Predicting the Hurricane Damage Ratio of Commercial Buildings by Claim Payout from Hurricane Ike

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Abstract

The increasing occurrence of natural disaster events and related damages have led to a growing demand for models that predict financial loss. Although considerable research has studied the financial losses related to natural disaster events, and has found significant predictors, there has not yet been a comprehensive study that addresses the relationship among the vulnerabilities, natural disasters, and economic losses of the individual buildings. This study identified hurricanes and their vulnerability indicators in order to establish a metric to predict the related financial loss. We identify hurricane-prone areas by imaging the spatial distribution of the losses and vulnerabilities. This study utilized a Geographical Information System (GIS) to combine and produce spatial data, as well as a multiple linear regression method, to establish a hurricane damage prediction model. As the dependent variable, we utilized the following ratio to predict the real pecuniary loss: the value of the Texas Windstorm Insurance Association (TWIA) claim payout divided by the appraised values of the buildings. As independent variables, we selected the hurricane indicators and vulnerability indicators of the built environment and the geographical features. The developed statistical

model and results can be used as important guidelines by insurance companies, government agencies, and emergency planners for predicting hurricane damage.

1 Introduction

1.1 Necessity of hurricane damage prediction

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

Our society is vulnerable to the effects from hurricanes. To reduce the damages from hurricanes, it is imperative to research previous hurricanes in order to assess those damages. Increasing natural disasters and the demands of hurricane damage prediction have motivated the development of methods to predict hurricane damage. Predicting hurricane damage is a complicated issue, because there is a lack of dependable data and appropriate analyzing methods (Boissonnade and 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.

In order to advance predictive models, this research comprehensively considers both hurricane indicators and vulnerability indicators of the built environment and geographical features, which provide a foundation for hurricane damage prediction. This research used Texas Windstorm Insurance Association (TWIA) claim payout records of commercial buildings from Hurricane Ike.

1.2 Research objectives and methods

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

This research used theTexas Windstorm Insurance Association (TWIA) claim payout records of commercial buildings from Hurricane Ike to identify hurricane and vulnerability predictors, establish a metric to predict the financial losses of hurricanes, and image the spatial distribution of the loss and vulnerabilities to identify hurricane-prone areas. This damage function will determine if the developed models are verifiable; additionally, this function will calculate the significant relationships among economic losses (i.e., insured loss payments), vulnerability indicators, and hurricane indicators. This model and findings may together become one of the most useful and vital references for hurricane damage prediction for public works, as well as other entities such as government agencies, emergency planners, and insurance companies. For instance, insurance companies may be able to adjust their policies to follow the indicators, and therefore enjoy more profit. This model should become an important guideline to be used by government agencies and local emergency planners who need to identify the exact relationship between hurricanes and vulnerability indicators.

This research was conducted as described in the following process (Figure 1). First, we used the ArcGIS address locator to overlap the TWIA claim payout properties onto the study areas. The Geographic Coordinate System was GCS_North_American_1983 and the Datum was D_North_American_1983. Next, we randomly chose our sample commercial buildings and identified each building's appraised values. Then the building environment vulnerabilities, geographical vulnerabilities, and hurricane indicators were mapped and joined using the Join Data function in ArcGIS. Lastly, a regression model was established and interpreted.

1.3 Texas windstorm insurance association and hurricane Ike

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 reaching as far as Cuba, the Bahamas, Florida, 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 twenty 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.

The Texas Windstorm Insurance Association (TWIA) was founded to guard the fatality and property insurance policy holders in Texas from unanticipated wind storms and hail. This Association consists of wind storm and hail insurance companies, which cover fatality and property insurance in the counties of Texas, gathering insurance premiums and paying related claims.

2 Data collection and management

2.1 Dependent variable

The observational units in this research are the insured claim payouts from TWIA, of the appraised commercial buildings hit by Hurricane Ike. The raw data was included; street address (number, street, city, zip code), commercial property damage loss($) (the TWIA payout associated with hurricane Ike), TWIA payout date (the date TWIA paid for the property damage loss). Private properties was not included due to the policy of the TWIA. Hurricane Ike hit on 13 September 2008 in Texas. The spatial distribution of the TWIA property claim payouts is shown in Figure 2. The overall amount of claim payouts per county and the number of claim payout records per county are shown in Table 1. The records were collected from 17 August 2008 to 22 February 2012.

As shown in Table 1, the damages were happened through Texas coastal counties. Galveston, Jefferson, Brazoria, and Chamber had most damage from Hurricane Ike. Especially, Galveston was most damaged in terms of the number of claims and the dollar amount of damage.

In this research, a random sample of 500 commercial buildings was selected from all of the damage records. The sample size can be determined when the sample population was 5,000 with a ±5% precision level, a 95% confidence level, and the sample size is larger than 370 (Israel 1992).

2.2 Explanatory variables

2.2.1 Hurricane Indicators

Several hurricanes occur throughout the United States every year, destroying private property and infrastructure. Several hurricane indicators may play a key role indetermining damage. For instance, wind parameters are significant hurricane indicators, as they are directly related to damages and surges.

