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Discussions

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

In the United States, the occurrence of natural disasters has been rising exponentially due to climate change and abnormal weather. In addition, population explosions in seaside provinces and the sudden expansion of citieshas magnified the risk in those areas (Pielke Jr. and Landsea, 1998). In general, meteorological disasters, such as tsunamis, cyclones, deluges, and hurricanes, impactour communities more frequently

NHESSD
1, 3449–3483, 2013

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.

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. Although some damage is unavoidable, establishing a hurricane damage prediction model provides a way to reduce some of the financial loss. 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). 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 the Texas 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 research was conducted as described in the following outline of our data collection process (Fig. 1). Initially, we used the ArcGIS address locator to overlap the TWIA claim payout properties onto the study areas. 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.

To analyze the data, we used a multiple linear regression method to make a global equation, which helps to identify the relationship between the dependent variable and independent variables. Utilizing the statistical method, this research then identified the relationship between TWIA claim payouts and the vulnerability indicators.

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 Andrew. 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. Hurricane Ike hit on 13 September 2008 in Texas. The distribution of the TWIA property claim payouts is shown in Fig. 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.

There were a total of 4150 claims, with an overall claim payout of \$450 518 330. The most damaged county was Galveston, both in terms of the number of claims (1807, 43.54 % of the total number of claims) and the dollar amount of damage (\$255 333 818, 56.68 % of the total dollar amount). The other damaged counties in Texas were: Jefferson County with \$104 249 917 in total losses and 1218 claims, Brazoria County with \$46 922 396 intotal losses and 597 claims, Chambers County with \$39 755 609 intotal losses and 470 claims, Harris County with \$4 126 821 in total losses and 45 claims, Matagorda County with \$36 981 in total losses and nine claims, Liberty County with \$67 501 intotal losses and two claims, and Nueces County with \$5287 in total losses and two claims.

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 5000 with a ±5 % precision level, a 95 % confidence level, and the sample size is larger than 370 (Israel, 1992).

NHESSD
1, 3449–3483, 2013

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 analysis 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

NHESSD
1, 3449–3483, 2013

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. In the Northern Hemisphere, the left side of a hurricane path generally creates more robust and variable winds, which makes properties on this side more vulnerable to hurricane damage. 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 probability of 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

NHESSD
1, 3449–3483, 2013

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. As geographical vulnerability indicators, FEMA Flood Zones, Hurricane Surge Zones, and distance from water should be considered when predicting hurricane damage.

NHESSD
1, 3449–3483, 2013

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 unconditional financial damage. The dependent variable is the ratio ($/$) of the value of the TWIA claim payout (in $) divided by the appraised values of the buildings (in $) (Eq. 1). The ratio can be predicted by the independent variables, as shown in Eq. (2).

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

$$\text{Ratio} = \beta_0 + \beta_1 \cdot \text{Wind\_Speed} + \beta_2 \cdot \text{Side\_Right} + \beta_3 \cdot \text{Age} + \beta_4 \cdot \text{Area}$$

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 Data management

This research used a Geographical Information System (GIS) to combine and produce spatial data (Fig. 4). The foundational layer was the TWIA claim payouts, and

NHESSD

1, 3449–3483, 2013

Hurricane damage ratio prediction

J.-M. Kim et al.

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 3. 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 4). 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 coefficients imply the linear relationship within a scale of −1 to +1, and the sign of the coefficients define whether the correlation is negative or positive.

Table 5 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 coefficients indicate the amount of the linear relationship within a scale of −1 to +1, and the sign of the coefficients defines whether the correlation is negative or positive.

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 6). Furthermore, the histogram of the standardized residuals and the Q-Q plot also show that the residuals of initial model are not normally distributed (Fig. 5a and b). Figure 6 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:

$$\text{Transformed Ratio} = \text{Log}\left(\frac{\text{TWIA Property Damage Loss}(S)}{\text{Building Apparaised Value}(S)}\right) \quad (2)$$

Followingthe log transformation of the ratio (Table 7), 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 (Fig. 7). Figure 8 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 8. The model is statistically significant because the calculated P value of 0.000 is less than 0.05. This means that there is a significant linear relationship between the dependent variable and the independent variables. The null hypothesis, which states that there is no linear relationship between the dependent variable and the independent variables, should be

