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Predicting hurricane wind damage by claim payout based on Hurricane Ike in Texas

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ABSTRACT

The increasing occurrence of natural disasters and their related damage have led to a growing demand for models that predict financial loss. Although considerable research on the financial losses related to natural disasters has found significant predictors, there has been a lack of comprehensive study that addresses the relationship among vulnerabilities, natural disasters, and the economic losses of individual buildings. This study identifies the vulnerability indicators for hurricanes to establish a metric to predict the related financial loss. We classify hurricane-prone areas by highlighting the spatial distribution of losses and vulnerabilities. This study used a Geographical Information System (GIS) to combine and produce spatial data and a multiple regression method to establish a wind damage prediction model. As the dependent variable, we used the value of the Texas Windstorm Insurance Association (TWIA) claim payout divided by the appraised values of the buildings to predict real economic loss. As independent variables, we selected a hurricane indicator and built environment vulnerability indicators. The model we developed can be used by government agencies and insurance companies to predict hurricane wind damage.

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Risk; hurricanes; GIS

1. Introduction

The occurrence of natural disasters has been rising exponentially in the United States (Cutter & Emrich 2005). In addition, population explosions in seaside provinces and the sudden expansion of cities in disaster-prone areas have magnified the risk (Pielke & Landsea 1998; Koks et al. 2012). In general, meteorological disasters, such as cyclones, deluges, and hurricanes, affect our communities more frequently and critically than any other kind of natural disaster (Cutter & Emrich 2005). Moreover, among the meteorological disasters, hurricanes cause the most losses to humankind; therefore, studying hurricanes is crucial in predicting natural disaster damage (Cutter & Emrich 2005).

Some methods to predict hurricane damage have already been developed but it is a complicated issue. Dependable data are scarce and appropriate analyzing methods have yet to be found (Boissonnade & Ulrich 1995; Colle et al. 2008; Lin et al. 2010). Thus, more reliable and methodical research needs to be conducted to provide more accurate loss predictions. To advance predictive models and provide a foundation for hurricane damage prediction, this research comprehensively considers both hurricane and the built environment vulnerability indicators.

Applied Insurance Research (AIR), Risk Management Solution (RMS), and EQECAT are considered as standard catastrophe loss modelling companies (Sanders et al. 2005; Kunreuther et al. 2004). The reinsurers and insurers use these models to estimate the risk from catastrophes such as earthquakes, floods, and tropical cyclones. Nevertheless, these models are only applicable to limited counties. A property located outside the scope of the catastrophe loss models would be hard to evaluate for the reinsurer and insurer. Moreover, the expensive service fee is another obstacle for most small-scale businesses. The yearly cost per country is more than \$100,000 (USD). In addition, the modelling companies warn not to rely entirely on their catastrophe models. They suggest that reinsurers and insurers have a self-determining catastrophe model to assess the risk regarding their portfolio, business preferences, and capital. They also require to use personal judgement as to the risk grades of the models are pessimistic or optimistic.

Furthermore, HAZUS-MH and Florida Pubic Hurricane Loss Model (FPHLM) are also well-known catastrophe loss models. HAZUS-MH was created by the National Institute of Building Sciences (NBS) and the Federal Emergency Management Agency (FEMA) to assess the loss from earthquakes and hurricanes using several categories of vulnerability indicators and disaster parameters (Lowther 2008). The FPHLM was developed by the State of Florida to assess the loss from hurricanes using vulnerability indicators and computer-generated climatological data (Hamid et al. 2010). Nevertheless, both models are not focused on insurance matters.

Hurricane Ike was a fatal disaster. It started on 1 September 2008 and lasted until 14 September 2008. During that time, the storm had deadly effects from Cuba, the Bahamas, and Florida to Louisiana and Texas. Hurricane Ike produced severe rainfall and winds, which also generated critical waves and surges. These effects created significant financial losses and fatalities (Kennedy et al. 2010). Hurricane Ike was the third most costly hurricane to hit the United States after Hurricanes Katrina and Sandy.

The total assessed financial damages were nearly \$24.9 billion, and there were in total 20 fatalities in Texas, Arkansas, and Louisiana (Berg 2009). In particular, Galveston Island and the Bolivar Peninsula of Texas were directly hit and had critical property damage resulting from the waves and storm surges.

Texas Windstorm Insurance Association (TWIA) was founded to protect personal and property insurance companies in Texas from unanticipated wind storms and hail. It offers personal injury and property insurance in Texas, gathering insurance premiums and paying related claims.

