Impact of Climate Change to Hurricane Loss to the Gulf Coast of the US

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ABSTRACT:

Hurricanes are one of the most destructive natural disasters in the US coastal region. The increasing trend of global temperature is expected to continue in the future, and the coincidentally increasing sea surface temperature has a potential effect on the hurricane intensity and frequency. However, the design wind load specified in ASCE 7 was derived based on long-term averaged hurricane statistics and does not consider the possible future climate conditions. Therefore, the objective of this study is to develop a non-stationary hurricane model to investigate the impact of climate change on the hurricane risk for buildings in the US Gulf Coast states.

Relationships between climate variables and hurricane parameters are investigated. This study considers regional sea surface temperature and relative humidity as changing climate variables, and the central pressure difference and the proportion of major hurricanes in all hurricanes are considered as changing hurricane characteristics. Using nonlinear autoregressive neural networks, the future hurricane parameters for near and long-term projections considering a climate scenario (RCP8.5) by the IPCC are predicted. Site-specific hurricane tracks considering climate change scenarios are developed, and consequent building-related economic losses are estimated using HAZUS-MH. It is suggested that a significant increase in building-related economic losses is expected in the future.

1. INTRODUCTION

Pielke et al. (2008) reported that the normalized annual average damage caused by hurricanes in the continental United States over the past one hundred years was about $10 billion dollars every year. Since 1980, there has been reported an increasing trend of the intensity, frequency and duration of North Atlantic hurricanes, and even the frequency of the most destructive hurricanes (Category 4 and 5) has increased (Garfin et al. 2014; Olsen et al. 2015). Moreover, a warming trend has been reported by the United Nations Intergovernmental Panel on Climate Change (IPCC 2013). The continually increasing trend of global temperature has a potential effect on hurricane intensity and frequency. However, the design wind load specified in ASCE 7 was derived based on long-term averaged hurricane statistics and does not consider possible future climate conditions. On the other hand, most of the existing studies assessing hurricane risk did not establish an explicit relationship between changing climate conditions and hurricane characteristics or by adopting a linear relationship between SST and hurricane wind speed (Bjarnadottir et al., 2011; Mudd et al., 2014; Pant and Cha, 2018). Therefore, a more sophisticated model for the relationship between changing climate conditions and the hurricane characteristics is needed to improve hurricane risk assessment.

This study aims to estimate the building-related economic loss of the US Gulf coast from hurricanes with considering the changing climate conditions. The relationship between hurricane characteristics and climate variables such as SST and relative humidity under changing climate is investigated, and the hurricane parameters in the future with climate change is predicted by using nonlinear autoregressive with exogenous input artificial neural networks (NARX-ANNs). Central pressure difference and the ratio of the number of major hurricanes to the number of total hurricanes in a year (RMH) are considered as the nonstationary hurricane parameters affected by climate change. The future hurricane parameters for near-term projection (2020 to 2030) and long-term projection (2090 to 2100) considering the climate scenario (RCP8.5) by the IPCC are predicted. Based on the projected hurricane parameters and regional hurricane statistics, hurricane tracks are simulated for three study regions in the US Gulf Coast that encompass five states from Texas to Florida to clarify the possible regional disparity in the hurricane risk considering climate change impact. Hurricanes are simulated at landfall for simplicity and reducing the computation time. To estimate the building-related potential damage and associated economic losses, the HAZUS-MH Hurricane Model is employed in this study for no climate change, near-term projection and the long-term projection scenarios.