NHESSD
1, 3449–3483, 2013

rejected. 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 33.7 % 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 transformed ratio regression 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, were scaled from 0 to 1 and then 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, (2) 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 Eqs. (3) and (4). The models are able to describe the 34.3 % variability of the transformed ratio.

$$\begin{aligned}\text{Log}\left(\text{Predicted Ratio}\left(\$/\$\right)\right) &= -1.167 + (\text{Side\_Right} \cdot 0.200) + (\text{Age} \cdot 0.010) \\ &+ (\text{Surge\_Zones} \cdot (-0.112)) + (\text{Dist\_Shore} \cdot (-8.605 \times 10^{-6}))\end{aligned} \tag{3}$$

$$\begin{aligned}&\text{Predicted Ratio}\left(\$/\$\right) \\ &= e^{(-1.167)+(\text{Side\_Right}\cdot 0.200)+(\text{Age}\cdot 0.010)+(\text{Surge\_Zones}\cdot(-0.112))+(\text{Dist\_Shore}\cdot(-8.605\times 10^{-6}))}\end{aligned} \tag{4}$$

NHESSD
1, 3449–3483, 2013

4.4 Statistic model and validity

In the ratio regression, four indicators were proven to be significant predicators for the transformed ratio. The scale of the Variance Inflation Factor (VIF), from 1.022 to 2.180, verified that there is no multicollinearity among the independent variables, which proved that the independent variables are not correlated. The adjusted R^2 valueof the model is 0.337; therefore, the transformed ratio is able to describe with 33.7 % of variability in the data with the four significant predictors. The scatter plot of the actual log-transformed ratio versus the predicted log ratio is depicted in Fig. 9.

5 Summary and 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, and created a map showing the spatial distribution of the loss and vulnerabilities to identify hurricane-prone areas. 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.

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 overall number of claims was 4150, and the overall claim payout amount was \$450 518 330. The county that suffered the most damage was Galveston, both in terms of the number of claims, (1807, 43.54 %) and the dollar amount of damage (\$255 333 818, 56.68 %). Thus, the damage distributions verify that Galveston county is the most vulnerable to hurricanes in Texas.

The ratio statistic model is significant because the calculated P value of 0.000 was less than 0.05. 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 Eq. (3).

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 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 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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NHESSD
1, 3449–3483, 2013

Hurricane damage ratio prediction

J.-M. Kim et al.

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NHESSD
1, 3449–3483, 2013

Title Page
Abstract Introduction
Conclusions References
Tables Figures
Back Close
Full Screen / Esc
Printer-friendly Version
Interactive Discussion

Table 1. TWIA claim payout per county.

County	Claim Payouts		Total Claim Payouts	
	No.	%	$	%
Galveston	1807	43.54	255 333 818	56.68
Jefferson	1218	29.35	104 249 917	23.14
Brazoria	597	14.39	46 922 396	10.42
Chambers	470	11.33	39 755 609	8.82
Harris	45	1.08	4 126 821	0.92
Matagorda	9	0.22	36 981	0.01
Liberty	2	0.05	67 501	0.01
Nueces	2	0.05	5287	0.00
Total	4150	100	450 518 330	100

NHESSD
1, 3449–3483, 2013

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

NHESSD
1, 3449–3483, 2013

Table 3. Descriptive statistics.

		Dependent Variables Ratio	Independent Variables							
		($/$)	Max. Sustained Wind Speed ($m\,s^{-1}$)	Right side of the hurricane track	Building Age	Building Floor Area ($100m^2$)	Appraised value of building ($10 000)	FEMA Flood Zones	Hurricane Surge Zones	Distance from Shoreline (1000 m)
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
	50	0.07	36.00	0.00	35.00	2.81	11.85	2.00	3.00	0.88
	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	0.45	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

NHESSD
1, 3449–3483, 2013

Hurricane damage ratio prediction

J.-M. Kim et al.

Title Page
Abstract | Introduction
Conclusions | References
Tables | Figures
◀| |▶
◀ ▶
Back | Close
Full Screen / Esc
Printer-friendly Version
Interactive Discussion

Table 4. Results of Pearson correlation analysis.

