees and poles that can affect the outages. We employ a probabilistic outage model developed for the 3.6 million historical outages caused by Hurricane Harvey (2017), Hurricane Michael (2018), and Hurricane Isaias (2020) in the United States states to investigate the expected performance of power systems to future hurricanes. This paper presents a generalized probabilistic framework coupling the expected frequency of future hurricane hazard levels and probabilistic outage predictions to understand the frequency of power system performance indices, namely the System Average Interruption Frequency Index and System Average Interruption Duration Index, from hurricanes. Results show that factors other winds, such as land use patterns, influence the risk of power outages across cities in New Jersey from future hurricanes.

1. INTRODUCTION

Hurricanes cause cascading power failures, and utilities often struggle to respond to these outages, leaving millions of consumers without power for days. In recent years, Hurricanes have been the cause of many prolonged power outages in the United States (US), e.g., Hurricane Michael (2018) was responsible for outages to 1.7 million consumers (EIA.GOV, 2018). Power outages can have critical consequences for critical infrastructures, e.g., in hospitals, power must be restored within a few hours after an impact from a disaster for their normal operations for a post-disaster emergency response to avoid distress in communities.(National Academies of Sciences, Engineering, and Medicine, 2017; Ceferino et al., 2020).

Many researchers (Liu et al., 2005, 2007; Han et al., 2009b; Guikema et al., 2010, 2014; Shashaani et al., 2018) have developed hurricane power outage prediction models to help utilities plan ahead of a storm for rapid deployments of resources and crews to expedite recovery from a storm. These models use input parameters, including hurricane winds, environmental parameters, power system information, and demographics to predict hurricane-induced outages (Arora and Ceferino, 2022). To benefit utilities in pre-storm planning, we present a probabilistic performance-based engineering approach to couple these methods with hurricane hazard models to inform planners on risk hotspots, i.e., where communities can face the largest and longest power outages from hurricanes.

Krawinkler (1995) first introduced the performance-based engineering approach to characterize earthquake risks and assess if buildings would achieve a satisfactory level of performance in future earthquakes. The existing probabilistic approaches for the reliability of power systems against hurricanes have focused mostly on winds as the reliability-reducing factor.(Brown, 2002). Zhang et al. (2022) presented a fragility-weighted methodology to assess the vulnerability of overhead power distribution systems to hurricanes. Lu and Zhang (2022) used a surrogate Machine Learning (ML) based approach to predict hurricane intensities that are used to assess the vulnerability of pole wire systems to high winds. However, these methods (Zhang et al., 2022; Lu and Zhang, 2022) require extensive data on power systems that are not easily accessible, and factors other than winds, such as grid topology, can affect the reliability of power systems (Petersen, 1982). Hence, we need a standard measure to compare the risk profile of power systems from hurricanes at a large scale. The performance of power systems is generally measured based on the Institute of Electrical and Electronics Engineers (IEEE) defined performance indices, namely System Average Interruption Frequency Index (SAIFI) and System Average Interruption Duration Index (SAIDI) (IEEE 1366, 2022). The US electric grid system constitutes about 700,000 miles of transmission lines, 7 million miles-long distribution lines, and more than 20,000 substations. These components of the US power grid are vulnerable and exposed to extreme weather events (National Academies of Sciences, Engineering, and Medicine, 2017). Utilities need informed decision-making to protect and prioritize the areas more vulnerable to extreme weather events.

To the best of the author's knowledge, this is the first attempt to probabilistically quantify power system performance indices, SAIFI and SAIDI, across multiple cities in the US to Hurricanes using power outage models to assess the risk of outages to future hurricanes. We used a power outage prediction model developed based on historical power outage data for multiple hurricanes in the US, which includes Hurricane Harvey (2017) in Texas, Hurricane Michael (2018) in Florida, and Hurricane Isaias (2020) in New Jersey and New York. Arora and Ceferino (2022) discussed the probabilistic distribution of outages for a given wind speed. We combined distribution on outages with the return period of future hurricanes to estimate the return period of different levels of performance determined by SAIFI and SAIDI. These indices can be determined for all types of system-wide power interruptions around the year. However, this study considers only hurricane-caused power interruption to determine SAIFI and SAIDI as extreme weather events have been the major causes of large-scale sustained outages (Ankit et al., 2021; Brown, 2002).