2. ARTIFICIAL NEURAL NETWORK FOR TIME SERIES PREDICTION

In this study, the nonlinear autoregressive network with exogenous inputs (NARX) is utilized for time series modeling. NARX is a recurrent dynamic network constructed by connecting its output to the input layer to enclose the network, and a dynamic feedback is achieved while the recurrent output as well as the external input is used in the regression. Except using the tapped time delay input and output variables and the recurrent output, the basic architecture and training procedure is similar to the usual FFBP-ANN (Menezes and Barreto, 2008). To train the network, an open-loop configuration (dash-dot line in Figure 1) is used to make the network learn a specific pattern. The training, validation and testing processes are conducted in an open-loop network. In Figure 1, u is the external input and y is the target response; TDL is the tap delay line for creating step delays; $\hat{y}$ is the prediction of the network; w and b are weight and bias, respectively and their subscripts h and o denote for hidden layers and the output layer, respectively. In this study, selected climate variables (e.g., SST and relative humidity) serve as the external inputs and the observed hurricane parameters (e.g., historical hurricane CPD and RMH) serve as the target response during the training process. For dynamic modeling, current hurricane parameters are regressed on current and previous climate variables as well as previous hurricane parameters.

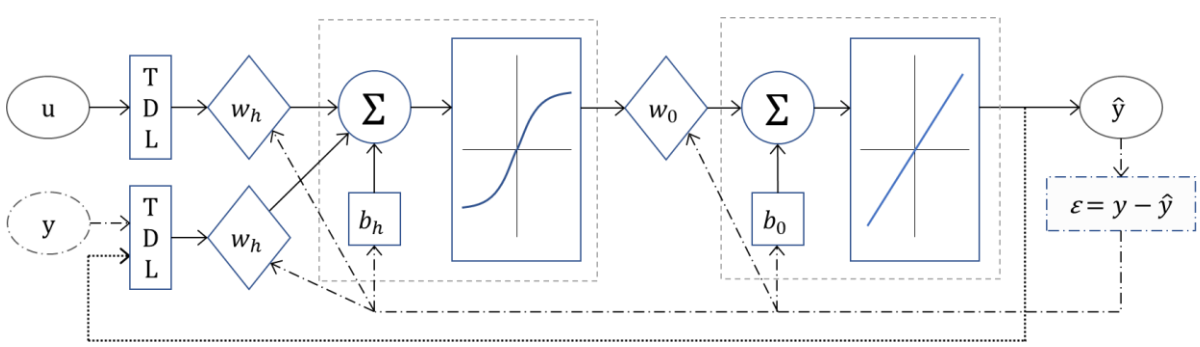

Figure 1 Configuration of the NARX network; the dash-dot line represents training process of open-loop form and dotted line represents prediction process of close-loop form

To conduct prediction, the configuration of the network is changed to a closed-loop (dotted line in Figure 1) while the trained network is ready to use for multi-step-ahead prediction. This closed-loop network is then used to predict future hurricane parameters by using the predicted hurricane parameters connected back to the input layer together with the external input, the projected climate variables.

3. HURRICANE PARAMETERS CONSIDERING CLIMATE CHANGE

In this study, NARX-ANNs are utilized to forecast the nonstationary hurricane parameters, and three variable selection approaches are applied to identify key climate variables to serve as input variables of NARX networks. Two of hurricane parameters used for simulation are considered as nonstationary parameters: the annual average of hurricane central pressure difference (CPD) and the ratio of the number of major hurricanes to the number of total hurricanes in a year (RMH).

3.1. Study Regions

In this study, for deriving the site-specific hurricane parameters, the US Gulf Coast region is divided to 3 study regions to simulate hurricanes on specified coastlines. Each region comprises coastlines where hurricanes landfall as shown in Figure 2. The accumulated hurricane economic loss is estimated within the specified region.