Analyzing damage of extreme catastrophes is essential in the insurance industry. Reinsurers and insurers should make provisions for the unanticipated loss that may be caused by extreme catastrophes. After extreme catastrophes, such as Hurricane Katrina, Ike, and Sandy, for instance, numerous insurance companies were greatly affected. They had to change the rates, and coverage was also rapidly modified owing to the remarkable unpredicted loss from these severe events (Watson and Johnson 2004). Therefore, they allocated their portfolio so as to consider the “worst case” situation and prepare for these difficulties. They established catastrophe zones and instituted a ceiling payout amount per capita to decrease the cost from these extreme events. The catastrophe zone and payout amount are generated based on the historical records of these occurrences. Accordingly, analysis of an extreme catastrophe is significant to distribute risk.

Furthermore, the maximum loss of these experiences is also critically important to the insurance industry. The critical values for the reinsurers and insurers, e.g., excess of loss reinsurance (XOL), limit of liability (LOL), and probable maximum loss (PML), are assessed by the maximum loss. XOL and LOL are employed to distribute their insured risk. PML is an expected loss, which is employed to decide the premium (Grossi et al. 2005). Reinsurers and insurers use the analysis of extreme events to decide these three fundamental values (Cummins et al. 1999). Consequently, analysis of similar catastrophes is essential for arranging for unanticipated loss and estimating the maximum damage.

This research addresses the following questions: (1) How is hurricane damage estimated? (2) What built environment vulnerabilities and a hurricane indicator are significant in terms of hurricane damage, and what are the relationships between them? and (3) Which Texas county is most vulnerable to hurricanes?

This research used TWIA claim payout records for commercial buildings following Hurricane Ike to identify hurricane and vulnerability predictors, establish a metric to predict the financial losses of hurricanes, and highlight the spatial distribution of the losses and vulnerabilities to identify hurricane-prone areas. We developed a damage function to determine whether our models are verifiable; it calculates the significant relationships among economic losses (i.e., insured loss payments), vulnerability indicators, and a hurricane indicator. Our model and findings could together become a useful and vital reference for public works' hurricane damage predictions, as well as for other entities such as government agencies, emergency planners, insurance companies, and any other group that needs to identify the exact relationship between hurricanes and vulnerability indicators. For instance, insurance companies might be able to adjust their policies according to the indicator, and therefore realize more profit.

2. Data collection and management

2.1. Dependent variable

The observational units in this research are the insured claim payouts by TWIA for appraised commercial buildings hit by Hurricane Ike. The raw data included street address (number, street, city, zip code), commercial property damage loss (\$; the TWIA payout associated with Hurricane Ike), and TWIA payout date (the date TWIA paid the property damage loss). This research only studied wind damage from Hurricane Ike due to the limitation of TWIA coverage. TWIA covers direct wind damage and evident indirect damage; however, the evident indirect damage will only be applicable when it is caused by direct damage. For example, if a wind-driven damage has been caused by an opening, the opening must be occurred by wind. Based on the inspection of the adjuster and engineer, the damage is determined whether it is resulted from wind or not. Private properties were not included due to TWIA policy. Hurricane Ike hit Texas on 13 September 2008. The spatial distribution of TWIA property claim payouts is shown in Figure 1. The number of claim payout records per county is shown in Figure 2. The records were collected from 17 August 2008 to 22 February 2012.

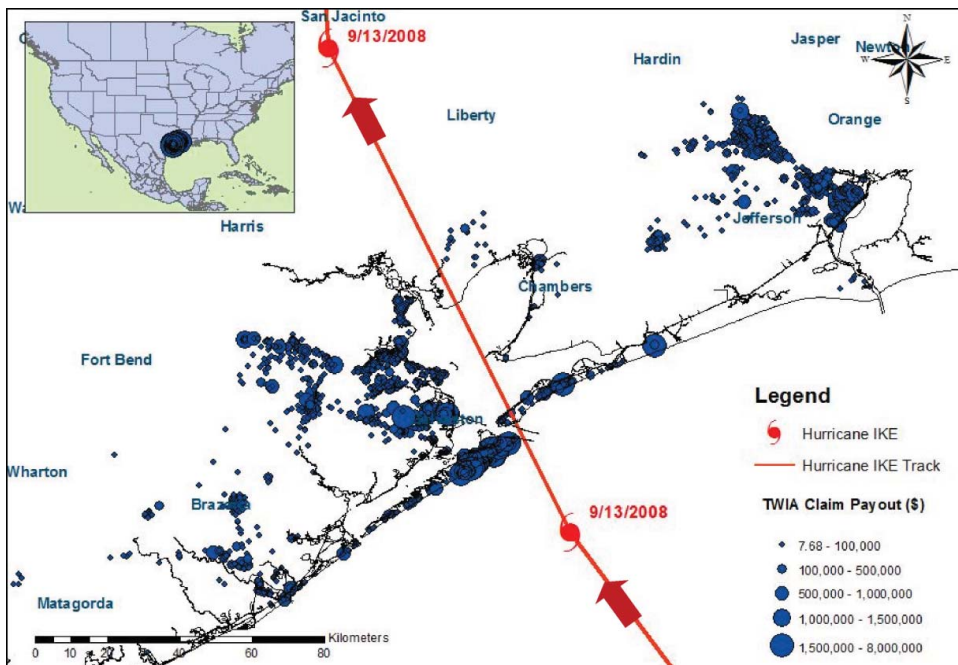


Figure 1. Distribution of TWIA claim payouts.