			Ratio ($/$)	Wind_Speed ($\mathrm{m\,s^{-1}}$)	Age	Area ($\mathrm{m^2}$)	Dist_Shore (m)
Ratio	($/$)	Pearson Correlation	1	0.126*	0.316*	−0.061	−0.171*
		Sig. (2-tailed)		0.005	0.000	0.173	0.000
Wind_Speed	($\mathrm{m\,s^{-1}}$)	Pearson Correlation	0.126*	1	0.040	−0.057	−0.183*
		Sig. (2-tailed)	0.005		0.375	0.199	0.000
Age		Pearson Correlation	0.316*	0.040	1	−0.123*	−0.062
		Sig. (2-tailed)	0.000	0.375		0.006	0.167
Area	($\mathrm{m^2}$)	Pearson Correlation	−0.061	−0.057	−0.123*	1	0.044
		Sig. (2-tailed)	0.173	0.199	0.006		0.322
Dist_Shore	(m)	Pearson Correlation	−0.171*	−0.183*	−0.062	0.044	1
		Sig. (2-tailed)	0.000	0.000	0.167	0.322	

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

NHESSD
1, 3449–3483, 2013

Hurricane damage ratio prediction

J.-M. Kim et al.

Table 5. Results of Pearson correlation analysis.

		Ratio ($/$)	FEMA_Zones	Surge_Zones	Side_Right
Ratio ($/$)	Spearman's rho Correlation	1.000	0.153*	−0.342*	0.066
	Sig. (2-tailed)		0.001	0.000	0.140
FEMA_Zones	Spearman's rho Correlation	0.153*	1.000	−0.521*	−0.243*
	Sig. (2-tailed)	0.001		0.000	0.000
Surge_Zones	Spearman's rho Correlation	−0.342*	−0.521*	1.000	0.071
	Sig. (2-tailed)	0.000	0.000		0.114
Side_Right	Spearman's rho Correlation	0.066	−0.243*	0.071	1.000
	Sig. (2-tailed)	0.140	0.000	0.114	

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

NHESSD
1, 3449–3483, 2013

Table 6. Results of Spearman's correlation analysis.

	Kolmogorov–Smirnov			Shapiro–Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Ratio	0.218	500	0.000	0.698	500	0.000

NHESSD
1, 3449–3483, 2013

Table 7. Test of normality for initial TWIA claim payout regression model.

	Kolmogorov–Smirnov			Shapiro–Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Log_Ratio	0.028	500	0.200	0.996	500	0.323

NHESSD
1, 3449–3483, 2013

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	0.000	0.343	0.337
Residual	50.078	495	0.101				
Total	76.168	499					

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

NHESSD
1, 3449–3483, 2013

Table 9. Coefficients of transformed ratio regression model.

Model	β	Std. Error	Beta	Sig.	VIF
Constant	−1.167	0.055		0.000	
Hurricane Indicators					
Right side of hurricane track	0.200	0.039	0.223	0.000	1.438
Built Environment Vulnerability Indicators					
Building age	0.010	0.001	0.441	0.000	1.022
Geographical Vulnerability Indicators					
Hurricane surge zones	−0.112	0.017	−0.305	0.000	1.685
Distance from shoreline	-8.605×10^{-6}	0.000	−0.146	0.007	2.180

NHESSD
1, 3449–3483, 2013

Hurricane damage ratio prediction

J.-M. Kim et al.

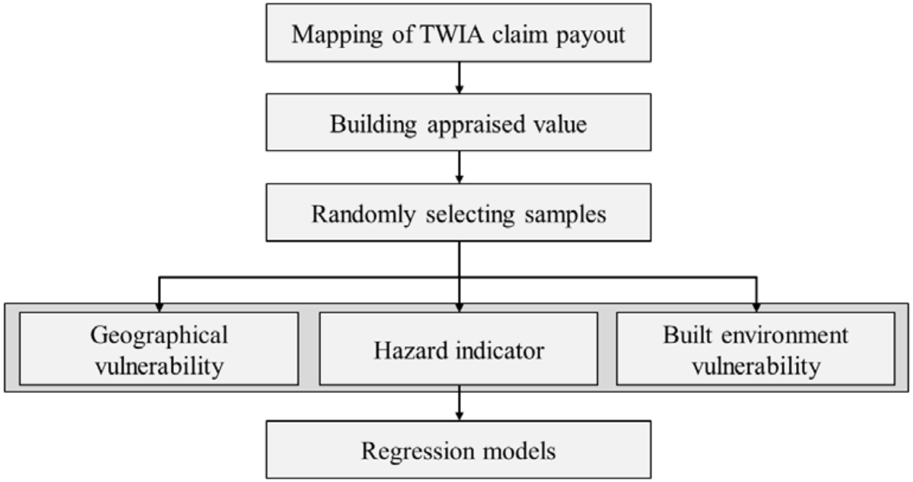


Fig. 1. Process of data collection.