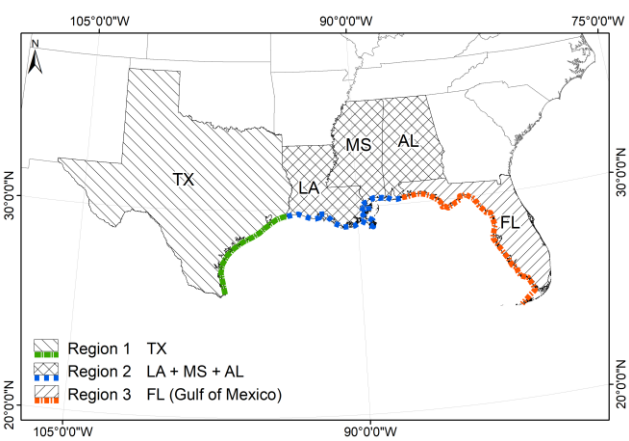

Figure 2 Study regions in this study

3.2. Hurricane Parameters

Six primary hurricane parameters including annual occurrence rate (AOR), approach angle (AAG), translation wind speed (TWS), central pressure difference (CPD), radius to maximum wind speed (RMW), and the filling rate constant (FRC) are used to simulate hurricanes at landfall. In this study, it is assumed that the AOR, AAG, TWS and FRC are stationary in hurricane simulation. The AAG and TWS of the storm is modeled with the discrete Markov chain to simulate complete storm track after landfall for the subsequent economic loss estimation, where the transition probabilities are calculated based on past hurricane records. On the other hand, nonstationary hurricane parameters include the RMW, CPD and the relative frequency of major hurricanes. The CPD is used to derive the radius to maximum wind speed (Vickery and Wadhera 2008). Therefore, there are two independent nonstationary hurricane parameters predicted in this study. Based on historical hurricane data, the central pressure difference for non-major hurricanes (CPDNM) and the central pressure difference for major hurricanes (CPDMH) are also derived to distinguish the CPD for hurricanes in different categories. It has been suggested that the frequency of high-intensity hurricanes is increasing (Emanuel 2008; Knutson et al. 2010). Therefore, this study considers changing climate conditions also influence the fraction of major hurricanes in all hurricanes (used as the acronym, RMH). Both the CPD and RMH are calculated based on historical data. Here, the site-specific CPD is defined as the annual average of the hurricane CPD of hurricanes making landfall at the study region coastline. On the other hand, RMH is defined as the ratio of the number of major hurricanes to the number of all hurricanes developed in the North Atlantic Ocean.

Historical hurricane data from 1944 to 2016 in the International Best Track Archive for Climate Stewardship (IBTrACS v03r10) data set is utilized to derive both nonstationary and stationary hurricane parameters. The storm track information including storm coordinates, central

pressure and wind speed for every 6 hours as well as at landfall in IBTrACS is used to determine necessary hurricane parameters for hurricane simulation.

4. TIME SERIES PREDICTION OF NONSTATIONARY HURRICANE PARAMETERS

4.1. Climate Variables for Nonstationary Hurricane Parameter Prediction

Two categories of climate variables including SST variables and relative humidity variables are considered to depict the trend of future hurricane characteristics. SST variables are calculated from the Extended Reconstructed Sea Surface Temperature (ERSST) Version 5 data set and relative humidity variables are calculated from International Comprehensive Ocean-Atmosphere Data Set (ICOADS) Release 3.0. Monthly values SST and relative humidity data are reported on a 2° × 2° grid in both datasets, and the data within the time span between 1944 and 2016 are extracted for analysis. Derivation of all climate variables are shown in Figure 3. Both SST and relative humidity are derived for six basins and three basic statistics. Beside these SST and RH variables, this study also considers annual mean SST difference (SSTD) between the tropical Atlantic Ocean and tropical Indian Ocean and between tropical Atlantic Ocean and tropical Pacific Ocean as variable candidates because they are directly related to the formation and intensity of the resulting hurricanes (Latif et al., 2007).

4.2. Climate Variable Selection

Before the climate variable selection, preselection of the group of the climate variables is performed. To reduce the number of predictors, the variables are grouped together to perform multivariate regression and evaluate the performance of each group, and the variables from the selected group are used for the following variable selection to further identify key climate variables. Consequently, variable group of 38 variables are selected for further variable selection, and the selected group includes the group of SST and RH variables of the North Atlantic Ocean (tropical Atlantic plus non-tropical Atlantic Ocean) with two SSTD variables.