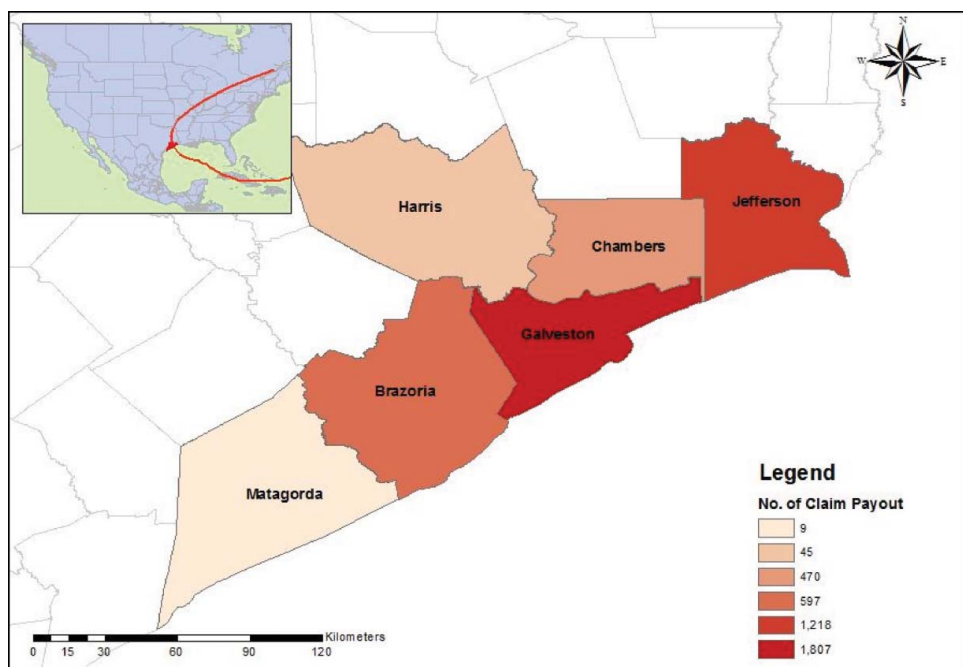


Figure 2. Number of claim payout records per county.

Damage occurred throughout coastal counties in Texas. Galveston, Jefferson, Brazoria, and Chambers counties had the most damage from Hurricane Ike. Galveston was the most damaged county in terms of the number of claims and the dollar amount of the damage.

In this research, we selected a random sample of 500 commercial buildings from all of the damage records. Figure 3 shows the spatial distribution of the random sample. The required sample size can be determined when the sample population is 5000 with a $\pm 5\%$ precision level, a 95% confidence level, and a sample size larger than 370 (Israel 1992).

2.2. Explanatory variables

2.2.1. Hurricane indicator

Hurricanes occur in certain regions of the United States every year, destroying private property and infrastructure. Several hurricane indicators could play a key role in determining damage. For instance, wind parameters, e.g., peak wind duration, wind speed, and wind steadiness, are significant hurricane markers because they are directly related to damage and surges (Dunion et al. 2003; Burton 2010).

The Hurricane Research Division (HRD) real-time hurricane wind analysis system (H²Wind) was produced by the National Oceanic and Atmospheric Administration (NOAA) to combine hurricane observation systems. During hurricanes, the HRD gauges wind parameters from every weather centre for a four- to six-hour interval. The gathered data, such as direction steadiness, speed, duration, and direction of maximum sustained wind, are then combined to create a wind swath map (Powell & Houston 1998; Dunion et al. 2003; Powell et al. 2010). Wind analysis then determines the hurricane's intensity and analyzes its winds. These data consist of shape files in a Geographical Information System (GIS) and of imaged and gridded data. Using the swath map, investigators can not only determine the wind parameters but also assess hurricane damage (Powell & Houston 1998; Powell et al. 1998; Dunion et al. 2003).