2. Power System Performance Index

Utilities are assigned performance ratings based on reliability indices defined by IEEE. Although utilities often exclude storm events while determining reliability indices (Brown, 2002) as old power systems are not designed to withstand shocks from extreme weather events, consumers are disturbed whether the reason for an outage is a storm or a non-storm event. Thus, we developed the probabilistic framework to measure these performance indices and comper the performance of power systems of different cities.

2.1. System Average Interruption Frequency Index (SAIFI)

SAIFI measures the number of sustained outages (outages more than a minute) a consumer will experience during a year given as:

$$SAIFI = \frac{Total\ Customer\ Interruptions}{Total\ Customers\ Served}\ /yr \quad (1)$$

For outages caused by one storm during a year, SAIFI will represent a fraction of customers without power during the storm. Cities with higher SAIFI are at more risk for power interruptions from storms.

2.2. System Average Interruption Duration Index (SAIDI)

SAIDI measures the number of sustained outages hours (outages more than a minute) a consumer will experience during a year given as:

$$SAIDI = \frac{\sum Customer\ Interruptions\ duration}{Total\ Customers\ Served} \quad hr/yr \tag{2}$$

To determine the total unserved power system supply (Brown, 2002), information on both the duration and the number of outages is required. A high SAIDI value for a city is indicative of longer sustained power outages.

3. Power Outage Model

Liu et al. (2005) used Negative Binomial Generalized Linear Model (GLM) to model power outages at the zip code level as a function of wind gusts, number of transformers, hurricane indicator, and company indicator. Han et al. (2009b) generalized the previous model using a Negative Binomial GLM that could evaluate outages for any hurricane and utility company using data from Gulf Coast's cities. Han et al. (2009a) developed a Negative Binomial Generalized Additive Model (GAM), which showed superior performance to the GLM model as GAM can handle high non-linearity in the relationship between input parameters and log of the mean of outages. Next, Nateghi et al. (2014); Guikema et al. (2014); Shashaani et al. (2018); McRoberts et al. (2018) used Random Forest for outage modeling, a tree-based method that grows parallel decision trees that improves outage predictions by reducing variance and capturing non-linearity of input parameters.

Arora and Ceferino (2022) studied the performance of Poisson GLM and GAM, Negative Binomial GLM, and GAM, and Random Forest-based power outage models. The study showed that Random Forest-based outage models lack the extrapolability to model outages for high winds. The study also highlighted that Poisson GLM and GAM could not account for overdispersion in the outage counts, i.e., variance in outage counts is greater than the mean, as also mentioned in the previous studies (Liu et al., 2005; Han et al., 2009b). Negative Binomial GAM can overpredict outages and lack physics-based variance shapes for outages. However, it can account for larger dispersions and capture outages at all wind levels (Arora and Ceferino, 2022). Hence, this paper uses the Negative Binomial GAM-based power outage model to demonstrate how outage models can be used to quantify power system performance indices (SAIFI and SAIDI) probabilistically.

3.1. Negative Binomial GAM

GLM and GAM models are extensions of linear regression models. However, GLMs and GAMs, unlike linear regression models, do not assume homoescadicity, *i.e.,* constant variance on output variables (Dunn and Smyth, 2018). Also, outage counts are always positive and cannot be modeled using linear regression. GLMs connect the input parameter via the log link with input parameters.

$$ln(\mu) = \beta X \tag{3}$$

where μ is the mean number of outages in a city, X are input parameters parameters, β are the coefficients determined using Maximum Likelihood Estimates (MLE) (Dunn and Smyth, 2018). From Eq. 3, GLM assumes a linear relationship between the log of the mean of outages and input parameters. Han et al. (2009a) showed that the log of the mean of outages and input parameters have a non-linear relationship, which could be better modeled with GAMs through smoothing functions:

$$ln(\mu) = \beta_0 + \sum \beta_j f_j(x_j) \tag{4}$$

where $f_j(x_j)$ are the smoothing splines to fit non-linear input parameters (Yee, 2012). Negative Binomial regression holds for variables with positive counts and overdispersion, such as outage counts, resulting in a Negative Binomial distribution on the number of outages.

$$P(y;\mu,k) = \frac{\Gamma(y+1/k)}{\Gamma(y+1)\Gamma(1/k)}\left(\frac{\mu}{\mu+1/k}\right)^{y} \left(1-\frac{\mu}{\mu+1/k}\right)^{1/k} \tag{5}$$

where y is the number of outages, μ is the mean number of outages connected to input parameters as in Eq. 4, k is the overdispersion parameter that links the variance on y ($var(y) = \mu + k\mu^2$) as a function of the square of the mean to handle the overdispersion in outage counts.