The purpose of variable selection is to determine a set of input variables that collectively interpret the output variables, and an adequate model can be developed to predict hurricane characteristics. This study adopts three variable

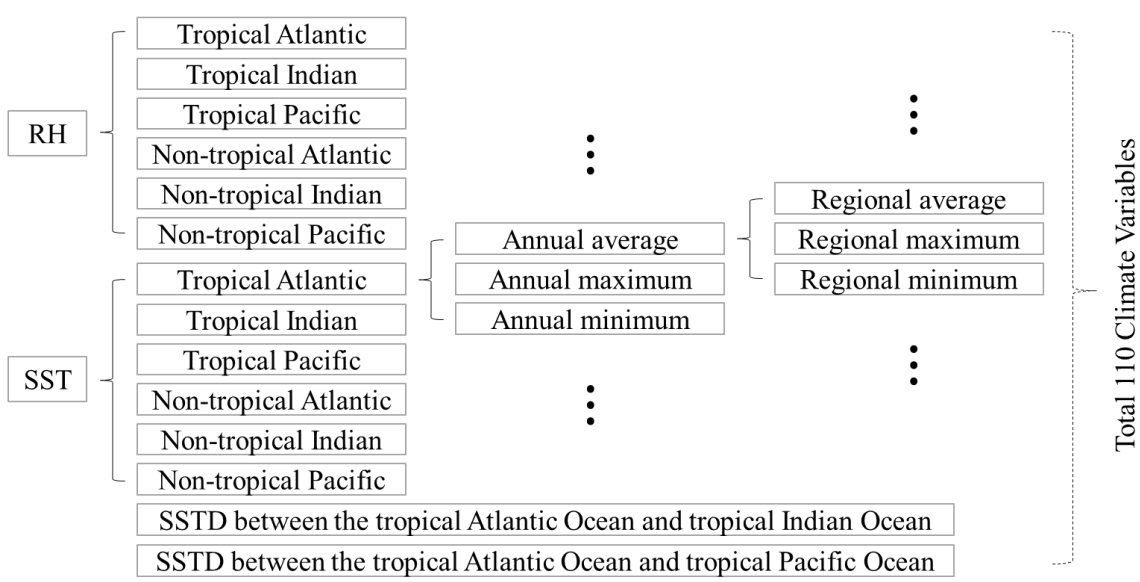

Figure 3. Derivation of climate variable candidates before variable selection

selection approaches, including marginal effect screening, Akaike information criterion (AIC) and elastic net variable selection to identify climate variables used to describe nonstationary hurricane parameters. The procedure of climate variable selection is shown in Figure 4.