Figure 4 presents the swath map for Hurricane Ike, which is made up of grids. These grids show the longitude and latitude and the measurements of the wind parameters listed above. With these

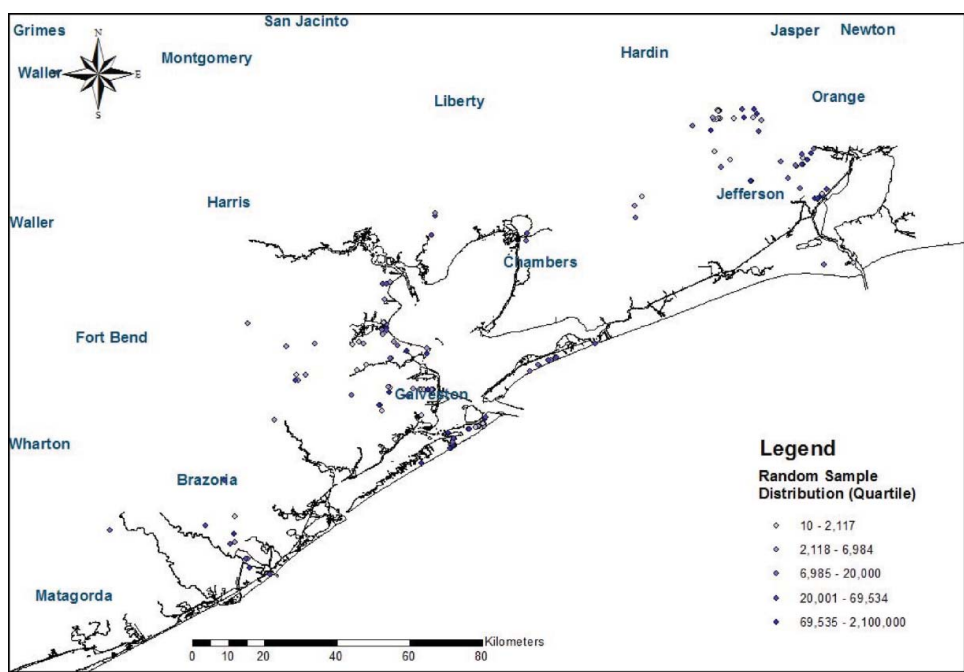


Figure 3. Spatial distribution of the random sample.

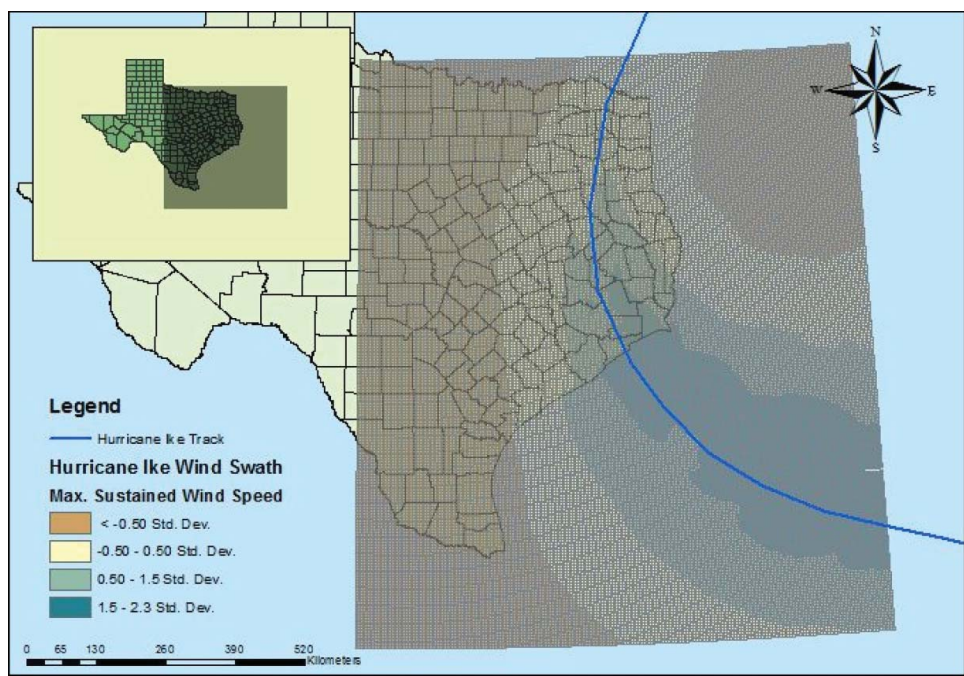


Figure 4. H*Wind swath of Hurricane Ike for Texas showing the maximum sustained wind speed over the duration of the hurricane.

data, researchers can examine the wind and hurricane damage (Powell et al. 1998; Burton 2010). This hurricane indicator could thus play a prominent role in determining damage; the H*Wind analysis should be considered when predicting hurricane damage.

