Application of a data-driven machine learning framework for predicting hurricane damage to buildings in Hurricane Ian

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SUMMARY:
A machine learning framework developed previously by the authors was employed to hindcast damage to residential buildings impacted by Hurricane Ian in September 2022. This data-driven framework considers three categories of input – building features, hazard intensity, and geospatial features – to predict hurricane damage at the building level. The framework was developed and internally validated with historical hurricanes, and Ian provided the first opportunity to test the model on a new hurricane which was not present in the training data. A validation set of residential buildings was compiled by referencing post-event aerial and street-view imagery. Modifications were then made to the framework via undersampling to balance the proportion of damage states represented in the training data and the inclusion of socioeconomic features. Preliminary results for Hurricane Ian indicated a need for input features that better capture the load effects of coastal hazards. To this end, computational simulations are being investigated to forecast wind, waves, and water levels for a given hurricane. Forecasted hazard features from simulations will then enable the machine learning model to operate in its objective as a tool for forecasting hurricane impacts on infrastructure before hurricanes make landfall.

Keywords: hurricane, damage prediction, machine learning

1. MOTIVATION

Hurricanes in the US Gulf of Mexico and Atlantic coasts represent the most significant natural hazards to human safety, infrastructure stability, and economic disruption. Annualized hurricane impacts in the US total billions of dollars, with single-year peaks reaching hundreds of billions (Pielke et al., 2008). Additionally, US landfalling hurricanes are directly responsible for an average of 50 fatalities each year, while a single event may reach over 1,000 (e.g., Hurricane Katrina)

(Rappaport, 2014). Both losses via infrastructure damage and loss of life stand to be mitigated by accurate predictions not only of hurricane track and intensity, but also impacts on coastal infrastructure. Modern meteorological forecasting has effectively informed coastal communities of expected hazards to drastically reduce hurricane-related deaths compared to mid-twentieth-century forecasting (Willoughby et al., 2007). However, improvements in forecasting structural impacts are still needed to better influence individuals' risk perception which largely relies upon metrics that can be interpreted and trusted across all demographics in a region (Bowser and Cutter, 2015; Willoughby et al., 2007). Klepac et al. (2022) developed a framework to provide such risk analysis throughout a community at the individual building scale. This model was refined and applied to Hurricane Ian in a hindcast mode as a first step in validating its performance as a tool for coastal community stakeholders to inform decision-making and provide insights into coastal infrastructure resilience.

2. METHODS

2.1. Machine Learning Framework

The model used for predicting hurricane damage to residential buildings during Hurricane Ian is an adaptation of the data-driven machine learning (ML) model developed previously by the authors (Klepac et al., 2022). This model uses the random forest (RF) algorithm, an ensemble of decision trees (DTs). In a DT, observations in the training data are sorted according to their feature values to establish decision rules for sorting new data and enable the output of probabilities that new data observations belong to available target classes (i.e., damage states) (Breiman et al., 1984). In an RF, an ensemble of such DTs is assembled, with each DT considering only a subset of features when sorting training data. The RF output for new data is the average of the probabilistic output of all its DTs (Breiman, 2001). The target class, damage state (DS) in this case, for each observation is determined as that with the greatest probability as output by the RF.

The RF model was fitted to training data of residential buildings whose categorical DS and building features were tabulated by National Science Foundation (NSF) funded Structural- and Geotechnical Extreme Events Reconnaissance (StEER and GEER) networks following Hurricanes Harvey (2017), Irma (2017), Michael (2018), and Laura (2020). The assigned DS in the reconnaissance data follows the methodology of Hazus of five DS ranging from "no damage" to "destruction" (Vickery et al., 2006). These DS were adapted for the ML model to DS-0: No Damage (Hazus DS-0), DS-1: Non-Structural (Hazus DS-1 and DS-2), and DS-2: Structural (Hazus DS-3 and DS-4), which coincide with Hazus DS descriptions. Each of the buildings (9 features) was also coupled with wind and water hazard (3 features), geospatial (5 features), and socioeconomic (5 features) data corresponding to the buildings' locations. The RF model was fitted to 2,403 single-family residential buildings containing all 22 features. A testing set of 100 single-family residential buildings impacted by Hurricane Ian was compiled by obtaining building features and assigning DS through the use of post-event aerial and street-view imagery provided by Site Tour 360 et al. (2022) and concatenating the remaining hazard, geospatial, and socioeconomic features associated with each building. These buildings were selected randomly throughout the imagery coverage area, without prior consideration of the damage they received.