The Hurricane Research Division (HRD) real-time hurricane wind analysis system (H*Wind) was produced by of the National Oceanic and Atmospheric Administration (NOAA) in order to combine hurricane observation systems. During hurricanes, the HRD gauges wind parameters from every weather center for a four to six hour interval. After collecting the gauged data, such as the direction steadiness, speed, duration, and direction of maximum sustained wind, these data are then combined to create a wind swath map (Dunion et al., 2003; Powell and Houston, 1998; Powell et al., 2010). Then, wind analysis is employed to determine the hurricane's intensity and to analyze the hurricane's winds. This data consists of shape files in a Geographical Information System (GIS), and imaged and gridded data. Using the swath map, investigators can not only determine the wind parameters but are also able to assess hurricane damage (Dunion et al., 2003; Powell and Houston, 1998; Powell et al., 1998).

Figure 3 presents the swath map of Hurricane Ike, which is made up of grids. These grids show the longitude and latitude information and the measurements of wind parameters, such as the direction steadiness, speed, duration, and direction of maximum sustained wind. With these data, researchers can create maps for their desired area, time, and hurricane, and can examine the wind and hurricane damage (Burton, 2010; Powell et al., 1998).

In addition, the side of a hurricane can act as a key indicator in determining hurricane damage. Properties that are located on the left side of a hurricane path typically have less damage than properties located on the right side of a hurricane path in the Northern Hemisphere (Keim et al., 2007; Noel et al., 1995). The reason for this is that a hurricane's forward movement and counter clockwise rotation interact with each other, which generates different wind directions and intensities on either side of the hurricane. The two different actions of hurricanes, counterclockwise rotation and forward movement, are combined in the right side of hurricanes and then the right side has broader and stronger winds. Conversely, properties on the left side of a hurricane path are less prone to losses. Conversely, properties on the right side of a hurricane path are less prone to losses. As a result, this hurricane indicator could play a prominent role in determining damage. Therefore, the H*Wind analysis and the side of the hurricane path should both be considered when predicting hurricane damage.

2.2.2 Built Environment Vulnerability Indicators

The insurer should evaluate the insured built environment to measure the vulnerability in order to assess the possible loss. The vulnerability of a built environment is determined by the intensity of exposure to natural disasters and the magnitude of loss (Khanduri and Morrow, 2003). On a large scale, water infrastructures (e.g., dams, dikes, and seawalls) built in hurricane and flood vulnerable areas can act to protect people and property (Brody et al., 2008). On a smaller scale, the building features (e.g., the building floor area and age), are the essential elements of exposure to natural disasters (Chock, 2005; Dehring and Halek, 2006; Highfield et al., 2010; Khanduri and Morrow, 2003). Dehring and Halek (2006) utilized the building floor area to measure hurricane damage from Hurricane Charley. They examined residential properties in Lee County and showed that as the building floor area increased, so did the hurricane loss (Dehring and Halek 2006). Highfield et al. (2010) utilized the buildings' ages to measure the hurricane damage from Hurricane Ike. They studied residential properties in Galveston Island and the Bolivar Peninsula, revealing that as building age increased, so did the hurricane damage (Highfield et al., 2010). These studies argue that the features of each building determine the intensity of vulnerability, as 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 taken into consideration as built environment vulnerability indicators when predicting hurricane damage.

2.2.3 Geographical Vulnerability Indicators

Geographical vulnerabilities are essential features of natural disaster exposure and vary by location (Cutter, 1996). For example, the Federal Emergency Management Agency (FEMA) generated the FEMA Q3 Flood Data to help identify flood risk. FEMA labeled flood zones on the basis of flood risk, and each labeled zone presents the amount of latent flood risk (Fulton County, 2012; Howard and Scott, 2005). Based on the flood records, there are three flood zones. Zone A has a 1%, or higher possibility of floods occurring. Zone X500 predicts a 0.2-1% possibility of flooding. Zone X has a 0.2% or less possibility of flood events. Floods can happen anywhere; however, the FEMA Q3 Flood Data makes it possible to identify flood prone areas.

The National Weather Service defined hurricane surge zones on a scale from one to five in order to identify hurricane prone areas. The zones are categorized based on surge height and sustained wind speed (Table 2). The scaled zones are expected to have an effect on the defined surge height and wind speed (Division of Emergency Management, 2003). Each scaled area shows not only the hurricane risk, but also the geographical vulnerability of the scaled area.

The distance from a property to a body of water acts a significant factor in determining the geographical vulnerability. Highfield et al. (2010) used the distance from a property to a body of water as a measure of hurricane damage. They examined the damaged residential properties in the Bolivar Peninsula and Galveston Island and revealed that as the distance from water increased, the hurricane damage decreased (Highfield et al., 2010). This implies that properties near water are more vulnerable than properties located farther away from water. Thus, assessing geographical vulnerability is crucial when measuring the hurricane damage. In this study we thus consider, FEMA Flood Zones, Hurricane Surge Zones, and distance from water for predicting hurricane damage. Table 3 shows the all variables used in this study.