2.2.2. Built-environment vulnerability indicators

Insurers should evaluate the insured built environment to measure vulnerability and assess possible losses to determine premium. The vulnerability of a built environment is determined by the intensity of its exposure to natural disasters and the magnitude of loss (Khanduri & Morrow 2003). On a large scale, water infrastructure (e.g., dams, dikes, and seawalls) built in hurricane- and flood-vulnerable areas can protect people and property (Brody et al. 2008). On a smaller scale, building features (e.g., the building floor area and age) are the essential elements of vulnerability to natural disasters (Khanduri & Morrow 2003; Chock 2005; Dehring & Halek 2006; Highfield et al. 2010). Dehring and Halek (2006) used building floor area to measure hurricane damage from Hurricane Charley. They examined residential properties in Lee County and showed that as a building's floor area increased, hurricane damage decreased (Dehring & Halek 2006). Highfield et al. (2010) used building age against hurricane damage from Hurricane Ike. They studied residential properties on Galveston Island and the Bolivar Peninsula, revealing that as building age increased, so did hurricane damage (Highfield et al. 2010). These studies argue that building features determine the intensity of vulnerability: each feature corresponds to the intensity of exposure, and the combination of all features determines the intensity of vulnerability (Chock 2005). Therefore, measuring the built-environment's vulnerability is significant in quantifying potential hurricane damage. Both the building floor area and building age should be considered as built-environment vulnerability indicators when predicting hurricane damage.

3. Methodology

For this research, we created a statistical model to predict the hurricane wind damage of commercial buildings specifically related to Hurricane Ike. Therefore, we assume that the methodology is limited to hurricanes with characteristics similar to Hurricane Ike. The purpose of this model is to predict the amount of damage to the building properties. The dependent variable, the ratio (\$/\$), is the value of the TWIA claim payout divided by the buildings' appraised values (Equation (1)). The ratio can be predicted by the independent variables, as shown in Equation (2).

$$\text{Ratio} = \frac{\text{TWIA claim payout (\$)}}{\text{Building appraised value (\$)}}, \quad (1)$$

$$\text{Ratio} = \beta_0 + \beta_1 \cdot \text{Wind_Speed} + \beta_2 \cdot \text{Age} + \beta_3 \cdot \text{Area} + \beta_4 \cdot \text{Appraised_Value}, \quad (2)$$

where β_0 is a constant; β_1 is the slope of the maximum sustained wind speed (Wind_Speed); β_2 is the slope of the building age (Age); β_3 is the slope of the building floor area (Area); β_4 is the slope of the appraised value of building (Appraised_Value).

This research used a GIS to combine and produce spatial data. The foundational layer was the TWIA claim payouts, and the hurricane indicator and built-environment vulnerability indicators were joined to the TWIA claim payouts using the Join Data function in ArcGIS to integrate the dependent variable and the independent variables.

4. Results

4.1. Descriptive analysis

The descriptive statistics for the dependent and independent variables are detailed in Table 1. The mean and median were used to examine the data's central tendencies. The standard deviations show the spread of the samples. The quartiles represent the data dispersion, and the skewness and

Table 1. Descriptive statistics.

	Dependent variables		Independent variables		
	Ratio (\$/\$)	Max. sustained wind speed (m/s)	Building age	Building floor area (100 m ²)	Appraised value of building (\$10,000)
<i>N</i>	500	500	500	500	500
Mean	0.10	36.17	34.32	3.64	15.03
Median	0.07	36.00	35.00	2.81	11.85
Std. deviation	0.11	2.11	18.00	2.68	11.72
Percentiles					
25	0.04	34.84	23.00	1.90	7.23
75	0.12	36.74	47.00	4.55	18.82
Skewness	3.00	0.23	.45	1.83	1.83
Kurtosis	13.32	0.76	1.32	3.89	3.99

kurtosis reveal the shape of the distribution. The distribution of the ratio of the value of TWIA claim payouts and the appraised values of the buildings is markedly skewed to the right, because the value of 3.00 is higher than 0, which implies that the distribution is positively skewed. The value of the kurtosis indicates that the distribution has sharper and higher peaks than a normal distribution because the value of 13.32 is higher than 3; therefore, the data are not normally distributed.

4.2. Correlation between ratio and variables

A Spearman correlation analysis examined the ratio and the continuous variables (Table 2). The building floor area is the only variable with an insignificant relationship to the ratio. The other variables (i.e., maximum sustained wind speed, building age, building area, building appraised value) have significant relationships with the ratio. The maximum wind speed and building age have positive coefficients; those indicators have a positive correlation with the ratio. On the other hand, the building area and building appraised value have negative coefficients; those indicators have a negative correlation with the ratio.

4.3. Analytic for residuals and transformation

The Kolmogorov–Smirnov value examined the normality of the residuals. The *P*-value of 0.000 was smaller than 0.05, which implies that the residuals are not normally distributed (Table 3).

Table 2. Spearman correlation analysis results.

