MULTIPLE LINEAR REGRESSION MODELS: PREDICTING THE TEXAS WINDSTORM INSURANCE ASSOCIATION CLAIM PAYOUT AND RATIO VERSUS THE APPRAISED VALUE OF COMMERCIAL BUILDINGS FROM HURRICANE IKE

A Dissertation

by

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ABSTRACT

Following growing public awareness of the danger from hurricanes and tremendous demands for analysis of loss, many researchers have conducted studies to develop hurricane damage analysis methods. Although researchers have identified the significant indicators, there currently is no comprehensive research for identifying the relationship among the vulnerabilities, natural disasters, and economic losses associated with individual buildings. To address this lack of research, this study will identify vulnerabilities and hurricane indicators, develop metrics to measure the influence of economic losses from hurricanes, and visualize the spatial distribution of vulnerability to evaluate overall hurricane damage. This paper has utilized the Geographic Information System (GIS) to facilitate collecting and managing data, and has combined vulnerability factors to assess the financial losses suffered by Texas coastal counties. A multiple linear regression method has been applied to develop hurricane economic damage predicting models. To reflect the pecuniary loss, insured loss payment was used as the dependent variable to predict the actual financial damage and ratio. Geographical vulnerability indicators, built environment vulnerability indicators, and hurricane indicators were all used as independent variables. Accordingly, the models and findings may possibly provide vital references for government agencies, emergency planners, and insurance companies hoping to predict hurricane damage.

DEDICATION

To Dr. Paul K. Woods, you do not need a costume to be a hero.

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To myself, when you think you have lost yourself, keep going because only "time will tell" where you will end up.

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1. INTRODUCTION

1.1 Background

Natural disasters in the United States have been increasing because abnormal weather and climate change have stimulated severe weather events. Increased populations in seaside areas and cities have become vulnerable to widespread risks including danger from cyclones, hurricanes, deluges, and even tsunamis (Pielke Jr and Landsea 1998). Furthermore, this rapid increase in disaster events has caused unavoidable damage to property and infrastructure during the past five decades. In a brief evaluation, direct losses per year have exceeded $7.6 billion in the United States (Cutter and Emrich 2005). This estimate does not cover indirect costs such as insurance compensation from the United States government or indirect costs to companies and individuals. Moreover, Hurricane Andrew, in August of 1992, created insured losses of $150 million in a single event (Boissonnade and Ulrich 1995). Not only has the United States suffered significant losses, it also has spent a tremendous amount of money on restoration: $150 billion between 2004 and 2005 alone (Pielke Jr et al. 2008).

Although a number of communities have recognized the seriousness of the damage and will spend their budgets on mitigation plans, the core problem is how and where to invest their limited funds to prevent and prepare for natural disasters. Therefore, research in this area may help analyze the damage suffered and reduce future monetary loss. Although damage is inescapable, creating damage prediction models may provide a key solution for decreasing these losses.

Following a growing public awareness of the danger from disasters and the tremendous demand for damage prediction, many researchers have conducted studies to develop natural disaster damage prediction methods. Nevertheless, their research has not comprehensively identified the interrelationships among the vulnerabilities, natural disasters, and economic losses of commercial buildings. Consequently, this research will fill this gap in hurricane damage prediction using Hurricane Ike in Texas's coastal counties as a case study.

1.2 Research Objective

The objectives of this research are: 1) to identify the relationships among hurricane damage loss, vulnerability indicators, and hurricane indicators for commercial buildings, 2) to predict hurricane damage and ratios by vulnerability factors and hurricane indicators, based on insured loss payments for the Texas coastal counties, 3) to decide the magnitude and significance of the indicators, and 4) to create a methodical process using Geographical Information Systems (GIS) to assess other times and states in order to predict hurricane damage. These factors provide the framework necessary to identifying the spatial distribution of financial hurricane loss.

1.3 Predicted Benefits and Importance

This hurricane damage prediction will determine if the developed models are verifiable; additionally, this prediction 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. Furthermore, this model will help to define the distribution of hurricane losses and hurricane-prone areas in order to diminish the perceived risks for residents who live in hurricane-vulnerable areas.

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. 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.

1.4 Structure of the Dissertation

This section discusses the background, objective, predicted benefits, and importance of this research. Section Two discusses the need and framework for hurricane damage assessment, and explains the indicators used. This second section also described previous studies in this research area. Section Three explains the research methodology used, as well as the research hypothesis, assumptions, and limitations. Section Four describes the data, as well as data collection and management. Sample selection, dependent variables, and independent variables are also described. Section Five discusses the analysis of the data and the results. Two regression models were established to perform this research. Lastly, research conclusions, a summary of the results, and recommendations for future research are discussed in Section Six.

2. LITERATURE REVIEW

The goal of this section is to provide an understanding of the basic knowledge and development of this research. Particularly, previous studies using various natural disasters and vulnerability indicators to predict natural disaster damage and losses were investigated to identify the significant indicators in damage prediction. The previous studies also provided frameworks used for this type of damage prediction.

2.1 Hazard, Vulnerability, and Risk

Damage and risk are significantly and positively correlated (Farber 1987). For this reason, an exact comprehension of risk is crucial to a successful damage prediction. The meaning of risk includes both anticipation and probability. Natural disasters impact different places and then, depending on the features of those places, the level of that risk is subject to modification (Taubenböck et al. 2008). Hence, risk refers to a combination of the vulnerabilities and hazards (Wisner 2004). The Equation (1) explains this relationship (Pelling et al. 2004):

$$\text{Risk} = \text{Hazards} \times \text{Vulnerability} \tag{1}$$

In this equation, Risk represents the expected loss or damage, and Hazards represents the probability of incidence of hazards in a certain area. Vulnerability stands for the inclination of damage from the Hazards (Crichton 1999). As a result, the amount of Risk depends upon the other two components in the equation. For instance, if one of the values (either Hazards or Vulnerability) is increased, then Risk also is increased.

2.2 Vulnerability Assessment

A Vulnerability Assessment examines a combination of vulnerabilities that exist among a certain people, in a particular environment, and within a given community. To measure vulnerability, a number of studies have selected different computable indicators.

2.2.1 Vulnerabilities

Vulnerability is a fundamental idea in natural disaster research (Wu et al. 2002), and researchers have made significant contributions to promote this idea. A vulnerability is defined as a “latent deficiency” or “the capacity to be injured” (Alexander 1997; Cutter 1996; Dow 1992). However, owing to such broad definitions, the terminology is considered debatable because the meaning of the term can be interpreted in different ways depending upon the research subject and method (Cutter 1996; Dow 1992).

However, three major viewpoints have become widely known. First, both property and people are vulnerable, in that they are subject to substantial exposure to disasters(Cutter 1996). To determine this type of vulnerability, researchers evaluate the distribution of certain hazardous conditions and assess their impact on humans and buildings (Wu et al. 2002). Second, hazard vulnerability is unevenly distributed among individuals and groups. This research focused on "coping ability." which includes both resistance and resilience. Resistance is the ability to tolerate disasters, and resilience is the capability of an individual to recover from hazard damage (Anderson and Woodrow 1991; Clark et al. 1998; Dow 1992; Wu et al. 2002). Third, S.L. Cutter integrated the two concepts discussed above and developed the hazard of place model. Due to the comprehensive nature of this approach, many researchers have adopted this model as the most adaptable to a pragmatic study and a geographic method (Cutter et al. 2000).

2.2.2 Geographical Vulnerability and Indicators

Geographical vulnerability is defined as a substantial exposure to peril (Cutter 1996). Since vulnerability is an essential feature of natural disasters, it can be explained by biophysical risks such as elevation and other geographical impacts (Cutter et al. 2003). In general, geographical features differ depending on the location, and the level and amount of exposure to natural hazards can also be diverse. For instance, the Federal Emergency Management Agency (FEMA) created the FEMA Q3 Flood Data study in an effort to understand the risks of hurricanes and floods. FEMA designated flood zones based on the level of flood risk (Fulton County 2012). The zones show the potential risk of flood in each defined area. As shown in Table 1, there are three types of flood zones. Zone A is an area anticipated to have a 1%, or larger chance to flood in any given year. Zone X500 is an area anticipated to have a 0.2% to 1% chance to flood in any given year. Zone X is an area anticipated to have a 0.2% or smaller chance to flood in any given year. Although floods can occur anywhere, flood prone areas exist. Based on historical flood data, geographical vulnerability presents flood prone areas.

Table 1. Definition of FEMA Flood Zone

Zone	Explanation
A	Areas have a 1%, or larger, chance to flood on any given year
X500	Areas have a 0.2% to 1% chance to flood on any given year
X	Areas have a 0.2%, or smaller, chance to flood on any given year

(Source: http://www.fema.gov/)

The National Weather Service created a five point scale to represent the hurricane surge zone in an effort to help clarify the dangers of hurricanes in coastal areas. As shown in Table 2, the categories created are based on sustained wind speed and surge height. Each scaled area is predicted to be influenced by a defined category called the Hurricane Surge Zone. This scale not only presents hurricane risks in scaled areas, but also compares the geographical vulnerability of each area.

Table 2. Definition of Hurricane Surge Zone

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

The distance from a building to the water also plays a key role in defining geographical vulnerability. Highfield et al. (2010) measured the distance from a building to the water to assess the damage to Galveston Island and Bolivar Peninsula caused by Hurricane Ike. They found that the damage increased as the distance from the water decreased (Highfield et al. 2010). These findings indicated that areas closer to water have more geographical vulnerability than areas further from water.

Accordingly, geographical vulnerability indicators should be considered in hurricane damage prediction. FEMA Flood Zones, Hurricane Surge Zones, and distance from water should all be integrated into the hurricane damage prediction model as geographical vulnerability indicators.

2.2.3 Built Environment Vulnerability and Indicators

Natural disasters have a tremendous impact on both people and property, and the level of exposure to the disaster determines the magnitude of the damage. Therefore, insurers must estimate the vulnerability of an insured built environment to measure the likelihood of economic loss (Khanduri and Morrow 2003). On a large scale, for instance, water-related infrastructure systems such as dams, seawalls, and dikes are constructed in flood and hurricane-prone areas, and play a prominent role in preventing damage from natural disasters (Brody et al. 2008). On a smaller scale, the building features of each building such as building age, building floor area, and building appraised value are important components of natural exposure (Chock 2005; Dehring and Halek 2006; Highfield et al. 2010; Khanduri and Morrow 2003). Highfield et al. (2010) used building age to assess the damage to Galveston Island and Bolivar Peninsula from Hurricane Ike. They found that the damage increased as the building age increased (Highfield et al. 2010). Dehring et al. (2006) used building floor area to assess the residential property damage from Hurricane Charley in Lee County. These researchers revealed that the damage increased as the building floor area increased (Dehring and Halek 2006). The research implies that the building's features decide the level of vulnerability, because each building can be classified by combining the characteristics of the buildings to determine the amount of damage and exposure (Chock 2005).

Consequently, quantifying built environment vulnerabilities are important for assessing the damage caused by natural disasters; built environment vulnerability indicators (e.g., building age, building floor area, and building appraised value) should be included in the hurricane damage prediction model.

2.2.4 Hurricane Assessment and Indicators

Every year, hurricanes impact large areas and frequently affect both people and property. Numerous parameters of hurricanes can act as key factors contributing to the amount of damage sustained, such as frequency, magnitude, and others. For example, wind parameters play a key role in hurricane damage and cause related disasters such as floods, hurricane surges, and landslides.

The Hurricane Research Division (HRD) of the National Oceanic and Atmospheric Administration (NOAA) created the HRD real-time hurricane wind analysis system (H*Wind) to make an integrated hurricane observation system. The

HRD collects measured wind data from meteorological observing stations every four to six hours during hurricanes and integrates the data into a wind field which contains information such as maximum sustained wind speeds, duration and direction of maximum sustained wind speeds, and wind direction steadiness (Dunion et al. 2003; Powell and Houston 1998; Powell et al. 2010). This wind analysis utilizes the information gathered by measuring a hurricane's intensity, and thus improves upon earlier hurricane wind analyses. H*Wind analyses include gridded data, image data, and Geographical Information System (GIS) shape files. Researchers can use the H*Wind analyses to assess both wind and storm surges. Additionally, the swath map can be useful for hurricane damage assessments (Dunion et al. 2003; Powell and Houston 1998; Powell et al. 1998). The map also includes gridded data, image data, and Geographical Information System (GIS) shape files. As shown in Figure 1, the swath map consists of grids. Each grid has location information (i.e., longitude and latitude) and wind measurements (i.e., maximum sustained wind speeds, duration and direction of maximum sustained wind speeds, and wind direction steadiness). Using the location information and the wind measurements, researchers should be able to plot the wind database based on their interest time, area, and particular hurricane, and be able to study the relationship between the hurricane's damage and wind (Burton 2010; Powell et al. 1998).

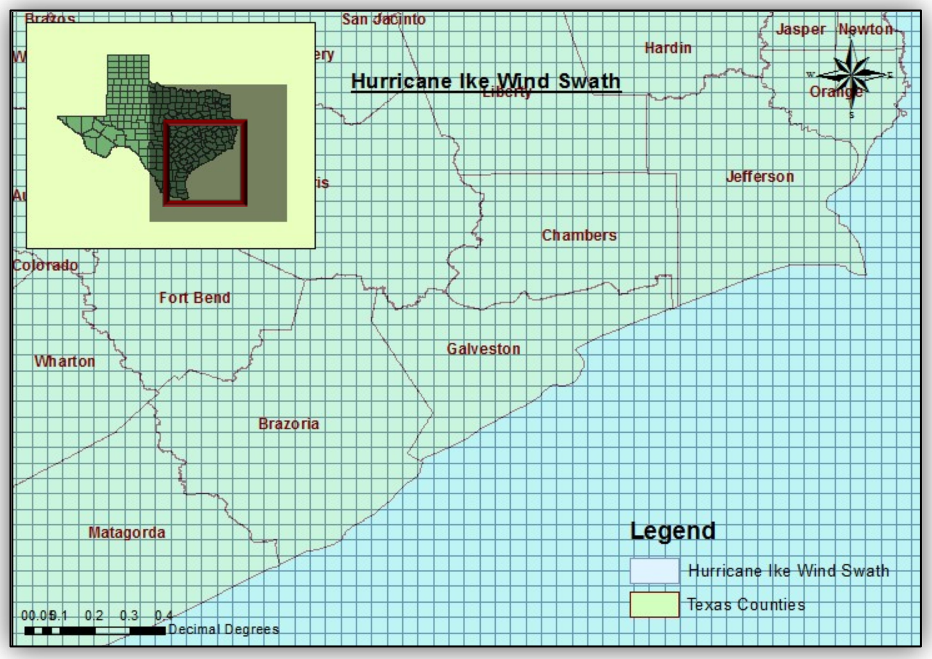


Figure 1. Hurricane Ike of H*Wind Swath for Texas Coastal Counties

The side of a hurricane also plays an important role in measuring damage. In the Northern Hemisphere, areas located on the right side of a hurricane track usually sustain more damage than the left side of a hurricane track (Keim et al. 2007; Noel et al. 1995). The difference occurs because of the differences in wind intensity and direction on either side, due to the interaction of the two opposing actions of a hurricane (i.e., forward movement and counterclockwise rotation). As a result of the interaction, the areas located on the right side of the hurricane always face stronger and more extensive winds, and therefore becomes prone to a greater level of hurricane damage. Hence, the right side of the hurricane track is significantly more exposed to damage than the left side of the hurricane track.