3 Regression model

In this research, a statistical model was created to predict the hurricane damage of commercial buildings, specifically related to Hurricane Ike. The purpose of this model is to predict the percentage of damages in the building properties. The dependent variable is the ratio ($/$) of the value of the TWIA claim payout (in $) divided by the appraised values of the buildings (in

$) (Equation 1). The ratio can be predicted by the independent variables, as shown in Equation (2).

$$Ratio = \left(\frac{TWIA claim\ payout(S)}{Building\ appraised\ value(S)}\right) \qquad (1)$$

$$\text{Ratio} = \beta_0 + \beta_1 \cdot \text{Wind\_Speed} + \beta_2 \cdot \text{Side\_Right} + \beta_3 \cdot \text{Age} + \beta_4 \cdot \text{Area} + \beta_5 \cdot \text{FEMA\_Zones} + \beta_6 \cdot \text{Surge\_Zones} + \beta_7 \cdot \text{Dist\_Shore} \qquad (2)$$

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 right side (Side_Right); β_3 is the slope of the building age (Age); β_4 is the slope of the building floor area (Area); β_5 is the slope of the FEMA flood zones (FEMA_Zones); β_6 is the slope of the hurricane surge zones (Surge_Zones); and β_7 is the slope of the distance from the property centroid to the shoreline (Dist_Shore). Side_Right is the right side of the hurricane track in which, a value of 1 indicates a building located on the right side of the hurricane track and a value of 0 indicates a building located on the left side of the hurricane track. The FEMA flood zones are as follows: 0 is an unregistered zone, 1 is a property on the FEMA flood zone X, 2 is a property on the FEMA flood zone X500, 3 is a property on the FEMA flood zone A.

4 Results

This research used a Geographical Information System (GIS) to combine and produce spatial data. The foundational layer was the TWIA claim payouts, and the hurricane indicators, building environment vulnerability indicators, and geographical 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.

4.1 Descriptive analysis

The descriptive statistics for the dependent and independent variables are detailed in Table 4. 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 kurtosis reveal the shape of the distribution. For the skewness values, the distribution of the ratio is markedly skewed to the right, since the value of 3.00 is higher than

0, which implies that the distribution is positively skewed. In compliance with the value of the kurtosis, the distribution of the ratio has sharper and higher peaks than a normal distribution, since the value of 13.32 is higher than 3, which indicates that the data is not normally distributed.

4.2 Correlation between ratio and variables

A Pearson Correlation analysiswas conducted to examine the ratio and the continuous variables (Table 5). The building floor area is the only variable that has an insignificant relationship to the ratio. The other variables (i.e., max. sustained wind speed, building age, and distance from the property centroid to shoreline) have significant relationships with the ratio. The max. wind speed and building age have positive sign of the coefficients. It defines the indicators have positive correlation with ratio. On the other hand, the building area and distance from the property centroid to shoreline have negative sign of the coefficients. It indicates the indicators have negative correlation with ratio.

Table 6 shows the results of our correlation analysis with the ratio and ordinal variables. Spearman's rho correlation analysis was adopted to examine the ordinal variables. The right side of the hurricane track is the only variable that has an insignificant relationship with the ratio. The FEMA flood zones and hurricane surge zones both have significant relationships with the ratio. The FEMA flood zones and the right side of the hurricane track have positive sign of the coefficients. It defines the indicators have positive correlation with ratio. On the other hand, the hurricane surge zones has negative sign of the coefficients. It indicates the indicators have negative correlation with ratio.

4.3 Analytic for residuals and transformation

The Kolmogorov-Smirnov value was used to exam 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 7). Furthermore, the histogram of the standardized residuals and the Q-Q plot also show that the residuals of initial model are not normally distributed (Figures 4a and b). Figure 5 displays the residuals plot. This plot shows the constant variance of the residuals, verifying that the residual plot has a pattern, implying that the residuals are not randomly distributed. Therefore, the test and diagnostic of the residuals prove that the dependent variable requires a transformation.

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

$$Transformed\ Ratio = Log\left(\frac{TWIA\ Property\ Damage\ Loss\ (S)}{Building\ Apparaised\ Value\ (S)}\right) \quad (3)$$

Followingthe log transformation of the ratio (Table 8), the Kolmogorov-Smirnov value has a P-value of 0.200, which verifies that the residuals ofthe transformed ratioare 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 6). Figure 7 displays the residuals plot to exam the homoscedasticity. The residuals are randomly distributed, without any tendencies. This implies that the variance of the residuals is constant.

To obtain the best-fit regression model, we utilized the backward elimination method. The summary of the transformed ratio regression modelis shown in Table 7. The model is statistically significant, which means there is a linear relationship between the dependent variable and the independent variables. Therefore, the multiple linear regression model can be used to predict the transformed ratio. The adjusted R^2 value is 0.337, which indicates that approximately 34% of the variability in the transformed dependent variable can be explained with the significant predictors (i.e., the right side of the hurricane track, building age, hurricane surge zones, and distance from the property centroid to shoreline).

Table 9 shows the summary of the coefficients for the original and transformed ratio regression model. In the transformed model, the four significant predictors, the right side of the hurricane track, the building’s age, the hurricane surge zone, and the distance from the property centroid to the shoreline, were identified and used to predict the transformed ratio. The FEMA flood zones, maximum sustained wind speed, and building floor area were eliminated, because their P-values were higher than 0.10. The range of the Variance Inflation Factor (VIF) was from 1.022 to 2.180. These values imply that there is no multicollinearity among the independent variables, which confirms that there is no correlation between the independent variables.