		Ratio (\$/\$)	Wind_Speed (m/s)	Age	Area (m ²)	Appraised_Value (\$)
Ratio (\$/\$)	Correlation	1	.126**	.316**	−.061	−.272**
	Sig. (two-tailed)		.005	.000	.173	.000
Wind_Speed (m/s)	Correlation	.126**	1	.040	−.057	.007
	Sig. (two-tailed)	.005		.375	.199	.879
Age	Correlation	.316**	.040	1	−.123**	−.383**
	Sig. (two-tailed)	.000	.375		.006	.000
Area (m ²)	Correlation	−.061	−.057	−.123**	1	.572
	Sig. (two-tailed)	.173	.199	.006		.000
Appraised_Value (\$)	Correlation	−.272**	.007	−.383**	.572**	1
	Sig. (two-tailed)	.000	.879	.000	.000	

**Correlation is significant at the 0.01 level (two-tailed).

Table 3. Test of normality for regression models.

	Kolmogorov–Smirnov			Shapiro–Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Ratio	.218	500	.000	.698	500	.000
Log_Ratio	.028	500	.200	.996	500	.323

Furthermore, the histogram of the standardized residuals and the Q–Q plot also shows that the residuals of the initial model are not normally distributed (Figure 5(a) and 5(b)). Figure 6 displays the residuals plot, which shows the constant variance of the residuals, verifying that it has a pattern and that the residuals are not randomly distributed. Thus, the test and diagnostic of the residuals prove that the dependent variable requires a transformation.

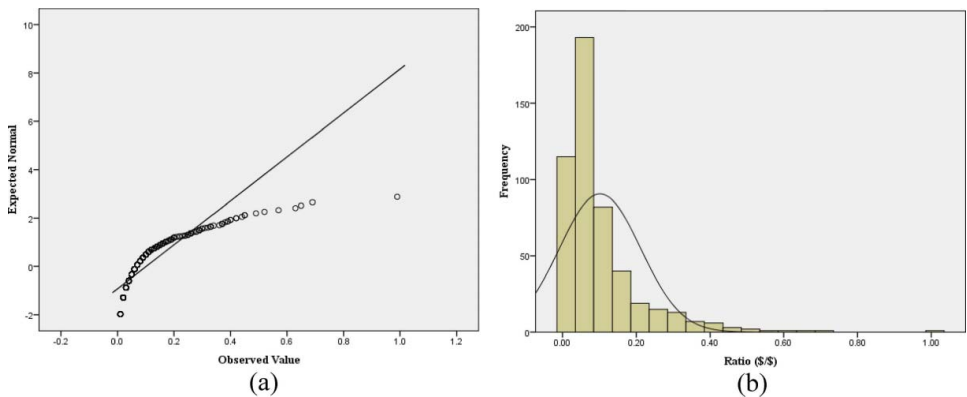


Figure 5. Q–Q plot and histogram of residuals for the initial ratio regression model.

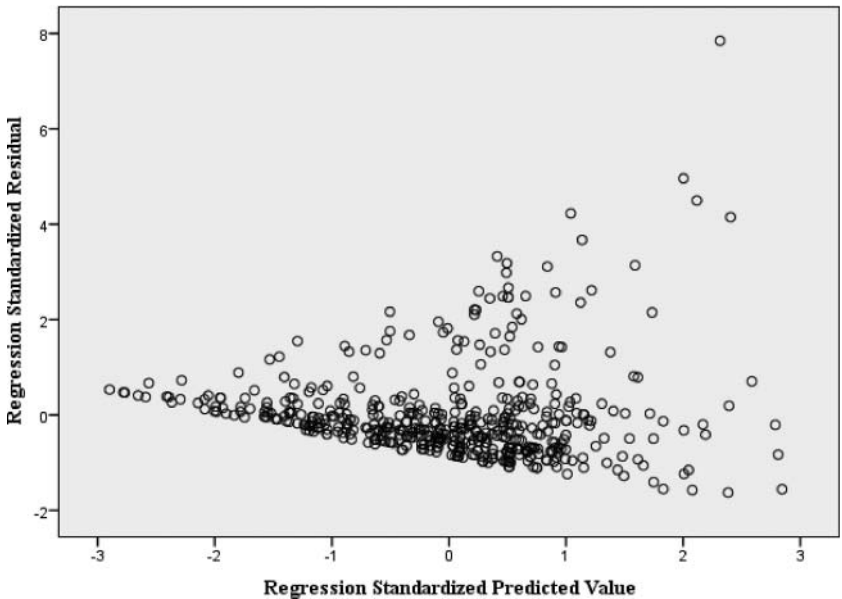


Figure 6. Residuals plot for the initial ratio regression model.