As a consequence, hurricane indicators should be considered in damage predictions, and H*Wind analyses and the side of the hurricane track an area falls on should also be integrated into the hurricane damage prediction model as hurricane indicators.

2.3 Hurricane Damage Prediction

To predict hurricane damage, this research utilized the risk assessment method. Risk assessment was applied to find the probability of results from inexact disasters through an investigation of diverse indicators (Dwyer et al. 2004). The integration of features determine the place vulnerability of a certain area. Accordingly, indicators also can amplify natural disaster risks at a given location.

The framework of this risk assessment offers a process of movement from risk elements to risk management. First, the risk elements need to be defined and the components divided into two parts: the vulnerability assessment and the hazard assessment. The vulnerability assessment tests the social vulnerability, geographical vulnerability, and built environment vulnerability, whereas the hazard assessment tests the hazard type and parameters. The combination of the vulnerabilities and the hazard assessment allows for the risk assessment. Finally, after risks have been assessed, a plan for risk management can be created (Peck et al. 2007).

After adopting the framework for risk assessment described above, hurricane damage prediction can be conducted following the process of risk assessment shown in Figure 2. In this process, hurricane risk elements are defined and then divided into two parts: a vulnerability assessment and a hurricane assessment. A vulnerability assessment tests a built environment's vulnerability and geographical vulnerability, whereas a hurricane assessment tests wind measurements. The combination of vulnerability information and a hurricane assessment allows for damage prediction. Lastly, after the hurricane damage is predicted, a plan for hurricane damage management can be created.

Consequently, this study applies the above framework for hurricane damage prediction to predict hurricane damage. To quantify the damage, this study utilizes the Texas Windstorm Insurance Association's (TWIA) reported property damage losses from Hurricane Ike as dependent variables to measure the actual financial damage and ratio. The ratio is defined as the value of Texas Windstorm Insurance Association claim payouts for commercial building damage from Hurricane Ike ($) divided by the appraised value of buildings ($) based on a 2008 roll of the appraisal district.

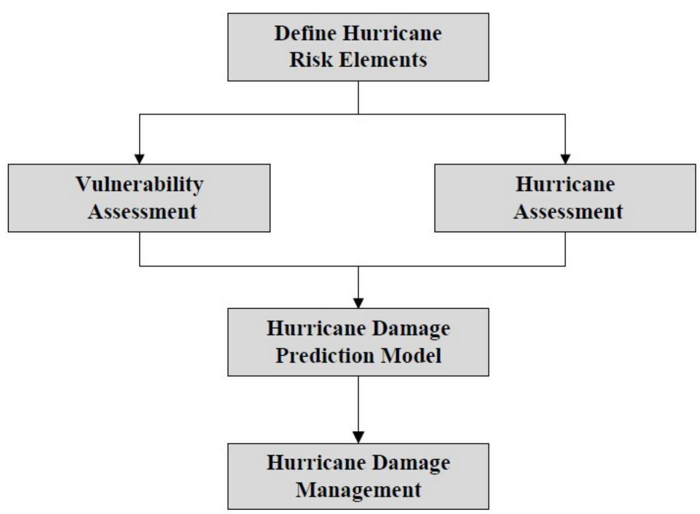


Figure 2. Framework of Hurricane Damage Prediction

2.3.1 Hurricane Ike

Hurricane Ike was a critical disaster which began on 1 September 2008 and ended on 14 September 2008; the storm struck the Bahamas, Cuba, and the Gulf Coast of the United States (i.e., Florida, Louisiana, and Texas), in that order. The hurricane formed on the African coast as a tropical depression and became a hurricane when it traveled through the eastern Caribbean Sea. After that, the storm arrived at Cuba and the Bahamas as a Category 4 hurricane on the Saffir-Simpson Scale. By the time Ike hit the coastlines of Louisiana and Texas, it had become a Category 2 storm with a central pressure of 950 mb and a maximum wind speed of 95 knots (Berg 2009). Due to its abnormally large size, Hurricane Ike impacted a wide area, accompanied by strong winds and heavy rainfall which created huge waves and extensive surges. This impact caused fatalities and substantial damage to properties along the hurricane's path (Kennedy et al. 2010). Particularly, the hurricane directly hit the Bolivar Peninsula and Galveston Island in Texas and devastated properties in those areas with severe storm surges and waves. The hurricane was recorded as the third costliest hurricane to strike the mainland of the United States, following hurricanes Katrina and Andrew. In Arkansas, Louisiana, and Texas, the estimated total monetary loss was approximately $24.9 billion with twenty human casualties (Berg 2009).

2.3.2 Texas Windstorm Insurance Association (TWIA)

The Texas Windstorm Insurance Association (TWIA) was established in 1971 to shield insurance policy holders in Texas coastal counties (see Table 3 and Figure 3) from unexpected meteorological catastrophes. This association is made up of a group of windstorm insurance companies that cover direct loss of property, indirect loss of property or income, and casualties suffered in the Texas coastal counties. TWIA not only provides hurricane protection and training for agents and policy holders, but also receives insurance premiums and makes payments for acceptable claims.

Table 3. TWIA Covers Counties

No.	County
1	Aransas
2	Brazoria
3	Calhoun
4	Cameron
5	Chambers
6	Galveston
7	Harris
8	Jefferson
9	Kenedy
10	Kleberg
11	Matagorda
12	Nueces
13	Refugio
14	San Patricio
15	Willacy

(Source: http://www.twia.org/)

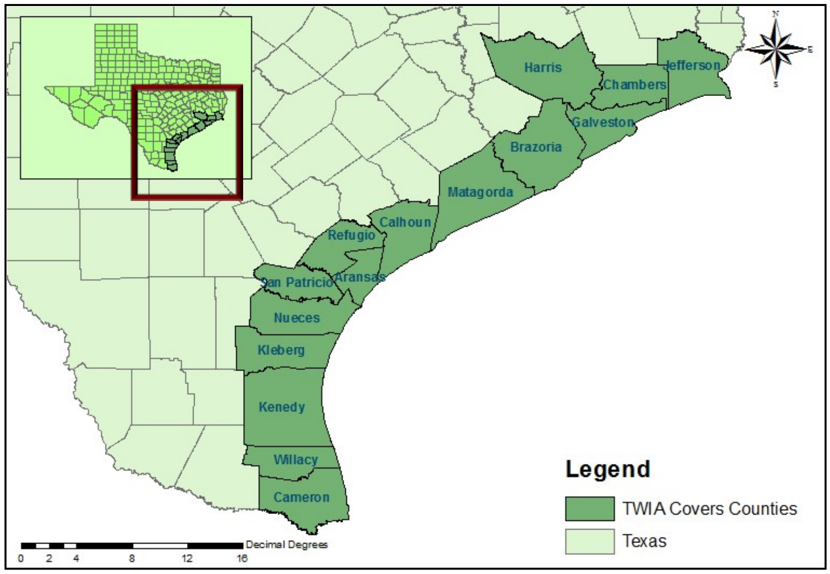


Figure 3. TWIA Covers Counties

2.4 Previous Studies

Much research has been conducted to predict the damage that various disasters may cause. That research also identified the relationships among vulnerabilities, natural disasters, and economic losses using several vulnerability indicators and various natural disasters as examples.

Sparks et al. identified the relationship between hurricane wind speeds and insurance losses in an effort to reduce hurricane damage suffered by residences in Florida and South Carolina. This study explained that damage and wind speed have a positive relationship and identified the area, South Florida, that is most vulnerable to hurricanes (Sparks et al. 1994). The study also showed how to identify the relationships between hurricane parameters and insurance losses. However, the study is not comprehensive, since it only considers hurricane parameters to the extent that they can be used to measure losses.

Borden et al. measured vulnerability in urban regions in the United States using the built environment, as well as social and physical vulnerability indicators to identify the relationships among various vulnerabilities and natural disasters. One of the key findings showed that New Orleans is exposed to more natural disasters than any other urban region in the United States (Borden et al. 2007). This study identified how various vulnerabilities impact urban regions and showed the relationships among the various indicators. However, the research did not study spatial variability because each region would have a different geographic environment.

Brody et al. surveyed flood damage in Texas using socioeconomic, built environment, and disaster indicators. These researchers described how flood damage is controlled by the hurricane period and the quantity of rainfall. Wetlands, dams, and the FEMA Community Rating System (CRS) also can play key roles in diminishing damage (Brody et al. 2008). These results showed that losses were a combination of several vulnerability indicators. Therefore, this study explained that various features of certain vulnerability indicators should be considered when attempting to predict disaster damage.

Burton explored the relationships among hurricane losses, social factors, and hurricane parameters in the Mississippi coastal counties of Jackson, Harrison, and Hancock. He determined that the maximum sustained wind is the most significant factor for predicting damage. However, social vulnerabilities (e.g. race, wealth, type of job, and population) had less of an impact on the level of damage. Hurricane parameters did affect the level of damage measured. On the other hand, social parameters were only significant at the critical level (Burton 2010). This study identified how various vulnerabilities impact urban regions and showed the relationships among the various indicators. However, this research did not study the losses of individual buildings because the study was based on the household as a survey unit.

Cutter described natural disasters and their loss distribution in the U.S. and assessed vulnerabilities in Richland County, South Carolina, using social, built environment, and geographical vulnerability. This study showed the distribution of natural disasters and their losses, as well as a methodology of predicating natural disaster damage (Cutter 2010). This study explained that the various features of the vulnerability indicators should be considered when predicting disaster damage.

Highfield et al. identified the relationship between vulnerability variables and hurricane damage on Galveston Island and the Bolivar Peninsula. Social, structural, and geographic factors were used as vulnerability indicators. These researchers identified vulnerability indicators and showed the relationships among the various indicators. This study found that the age of the house, its distance from water, its appraised value, FEMA flood zones, and non-white populations were all significantly related to the level of damage (Highfield et al. 2010). However, though this research identified relationships, the results were difficult to generalize to other coastal counties and to commercial buildings due to the small study area and survey unit. The researchers collected the damage data from households on Galveston Island and the Bolivar Peninsula. Moreover, using a damage index as a dependent variable made it difficult to see the financial loss.

As shown in Table 4, a number of researchers have attempted to predict natural disaster damage and losses using vulnerability indicators, and have provided frameworks for damage prediction. However, they have not utilized multiple vulnerability categories in their damage predictions, nor has there been a study dealing with commercial buildings. Therefore, there is a gap in the research to be filled by developing a hurricane damage prediction model for individual buildings.

Table 4. Summary of Previous Studies

Author (year)	Damage	Survey Unit	Study Area	Disaster	Vulnerability
Sparks, P. R. et al. (1994)	Insured loss	Household	Florida, South Carolina	Hurricane	• Hurricane parameters
Borden, K. A. et al. (2007)	Property damage	City	U.S.	Natural disasters	• Built environment • Social • Disaster Parameters
Brody, S. D. et al. (2008)	Property damage	County	Texas	Flood	• Socioeconomic • Built environment • Disaster Parameters

Table 4. Continued

Author (year)	Damage	Survey Unit	Study Area	Disaster	Vulnerability
Burton, C. G. (2010)	FEMA Residential Substantial Damages Estimates	Household	Mississippi Coastal Counties	Hurricane	• Social • Hurricane parameters
Cutter, S. L. (2010)	Crops and property damages	County	U.S.	Natural disasters	• Social • Built environment • Geographical
Highfield, W. E. et al. (2010)	Property damage	Household	Galveston Island, Bolivar Peninsula	Hurricane	• Social • Structural • Geographic

3. RESEARCH METHODOLOGY

The purpose of this section is to describe the methodology of this research. First, data collection and data analysis methods are discussed. Two statistical models and their hypotheses are then described. Finally, assumptions, limitations, and definitions for this research are discussed, in that order.

3.1 Process of Data Collection

Figure 4 shows the outline of the data collection process used for this research. First, the TWIA claim payout properties were mapped within the study area using the ArcGIS address locator. Second, sample payouts were randomly selected. Third, geographical vulnerabilities, building environment vulnerabilities, and hurricane indicators were combined, respectively, with the TWIA claim payouts by joining them with the data obtained from ArcGIS by using the Join Data function. Finally, regression models were generated and analyzed.

3.2 Process of Data Analysis

After the creation of the data, a multiple linear regression method was applied to analyze the data, which resulted in two global equations that allowed for an understanding of the relationship between the dependent and independent variables. The global model assumes that the relationships are fixed and coherent throughout all of the data. This study identified the interrelationships among the vulnerability indicators and

TWIA claim payouts using a statistical method. The statistical method order is listed below.

1. Descriptive statistics: mean, max, min, median, and standard deviation.
2. Scatter plots: to check the relationships among the dependent and independent variables.
3. Correlation test: Pearson's and Spearman's Tests to check the relationships among the variables.
4. Multi-collinearity analysis: to check the correlations among the variables.
5. ANOVA test and linear regression: to check the significance of the regression model.
6. Test of normality: to check the normality of the data.
7. Test of homoscedasticity: to use residual plots to check the variance of errors.
8. Transformation: to use log transformation analysis, if required.
9. A regression model.