3.2. *Modeling Historical Outages*

We used historical data of 3.6 million power outages for Hurricane Harvey (2017), Hurricane Micahel (2018), and Hurricane Isaias (2020) obtained from (poweroutage.us) aggregated at the city level for 1910 cities. This study is aimed at quantifying uncertainty in outages as a function of wind speeds. Hence, we only use three input parameters, including 3-s wind gust, population density as an indicator of the number of transformers (Liu et al., 2008), and percentage of the developed area as an indicator of the difference in the topological structure of the power grid in urban versus rural area (Petersen, 1982). A detailed explanation of the datasets is available in Arora and Ceferino (2022)

We used *MCGV* library in *R program* to fit Negative Binomial regression from Eq. 4 and 5 (Wood, 2017). We fitted quartic polynomials to the population density and developed land cover. For the 3-s wind gust, we fitted a polynomial of degree 1 to obtain a monotonically increasing behavior for outages with the 3-s wind gust.

R^2 is generally used to measure the goodness-of-fit for the linear regression model. Similarly, a pseudo - R^2 (also, R^2_{DEV}) is used to measure the goodness-of-fit for non-linear GAM models.

$$R^2_{DEV} = 1 - \frac{D(y,\hat{y})}{D(y,\bar{y})} \tag{6}$$

where $D(y,\hat{y})$ is the deviance for the fitted model, and $D(y,\bar{y})$ is the deviance for the null model. The output for the null model is the average of observed historical outages. Deviance measures the amount of variance explained by the fitted model, as explained in Dunn and Smyth (2018). For our fitted model, we observed a R^2_{DEV} of 0.50, which is less than the reported value of 0.81 for Negative Binomial Regression in Arora and Ceferino (2022) since the model in this paper only uses three input parameters instead of the 7 in Arora and Ceferino (2022). Note that R^2_{DEV} always increases with more input parameters. We used a fitted outage model to compute SAIFI (Eq. 1).

3.3. *Modeling Total Customer Interruption Duration*

According to the definition of SAIDI (Eq. 2), we need the total customer power interruption duration. Liu et al. (2007) modeled the time to recover the storm-induced power outages as a function of outage size since cities with more outages recover more slowly. Similarly, we model total customer power interruption duration as a function of outages.

$$ln(CD) = a * ln(O) + b \tag{7}$$

where CD is the total customer power interruption duration and O is the number of outages. We use *scikit* library in python (Pedregosa et al., 2011) to obtain coefficients a and b in Eq. 7. We used the log link in Eq. 7 as total interruptions will always be greater than zero for an outage event. We used historical data for Hurricane Isaias (2020), obtained from (poweroutage.us), for outages and total customer interruption duration to perform regression in Eq. 7. We show the regression line for total interruption duration and number of outages in Figure 1.

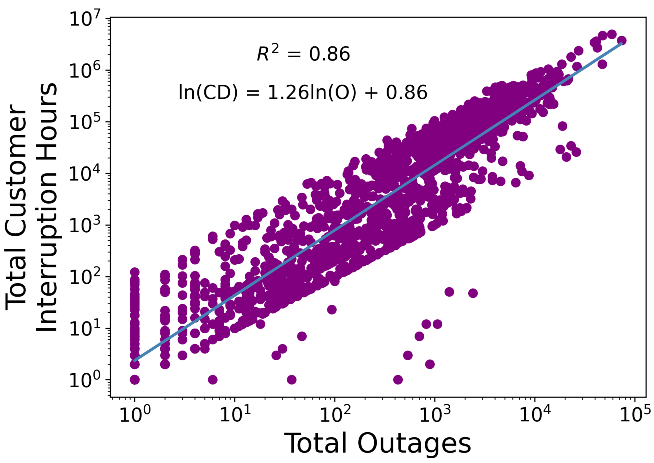

Figure 1: Regression between total customers interruption hours and total outages.