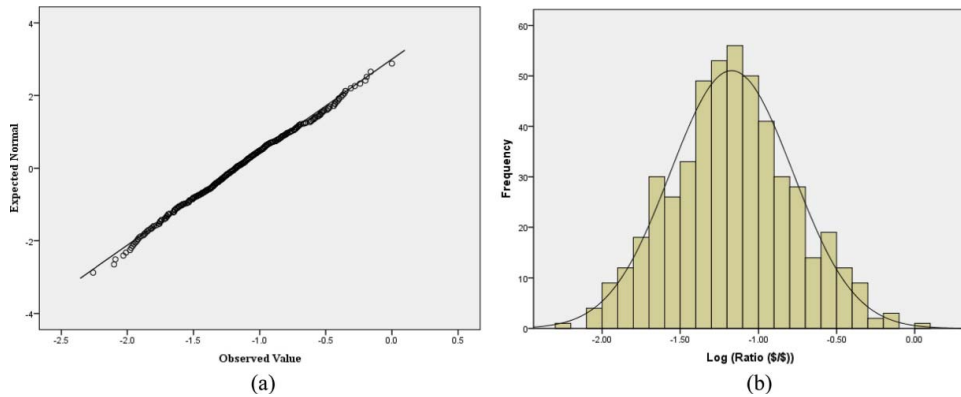


Figure 7. Q–Q plot and histogram of residuals for the transformed ratio regression model.

Therefore, the ratio was transformed by a natural log as follows:

$$\text{Transformed ratio} = \text{Log} \left(\frac{\text{TWIA property damage loss (\$)}}{\text{Building appraised value (\$)}} \right). \quad (3)$$

Following the log transformation of the ratio (Table 3), the Kolmogorov–Smirnov value has a P -value of 0.200, which verifies that the residuals of the transformed ratio are normally distributed. In addition, the Q–Q plot and the histogram of the standardized residuals also indicate that the residuals of the transformed ratio are normally distributed (Figure 7). Figure 8 displays the residuals plot to examine the homoscedasticity. The residuals are randomly distributed, without any tendencies, which implies that the variance of the residuals is constant.

To obtain the best-fit regression model, we used the backward elimination method. The summary of the transformed ratio regression model is shown in Table 4. The model is statistically significant, which means that the relationship between the dependent variable and the independent variables is

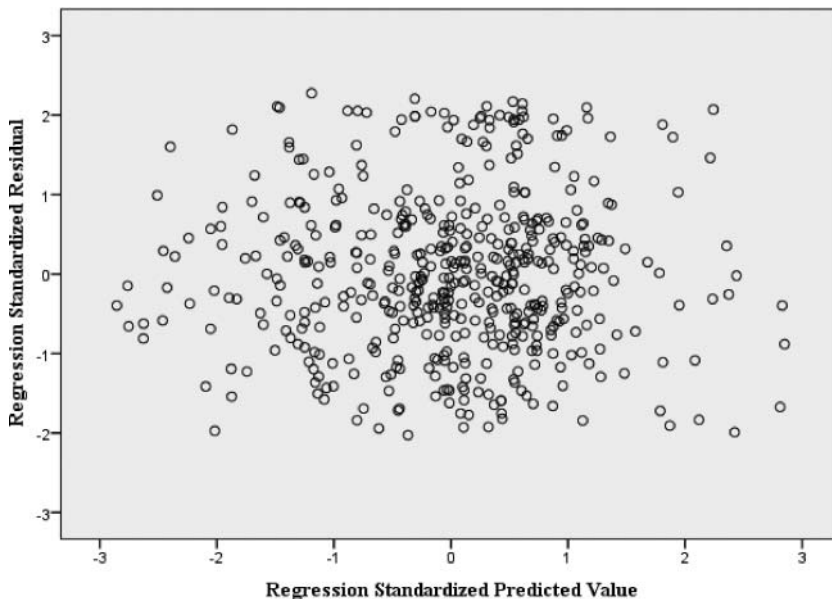


Figure 8. Residuals plot for the transformed ratio regression model.

Table 4. Summary of the transformed ratio model.

Model	Sum of squares	df	Mean square	F	Sig.	R ²	Adj-R ²
Regression	25.946	6	4.158	40.017	.000	.328	.319
Residual	51.221	493	.104				
Total	76.168	499					

Predictors: (Constant), Wind_Speed, Age, Area, log(Imp_Value).
Dependent variable: Log_Ratio.

linear. Therefore, the multiple regression model can be used to predict the transformed ratio. The adjusted R^2 value is 0.319, which indicates that approximately 31.9% of the variability in the transformed dependent variable can be explained by the significant predictors.

Table 5 shows the summary of the coefficients for the transformed ratio regression model. In the transformed model, the four significant predictors, the wind speed, building age, building area, and appraised value of building were identified and used to predict the transformed ratio. The range of the variance inflation factor was 1.022–1.666. These values imply that there is not high multicollinearity among the independent variables, which confirms that there is not high correlation among the independent variables.

The standardized coefficients, also called beta coefficients, reveal which independent variables had more effect on the ratio when the variables are various units. When considering the values of the coefficients, the ranking used is as follows: (1) appraised value of building, (2) building age, (3) wind speed, and (4) building area.