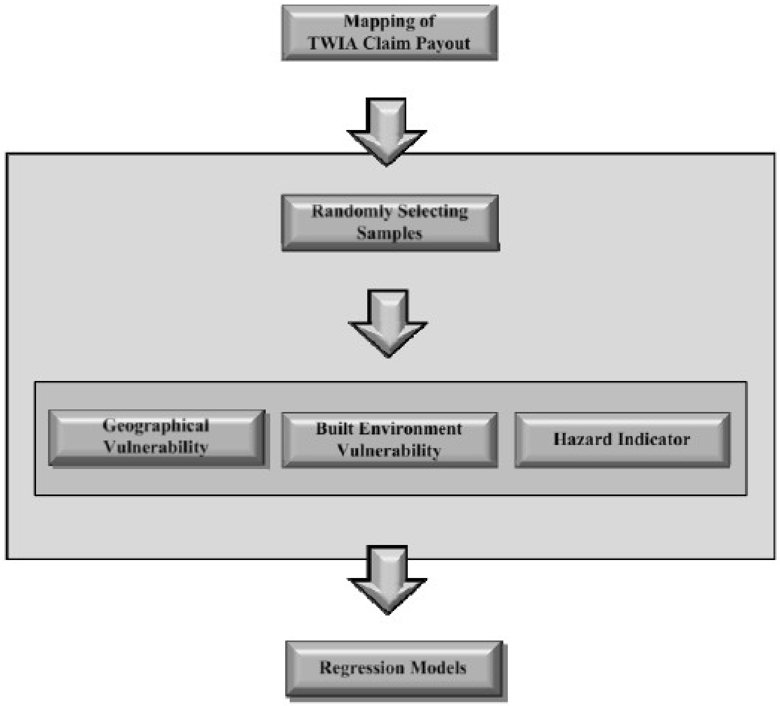


Figure 4. Data Collection Process

3.3 Research Hypothesis

3.3.1 TWIA Claim Payout Regression Model

- The TWIA claim payout *increases* as the *maximum sustained wind speed increases*.
- The TWIA claim payout *increases* if the building is located *on the right side of the hurricane track.*
- The TWIA claim payout *increases* as the *building age increases.*
- The TWIA claim payout *increases* as the *building floor area increases.*

- The TWIA claim payout *increases* as the *appraised value of the building increases.*
- The TWIA claim payout *increases* as the *number of FEMA floodplain zones increases.*
- The TWIA claim payout *increases* as the *number of hurricane surge zones decreases*.
- The TWIA claim payout *increases* as the *distance between the property centroid and the shoreline decreases.*

3.3.2 Ratio Regression Model

- The ratio *increases* as the *maximum sustained wind speed increases*.
- The ratio *increases* if the building is located *on the right side of the hurricane track.*
- The ratio *increases* as the *building age increases.*
- The ratio *increases* as the *building floor area increases.*
- The ratio *increases* as the *number of FEMA floodplain zones increases.*
- The ratio *increases* as the *number of hurricane surge zones decreases*.
- The ratio *increases* as the *distance between the property centroid and the shoreline decreases.*

3.4 Models

In this study, two statistical models were generated to predict the hurricane damage and ratio caused by Hurricane Ike in Texas coastal counties for commercial buildings. Each regression model had different dependent and independent variables, as shown in Equations (2) and (4), and Table (5).

3.4.1 TWIA Claim Payout Regression Model

The goal of this model is to predict the insured claim payout. The dependent variable, the Texas Windstorm Insurance Association (TWIA) claim payout ($), can be predicted by the independent variables, as shown in Equation (2).

$$PDL = \beta_0 + \beta_1 \cdot Wind\_Speed + \beta_2 \cdot Side\_Right + \beta_3 \cdot Age + \beta_4 \cdot Area + \beta_5 \cdot Imp\_Value + \beta_6 \cdot FEMA\_Zones + \beta_7 \cdot Surge\_Zones + \beta_8 \cdot Dist\_Shore \quad (2)$$

3.4.2 Ratio Regression Model

The goal of this model is to predict the unconditional financial damage. The dependent variable, the ratio ($/$), is the value of the Texas Windstorm Insurance Association (TWIA) claim payout ($) divided by the appraised values of the buildings ($), as shown in Equation (3). The ratio can be predicted by the independent variables, as shown in Equation (4).

$$\text{Ratio} = \left(\frac{\text{TWIA claim payout (\$)}}{\text{Building appraised value(\$)}}\right) \tag{3}$$

$$\text{Ratio} = \beta_0 + \beta_1 \cdot \text{Wind\_Speed} + \beta_2 \cdot \text{Side\_Right} + \beta_3 \cdot \text{Age} + \beta_4 \cdot \text{Area} + \beta_5 \cdot \text{FEMA\_Zones} + \beta_6 \cdot \text{Surge\_Zones} + \beta_7 \cdot \text{Dist\_Shore} \tag{4}$$

Table 5. Model Component Definitions

Variables	**Variable Name**	**Abbreviation**	**Description**
Dependent	TWIA claim payout	PDL	Texas Windstorm Association claim payouts for property damage from Hurricane Ike ($)
	Ratio	Ratio	Texas Windstorm Association claim payouts for property damage from Hurricane Ike ($) / Appraised value of building ($) (Based on 2008 roll)
Hurricane Indicators			
Independent	Max. sustained wind speed	Wind_Speed	Max. Sustained wind speed (m/s)
	Right side of the hurricane track	Side_Right	Dummy variable • 1 : A building locates on the right side of the hurricane track • 0 : A buildings locates on the left side of the hurricane track

Table 5. Continued

Variables	Variable Name	Abbreviation	Description
Built Environment Vulnerability Variables			
Independent	Building age	Age	Building Age (Based on 2008 roll)
	Building floor area	Area	Building floor area (m^2) (Based on 2008 roll)
	Building appraised value	Imp_Value	Appraised value of building ($) (Based on 2008 roll)
Geographical Vulnerability Variables			
Independent	FEMA Flood Zones	FEMA_Zones	Ordinal Variable • 0: Unregistered zone • 1 : A building on the FEMA flood zone X • 2: A building on the FEMA flood zone X500 • 3 : A building on the FEMA flood zone A
	Hurricane surge zones	Surge_Zones	Ordinal Variable • 1 ~ 5
	Distance from shoreline	Dist_Shore	Distance from the property centroid to shoreline (m)

3.5 Assumption

- The Hurricane Ike surface wind analysis made by the Atlantic Oceanographic and Meteorological Laboratory (AOML) is accurate, and the wind attributes are the same within each grid.
- Parcel information received from the appraisal district of each Texas coastal county is accurate because the data were obtained from official documentation.
- The TWIA claim payout is an indicator that represents the economic loss from hurricanes.
- The appraised value of the buildings is accurate because the value is based on property taxes evaluated by each office of the Assessor-Recorder of each of the Texas coastal counties.

3.6 Limitations

- The study unit is limited to commercial buildings in the Texas coastal counties.
- The insured claim payouts only include structural damage.
- Mitigation, safety nets, and preventive measures for natural disasters have not been considered in this study.
- Only the direct effects of the dependent variables and independent variables have been taken into account.
- Inflation and deflation were not factored in to insured loss payments.

4. DATA COLLECTION AND MANAGEMENT

4.1 Population of Interest

This study considered as observational units only improved commercial buildings that had insured claim payouts from the Texas Windstorm Insurance Association (TWIA) in Texas coastal counties from Hurricane Ike.

As shown in Figure 5, Hurricane Ike, a Category 2 hurricane on the Saffir-Simpson Scale, struck the Texas coastal counties on 13 September 2008. The financial damages suffered by Texas coastal counties are shown in Figure 6.

Table 6 and Figures 7 and 8 show the total amount of claim payouts and the number of claim payouts collected from the Texas Windstorm Insurance Association (TWIA) for commercial property damage from Hurricane Ike from 17 August 2008 to 22 February 2012.

The total claim payout was $450,518,330 and the total number of claims was 4,150. Galveston County received the most damage from Hurricane Ike in terms of both dollar amount of damage ($255,333,818; 56.68%) and the number of claims (1,807; 43.54%). Other damaged counties included: Jefferson County (1,218 claims totaling $104,249,917); Brazoria County (597 claims totaling $46,922,396); Chambers County (470 claims totaling $39,755,609); Harris County (45 claims totaling $4,126,821); Matagorda County (9 claims totaling $36,981); Liberty County (2 claims totaling $67,501); and Nueces County (2 claims totaling $5,287).

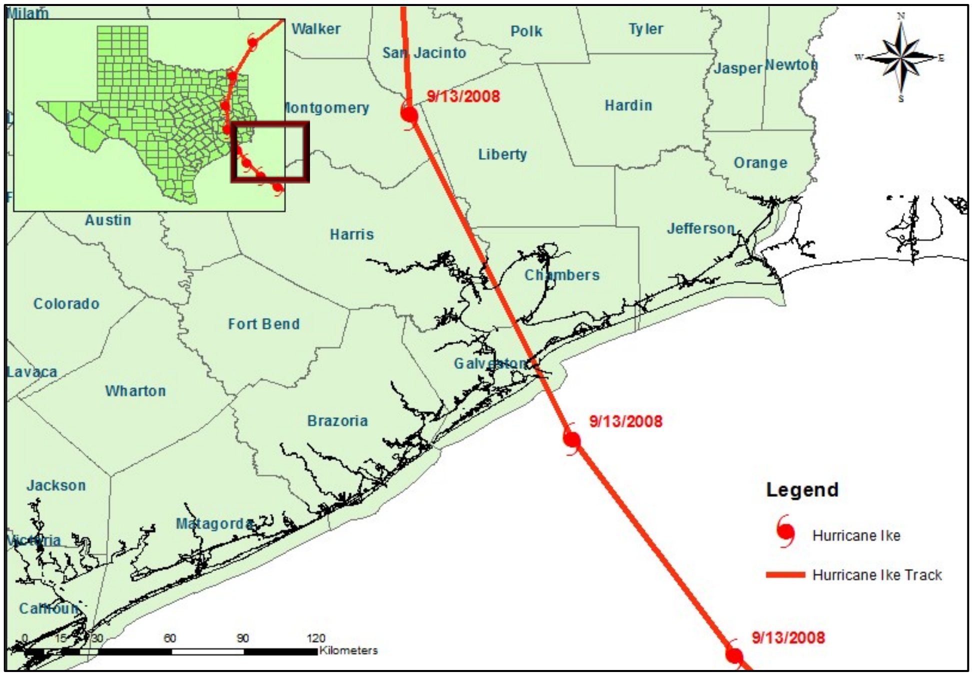


Figure 5. Hurricane Ike

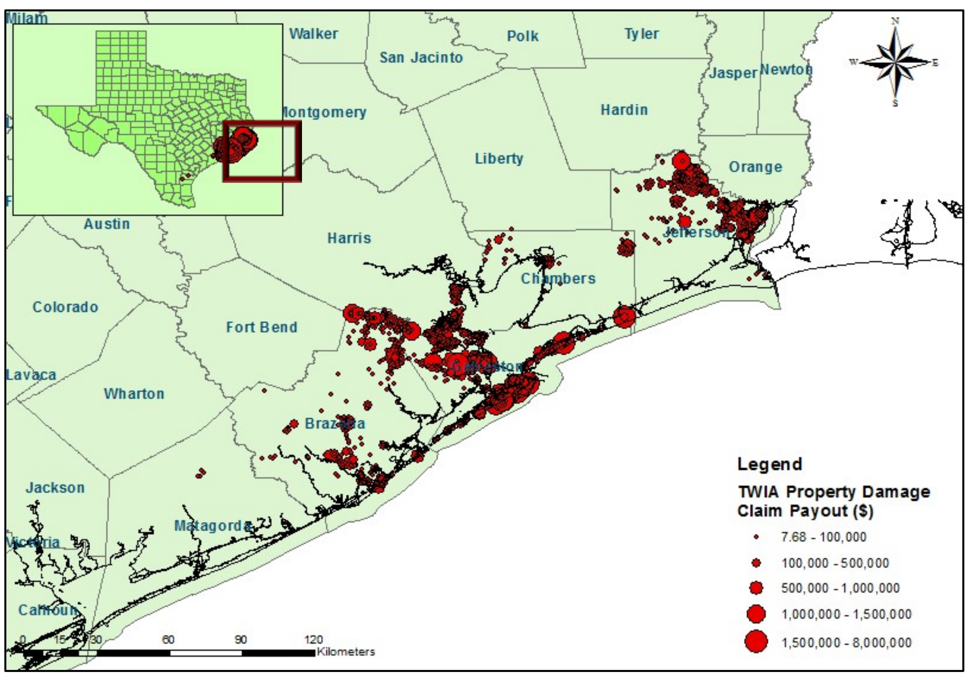


Figure 6. Distribution of TWIA Property Claim Payouts

Table 6. TWIA claim payout Records per County from Hurricane Ike

County	Total Claim Payouts($)	No. of Claim Payouts
Galveston	255,333,818	1807
Jefferson	104,249,917	1218
Brazoria	46,922,396	597
Chambers	39,755,609	470
Harris	4,126,821	45
Matagorda	36,981	9
Liberty	67,501	2
Nueces	5,287	2
SUM	450,518,330	4150

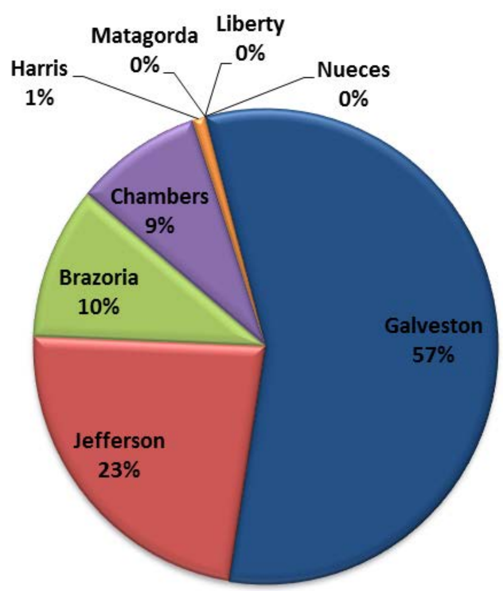


Figure 7. Distribution of Total Claim Payout Amounts ($) per County from Hurricane Ike

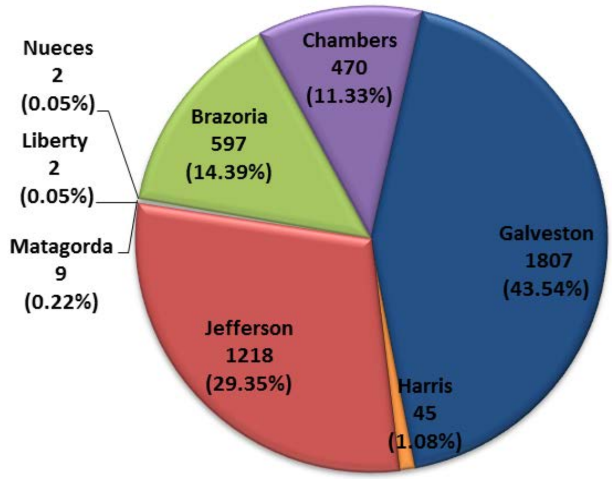


Figure 8. Distribution of Number of Claim Payout Records per County from Hurricane Ike

4.2 Sample Selection

In this study, 500 of the total damage reports (4,150) were randomly selected as samples.

4.3 Description of Collected Data

The focus of this study was to identify the interrelationships among vulnerabilities, a hurricane, and the economic losses suffered by commercial buildings. In order to predict these losses, this research used the Hurricane Ike claim payout records of commercial buildings from the Texas Windstorm Insurance Association (TWIA). In addition, to measure the vulnerabilities of each building, this study used the spatial data and structural information of each building. As shown in Table 7, the necessary spatial data was acquired from the websites of related associations, and building information was obtained from the websites of the appraisal districts of each Texas coastal county.