2.2. Revised Input Features

The input features for training and testing data mostly coincide with those in the model formulation of Klepac et al. (2022) with one substituted feature and several additional features. At the time of analysis, Federal Emergency Management Agency depth grids, which were used to obtain total water levels at building locations for the training data, were not available for the Ian impact area. Instead, this feature was substituted with high water marks (HWMs) obtained for each hurricane in the training and testing data from the US Geological Survey Flood Event Viewer (2022), and the elevation of the nearest HWM was assigned to each building.

Literature pertaining to hurricane risk assessment suggests a correlation between residential building damage and socioeconomic demographics of the building's occupants. Two sources were identified to leverage these factors in DS predictions. First, median household income at the Census tract-level from Federal Financial Institutions Examination Council Census data (2022) was assigned to each building. Second, the Centers for Disease Control and Prevention Social Vulnerability Index (SVI) (2020) was used to obtain 4 additional features related to socioeconomic factors. These SVI features are Census tract-level rankings of "socioeconomic status", "household characteristics", "racial and ethnic minority status", and "housing type and transportation" determined from US Census data.

3. PRELIMINARY RESULTS AND DISCUSSION

The RF model was tuned and fitted to all the training data, then Hurricane Ian testing data were introduced to make DS predictions. Initial testing results of 35% accuracy and an average f1-score of 0.18 were considerably lower than the 76% accuracy on a validation set during initial model development by Klepac et al. (2022). Specifically, the model predicted all Hurricane Ian testing observations as DS-1. A potential explanation lies in the DS distribution among the training dataset, in which DS-1 represented 62% of observations while DS-0 and DS-2 represented 18% and 20%, respectively. When training data contains a target class imbalance, decision rules in the RF are more likely to lead to a majority class prediction while providing lesser reinforcement of minority classes.

A common method to counter class imbalance is undersampling, or eliminating some training observations belonging to the majority class, DS-1 in this case. The Near Miss algorithm, a k-Neighbors undersampling method in the Imbalanced Learn package for Python, was employed to balance DS representation in the training data (Lemaître et al., 2017). This algorithm eliminates majority class (DS-1) samples based on their proximity in the feature space to minority class (DS-0 and DS-2) samples until the number of majority class samples is equal to that of the next largest class. Undersampling proved to assist prediction accuracy as indicated by 53% accuracy and an average f1-score of 0.41 among testing data when the RF was fitted to undersampled training data.

In addition to class imbalance, at least two other factors are believed to hinder the RF model's predictive performance. First, the surface roughness feature used in the RF model was the roughness length obtained at the Census tract-level, which is too coarse of a resolution. For example, a given Census tract on Pine Island, FL contains urbanized areas, agricultural fields, and dense mangrove forests, but the entire region would be assigned the same roughness value. An ongoing step forward is evaluating the fidelity and resolution of available land cover products which contain more detailed information than simply a roughness length. Second, the hazard features used in this model likely do not provide an adequate representation of hurricane hazard loading. Particularly, the HWMs representing water levels do not have sufficient resolution, nor do HWMs explain the cause of the observed water level (e.g., storm surge, precipitation, or riverine flooding) or account for wave forcing. Rather than utilize such a coarse data source, a higher resolution feature may come from computer modeling, which is currently being explored. With this method, meteorological forcing will be obtained as hurricanes develop and used to conduct simulations which output water levels, wave height, and wind speeds on finer resolution grids.

The ongoing process to include hurricane simulation output as hazard feature input into the ML model will move the model forward toward its objective function as a forecasting tool for impacts to infrastructure. When this methodology is implemented, hazard features will be obtained as the hurricane develops and updated as the track progresses, geospatial and socioeconomic features will be readily obtained for the expected impact region, and building features will be generated from either publicly available or artificial intelligence assisted building inventories for the impact region. The resulting product will then work in real-time to predict hurricane damage to buildings and update those predictions as the hurricane approaches and uncertainty in the track is reduced.

ACKNOWLEDGEMENTS

This research is supported by the National Oceanographic Partnership Program (Project Grand N00014-21-1-2203) and the University of Florida. This support is gratefully acknowledged.

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