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INNOVATIVE RISK ASSESSMENT APPROACH FOR STORM SURGE LOSSES USING ADAPTIVE MODELS AND MACHINE LEARNING ALGORITHMS

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Abstract. The increasing frequency and intensity of natural hazards have caused weather-related losses in the United States of more than $2.7 trillion from 1980 to 2024, with coastal communities being especially vulnerable. Beyond economics is the social and longer-term economic disruption resulting in a lack of resilience for many of these communities. This study addresses the limitations of current loss functions used in storm surge assessments, which often fail to propagate uncertainties or account for diverse building types. By using dynamically adaptive models to simulate the properties of contents, non-structural, and structural elements of buildings, a robust element-wise approach is achieved that considers both the uncertainty and variation in building properties. Monte Carlo simulations are used to derive loss functions for individual buildings, along with machine learning algorithms that predict building losses more efficiently by capturing the relationships between relevant variables, resulting in a more cost-effective model. This integration of AI-driven optimization and predictive modeling leads to the development of risk maps based on the existing hazard maps and building inventory data available for coastal communities. The results help improve decision-making for stakeholders and policymakers, leading to more accurate risk maps and better-informed mitigation strategies for coastal communities.

1 INTRODUCTION

From 1980 to 2024, weather disasters in the U.S. have caused losses of more than $2.7 trillion, with hurricanes alone accounting for about $1.3 trillion in damages [1]. Although natural hazard warning systems have been developed [2], the rising frequency and intensity of hurricanes underscores the need for improving resilience in coastal communities [3,4].

Hurricanes cause damage through both wind and storm surge, with storm surge often being the more destructive (and deadly) force in coastal communities due to severe flooding and infrastructure damage. Risk maps help visualize the likelihood and impact of these hazards, giving communities and decision-makers clearer insight into their vulnerabilities and loss [5]. Wind hazard maps initially relied on mathematical methods [6] but have since evolved through simulated hurricane catalogs [7–9]. For storm surge, early approaches like NOAA’s Joint Probability Method [10] and models such as Advanced Three-Dimensional Circulation Model for Shelves, Coasts, and Estuaries (ADCIRC) [11] and Sea, Lake, and Overland Surges from Hurricanes (SLOSH) [12] are used to simulate coastal inundations.

Loss assessments have traditionally relied on historical data [13] or fragility curves addressing structural failures [14,15]. Nonstructural damage also matters, as shown in models that estimate losses based on component repair costs [16]. FEMA’s HAZUS model includes structural and nonstructural damage along with contents [17], but its deterministic approach limits uncertainty propagation. By contrast, probabilistic analyses like Monte Carlo simulation offer broader outcome representation.

This paper enhances the element-wise storm surge loss approach by expanding building types and propagating uncertainties in resistance elevations (the elevation of a component at which it becomes damaged beyond repair) and costs using Monte Carlo simulation. With building inventories from the NSI dataset [18] and SLOSH surge data used as inputs, a machine learning model was developed for large-scale analysis. This study aims to align SLOSH and ASCE 7 maps [19] for multiple hurricane categories and return periods and generate annual hurricane surge loss risk maps to guide policy and insurance decisions.

2 METHODOLOGIES

2.1 Loss assessment model development

In previous works [16], the element-wise loss estimation process involves modeling each damageable component of a building by assigning probabilistic distributions to their replacement costs and the height at which an element fails due to flooding. Using Monte Carlo simulations, random values for these parameters are generated across several iterations for each flood height. At each height, the model evaluates whether elements fail, sums the associated losses, and averages them across iterations to compute the expected loss. Repeating this for all flood heights produces a loss curve for the building, representing its vulnerability to storm surge.

To efficiently generate loss curves for a wide range of building types across large coastal regions, an adaptive modeling approach is used [20]. In this method, instead of manually creating models for every structure, 25 base models were developed using the HAZUS occupancy types. These base models are then calibrated using key building attributes such as number of stories, foundation height, and building area, referred to as dynamic variables in this study. Applying dynamic variables to base models for each occupancy allows for the representation of buildings within the same occupancy class but with varying dimensional characteristics, enabling scalable loss estimation while capturing variability in building features.

Each building element’s cost is calculated using a “quantity function,” which links dynamic variables to the quantity and cost of components. By automating this process, the model can efficiently produce loss curves across thousands of buildings using a combination of probabilistic input and scalable cost estimation.

Although dynamic models prioritize uncertainty propagation, they are computationally demanding for large communities. To address this, a machine learning (ML) approach is explored. For each occupancy, over 2000 buildings are used to train ML models that can predict loss. Figure 1 shows the results of a sensitivity analysis used to determine the appropriate number of buildings for the training process. Various regression models are tested, with linear regression and regularized linear models failing to capture the non-linear relationships between dynamic variables and loss. The XGBoost model is selected, as it effectively handles complex non-linear relationships and overfitting, showing improved performance in predicting loss. Figure 2 shows the predicted vs. actual values for COM2 occupancy.