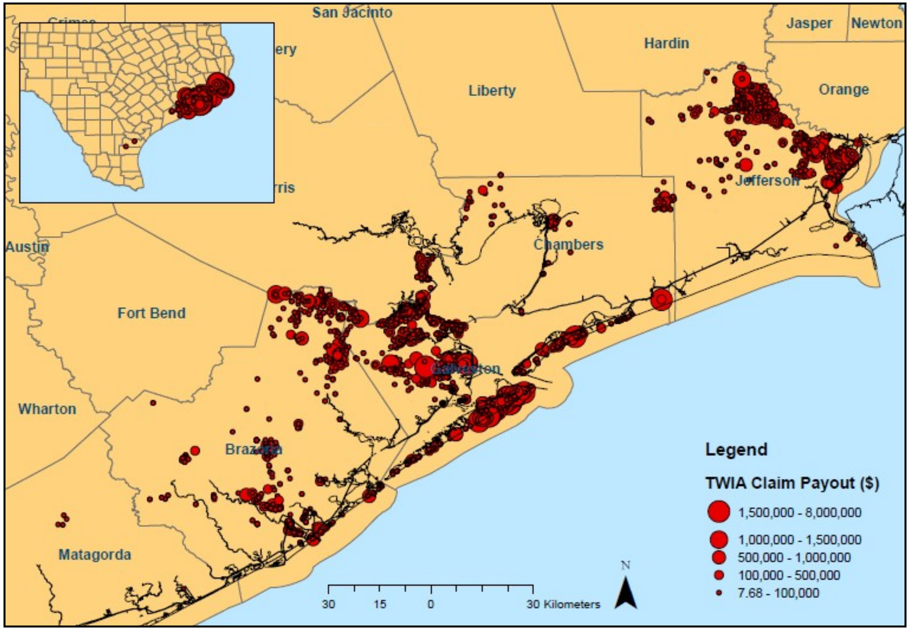


Fig. 2. Distribution of TWIA claim payouts.

NHESSD
1, 3449–3483, 2013

Hurricane damage ratio prediction

J.-M. Kim et al.

Title Page
Abstract Introduction
Conclusions References
Tables Figures
◀ ▶
Back Close
Full Screen / Esc
Printer-friendly Version
Interactive Discussion