R^2 of 0.86 in Figure 1 represents a good fit between total interruption duration and outages, as more outages would require more time to recover, resulting in more total hours of customer interruptions. From Eq. 7, $ln(CD)$ is normally distributed as

$$ln(CD) \sim N(a * log(O) + b, \sigma^2) \tag{8}$$

where σ^2 is the standard deviation for the best-fit line in Figure 1. We used a fitted total customer interruption duration to compute SAIDI (Eq. 2).

4. Probabilistic Framework

Utilities mostly design their power systems to reduce the number of power interruptions under normal operating conditions. Utilities are rated based on their performance to reduce SAIFI, and SAIDI IEEE 1366 (2022); Brown (2002). Performance-based engineering can give the rate of observing performance indices for extreme events (Krawinkler, 1995).

$$\lambda(DV > x) = \int (P(DV > x|H) d\lambda_H \tag{9}$$

where DV in performance engineering is the decision variable (DV) (i.e., performance indices in this study), $\lambda(DV > x)$ is the rate of DV exceeding a value of x, λ_H is the hazard rate whose intensity H affects the decision variable, and $P(DV > x|H)$ is the probability of exceeding the decision variable given hazard. We adopted this methodology to assess the performance of power systems of cities in New Jersey, US. prone to hurricane hazards. For this study, we assume a city will observe only one in a year. However, a city might observe more than one hurricane in a year.

4.1. Wind Hazard

Strong hurricane winds devastate power systems, so the hazard for this study is wind speeds. We obtained 3-s wind speeds for return periods for 10, 25, 50, 100, 300, 700, 1700, and 3000 years from ASCE 7-16 wind maps (ASCE 7, 2016). Figure 2 presents the 3-s gust wind speeds for 10 year return period for cities in New Jersey.

4.2. SAIFI for 10-year return period

Using the probabilistic framework in Eq. 9, we can obtain the rate of outages.

$$\lambda(O > x) = \int (P(O > x|w) d\lambda_w \tag{10}$$

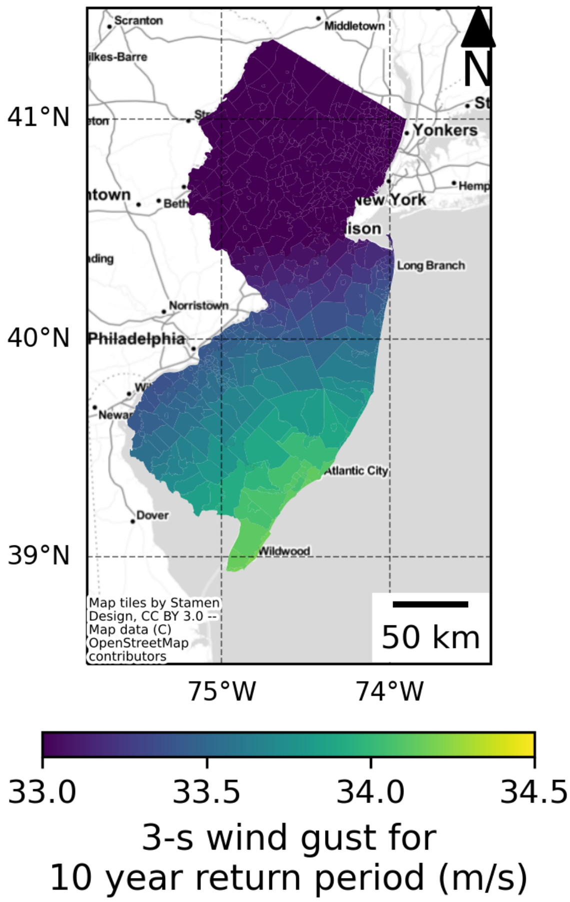

Figure 2: 3-s wind gust for 10-year return period in New Jersey

where $\lambda(O > x)$ is the rate of exceeding x outages, $P(O > x|w)$ is the proabability of exceeding x outages given a wind speed of w obtained from Eqs. 4 and 5, and λ_w is the rate of exceeding a particular wind speed which is the inverse of the return period obtained from ASCE 7-16 wind maps. Eq. 4 gives the link between mean outages and winds, and Eq. 5 gives the probability distribution of outages. However, ASCE 7-16 wind maps provide wind speeds at discrete return period intervals, so we perform a linear regression between the log of λ_w and w to obtain λ_w at all winds. A closed form is not available for integral Eq. 10, but a discretized sum can be performed to obtain $\lambda(O > x)$.