Table 7. List of Acquired Data

Variable	Variable Name	Description	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.nuecescad.net/)

Table 7. Continued

Variable	Variable Name	Description	Source
Hurricane Indicators			
Independent	Max. sustained wind speed	Max. sustained wind speed from the grid of Hurricane Ike surface wind analysis (m/s)	Atlantic Oceanographic and Meteorological Laboratory (http://www.aoml.noaa.gov/hrd/Storm_pages/ike2008/wind.html)
	Side of the hurricane track	Left or right side of the hurricane track	
Built Environment Vulnerability			
Independent	Building age	Building age (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.nuecescad.net/)
	Building floor area	Building floor area (m^2) (Based on 2008 roll)	
	Building appraised value	Appraised value of building ($) (Based on 2008 roll)	

Table 7. Continued

Variable	Variable Name	Description	Source
Geographical Vulnerability			
Independent	FEMA Q3	FEMA digital Q3 flood data	Texas Natural Resources Information System (TNRIS) 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)	

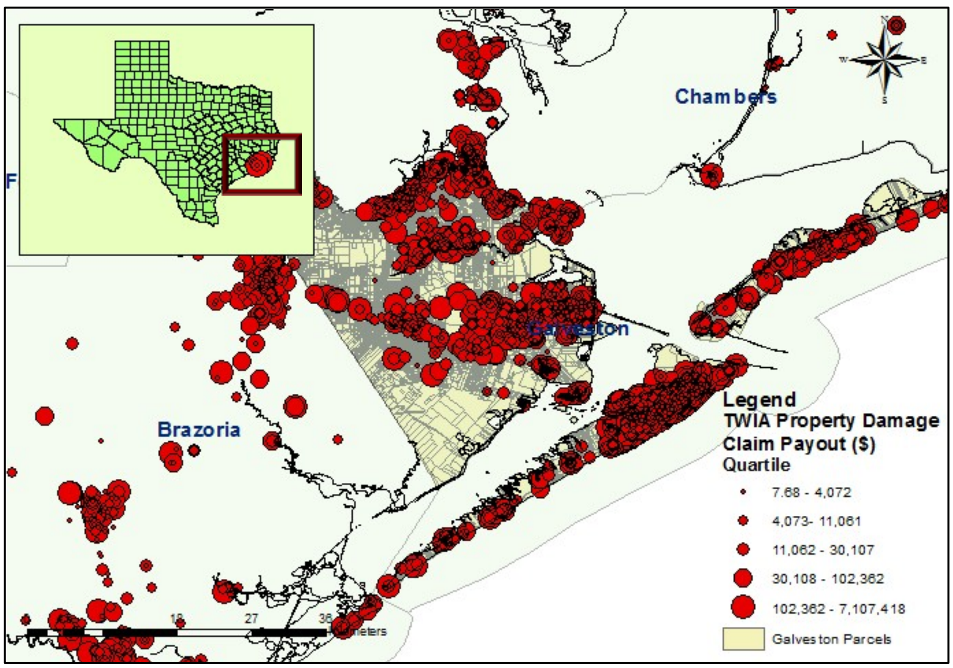
4.4 Dependent Variables

4.4.1 TWIA Claim Payout

The selected samples from the Texas Windstorm Insurance Association property damage claim payouts resulting from Hurricane Ike were plotted on each county parcel of the shape files by using the ArcGIS address locator. For instance, as shown in Figures 9 (a) and (b), each incident of damage was mapped on the centroid of the parcel within the study area.

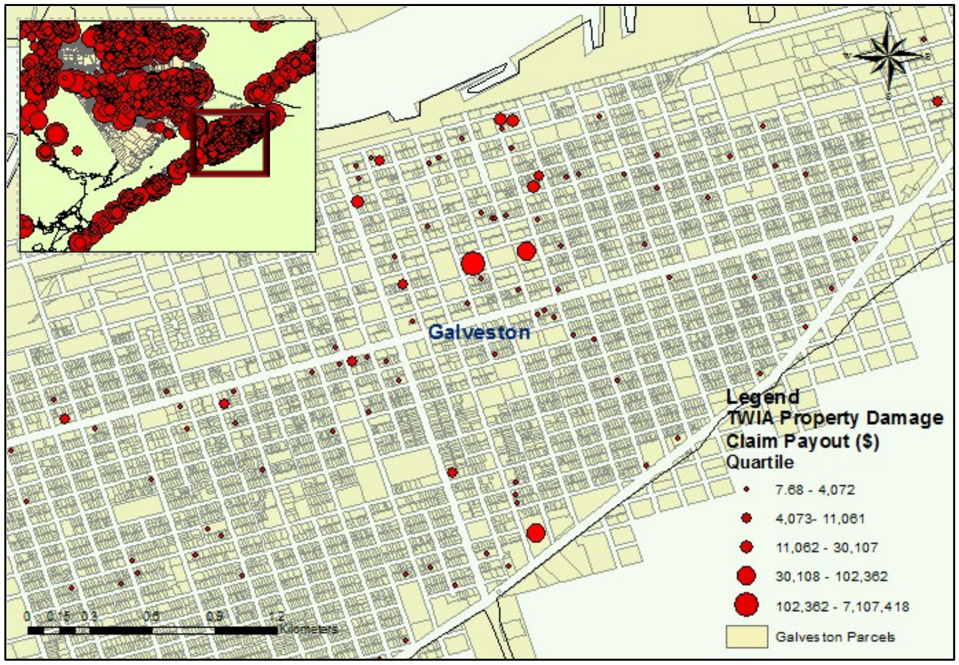
4.4.2 Ratio

Samples from the Texas Windstorm Insurance Association property damage claim payouts from Hurricane Ike ($) were randomly selected. Then the appraised values of the samples were identified from each appraisal district. The ratio was calculated by dividing the Texas Windstorm Insurance Association (TWIA) claim payout ($) by the sum of the appraised values of the buildings ($).



(a)

Figure 9. TWIA Claim Payouts in Galveston : (a) and (b)



(b)

Figure 9. Continued

4.5 Independent Variables

4.5.1 Geographical Vulnerability Variables

4.5.1.1 FEMA Flood Zones

Federal Emergency Management Agency (FEMA) Q3 Flood Data was then mapped onto the Texas coastal counties. As shown in Figure 10, the zones are located along the coastline of Texas. There are four flood zones, each based on the level of flood risk. They include: the Undersigned area, Zone X, Zone X500, and Zone A. These zones show the potential risk of flooding along the Texas coast.

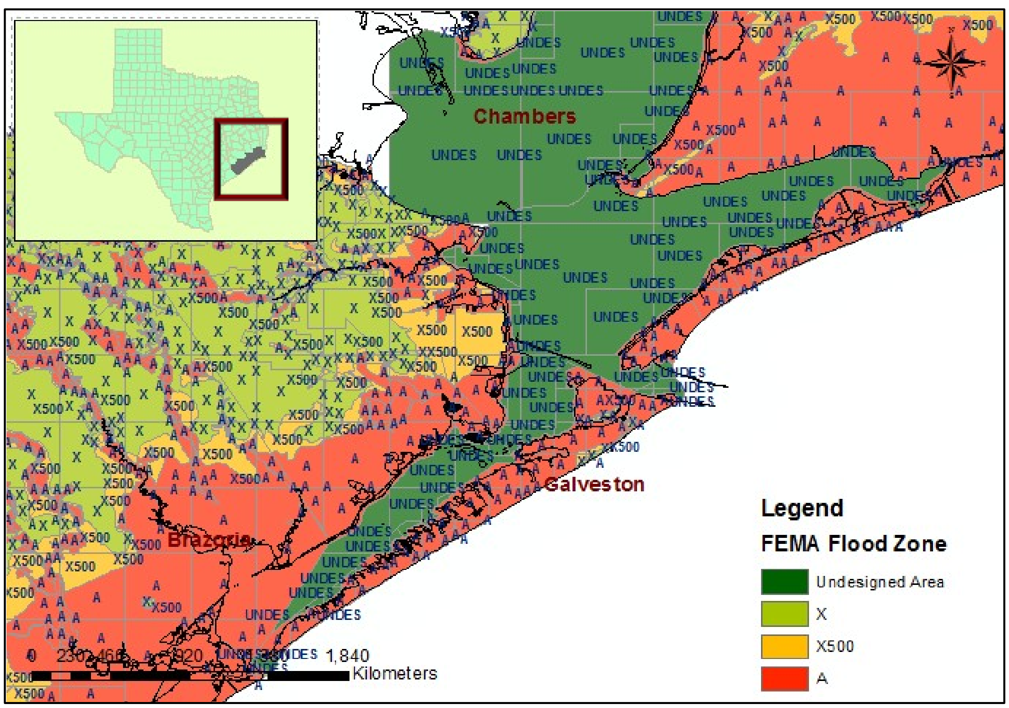


Figure 10. Map of FEMA Flood Zones in the Texas Coastal Counties

4.5.1.2 Hurricane Surge Zones

The hurricane surge zones created by the National Weather Service were plotted on the map of Texas coastal counties. As shown in Figure 11, the zones are located along the coastline of Texas. There are five levels based on sustained wind speeds and surge heights. The number of each scaled area predicts the influence of the sustained wind speed and the surge height at that location. The number of each scaled area also shows the potential risk of hurricanes at that Texas coastal county.

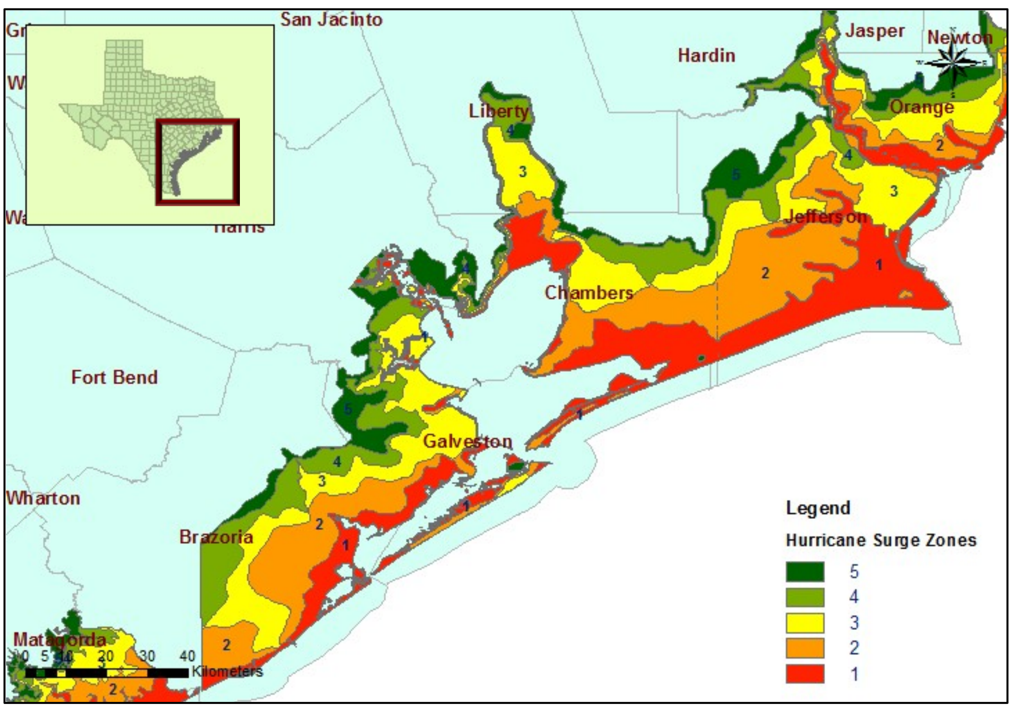


Figure 11. Map of Hurricane Surge Zones in the Texas Coastal Counties

4.5.1.3 Distance from Shoreline

The distance from the shoreline was calculated by using the Near Analysis function of ArcGIS. This analysis measures the distance between an imputed feature (which can be a polyline, point, polygon or multiple type) and the nearest feature (which also can be a polyline, point, polygon or multiple type). As a result of the analysis, Near_Dist (distance) and Near_FID (identification number) were recorded in order to save the nearest distance from an inputted feature to the nearest feature, and the feature identification number, respectively. In this research, the damage data (point) and the shoreline (polyline) were inputted into the analysis to calculate the nearest distance. Following the analysis, the distance from the shoreline was measured, as shown in Figure 12.

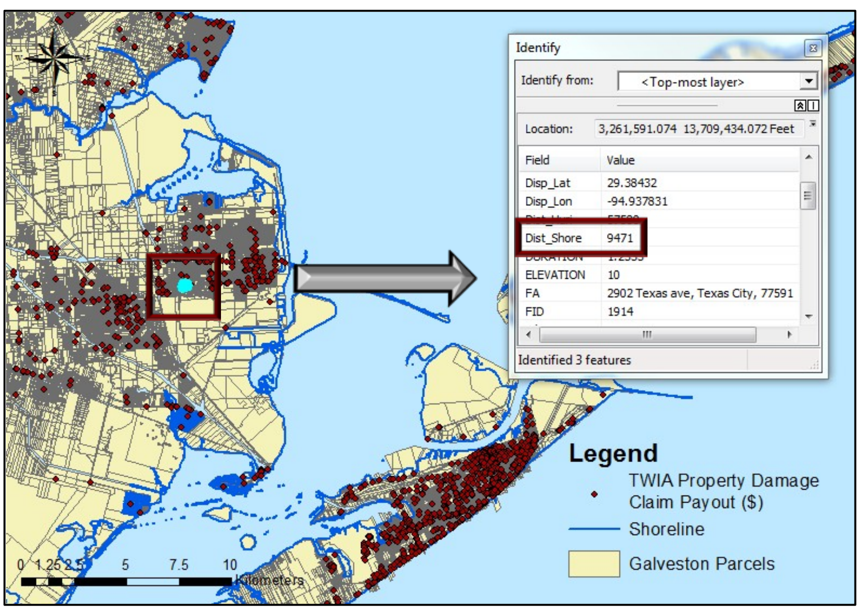
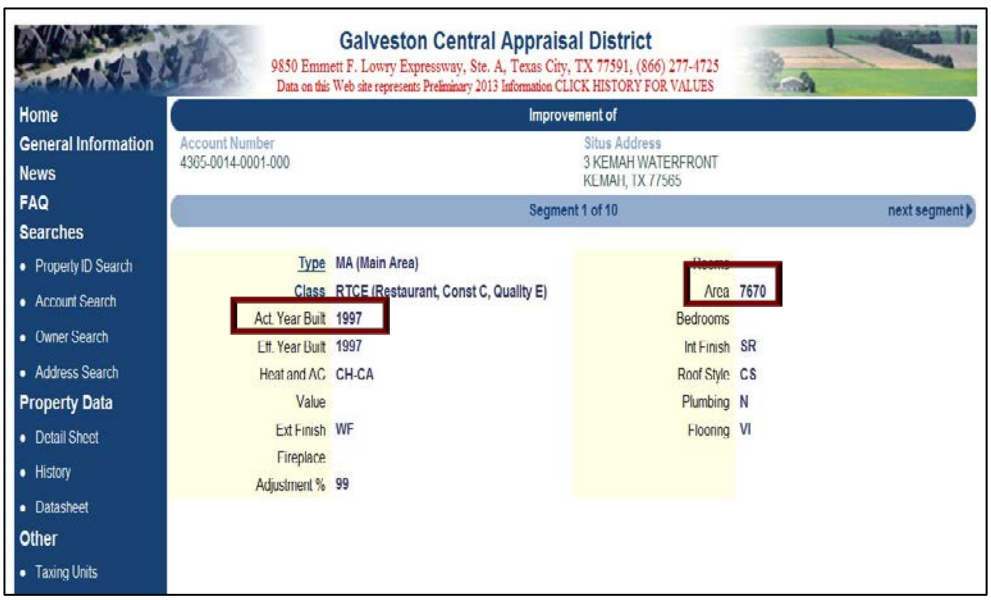