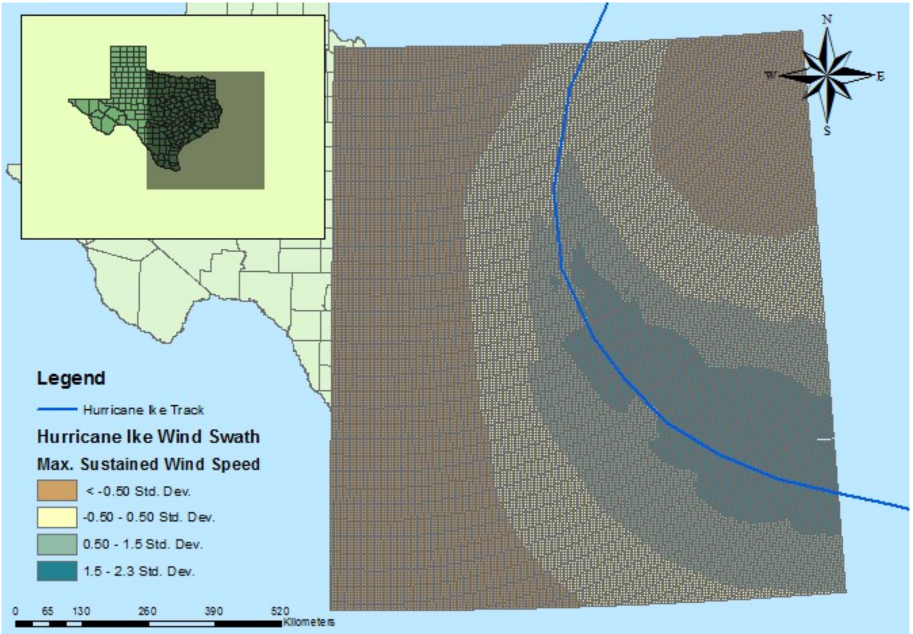


Fig. 3. H*wind swath of Hurricane Ike for Texas showing the maximum sustained wind speed over the duration of the hurricane.

NHESSD
1, 3449–3483, 2013

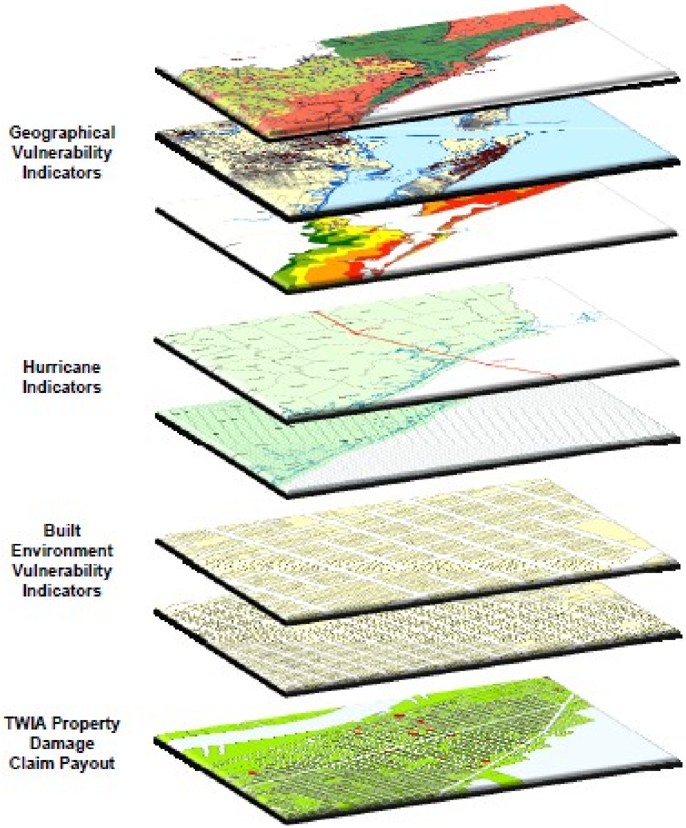


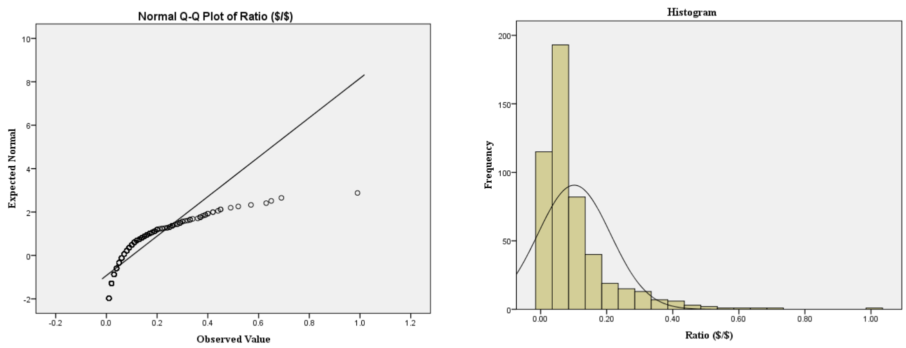
Fig. 4. Distribution of number of claim payout records per County from hurricane IKE.

NHESSD
1, 3449–3483, 2013

Hurricane damage ratio prediction

J.-M. Kim et al.

Title Page
Abstract | Introduction
Conclusions | References
Tables | Figures
◄ | ►
◄ | ►
Back | Close
Full Screen / Esc
Printer-friendly Version
Interactive Discussion



(a) (b)

Fig. 5. (a) Q-Q plot and **(b)** histogram of residuals for the initial ratio regression model.