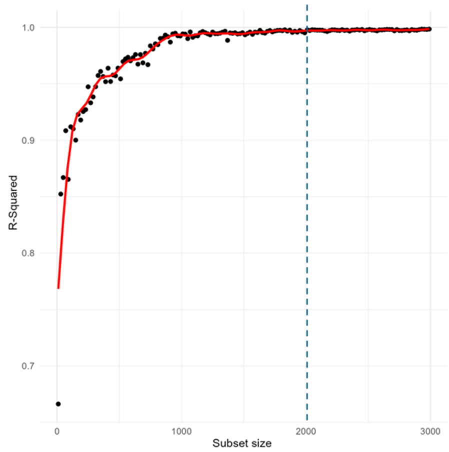

Figure 1: Sensitivity analysis R-squared results for RES4 occupancy

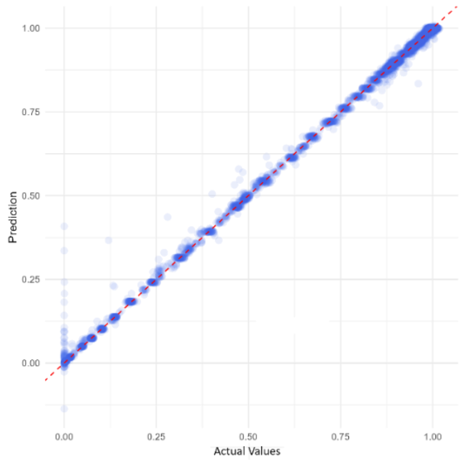

Figure 2: Predicted vs. actual values for COM2 occupancy

2.2 Probabilistic loss assessment

By integrating SLOSH storm surge maps with ASCE 7-22 wind maps, a synchronized hazard platform is developed from publicly available data. The annual loss for a building inventory is computed using the conditional probability of loss given a hurricane category and the annual probability of each category's occurrence. This can be expressed as

$$Annual\ Loss = \sum_{i=1}^{4} P(Loss_i|Cat_i) \times P(Cat_i) \tag{1}$$

where $P(Loss_i \mid Cat_i)$ is the probabilistic loss for category *i* hurricane and $P(Cat_i)$ is the Annual likelihood for Category *i* hurricane.

To synchronize wind and surge data, 3-second gust wind speeds over land (from ASCE) are converted to 1-minute average speeds over open water, using standard coefficients from ASCE 7-22. High-resolution ASCE 7-22 wind maps for 11 mean recurrence intervals are used to calculate $P(Cat_i)$. A wind speed vs. return period can be developed for any location, from which a wind speed vs. annual probability curve (Figure 3) is derived. A reverse Weibull distribution is then fitted to estimate the annual probability of each hurricane category using its average wind speed. Using SLOSH surge maps, $P(Loss_i|Cat_i)$ is predicted, with SLOSH data and the NSI dataset as inputs. Combining these results with the location-specific probability of each hurricane category yields the annual probabilistic loss from surge.

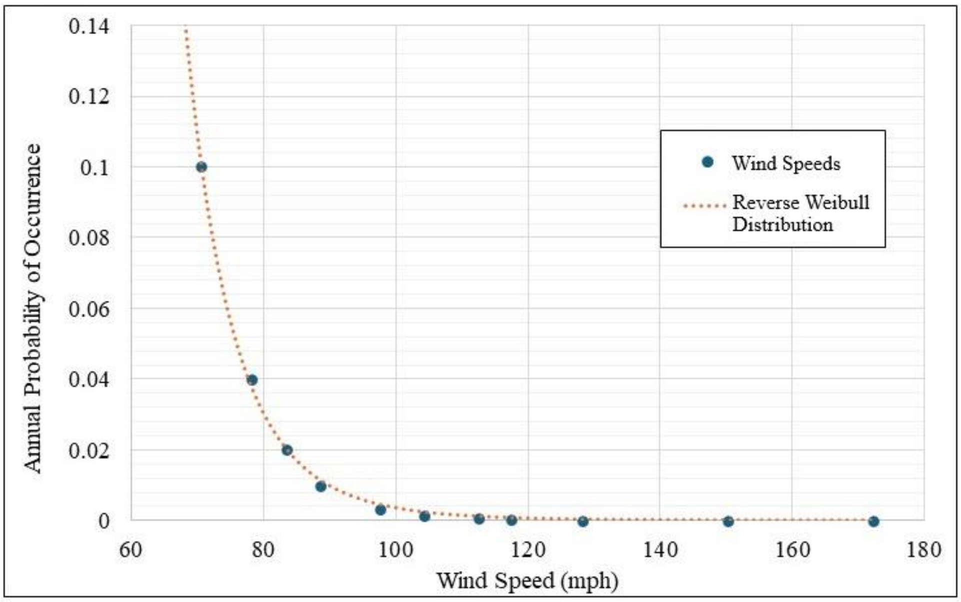

Figure 3: Wind speed vs. annual probability curve for a sample location

3 RESULTS

The annual probabilistic loss is estimated for over 17 million wood buildings in the NSI dataset across East and Gulf Coast communities using the proposed probabilistic framework. These results are aggregated at census tract level to provide a clear spatial understanding of hurricane surge risk across communities (Figure 4). However, the methodology is flexible and scalable, capable of producing loss estimates at the individual building level, or aggregated to broader spatial units such as counties, states, or even nationwide. This adaptability supports both localized resilience planning and regional or state-scale risk assessment.