$$\lambda(O > x) = \Sigma P(O > x|w) |\frac{d\lambda_w}{dw}| dw \tag{11}$$

where $\frac{d\lambda_w}{dw}$ is the slope of best fit line between

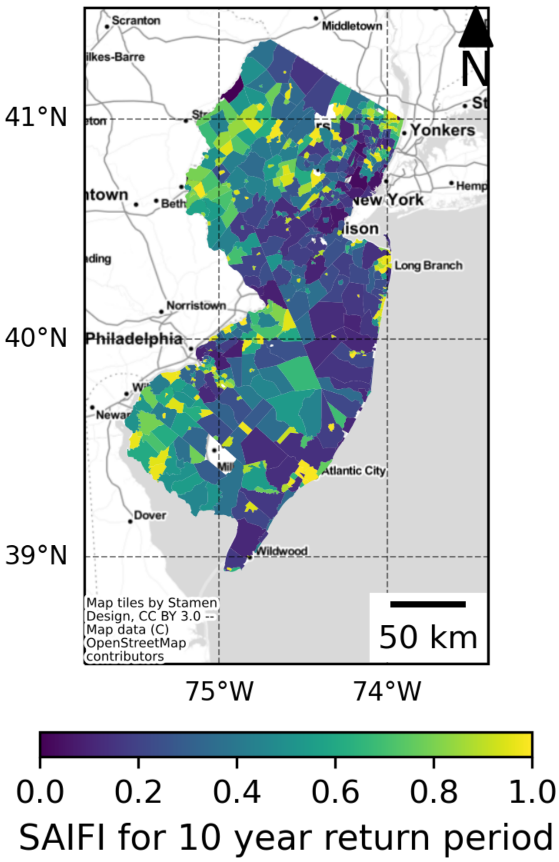

Figure 3: SAIFI for 10-year return period in New Jersey, US

$ln(\lambda_w)$ and w multiplied with λ_w. In equation 10, we can obtain outages x for a particular $\lambda(O > x)$. From Eq. 1, SAIFI is the fraction of total outages, and total customers served. Since the number of customers served is constant, we can find the rate of SAIFI as

$$\lambda(SAIFI) = \frac{\lambda(O > x)}{Total\ Customers\ Served} \tag{12}$$

For decision-making and prioritizing the upgrade of the power grid, utilities can compare the SAIFI of different cities for a fixed $\lambda(SAIFI)$. We present in Figure 3 SAIFI for cities in New Jersey for a 10-year return period (or $\lambda(SAIFI)$ = 0.1). Thus, in 10 years, cities will exceed the SAIFI presented in Figure 3.

SAIFI distribution in Figure 3 does not follow a pattern as such for winds in Figure 2. This is counterintuitive as high-value SAIFI is expected for high winds. The power outage model developed for this paper is also a function of the percent area covered by the developed area and population. The winds for the same return period have a low variation of only from 33m/s to 34.5 m/s within New Jersey, so other input features have more impact on the spatial variations of SAIFI. Therefore, we investigated the correlation between SAIFI and other input parameters. We found a small negative correlation (Pearson coefficient = -0.1) between SAIFI and the percent developed area in a city. The negative correlation can be attributed to varying grid patterns between rural and urban areas, as rural areas generally have radial grids which can have more power outages compared to gridded patterns in urban areas (Petersen, 1982; Brown, 2002). Also, we found a negative correlation (Pearson coefficient = -0.3) between SAIFI and population density, as low population density can indicate the low density of transformers in a city (Liu et al., 2008). The sparsity of components in power grids can reduce the resilience and lead to more outages (Brown, 2002).