The standardized coefficients, also called beta coefficients, employed to 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) building age, (2) hurricane surge zone, (3) right side of the hurricane track, According to the unstandardized coefficients, a multiple linear 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 34% variability of the transformed ratio.

$$Log(Predicted\ Ratio) = -1.167 + (Side\_Right \bullet 0.200) + (Age \bullet 0.010) + (Surge\_Zones \bullet (-0.112)) + (Dist\_Shore \bullet (-8.605E-6) \quad (4)$$

$$Predicted\ Ratio = e^{-1.167\ (Side\_Right \bullet 0.200)+(Age \bullet 0.010)+(Surge\_Zones \bullet (-0.112))+(Dist\_Shore \bullet (-8.605E-6))} \quad (5)$$

5 Discussion

This research used the appraised commercial building’s claim payouts from the Texas Windstorm Insurance Association (TWIA) for damages 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 are able to predict the ratio. The adjusted R^2 value of 0.337 indicates that 33.7% of the variability in the transformed ratio can be described by the significant predictors. The P-values show that four variables are significant: the right side of the hurricane track, the building age, the hurricane surge zone, and the distance from the property centroid to the shoreline. The variables of maximum sustained wind speed, FEMA flood zone, and building floor area were excluded because of their high P-values. Based on the values 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 right side of the hurricane path and the ratio showed a positive relationship, meaning that the ratio increased when properties were located on the right-hand side of the hurricane path. This finding supports previous research, which found that properties located on the right-hand side of a hurricane path generally receive more losses than ones located on the left-hand side of the hurricane path (Keim et al., 2007; Noel et al., 1995), and verifies that this particular variable is a significantpredictor for forecasting hurricane damage. Building age and the ratio also have a positive relationship, where the ratio increases with increasing 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).There is a negative relationship between hurricane surge zones and the ratio that decreases as the hurricane surge zone number increases. This shows that hurricane surge zones are also a significant predictor. The distance from the property centroid to the shoreline and the ratio also have a negative relationship. The ratio decreases if the distance increases. This is also in agreement with previous research arguing that distance from water is correlated to hurricane damage and is a critical predictor for forecasting hurricane damage (Highfield et al., 2010).

6 Conclusions

Due to the increasing frequency and intensity of natural disaster events and the resulting damages, the demand for predicting the related financial losses has been growing. There has been a considerable amount of work that has studied the financial loss from natural disasters and has found significant predictors; however, there has yet been no study that has addressed the relationship between the vulnerabilities, natural disasters, and economic losses of individual buildings in a comprehensive way. This study identified the vulnerability predictors for hurricanes, establishing a metric to predict the financial losses from hurricanes. As the dependent variable, we used the ratio ofthe value of the Texas Windstorm Insurance Association's (TWIA) claim payout divided by the appraised values of the buildings to predict the real pecuniary loss, to determine the actual amounts, and to find significant predictors. As independent variables, we choose the hurricane indicators, built environment vulnerability indicators, and geographical vulnerability.

The developed statistical model and results form an important guideline for insurance companies and emergency planners 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 hurricanes and the built environment and geographic vulnerability indicators, and then evaluate the effects of each factor with respect to hurricane risk for improved hurricane damage predictions. It is possible that, at a later date, other states will be able to identify the significant relationships between the indicators and predicting hurricane damage. Through developed statistical models, it is possible that other states may at some point be able to identify the significant relationships among the indicators in order to assess their own possible hurricane losses. The vulnerability indicators included in this study will help to identify building environment and geographic vulnerabilities, as well as evaluate the effect of each factor with respect to damage from hurricanes in order to mitigate perceived danger. Additionally, the significant hurricane indicators will help to improve hurricane damage prediction and also would help to build other damage functions by the indicators. Moreover, the damage function might have reduce uncertainties of the modeling tools, since we statistically investigated real damage records. However, the damage function would be limited in mega hurricane like Hurricane Ike, since we investigated only a mega hurricane.

7 Recommendations

This research only addressed appraised commercial buildings in Texas and therefore these results may or may not apply to residential buildings. Future research should address residential buildings using the same predictors. Moreover, only the damages causing by Hurricane Ike were taken into account in this research. Future research should investigate more diverse levels of hurricanes.

Furthermore, the established method and predictors of this research can be applied to other hurricane affected states, such as Louisiana, South Carolina, Alabama, North Carolina, and Florida, to predict the financial losses from hurricanes. The value of the adjusted R^2 is 0.337, which indicates the rest of the variability in the dataisdescribed by unknown predictors. Accordingly, it could be valuable to determine other potential predictors and add them to the model.