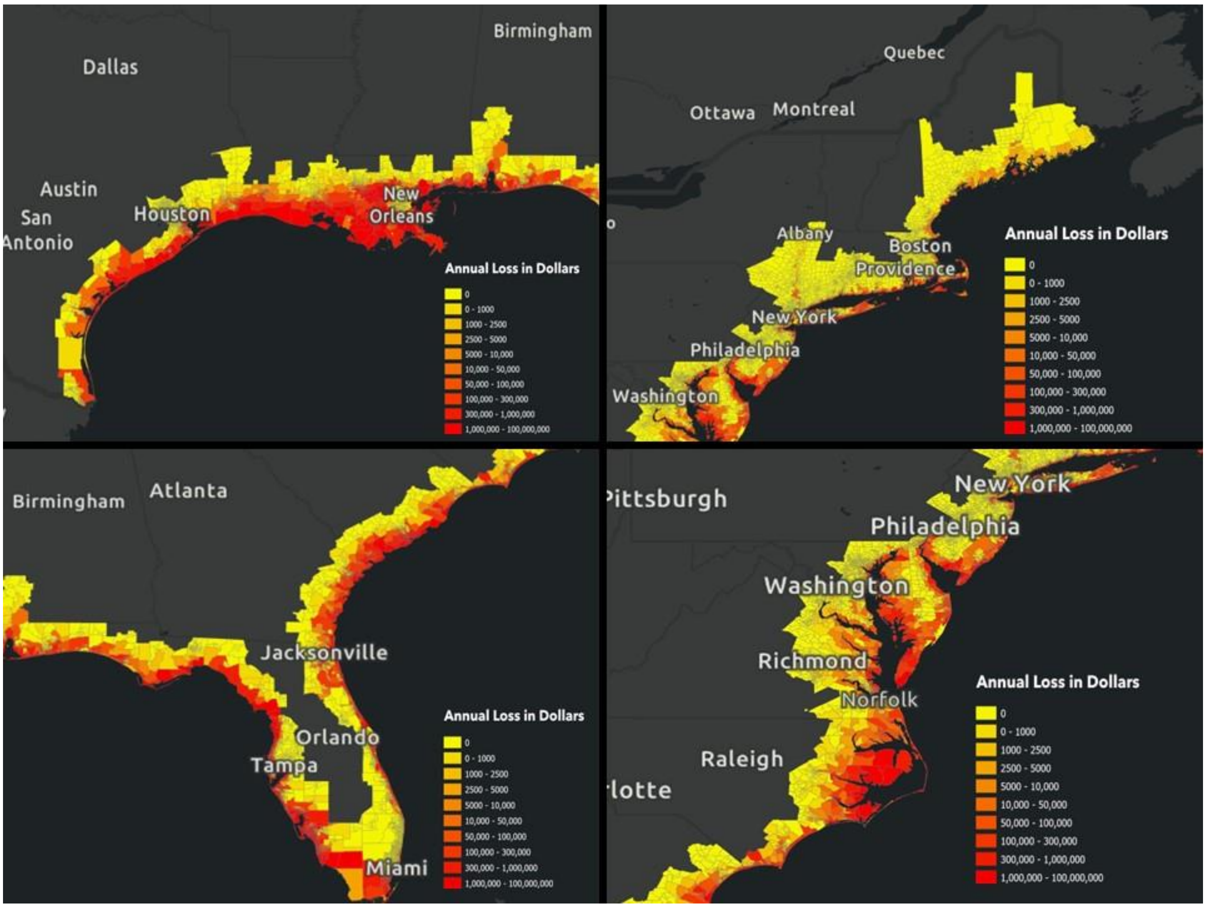

Figure 4: Loss based risk map for East and Gulf Coast communities in census tract scale.

The resulting loss maps highlight the spatial variability in surge-induced damage, shaped by both hazard intensity and local exposure. It is evident from Figure 4 that certain tracts do not experience significant damage due to the absence of substantial exposure or hazard. In other words, in areas with low construction rates or low surge values, the local loss is inherently lower as one would expect.

4 CONCLUSIONS

This study demonstrates a novel, scalable approach to quantifying hurricane surge risk at the building level across coastal U.S. communities. While an adaptive model was developed in the initial phase, the final machine learning-based loss model retains the precision of the original element-wise methodology. This significantly reduces computation time, making it practical for large-scale applications. Embedded within a probabilistic framework, the model enables the development of detailed risk maps that support resilience planning and resource allocation. Notably, the entire workflow relies solely on publicly available data sources, ensuring transparency and reproducibility.

By enabling annualized loss estimates at varying spatial resolutions, the framework supports diverse decision-making needs, from federal policy development to community-level hazard mitigation and household preparedness. This framework allows for more precise allocation of resources, improving the cost-effectiveness of resilience investments and enhancing the responsiveness of adaptation strategies across all levels of governance and society.

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