4.3. SAIDI for 10-year return period

Similar to the rate for total outages, we can get the rate of total customer interruption duration. From Eq. 10, we can get $\lambda(O)$ (also, $\lambda(O > x)$). Further, Eq. 8 represents the distribution of total customer interruptions duration as a function of O. Hence, we can obtain the rate of total customer interruptions duration.

$$\lambda(CD > x) = \int (P(CD > x|O) d\lambda_O \tag{13}$$

where is $P(CD > x|O)$ is the probability of exceeding x total customer interruption hours given outages (O) obtained from Eq. 8. Similar to Eq. 11, we can discretize Eq. 13.

$$\lambda(CD > x) = \Sigma P(CD > x|O) |\frac{d\lambda_O}{dO}| dO \tag{14}$$

we perform a linear regression between $ln(\lambda_O)$ and O to obtain $|\frac{d\lambda_O}{dO}|$ for different outage counts. Eq. 2 gives the relationship between total customer interruption hours and SAIDI. Thus, we can find the rate of SAIDI as

$$\lambda(SAIDI) = \frac{\lambda(CD > x)}{Total\ Customers\ Served} \tag{15}$$

We present in Figure 4 SAIFI for cities in New Jersey for a 10-year return period (or $\lambda(SAIDI) = 0.1$). We found a negative correlation (Pearson coefficient = -0.22) between SAIDI and percent developed area, and also a negative correlation (Pearson coefficient = -0.20) between SAIDI and population. The results for SAIFI and SAIDI show that the presented framework can capture the behavior of power systems in large regions without using extensive information on power system components.

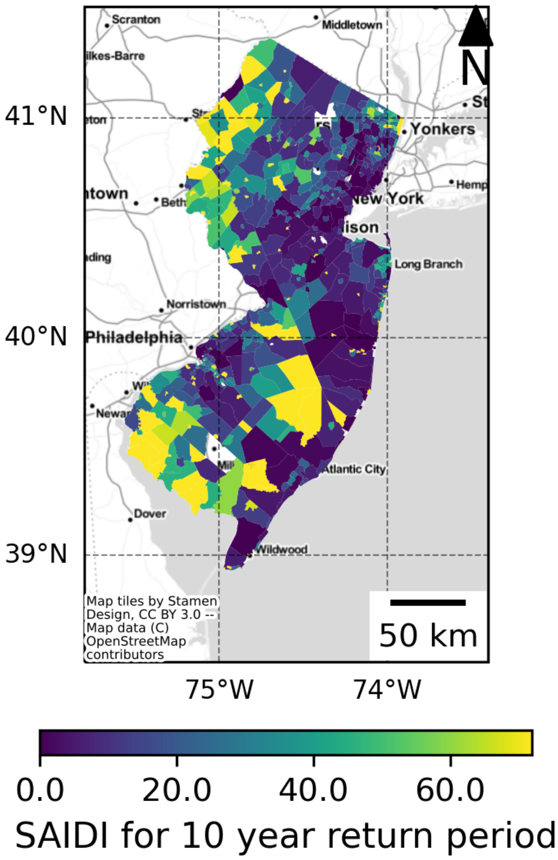

Figure 4: SAIDI for 10-year return period in New Jersey, US

5. Conclusions

We presented a probabilistic framework that couples a probabilistic outage model and wind hazard to estimate the rate of observing power system performance indices, SAIFI and SAIDI. We presented the results for SAIFI and SAIDI in New Jersey, US, for a return period of 10 years. We observed that including parameters such as land cover and population density could capture the behavior of power systems to hurricanes. For future work, a comprehensive power outage model could be adopted to consider the uncertainty not only in winds but also in other environmental parameters such as precipitation and soil moisture. Also, the possibility of multiple hurricanes in a year could be considered in future studies. The presented performance-based probabilistic study can inform stakeholders, such as utilities and regulatory bodies, like the Board of Public Utilities in New Jersey, about the expected performance of a system for different hazard levels.

6. ACKNOWLEDGEMENT

We are thankful for the financial support from the NYU Tandon School of Engineering Fellowship. Additionally, the Coalition for Disaster Resilient Infrastructure (CDRI) fellowship program supports this research.

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