Figure 12. Calculating Distance from the Shoreline

4.5.2 Built Environment Vulnerability Variables

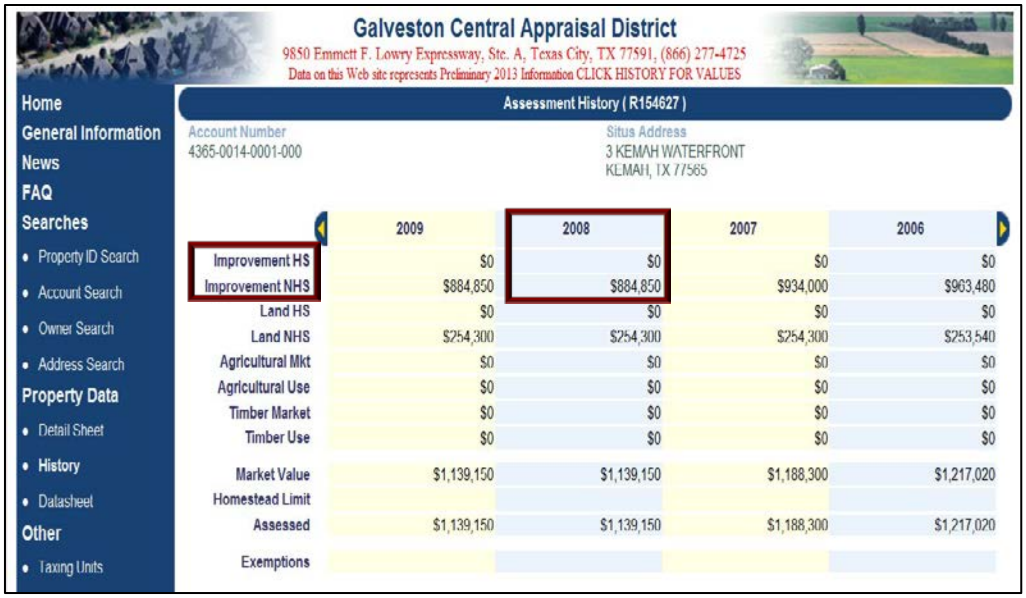
4.5.2.1 Building Age, Floor Area, and Appraised Value

The building information (i.e., building age, building floor area, and appraised value of the building) was collected from each website of the appraisal district for each Texas coastal county, based on a 2008 roll, as shown in Figure 13. The appraised value of each building was calculated as the total value of improvement homesite (HS) and improvement non-homesite (NHS). The improvement homesite value pertains to a residential property that is a taxpayer's homesite. The non-homesite value pertains to any improvements that are not part of the homesite or actual home.



Building Age & Building Area (a)

Figure 13. Parcel Information of Damaged Property on the Website of Galveston Central Appraisal District : Building Age & Building Area (a), Appraised Value (b)



Galveston Central Appraisal District
9850 Emmett F. Lowry Expressway, Ste. A, Texas City, TX 77591, (866) 277-4725
Data on this Web site represents Preliminary 2013 Information CLICK HISTORY FOR VALUES

Home
General Information
News
FAQ
Searches
- Property ID Search
- Account Search
- Owner Search
- Address Search

Property Data
- Detail Sheet
- History
- Datasheet

Other
- Taxing Units

Assessment History (R154627)

Account Number
4365-0014-0001-000

Situs Address
3 KEMAH WATERFRONT
KEMAH, TX 77565

	2009	2008	2007	2006
Improvement HS	$0	$0	$0	$0
Improvement NHS	$884,850	$884,850	$934,000	$963,480
Land HS	$0	$0	$0	$0
Land NHS	$254,300	$254,300	$254,300	$253,540
Agricultural Mkt	$0	$0	$0	$0
Agricultural Use	$0	$0	$0	$0
Timber Market	$0	$0	$0	$0
Timber Use	$0	$0	$0	$0
Market Value	$1,139,150	$1,139,150	$1,188,300	$1,217,020
Homestead Limit				
Assessed	$1,139,150	$1,139,150	$1,188,300	$1,217,020
Exemptions				

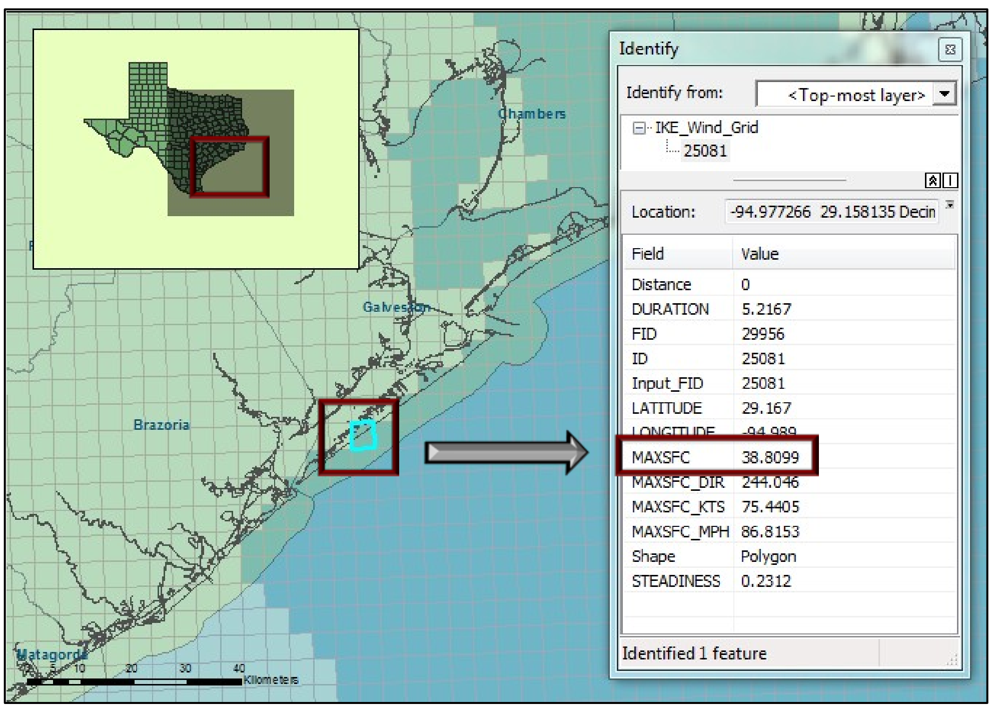
(b)

Figure 13. Continued

4.5.3 Hurricane Indicators

4.5.3.1 Max. Sustained Wind Speed

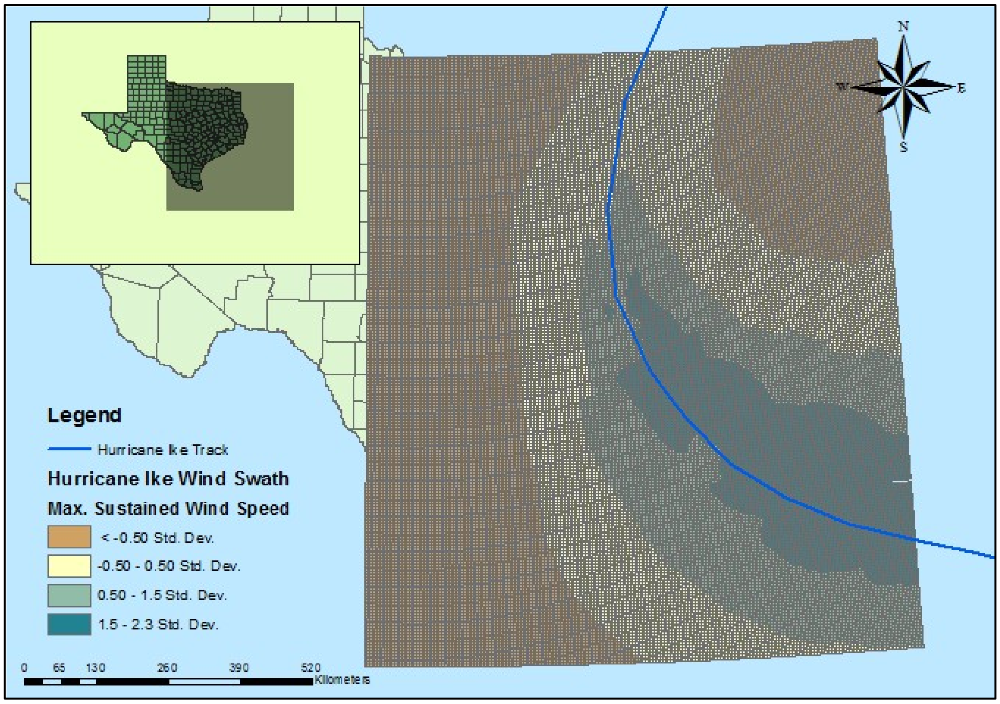
The map of the HRD real-time hurricane wind analysis system (H*Wind) for Hurricane Ike was mapped for the Texas coastal counties. As shown in Figure 14 (a), the swath map consists of grids. Each grid contains location information (i.e., longitude and latitude) and maximum sustained wind speeds (i.e., maxfc). The swath map covers the entire study area and has different wind speeds following the hurricane track, as shown in Figure 14 (b).



(a)

Figure 14. Map of Hurricane Ike of H*Wind Swath :

Polygon Information (a) and Std. Dev. of Max. Sustained Wind Speed (b)



(b)

Figure 14. Continued

4.5.3.2 Side of the Hurricane Track

The side of the hurricane was determined by the track of Hurricane Ike. As shown in Figure 15, buildings located on the right side of the hurricane track defined the right side damages. On the other hand, buildings located on the left side of the hurricane track defined the left side damages. The left side total damage costs were $315,828,010 (70%) and the right side total damage costs were $134,690,319 (30%). The left side total number of claims were 2,630 (63%) and the right side total number of claims were 1,530 (37%).

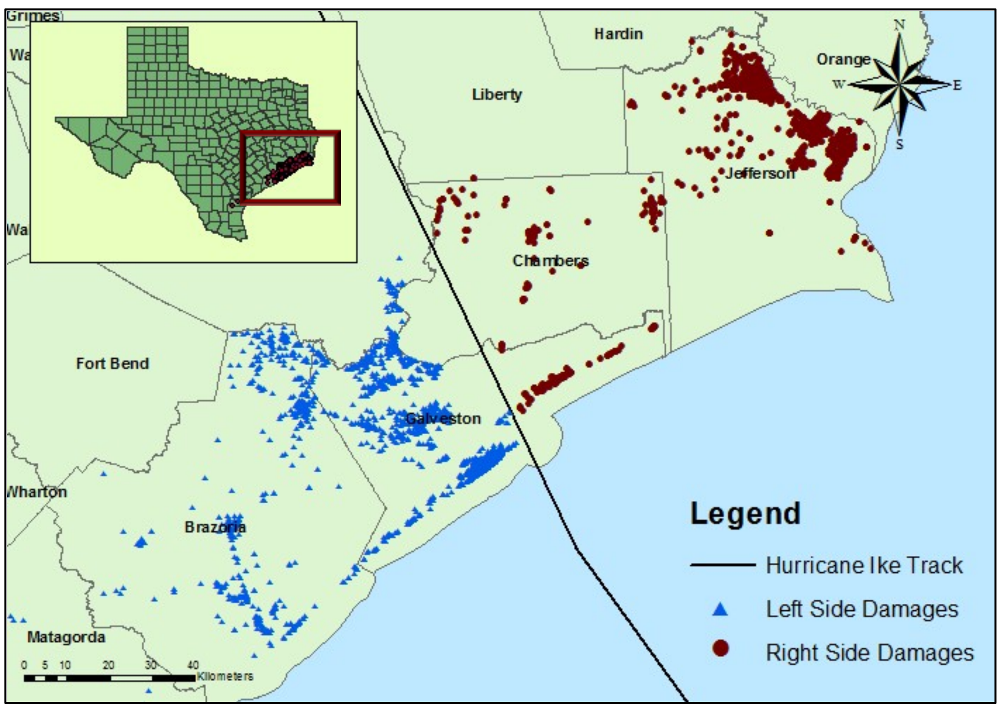


Figure 15. Damages Depending on the Side of the Hurricane Track

4.6 Data Management

This study utilized GIS to combine, manage, and create spatial information for a statistical examination. As a computerized database management system, GIS facilitates spatial data to store, capture, control, make, analyze, and present geographically referenced data (Bill 1994). Generally, spatial data presents the figure and position of the data by layers using raster data, digitally imaged grid data, and vector data, based on polygons, points, and lines, respectively (Hellawell et al. 2001). The primary benefit of using this application is in creating a new layer of data by using various useful functions such as merge, clip, union, intersection, join, buffer, overlay, and dissolve. Particularly, this research produced a new layer of data by using the overlay function to combine diverse sorts of obtained data from the related organizations, based on their locations.

Figure 16 presents an outline of the GIS process. This research utilized ArcGIS tools to combine both a dependent variable and independent variables. After the GIS process, data collection was completed as shown in Table 8. The process described below explains the GIS process.

1. The TWIA claim payout properties were mapped in the study area using the ArcGIS address locator.
2. Geographical vulnerability indicators, building environment vulnerability indicators, and hurricane indicators were joined with the TWIA claim payouts by joining the data of with ArcGIS.
3. The data was completed for the regression models.