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Table 1. TWIA claim payout per county

County	No. of Claim Payouts		Total Claim Payouts	
	No.	%	$	%
Galveston	1,807	43.54	255M	56.68
Jefferson	1,218	29.35	104M	23.14
Brazoria	597	14.39	46M	10.42
Chambers	470	11.33	39M	8.82
Harris	45	1.08	4M	0.92
Matagorda	9	0.22	0.036M	0.01
Liberty	2	0.05	0.067M	0.01
Nueces	2	0.05	0.005M	0.00
Total	4,150	100	450M	100

Table 2. Description of Hurricane Surge Zone

Hurricane Surge Zone	Surge Height (ft)	Wind Speed (mph)
5	4 - 5	74 - 95
4	6 - 8	96 - 110
3	9 - 12	111 - 129
2	13 - 18	130 - 156
1	> 18	> 157

Table 3. Variables Description

Variable	Variable Name	Description	Previous Studies	Source
Dependent	TWIA	Texas Windstorm Association claim payouts for property damage from Hurricane Ike ($)	-	Texas Wind Insurance Association (http://www.twia.org/)
	Building appraised value	Appraised value of building ($) (Based on 2008 roll)	-	• Galveston County Appraisal District (http://www.galvestoncad.org/) • Jefferson County Appraisal District (http://www.jcad.org/) • Brazoria County Appraisal District (www.brazoriacad.org/) • Chambers County Appraisal District (www.chamberscad.org/) • Harris County Appraisal District (www.hcad.org/) • Matagorda County Appraisal District (www.matagorda-cad.org/) • Liberty County Appraisal District (http://www.libertycad.com/) • Nueces County Appraisal District(www.nuecenet/)
Independent	Building age	Building age (Based on 2008 roll)	• Highfield et al (2010)	
	Building floor area	Building floor area (m^2) (Based on 2008 roll)	• Dehring and Halek (2006)	
	Max. sustained wind speed	Max. sustained wind speed from the grid of Hurricane Ike surface wind analysis (m/s)	• Burton (2010) • Dunion et al. (2003) • Powell and Houston (1998) • Powell et al. (1998) • Keim et al. (2007) • Neol et al. (1995)	Atlantic Oceanographic and Meteorological Laboratory (http://www.aoml.noaa.gov/hrd/Storm_pages/ike2008/wind.html)
	Side of the hurricane track	right side of the hurricane track		
	FEMA Q3	FEMA digital Q3 flood data	-	Texas Natural Resources Information System (http://www.tnris.org/)
	Rate of hurricane surge zone	Rate of hurricane surge zone (1~5)	-	Coastal Communities Planning Atlas Mapping Service (http://coastalatlas.tamu.edu/)
	Distance from shoreline	Distance from shoreline (m)	• Highfield et al (2010)	Calculated by using the Near Analysis function of ArcGIS.

Table 4. Descriptive Statistics

	Dependent Variables	Independent Variables							
	Ratio ($/$)	Max. Sustained Wind Speed (m/s)	Right side of the hurricane track	Building Age	Building Floor Area (100 m^2)	Appraised value of building ($10,000)	FEMA Flood Zones	Hurricane Surge Zones	Distance from Shoreline (1,000m)
N	500	500	500	500	500	500	500	500	500
Mean	0.10	36.17	-	34.32	3.64	15.03	-	-	4.49
Median	0.07	36.00	-	35.00	2.81	11.85	-	-	0.88
Std. Deviation	0.11	2.11	-	18.00	2.68	11.72	-	-	6.64
Percentiles 25	0.04	34.84	0.00	23.00	1.90	7.23	1.00	3.00	0.37
Percentiles 75	0.12	36.74	1.00	47.00	4.55	18.82	3.00	3.75	6.03
Skewness	3.00	0.23	1.13	.45	1.83	1.83	-0.07	-0.05	1.64
Kurtosis	13.32	0.76	-0.72	1.32	3.89	3.99	-1.58	0.04	1.49

Table 5. Results of Pearson Correlation Analysis for Continuous Variable Used in Regression

		Ratio ($/$)	Wind_Speed (m/s)	Age	Area (m^2)	Dist_Shore (m)
Ratio ($/$)	Pearson Correlation	1	.126**	.316**	-.061	-.171**
	Sig. (2-tailed)		.005	.000	.173	.000
Wind_Speed (m/s)	Pearson Correlation	.126**	1	.040	-.057	-.183**
	Sig. (2-tailed)	.005		.375	.199	.000
Age	Pearson Correlation	.316**	.040	1	-.123**	-.062
	Sig. (2-tailed)	.000	.375		.006	.167
Area (m^2)	Pearson Correlation	-.061	-.057	-.123**	1	.044
	Sig. (2-tailed)	.173	.199	.006		.322
Dist_Shore (m)	Pearson Correlation	-.171**	-.183**	-.062	.044	1
	Sig. (2-tailed)	.000	.000	.167	.322	

** Correlation is significant at the 0.01 level (2-tailed).

Table 6. Results of Spearman Correlation Analysis for Ordinal Variables Used in Regression

		Ratio ($/$)	FEMA_Zones	Surge_Zones	Side_Right
Ratio ($/$)	Spearman's rho Correlation	1.000	.153**	-.342**	.066
	Sig. (2-tailed)	.	.001	.000	.140
FEMA_Zones	Spearman's rho Correlation	.153**	1.000	-.521**	-.243**
	Sig. (2-tailed)	.001	.	.000	.000
Surge_Zones	Spearman's rho Correlation	-.342**	-.521**	1.000	.071
	Sig. (2-tailed)	.000	.000	.	.114
Side_Right	Spearman's rho Correlation	.066	-.243**	.071	1.000
	Sig. (2-tailed)	.140	.000	.114	.