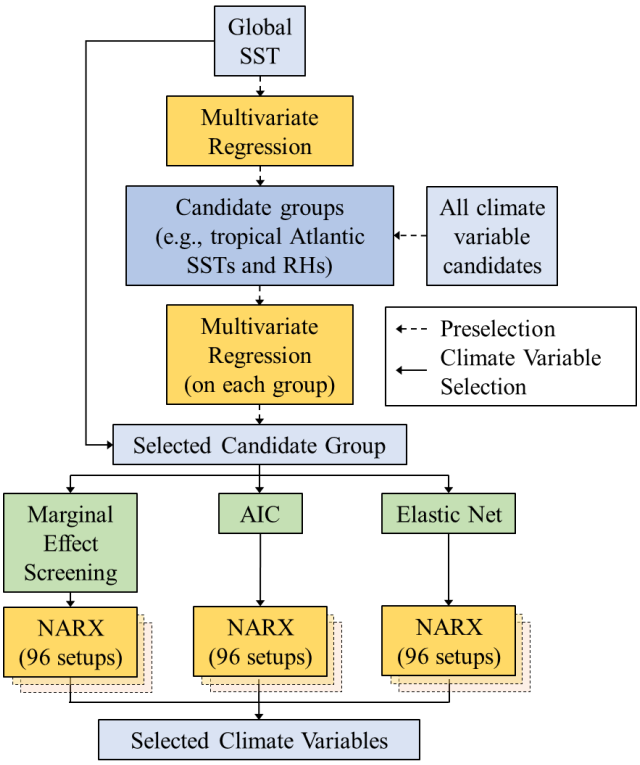

Figure 4 Flow chart of climate variable selection

4.3. NARX Network Setup and Ensemble Modeling

Different network setups are investigated for enhancing the prediction accuracy. In this study, five NARX network attributes are investigated as shown in Table 1, and totally 96 combinations of network setups are considered. Furthermore, there are three sets of climate variables selected by the three variable selection methods for each NARX network. Subsequently, each hurricane parameter is predicted by the 288 networks.

Weighted ensemble modeling (Zhou et al. 2002) is employed in this study to improve the network performance and prediction robustness. During weighted ensemble modeling, weighted ensemble of 500 individual networks with the same network setup form a combined NARX model. The mean square error (MSE) of the training data is calculated for the network after the training of each individual network. The MSE is then used to determine the weight of an individual network as

$$w_i = \frac{1/MSE_i}{\sum_{i=1}^{N} 1/MSE_i} \tag{1}$$

where $N = 500$. MSE of the testing data is then used to evaluate the performance of the ensemble model. The model with the lowest test MSE is selected from 288 models (96 NARX network setup and 3 variable selection methods) for the hurricane parameter prediction.

Table 1. NARX network setup for investigation

Network Attributes	**Tested Setups**
Number of hidden layers	1 or 2 hidden layers
Number of hidden nodes	10 or 15 hidden nodes in a hidden layer
Number of feedback delay	2 to 5 steps of tapped delay applied to variables
Training algorithm	- Levenberg-Marquardt algorithm - Resilient backpropagation algorithm
Transfer function	- Hyperbolic tangent sigmoid function - Log-sigmoid transfer function - Symmetric saturating linear transfer function

4.4. Nonstationary Hurricane Parameter Predictions

By using the selected ensemble model, hurricane parameters for future climate conditions are predicted based on the RCP 8.5 climate change scenario proposed by the IPCC (2013). It is assumed that the global SST linearly increases 3.1°C relative to the reference period, 1986 to 2005 for simplicity. Consequent selected climate variables and hurricane parameters are predicted by using the projected global SST. Figure 5 shows the five-year moving average of forecasted CPD (solid line) and RHM (dotted line). The annually average hurricane CPD is projected to

dramatically increases from 29 to 53 mb from 2020 to 2100, and the increasing CPD is likely to result in higher intensity hurricanes. On the other hand, RMH is projected to increase 6%, and this suggests that although hurricane frequency may not be affected by climate change, the number of intense hurricanes is expected to increase and can reduce in a higher overall economic loss.