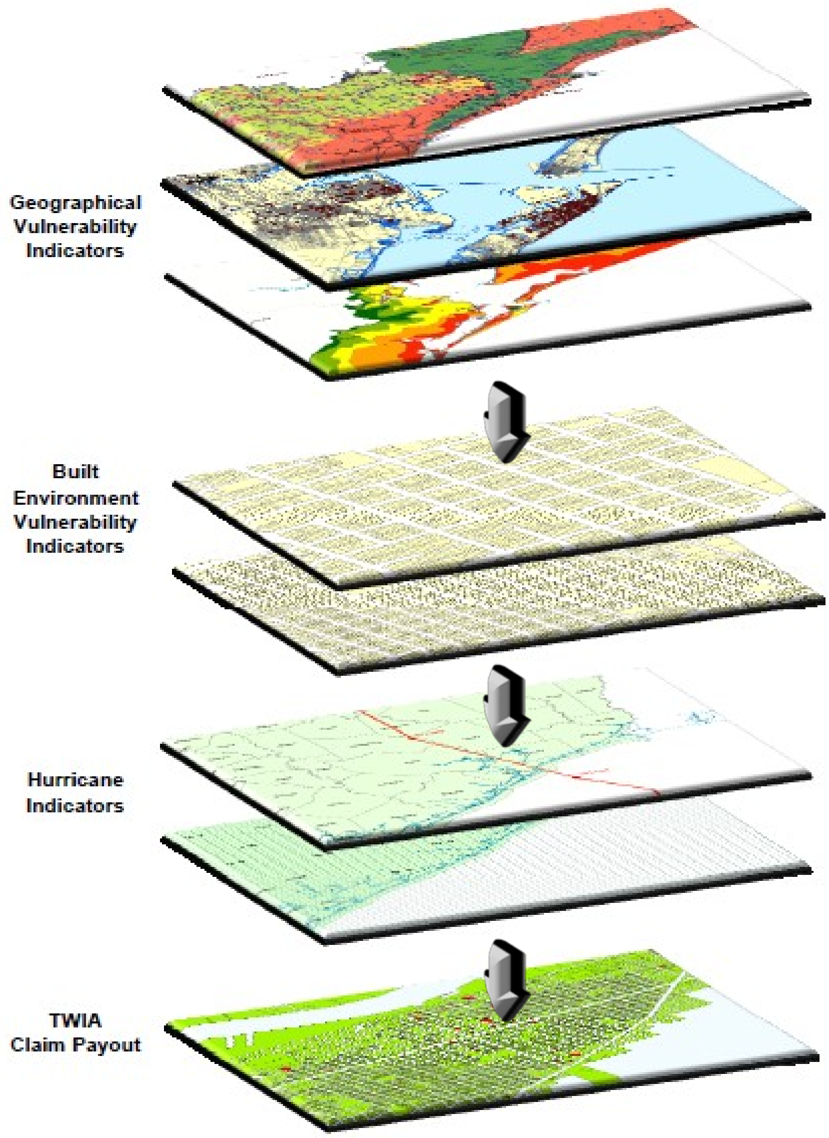


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Figure 16. GIS Process

Table 8. Sample of Data Matrix

County	PDL ($)	Ratio ($/$)	Wind Speed (m/s)	Side_Right	Age	Area (m^2)	Imp_Value ($)	FEMA_Zones	Surge_Zones	Dist_Shore (m)
Galveston	7,118.00	0.06	36	0	33	303.51	127,940	A	3	409.00
Galveston	22,499.75	0.08	34.72	0	24	256.78	281,290	X	4	975.36
Brazoria	15,306.00	0.15	35.22	0	34	384.99	105,140	X500	5	11,908.23
Galveston	52,405.22	0.17	39.8	0	43	305.65	300,270	A	2	490.42
Brazoria	4,121.71	0.05	35.2	0	33	487.74	76,410	X	5	17,067.58
Jefferson	8,755.04	0.08	36.75	1	41	219.44	114,670	X	3	9,249.46
Galveston	23,860.82	0.08	37.55	1	79	494.24	294,540	A	2	784.86
Jefferson	8,341.57	0.2	36.18	1	51	84.73	41,890	X	4	13,906.20
Galveston	10,676.51	0.08	36	0	45	337.98	138,190	X500	3	645.26
Galveston	8,098.17	0.04	39.49	0	22	383.13	209,920	A	3	747.67
Galveston	2,756.03	0.04	36	0	48	218.32	62,170	A	3	282.55
Jefferson	4,736.81	0.06	35.66	1	31	143.63	75,550	X500	3	4,025.80
Jefferson	26,294.18	0.17	36.06	1	36	425.12	150,510	X	3	20,566.68
Brazoria	2,371.83	0.1	31.48	0	36	139.35	22,750	A	3	1,778.81
Jefferson	6,755.17	0.07	35.58	1	47	234.86	92,480	X	3	18,672.96
Galveston	5,825.56	0.06	37.43	0	12	226.68	91,560	A	3	726.34

5. DATA ANALYSIS AND DISCUSSION

The aim of this section is to describe the creation of multiple regression models that predict the TWIA claim payouts and ratios, and to describe how this research determined the magnitude and significance of the indicators. The TWIA claim payout regression model and the ratio model are both described below.

5.1 Descriptive Analysis

Descriptive statistics present important properties such as number of samples, mean, median, standard deviation, quartiles, skewness, and kurtosis. Table 9 numerically shows the descriptive statistics of the dependents and independent variables used in this study. The mean and median present the central tendency of the data. The standard deviations measure the spread of the samples. The quartiles show the dispersion of data, and the skewness and kurtosis describe the distribution shape. In accordance with the skewness, the distribution of the Ratio and PDL are excessively skewed to the right. The values, 3.00 and 2.61, both higher than 0, indicate that the distribution is positively skewed (i.e., that the left of the tail is shorter than the right side of the tail, and the data distribution is left sided). According to the kurtosis, the distribution of the Ratio and PDL are leptokurtic, which indicates higher and sharper peaks than a normal distribution. The values, 13.32 and 9.41, both higher than 3, mean that the data is not normally distributed.

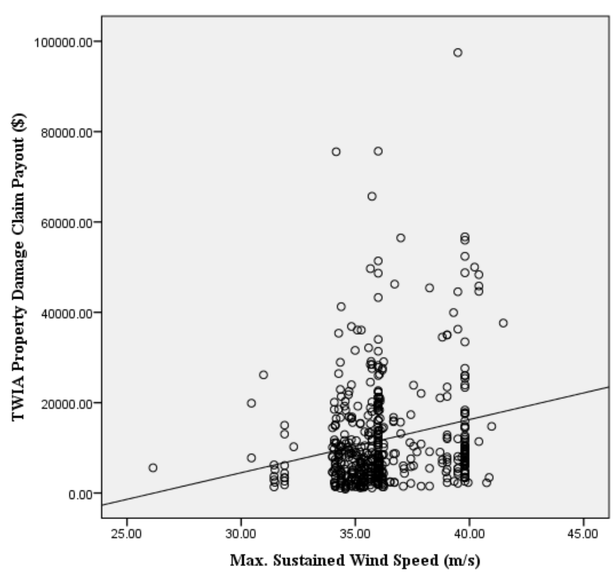
Table 9. Descriptive Statistics

		Dependent Variables		Independent Variables							
		Ratio ($/$)	PDL ($10,000)	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	500
Mean		.10	1.18	36.17	-	34.32	3.64	15.03	-	-	4.49
Median		.07	0.77	36.00	-	35.00	2.81	11.85	-	-	0.88
Std. Deviation		.11	1.22	2.11	-	18.00	2.68	11.72	-	-	6.64
Percentiles	25	.04	0.41	34.84	.00	23.00	1.90	7.23	1.00	3.00	0.37
	50	.07	0.77	36.00	.00	35.00	2.81	11.85	2.00	3.00	0.88
	75	.12	1.50	36.74	1.00	47.00	4.55	18.82	3.00	3.75	6.03
Skewness		3.00	2.61	.23	1.13	.45	1.83	1.83	-.07	-.05	1.64
Kurtosis		13.32	9.41	.76	-.72	1.32	3.89	3.99	-1.58	.04	1.49

5.2 TWIA Claim Payout Regression Model

5.2.1 Scatter Plots

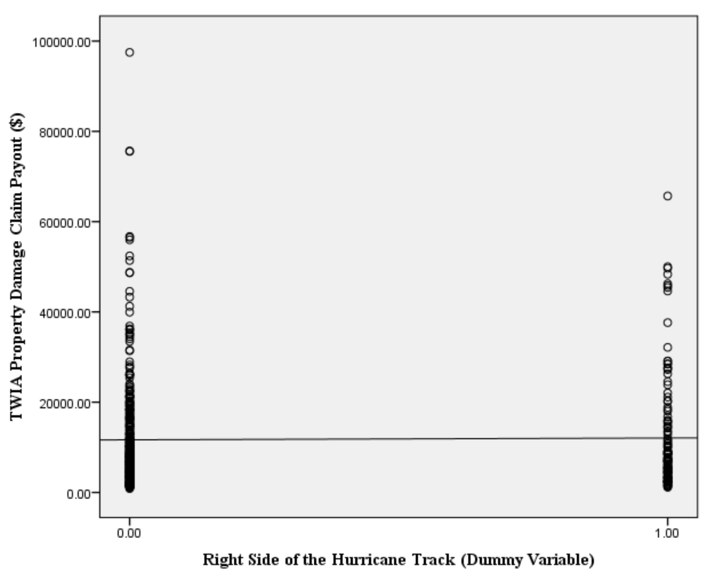
The scatter plot of the TWIA claim payout versus the maximum sustained wind speed in Figure 17 shows a positive relationship. This means that as the maximum sustained wind speed increases, the claim payout increases. The intercept, also called the starting value, of -30,838.50 means that when the wind speed is 0 m/s, the claim payout is -$30,838.50. The slope, also called the rate of change, of 1,177.77 indicates that if the maximum sustained wind speed increases by 1 m/s, the claim payout will increase by $1,177.77. The R-square of 0.041 signifies that this relationship can be explained with a 4.1% margin of variance. In addition, the P-value of 0.000 is less than 0.05, which represents that the relationship is significant.



- Intercept : -30,838.50
- Slope : 1,177.77
- R-square: 0.041
- P-value: 0.000

Figure 17. Scatter Plot of TWIA Claim Payout vs. Max. Sustained Wind Speed (m/s)

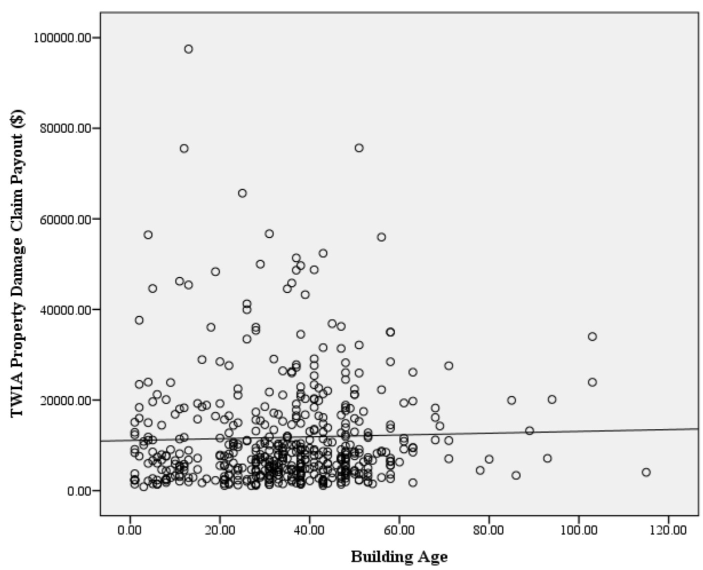
Figure 18 shows the TWIA claim payout versus the right side of the hurricane track. The right side of the hurricane track is a dummy variable, either 0 or 1. If a building is located on the right side of the hurricane track, it is dummy variable 1. If a building is located on the left side of the hurricane track, it is dummy variable 0. The two variables have a positive relationship which reveals that the TWIA claim payout increases if the building is located on the right side of the hurricane track. The intercept of 11,659.37 means that when the building is located on the left side of the hurricane track , the claim payout is $11,659.37. The slope of 402.57 indicates that if the building is located on the right side of the hurricane track, the payout will increase by $402.57. However, the R-square is close to 0 and the P-value is 0.75, which indicates that the relationship is not significant.



- Intercept : 11,659.37
- Slope : 402.57
- R-square: 0.00
- P-value: 0.75

Figure 18. Scatter Plot of TWIA Claim Payout vs. the Right Side of the Hurricane Track

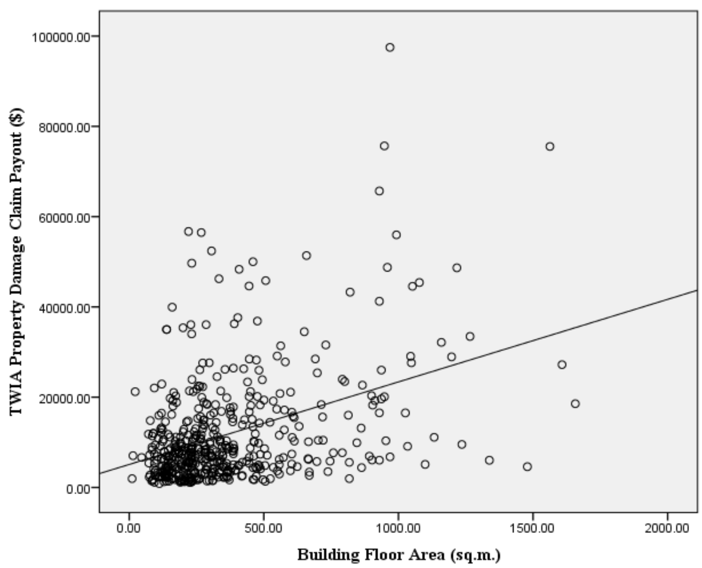
Figure 19 represents the relationship between the claim payout and the building age. This shows a positive relationship that as the building age increases, the claim payout also increases. The intercept of 11,075.69 means that when the building age is 0, the claim payout is $11,075.69. The slope of 19.98 indicates that if the building age increases by 1, the claim payout will increase by $19.98. The two variables have a low-significance relationship because the P-value of 0.51 is higher than 0.05.