** Correlation is significant at the 0.01 level (2-tailed).

Table 7. 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

Table 8. Summary of the Transformed Ratio Model

Model	Sum of Squares	Df	Mean Square	F	Sig.	R^2	Adj-R^2
Regression	26.089	4	6.522	64.471	.000	.343	.337
Residual	50.078	495	.101				
Total	76.168	499					

1. Predictors: (Constant), Dist_Shore, Age, Side_Right, Surge_Zones
2. Dependent Variable: Log_Ratio

Table 9. Coefficients of Original and Transformed Ratio Regression Model

	Content	β	Std. Error	Beta	Sig.	VIF
Original Model	Constant	-1.347	.276		.000	
	Hurricane Indicators					
	Right side of hurricane track	.185	.041	.206	.000	1.545
	Built Environment Vulnerability Indicators					
	Building age	.010	.001	.440	.000	1.042
	Geographical Vulnerability Indicators					
	Hurricane surge zones	-.119	.019	-.323	.000	1.907
	Distance from shoreline	-2.701E-6	.000	-.151	.006	2.226
Transformed Model	Constant	-1.167	.055		.000	
	Hurricane Indicators					
	Right side of hurricane track	.200	.039	.223	.000	1.438
	Built Environment Vulnerability Indicators					
	Building age	.010	.001	.441	.000	1.022
	Geographical Vulnerability Indicators					
	Hurricane surge zones	-.112	.017	-.305	.000	1.685
	Distance from shoreline	-8.605E-6	.000	-.146	.007	2.180