Discussion Paper | Discussion Paper | Discussion Paper | Discussion Paper |

NHESSD

1, 3449–3483, 2013

Hurricane damage ratio prediction

J.-M. Kim et al.

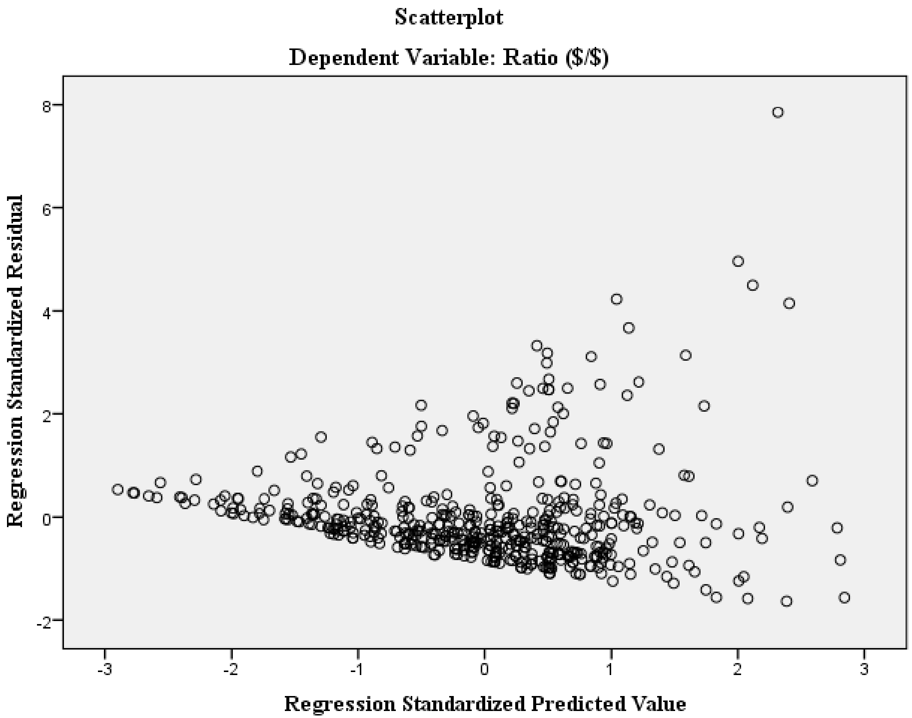


Fig. 6. Residuals plot for the initial ratio regression model.

NHESSD
1, 3449–3483, 2013

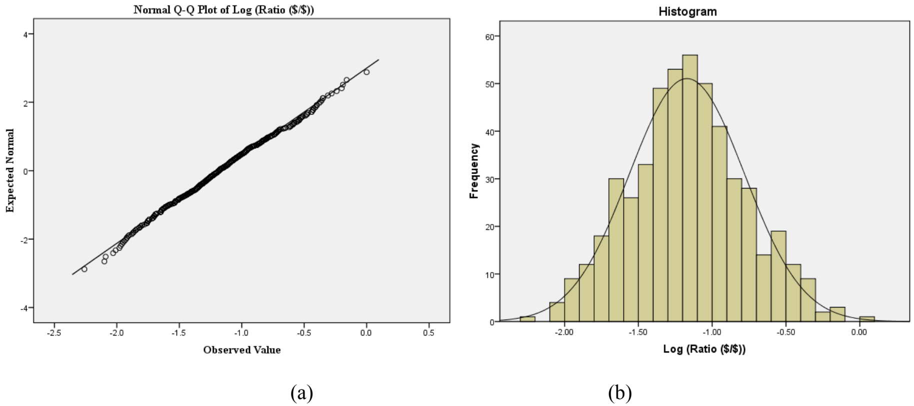


Fig. 7. (a) Q-Q plot and **(b)** histogram of residuals for the transformed ratio regression model.