- Intercept : 11,075.69
- Slope : 19.98
- R-square: 0.001
- P-value: 0.51

Figure 19. Scatter Plot of TWIA Claim Payout vs. Building Age

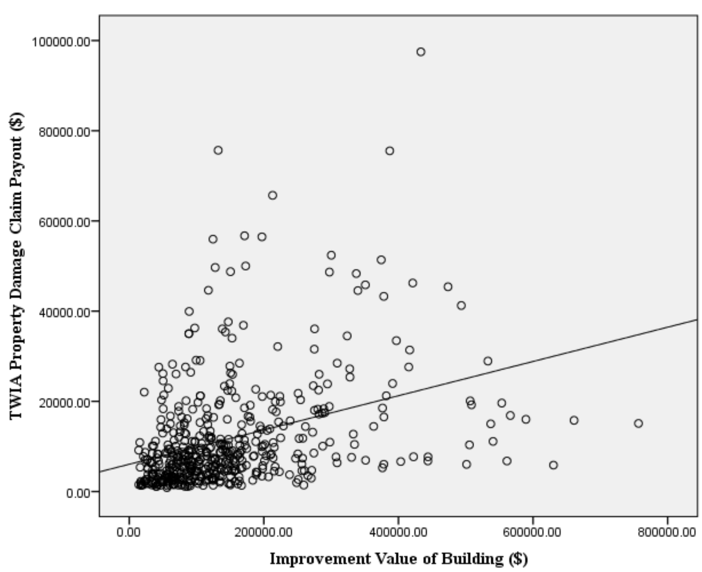
The relationship between the TWIA claim payout versus the building floor area is shown in Figure 20. The scatter plot displays a positive relationship which indicates that as the building floor area increases, the claim payout increases. The intercept of 5,107.71 represents that when the building floor area is 0, the claim payout is $5,107.71. The slope of 18.29 implies that if the building floor area increases by 1 m^2, the claim payout will increase by $18.29. The R-square of 0.16 signifies that this relationship can be explained with a 16% margin of variance. The P-value of 0.000 is less than 0.05, which verifies that the two variables have a significant relationship.



- Intercept : 5,107.71
- Slope : 18.29
- R-square : 0.16
- P-value : 0.000

Figure 20. Scatter Plot of TWIA Claim Payout vs. Building Floor Area (m^2)

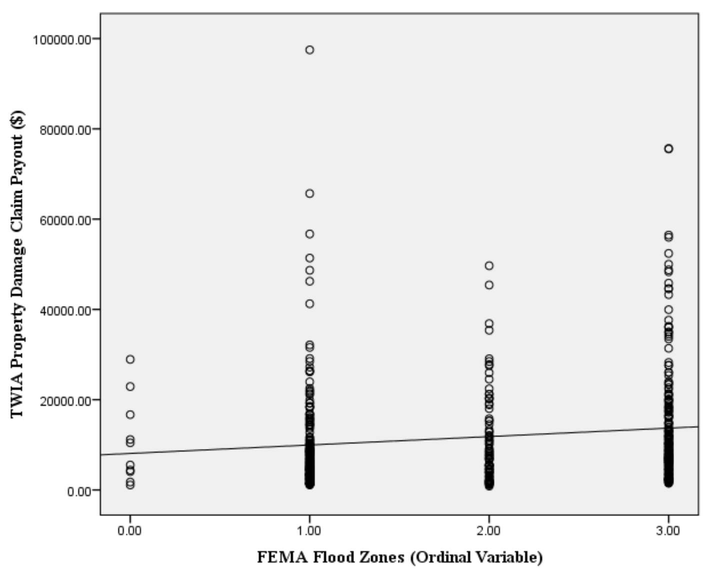
The scatter plot of the TWIA claim payout versus the appraised value of the building in Figure 21 represents a positive relationship, which means that as the appraised value of the building increases, the claim payout also increases. The intercept of 6,053.74 implies that when the appraised value of the building is 0, the claim payout is $6,053.74. The slope of 0.04 indicates that if the appraised value of the building increases by $1, the claim payout will increase by $0.04. The R-square of 0.13 explains that there is a 13% margin of variance in the relationship between the variables. It demonstrates that the two variables have a significant relationship, because the P-value of 0.000 is less than 0.05.



- Intercept : 6,053.74
- Slope : 0.04
- R-square : 0.13
- P-value : 0.00

Figure 21. Scatter Plot of TWIA Claim Payout vs. Appraised Value of Building ($)

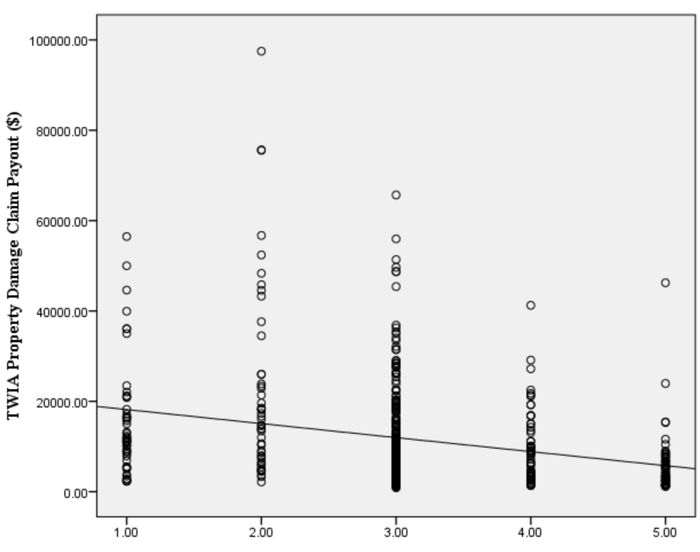
Figure 22 shows the TWIA claim payout versus the FEMA flood zones. The FEMA flood zones are represented by an ordinal variable ranging from 0 to 3. 0 means that the zone is unregistered. The variable 1 signifies that the area is categorized in the FEMA flood zone X. The variable 2 signifies that the area is categorized in the FEMA flood zone X500. The variable 3 signifies that the area is categorized in the FEMA flood zone A. The two variables have a positive relationship which reveals that as the FEMA flood zone number increases, the claim payout increases. The intercept of 8,091.73 means that when the building is located on the unregistered zone, the claim payout is \$8,091.73. The slope of 1,868.58 indicates that if the FEMA flood zone number increases by 1, the claim payout will increase by \$1,868.58. The R-square value of 0.02 signifies that this relationship can be explained with a 2% margin of variance. The P-value of 0.000 is less than 0.05, which reveals that the relationship is significant.



- Intercept : 8,091.73
- Slope : 1868.58
- R-square : 0.02
- P-value : 0.001

Figure 22. Scatter Plot of TWIA Claim Payout vs. FEMA Flood Zones

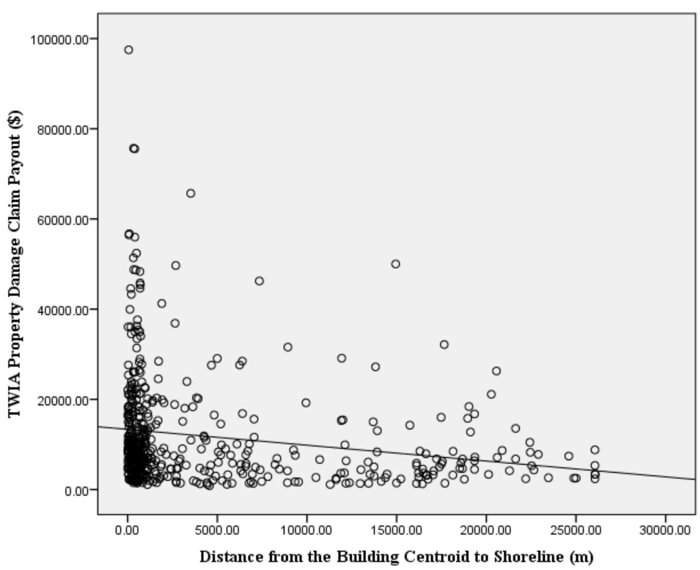
The relationship between the TWIA claim payout and the hurricane surge zone is illustrated in Figure 23. The hurricane surge zone is represented by an ordinal variable, from 0 to 5. The scatter plot shows a negative relationship which means that as the hurricane surge zone number increases, the claim payout decreases. The intercept of 21,283.40 represents that when the hurricane surge zone is 0, the claim payout is \$21,283.40. The slope of -3,103.58 implies that if the hurricane surge zone number increases by 1, the claim payout decreases by \$3,103.58. The R-square of 0.072 explains that there is a 7.2% margin of variance in the relationship between the variables. The P-value of 0.000 is less than 0.05, which verifies that the two variables have a significant relationship.



- Intercept : 21,283.40
- Slope : -3,103.58
- R-square : 0.072
- P-value : 0.00

Figure 23. Scatter Plot of TWIA Claim Payout vs. Hurricane Surge Zones

Figure 24 represents the relationship between the TWIA claim payout and the distance from the property centroid to the shoreline. This shows a negative relationship which means that as the distance from the property centroid to the shoreline increases, the claim payout decreases. The intercept of 13,339.47 means that when the distance from the property centroid to the shoreline is 0, the claim payout is $13,339.47. The slope of -0.35 indicates that if the distance from the property centroid to the shoreline increases by 1 m, the claim payout decreases by $0.35. The R-square of 0.036 signifies that this relationship can be explained with a 16% margin of variance. The two variables have a significant relationship because the P-value of 0.000 is less than 0.05.



- Intercept : 13,339.47
- Slope : -0.35
- R-square: 0.036
- P-value : 0.000

Figure 24. Scatter Plot of TWIA Claim Payout vs. Distance from the Property Centroid to Shoreline (m)

5.2.2 Correlation Analysis

Table 10 shows the summary of the correlation results with the TWIA claim payouts and continuous variables. A Pearson Correlation analysis was used for testing the continuous variables. Each result represents the relationship between two variables. The building age has only an insignificant relationship with the claim payout. On the other hand, other variables (i.e., max. sustained wind speed, building floor area, appraised value of the building, and distance from the property centroid to the shoreline) have significant relationships with the claim payout. The sign of the coefficients determine whether the relationship is positive or negative, and the coefficients indicate the amount of the linear relationship with a range of +1 to -1.

Table 11 displays the summary of the correlation results with the TWIA claim payout and the ordinal variables. Spearman's rho Correlation analysis was used to test the ordinal variables. Each result represents the relationship between two variables. The right side of the hurricane track has only an insignificant relationships with the claim payout, while the FEMA flood zones and hurricane surge zones each have significant relationships with the claim payout. The sign of the coefficients determines whether the relationship is positive or negative, and the coefficients indicate the amount of the linear relationship with a range of +1 to -1.

Table 10. Results of Pearson Correlation Analysis

		PDL ($)	Wind_Speed (m/s)	Age	Area (m^2)	Imp_Value ($)	Dist_Shore (m)
PDL ($)	Pearson Correlation	1	.203**	.029	.400**	.364**	-.190**
	Sig. (2-tailed)		.000	.512	.000	.000	.000
Wind_Speed (m/s)	Pearson Correlation	.203**	1	.040	-.057	.007	-.183**
	Sig. (2-tailed)	.000		.375	.199	.879	.000
Age	Pearson Correlation	.029	.040	1	-.123**	-.383**	-.062
	Sig. (2-tailed)	.512	.375		.006	.000	.167
Area (m^2)	Pearson Correlation	.400**	-.057	-.123**	1	.572**	.044
	Sig. (2-tailed)	.000	.199	.006		.000	.322
Imp_Value ($)	Pearson Correlation	.364**	.007	-.383**	.572**	1	.006
	Sig. (2-tailed)	.000	.879	.000	.000		.899
Dist_Shore (m)	Pearson Correlation	-.190**	-.183**	-.062	.044	.006	1
	Sig. (2-tailed)	.000	.000	.167	.322	.899	

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Table 11. Results of Spearman's Correlation Analysis

		PDL ($)	FEMA_Zones	Surge_Zones	Side_Right
PDL ($)	Spearman's rho Correlation	1.000	.186**	-.321**	-.011
	Sig. (2-tailed)	.	.000	.000	.803
FEMA_Zones	Spearman's rho Correlation	.186**	1.000	-.521**	-.243**
	Sig. (2-tailed)	.000	.	.000	.000
Surge_Zones	Spearman's rho Correlation	-.321**	-.521**	1.000	.071
	Sig. (2-tailed)	.000	.000	.	.114
Side_Right	Spearman's rho Correlation	-.011	-.243**	.071	1.000
	Sig. (2-tailed)	.803	.000	.114	.

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

5.2.3 Initial Multiple Regression Analysis and Check for Assumptions

In this study, the backward elimination method was used to find the best-fit regression model. Table 12 provides a summary of the initial TWIA claim payout regression model. The model is statistically significant because the P-value of 0.000 is less than 0.05. The R-square of 0.036 signifies that this relationship can be explained with a 16% margin of variance.

Table 13 shows the coefficients of the initial TWIA claim payout regression model. There are five significant variables: max. sustained wind speed, building age, building floor area, appraised value of building, and hurricane surge zone. However, it was necessary to check the linear regression assumptions before interpreting them.

Table 12. Summary of Initial TWIA Claim Payout Regression Model

Model	Sum of Squares	df	Mean Square	F	Sig.	R^2	Adj-R^2
Regression	2.409E10	5	4.819E9	46.898	.000	.322	.315
Residual	5.076E10	494	1.027E8				
Total	7.485E10	499					

1. Predictors: (Constant), Imp_Value, Wind_Speed, Age, Area, Surge_Zones
2. Dependent Variable: PDL

Table 13. Coefficients of Initial TWIA Claim Payout Regression Model

Model	β	Std. Error	Beta	Sig.	VIF
Constant	-20722.050	8614.942		.017	
Hurricane Indicators					
Max. sustained wind speed	789.583	224.454	.136	.000	1.094
Built Environment Vulnerability Indicators					
Building age	126.947	27.722	.187	.000	1.209
Building floor area	12.854	2.089	.281	.000	1.521
Appraised value of building	.030	.005	.285	.000	1.761
Geographical Vulnerability Indicators					
Hurricane surge zones	-3121.964	447.780	-.270	.000	1.096

The Kolmogorov-Smirnov value was adopted to test for the normality of the residuals. In Table 14, the p-value of 0.000 is smaller than 0.05, which implies that the residuals are not normally distributed. Moreover, in Figures 25 (a) and (b), the standardized residuals histogram and the Q-Q plot also verify that the initial model's residuals are not normally distributed.

The residual plot tested whether the residuals have the constant variance to check for homoscedasticity, as shown in Figure 26. The fan-shaped residuals plot determined that the residuals have demonstrated a trend (i.e., that there is no dispersion based on the regression line). This means that the residuals' variance is not constant.

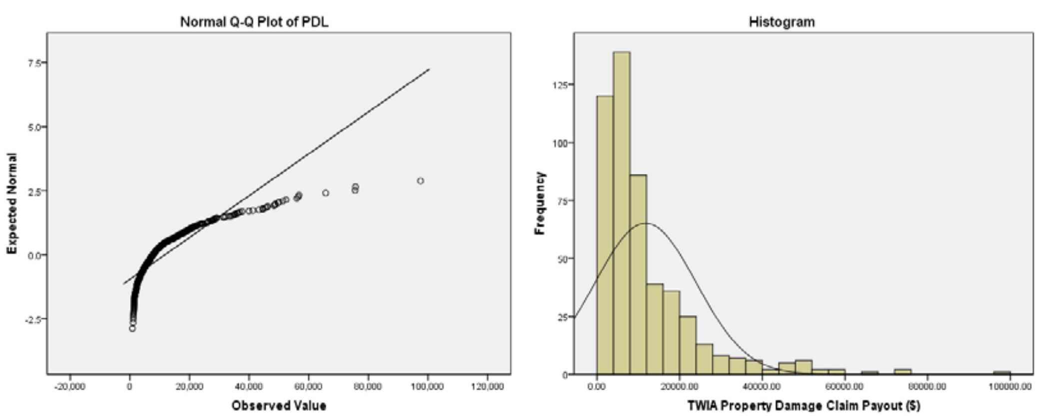
In conclusion, these results, the residuals analyses, and the test all prove that the dependent variable needed a transformation.