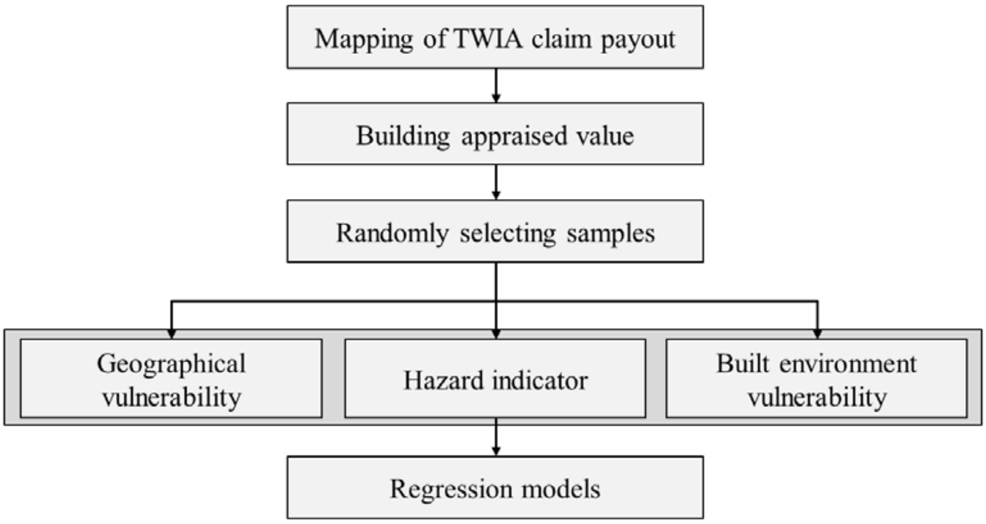


Figure 1. Research Methodology

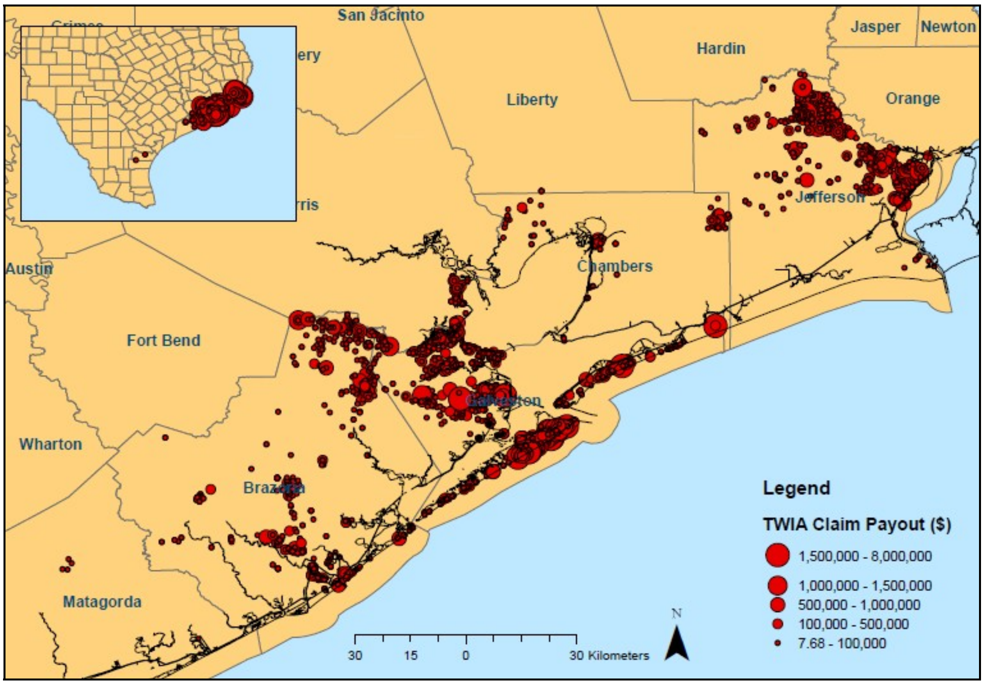


Figure 2. Distribution of TWIA claim payouts

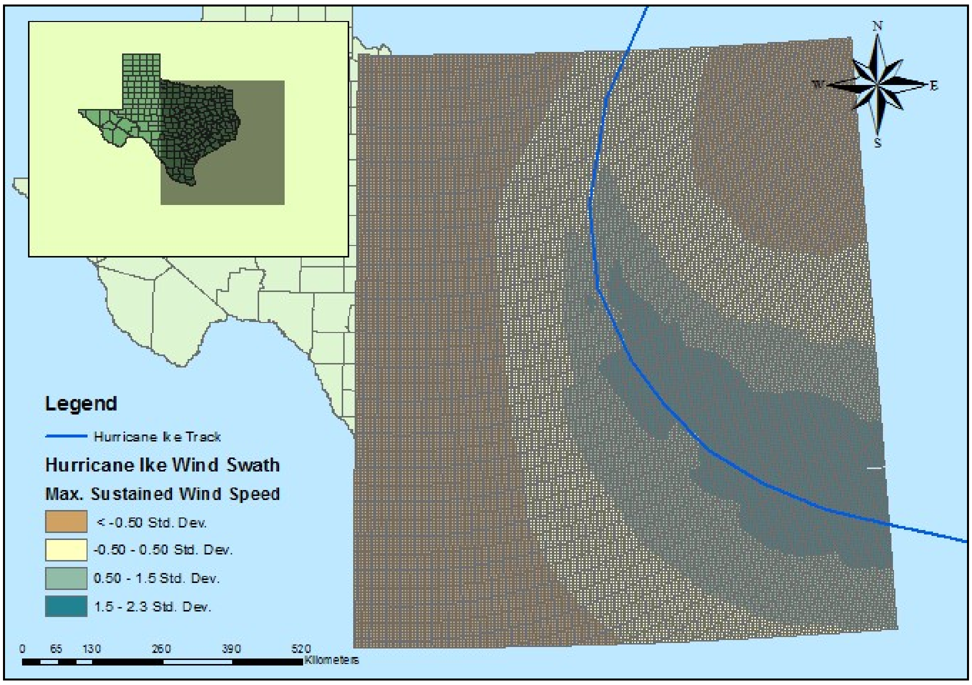
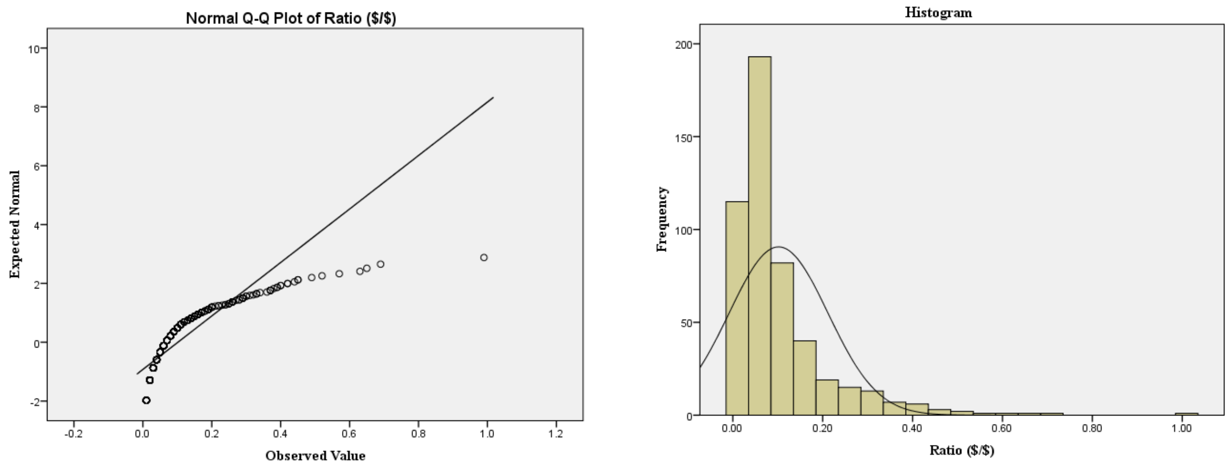


Figure 3. H*wind swath of hurricane Ike for Texas showing the maximum sustained wind speed over the duration of the hurricane



(a) (b)

Figure 4. Q-Q plot and histogram of residuals for the initial ratio regression model