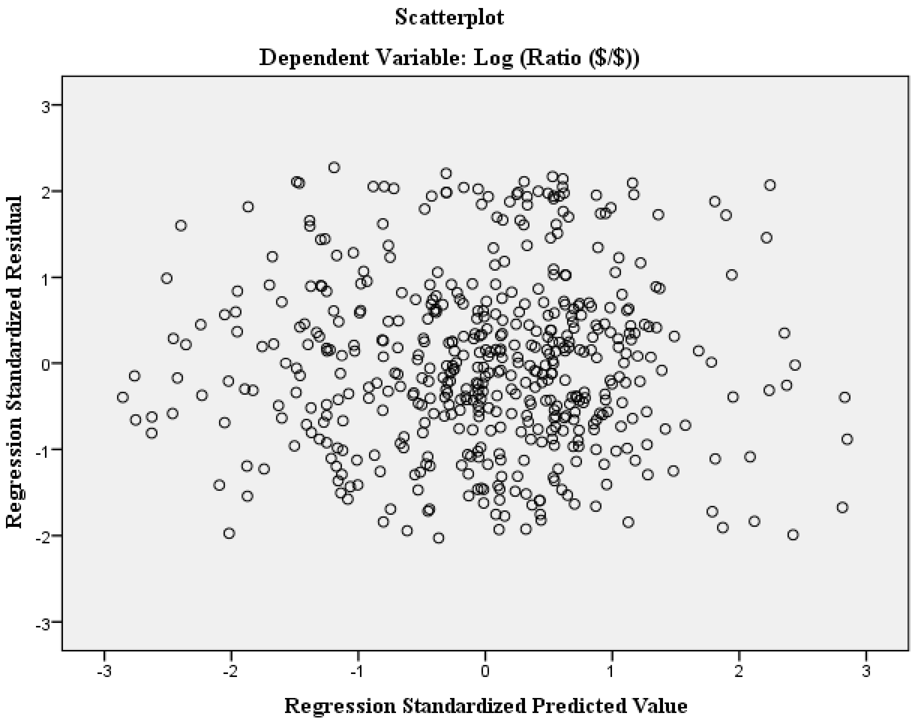


Fig. 8. Residuals plot for the transformed ratio regression model.

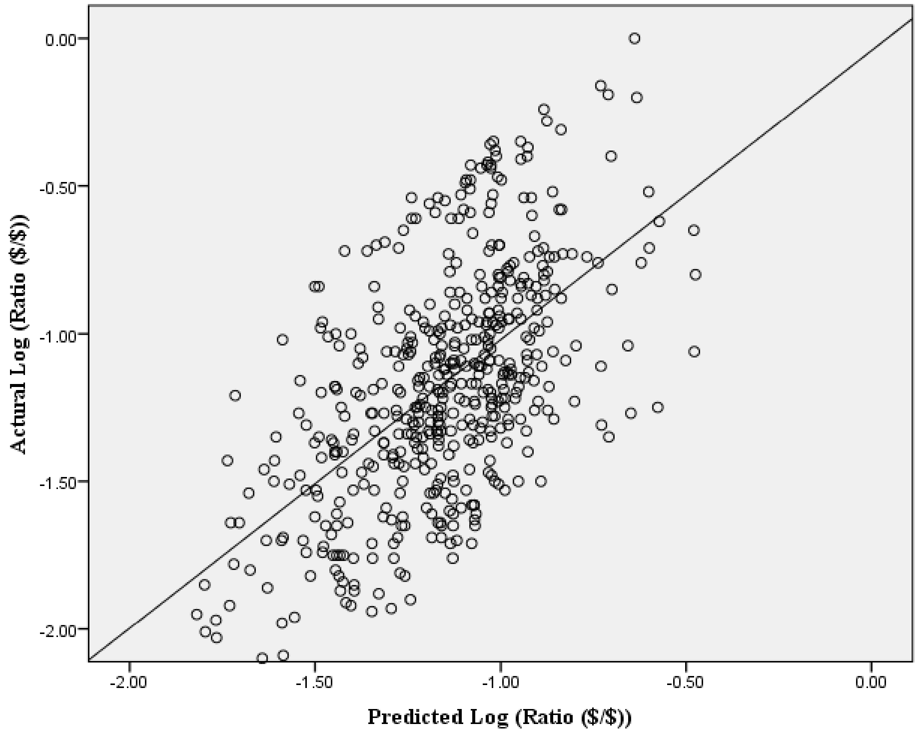


Fig. 9. Actual vs. predicted log ratio ($/$).

NHESSD
1, 3449–3483, 2013

Hurricane damage ratio prediction

J.-M. Kim et al.