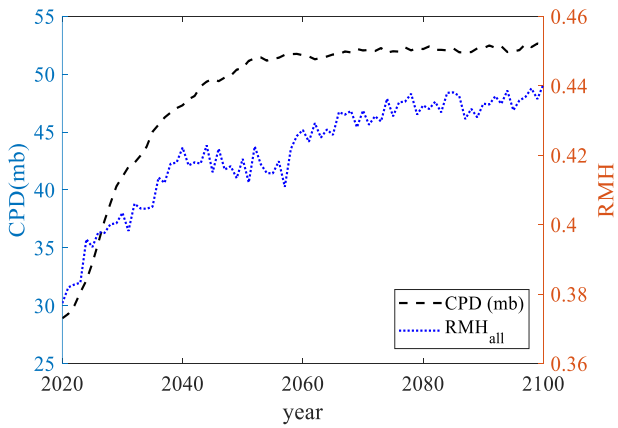

Figure 5 Projected Hurricane CPD and RHM under changing climate conditions

5. FUTURE HURRICANE LOSS REDICTION

5.1. Hurricane Simulation

By using Latin hypercube sampling to reduce computation time, hurricane parameters are simulated for generating hurricanes at landfall, and subsequent inland storm tracks are constructed by using derived transition matrices. For each study region, ten simulations are conducted under three climate conditions: 1) no climate change, 2) year 2020 to 2030 under RCP8.5 and, 3) year 2090 to 2100 under RCP8.5. The total number of hurricanes is determined by the annual occurrence rate for each study region of each scenario in each simulation, and then the projected RMH_{ldf} is used to determine the number of the major and non-major hurricanes simulated on the coastline. Through simple linear regression of historical data, the relationship between the forecasted RMH for all hurricanes formed on the Atlantic Ocean (denoted as RMH_{all}) and landfall RMH (denoted as RMH_{ldf}) is established as shown in Eq.2.

$$RMH_{ldf} = 0.846RMH_{all} + 0.130 \qquad (2)$$

A 10-year time interval is adopted to avoid the non-occurrence as the limited number of simulations since major hurricanes are considered as rare events. Within the 10-year simulation span, landfall hurricanes are generated by using the Poisson distribution and uniformly located along the coast of a study region (see Figure 2). Storm tracks together with the hurricane parameters are simulated and provided as the input for conducting the loss estimation in HAZUS-MH.

5.2. Estimated Building-related Economic Loss

The HASUZ-MH is utilized to estimate hurricane building-related economic loss under three climate change scenarios with simulated hurricane storm tracks. In HAZUS-MH, building-related economic loss includes property damages and business interruption loss for four building categories: residential, commercial, industrial and others. As shown in Figure 6, total estimated losses are then fitted with exponential distribution for demonstration.

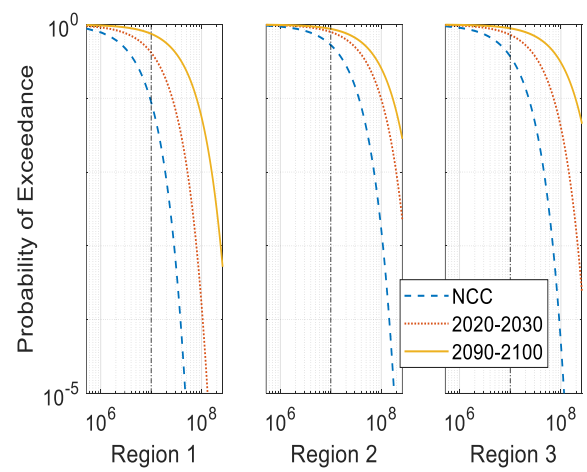

Figure 6 Probability exceedance curves of 10-year-accumulated economic loss estimation

As shown in Figure 6, from both near-term (2020 to 2030) and long-term perspectives (2090 to 2100), the estimated building-related economic loss under climate scenario RCP8.5 significantly increases compared with to the no climate change