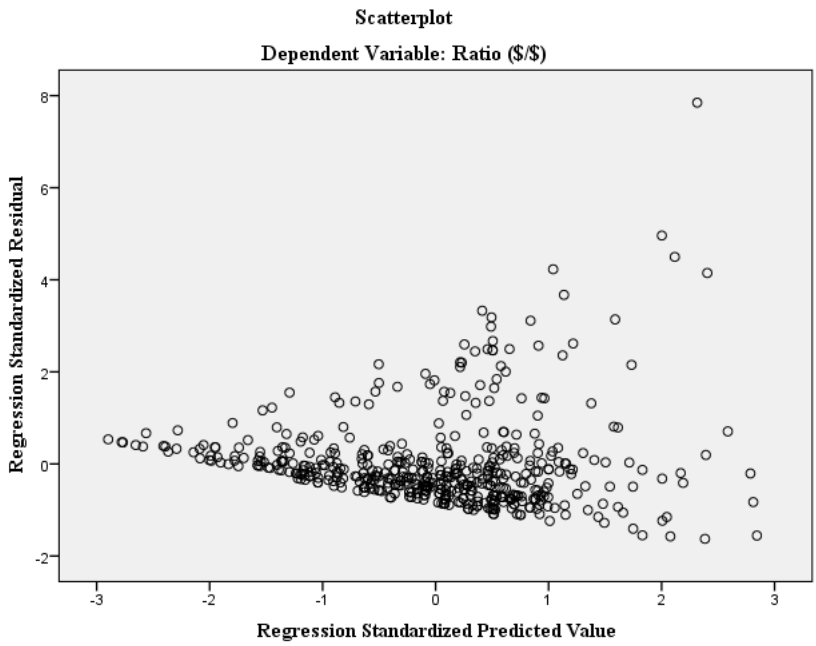
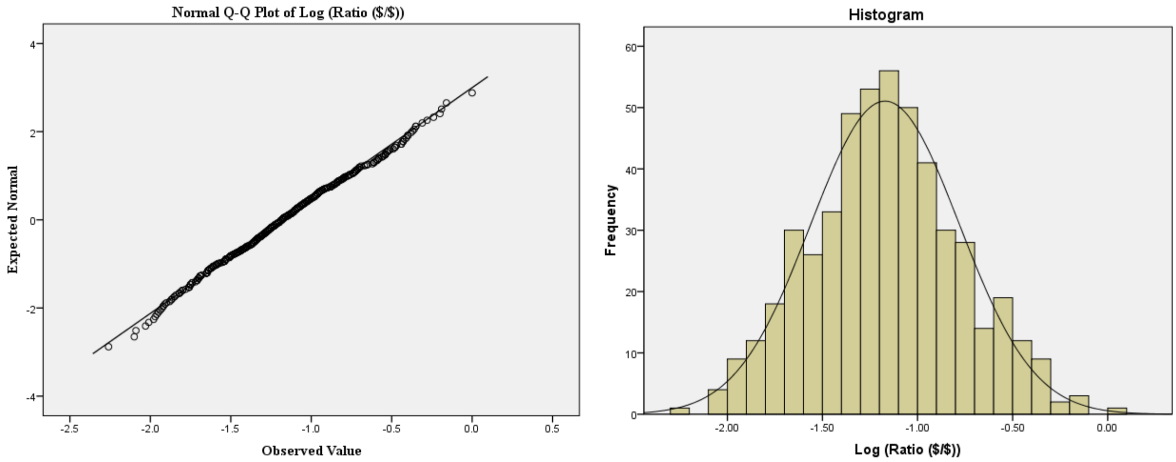


Figure 5. Residuals plot for the initial ratio regression model



(a) (b)

Figure 6. Q-Q plot and histogram of residuals for the transformed ratio regression model

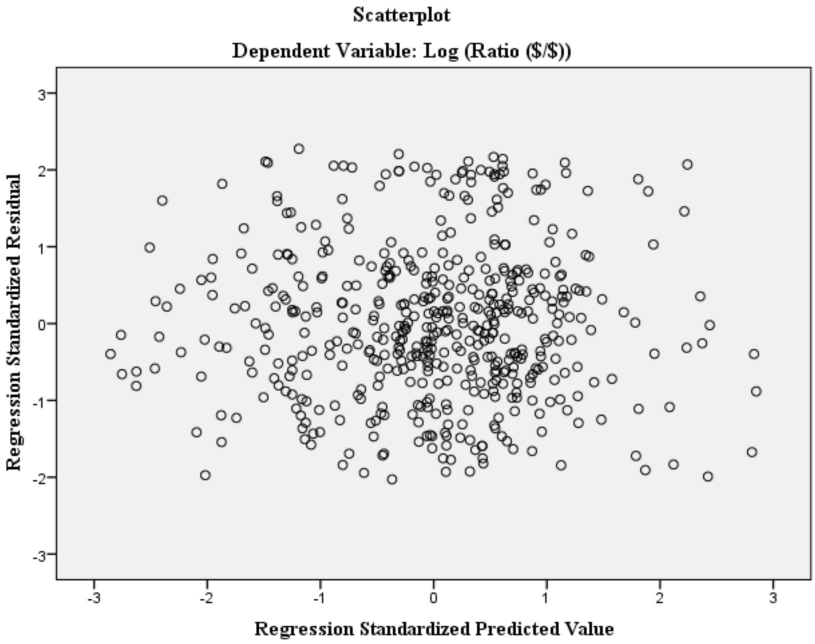


Figure 7. Residuals plot for the transformed ratio regression model