Using the unstandardized coefficients, a multiple regression model was established with four significant predictors to predict the transformed ratio, as shown in Equations (4) and (5). The models are able to describe approximately 31.9% of the variability of the transformed ratio.

$$\text{Log(Predicted ratio)} = 0.297 + (\text{wind_speed}^2 \times 0.000483) + (\text{Age} \times 0.006) + (\text{Area} \times 0.000259) + (\text{Log(Appraise_Value)} \times (-0.206)). \quad (4)$$

$$\text{Predicted ratio} = e^{0.297 + (\text{wind_speed}^2 \times 0.000483) + (\text{Age} \times 0.006) + (\text{Area} \times 0.000259) + (\text{Log(Appraise_Value)} \times (-0.206))}. \quad (5)$$

5. Discussion

This research used TWIA claim payouts for damage to appraised commercial buildings caused by Hurricane Ike in Texas. The range of the observational unit was from 17 August 2008 to 22 February 2012. The ratio model is statistically significant. This proves that the independent variables predict a portion of the ratio of the value of TWIA claim payouts and the appraised values of the buildings. The adjusted R^2 value of 0.319 indicates that 31.9% of the variability in the transformed ratio can be described by the significant predictors. The P -values show that four variables are significant: the wind speed, the building age, the building area, and the appraised value of building. Based on the values

Table 5. Coefficients of transformed ratio regression model.

	Content	β	Std. error	β	Sig.	VIF
Transformed model	Constant	0.297	.262		.000	
	Hurricane indicator (Wind Speed)	.000	.000	.190	.000	1.022
	Built-environment vulnerability indicators					
	Building age	.006	.001	.280	.000	1.170
	Building area	.000	.000	.178	.011	1.463
	Log(appraised value of building)	-.206	.020	-.397	.000	1.666

of the coefficients, the significant variables were also used to measure the magnitude of the dependent variable; therefore, the ratio can be measured using the prediction model in Equation (4).

In this model, the building age and the ratio have a positive relationship; the ratio increases with building age. This is in accordance with previous research that found that building age is a critical predictor for forecasting hurricane damage (Highfield et al. 2010). The maximum sustained wind speed and the ratio also have a positive relationship; the ratio increases with the wind speed. This strengthens the findings of previous studies that discovered that the swath map can be utilized to assess hurricane damage (Powell & Houston 1998; Powell et al. 1998; Dunion et al. 2003).

The building floor area has a negative relationship with the ratio. This is in concurrence with previous research that building area is related with hurricane damage (Dehring & Halek 2006). We found a negative relationship between the appraised value of building and the ratio, which decreases as the value increases. This shows that appraised value of building is also a significant predictor.

6. Conclusions

Due to the increasing frequency and intensity of natural disasters and the resulting damage, demand has been growing for a reliable way to predict related financial losses. A considerable amount of work has gone into studying the financial losses from natural disasters, and it has found significant predictors; however, until now, there was a shortage of studies that addressed the relationships among vulnerabilities, natural disasters, and the economic losses of individual buildings in a comprehensive way. This study identified the vulnerability predictors for hurricanes and established a metric to predict financial losses from hurricanes. As the dependent variable, we used the ratio (\$/\$) of the value of TWIA claim payouts and the appraised values of the buildings to predict the real pecuniary loss, determine the actual amounts of loss, and find significant predictors. As independent variables, we chose a hurricane indicator and built-environment vulnerability indicators.

The developed statistical model and results form an important guideline for insurance companies and emergency planners to use when predicting hurricane damage. For instance, following our indicators, insurance companies can adjust and reconsider their policies for increased profits. Using our model, government agencies and emergency planners can identify the built-environment vulnerability indicators and evaluate the effects of each factor with respect to hurricane risk for improved hurricane damage prediction. Through the developed statistical models, other states might at some point be able to identify significant relationships among the indicators to assess their own possible hurricane losses. The vulnerability indicators included in this study will help identify built-environment vulnerabilities as well as evaluate the effect of each factor with respect to damage from hurricanes to mitigate perceived danger. Additionally, the significant hurricane indicator will improve hurricane-damage prediction and help to build other damage functions. The damage function described here could reduce uncertainties in the modelling tools because we statistically investigated real damage records. However, it remains limited to mega hurricanes such as Hurricane Ike because we investigated only a mega hurricane.

This research addressed only appraised commercial buildings in Texas; therefore, these results might not apply to residential and industrial buildings. Future research should address residential or industrial buildings using the same predictors. Moreover, only the wind damage caused by Hurricane Ike was considered in this research. Future research should investigate more diverse hurricanes and flood damage as well.

Nonetheless, the method and predictors established in this research can be applied to other hurricane-affected states, such as Louisiana, South Carolina, Alabama, North Carolina, and Florida, to predict financial losses from hurricanes. The value of the adjusted R^2 is 0.319, which indicates that the rest of the variability in the data is described by unknown predictors. Accordingly, it could be valuable to determine other potential predictors and add them to the model.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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