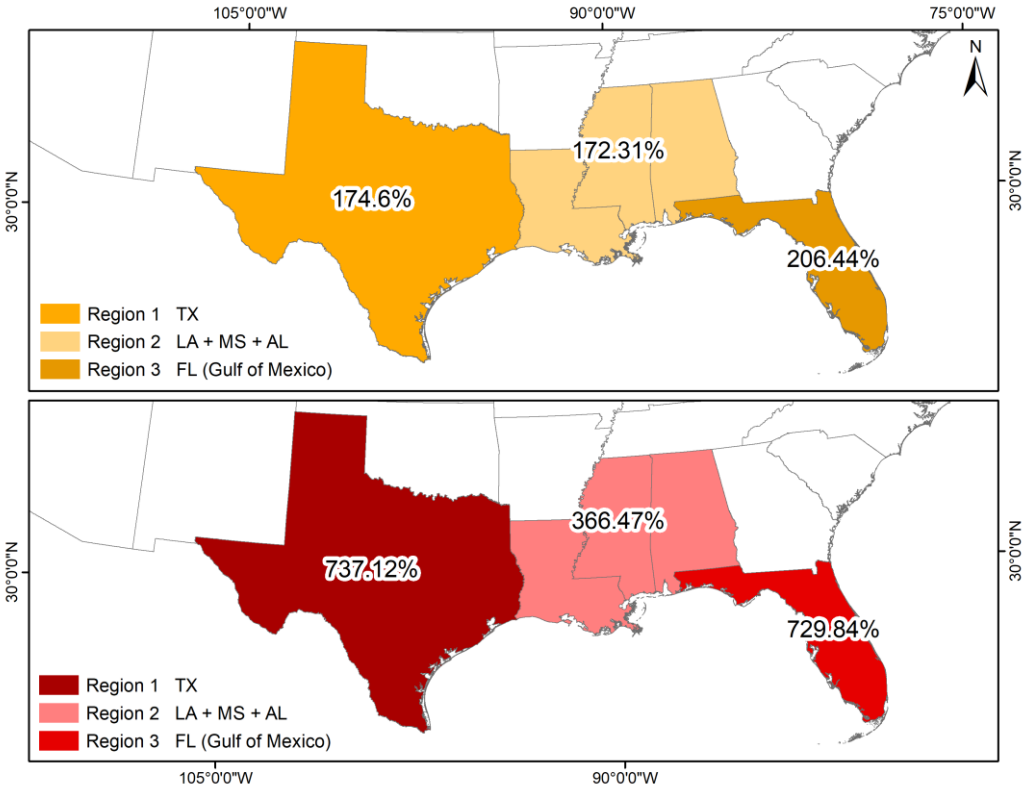

Figure 7 Near- (upper) and long-term (lower) percentage increase of expected 10-year-accumulated estimated loss

condition. The expected 10-year-accumulated estimated loss in study region 1 makes the highest increase; the estimated loss increases 174% for the near term and 737% for the long term compared to no climate change. It is observed that the increase of projected CPD contributes the most to the percentage increase of estimated loss. Comparing the near-term and long-term projection cases, CPD and RMH increase 122% and 11%, respectively, and the average percentage increase in the estimated loss across study regions is about 120%. According to Bjarnadottir et al. (2011), a 10% increase in wind speed induces 66-82% increase in annual hurricane damage. Considering that square of wind speed is approximately proportional to CPD and adding up the additional effect of increase in RMH, result of this study is consistent with their study.

It is also found that changing climate conditions might have higher impact on lower latitude regions (see Figure 7). Two lower latitude regions, region 3 (Florida) and region 1 (TX), have higher hurricane catastrophe losses in the US (Insurance Information Institute 2018). Region 3 (FL) has the largest increase in the near-term projection (206%) and region 1 (TX) has the largest increase in the long-term projection (737%) in terms of percentage increase in the expected 10-year-accumulated estimated loss. In contrast, region 2 (LA+MS+AL) has lower percentage increase in estimated loss for both near-term (172%) and long-term (366%) projections.

6. CONCLUSION

This paper investigates the hurricane-induced building-related economic loss for the US Gulf Coast regions under changing climate conditions. The building-related economic loss is projected to increase significantly considering the climate change in RCP8.5 scenario. The predicted expected 10-year-accumulaed estimated loss has 172%-206% increase in near-term projection (2020-2030) and 366%-737% increase in long-term projection (2090-2100). Furthermore, the

result indicates that in the changing climate conditions, lower latitude regions such as Florida and Texas, two of the most hurricane-prone states in the US, have higher percentage increase in hurricane losses. This result suggests that the safety level provided by current building design standards is insufficient and might underestimate the future hurricane loss. Moreover, the result also implies the regional disparity in impact of climate change on hurricane losses.

Population growth, economic inflation, change of building inventory, deterioration of existing building, etc., are not considered in the loss estimation in HAZUS-MH, and the damage caused by flood and storm surge in coastal areas are also not included in the loss estimation. Accounting for those factors, it is expected to have even higher climate change impact on hurricane economic loss; therefore, for mitigating the increasing risk, it is urgent to comprehensively evaluate climate change impact to make adequate revision on current design codes and standards.

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