Table 14. Test of Normality for Initial TWIA Claim Payout Regression Model

Tests of Normality

	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
PDL	.190	500	.000	.734	500	.000

a. Lilliefors Significance Correction



(a) (b)

Figure 25. Q-Q plot and Histogram of Residuals for Initial TWIA Claim Payout Regression Model

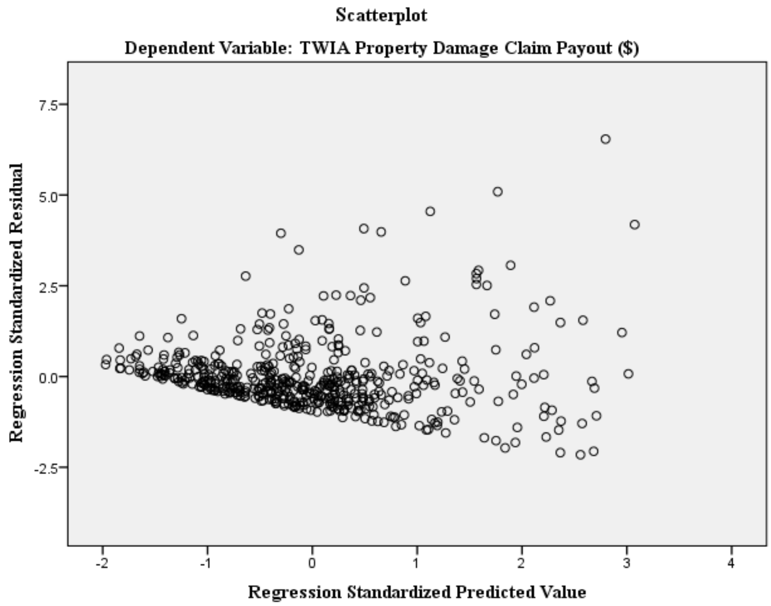


Figure 26. Residuals Plot for Initial TWIA Claim Payout Regression Model

5.2.4 Transformation of Dependent Variable

The TWIA claim payout was transformed by a natural log. The transformed dependent variable is as follows:

Transformed PDL = *Log (TWIA Claim Payout ($))*

After the log transformation of the dependent variable, the Kolmogorov-Smirnov value shows that the transformed model's residuals are normally distributed because the P-value of 0.200 is higher than 0.05, as seen in Table 15. Moreover, the standardized residuals histogram and the Q-Q plot also confirm that the transformed model's residuals are normally distributed, as shown in Figure 27.

The residual plot checks the homoscedasticity, as shown in Figure 28. The residuals are randomly spread without any systematic patterns. This represents that the residuals' variance is constant.

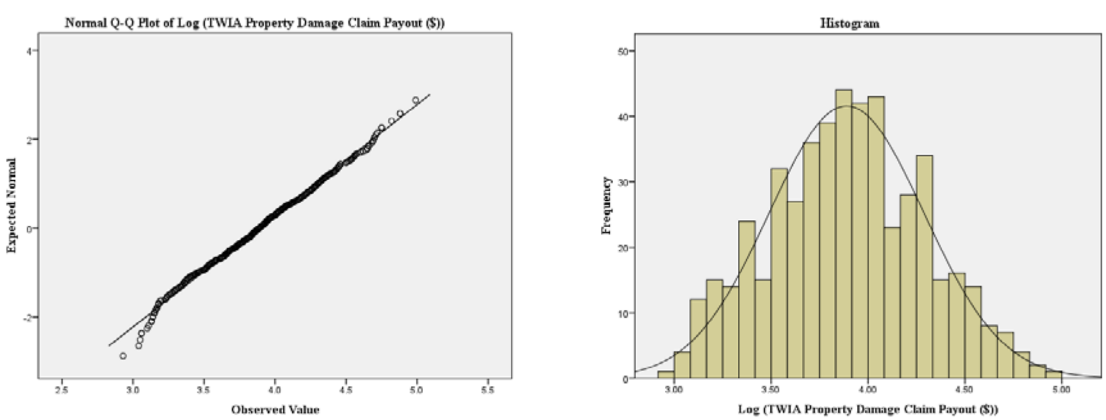
Table 15. Test of Normality for Transformed TWIA Claim Payout Regression Model

Tests of Normality

	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Log_PDL	.028	500	.200*	.993	500	.029

a. Lilliefors Significance Correction

*. This is a lower bound of the true significance.



(a) (b)

Figure 27. Q-Q Plot and Histogram of Residuals for Transformed TWIA Claim Payout Regression Model

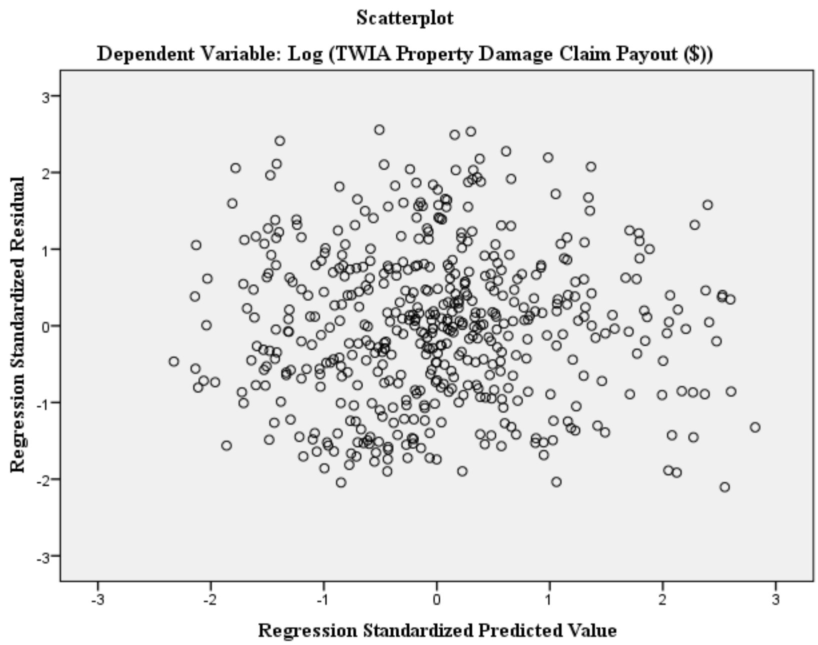


Figure 28. Residuals Plot for Transformed TWIA Claim Payout Regression Model

5.2.5 Multiple Linear Regression Analysis

The backward elimination method was used to find the best-fit regression model. Table 16 includes a summary of the transformed TWIA claim payout regression model. The model is statistically significant because the P-value of 0.000 is less than 0.05, which represents that independent variables and the dependent variable have a significant linear relationship. Also, the null hypothesis which states that there is no linear relationship between the independent variables and the dependent variable can be rejected. Thus, the regression model is allowed to predict the transformed dependent variable.

The adjusted R-square of 0.401 indicates that the transformed dependent variable can be explained with 40.1% of variability by the significant variables (i.e., max. sustained wind speed, the right side of the hurricane track, building age, building floor area, appraised value of building, hurricane surge zones, and distance from the property centroid to shoreline). On the other hand, this study disregards the rest of the variability of 59.9%. The remainder could be explained by some unidentified variables.

Table 16. Summary of Transformed TWIA Claim Payout Regression Model

Model	**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**	**R^2**	**Adj-R^2**
Regression	32.628	7	4.661	48.721	.000	.409	.401
Residual	47.071	492	.096				
Total	79.699	499					

1. Predictors: (Constant), Dist_Shore, Imp_Value, Wind_Speed, Age, Side_Right, Area, Surge_Zones
2. Dependent Variable: Log_PDL

Table 17. Coefficients of Transformed TWIA Claim Payout Regression Model

Model	β	Std. Error	Beta	Sig.	VIF
Constant	2.973	.269		.000	
Hurricane Indicators					
Max. sustained wind speed	.019	.007	.099	.007	1.130
Right side of the hurricane track	.100	.039	.109	.011	1.506
Built Environment Vulnerability Indicators					
Building age	.007	.001	.317	.000	1.246
Building floor area	.000	.000	.169	.000	1.537
Appraised value of building	1.526E-6	.000	.448	.000	1.808
Geographical Vulnerability Indicators					
Hurricane surge zones	-.111	.017	-.295	.000	1.741
Distance from shoreline	-5.254E-6	.000	-.087	.090	2.208

Table 17 illustrates a summary of the coefficients for the transformed TWIA claim payout regression model. The seven significant predictors include: (1) max. sustained wind speed, (2) the right side of the hurricane track, (3) building age, (4) building floor area, (5) appraised value of the building, (6) hurricane surge zone, and (7) distance from the building property to the shoreline; each were identified as able to predict the transformed claim payout. The FEMA flood zones, however, were eliminated because the P-value was higher than 0.10. The Variance Inflation Factor (VIF) ranged from 1.130 to 2.208. These values verify that the individual predictors have no serious multicollinearity.

The beta coefficients, also called the standardized coefficients, were used to determine which independent variables have a significant influence on the claim payout; they ranged from 0 to 1, reflecting when the variables have different units. Following the amount of the coefficients, the rank was listed in sequence: (1) the appraised value of building, (2) building age, (3) hurricane surge zone, (4) building floor area, (5) right side of the hurricane track, (6) maximum sustained wind speed, and (7) distance from property centroid to the shoreline.

Based on the unstandardized coefficients, a multiple linear regression model was created with seven predictors to predict the transformed claim payout, as shown in Equations (5) and (6). The model can explain a 40.9% variability of the transformed dependent variable.

Based on Equation (5), the interpretation of the unstandardized coefficients in the regression model are as follows:

1. $\widehat{\beta_1}$ is 0.019 which implies that if the maximum sustained wind speed increases by 1 m/s, the log transformed claim payout increases by 1.9.
2. $\widehat{\beta_2}$ is 0.100 which implies that if a building is located on the right side of the hurricane track, the log transformed claim payout increases by 10.
3. $\widehat{\beta_3}$ is 0.007 which implies that if the building age increases by 1, the log transformed claim payout increases by 0.7.

4. $\widehat{\beta_4}$ is 2.522E-4 which implies that if the building floor area increases by 1 m^2, the log transformed claim payout increases by 0.025.
5. $\widehat{\beta_5}$ is 1.526E-6 which implies that if the appraised value of the building increases by $1, the log transformed claim payout increases by 0.00015.
6. $\widehat{\beta_6}$ is -0.111 which implies that if the hurricane surge zone number increases by 1, the log transformed claim payout decreases by -11.1.
7. $\widehat{\beta_7}$ is -5.254E-6 which implies that if the distance from the property centroid to the shoreline increases by 1, the log transformed claim payout decreases by -0.0005254.

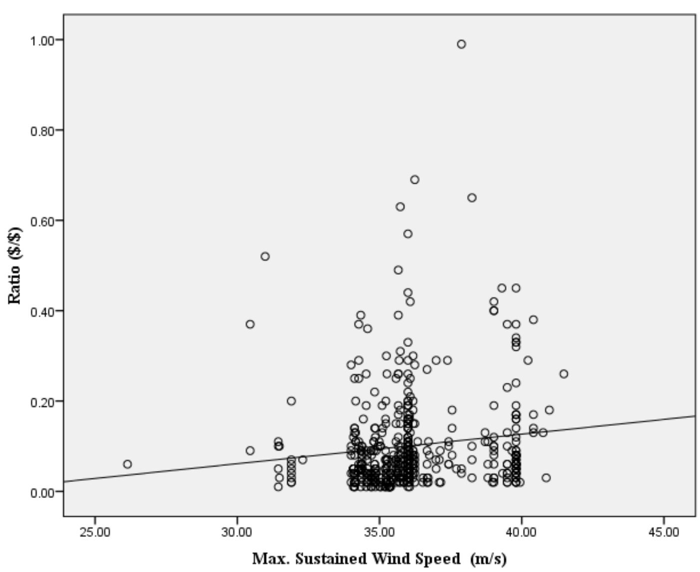
$$\text{Log (Predicted TWIA Claim Payout (\$))} = 2.973 + (\text{Wind\_Speed} * 0.019) + (\text{Side\_Right} * 0.100) + (\text{Age} * 0.007) + (\text{Area} * 2.522\text{E}-4) + (\text{Imp\_Value} * 1.526\text{E}-6) + (\text{Surge\_Zones} * -0.111) + (\text{Dist\_Shore} * -5.254\text{E}-6) \tag{5}$$

$$\text{Predicted TWIA Claim Payout (\$)} = e^{\substack{2.973 + (\text{Wind}_{\text{Speed}} * 0.019) + (\text{Side}_{\text{Right}} * 0.100) + (\text{Age} * 0.007) + (\text{Area} * 2.522\text{E}-4) + \\ (\text{Imp}_{\text{Value}} * 1.526\text{E}-6) + \\ (\text{Surge\_Zones} * -0.111) + (\text{Dist\_Shore} * -5.254\text{E}-6)}} \tag{6}$$

5.3 Ratio Regression Model

5.3.1 Scatter Plots

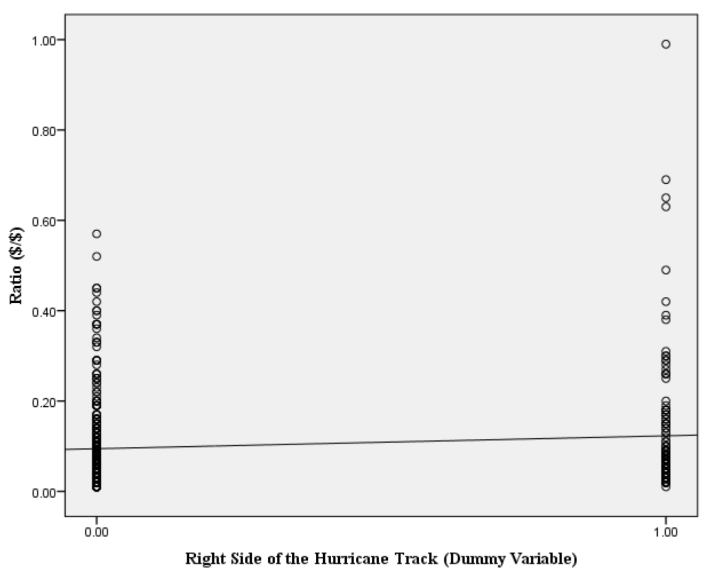
The scatter plot of the ratio versus the maximum sustained wind speed is shown in Figure 29. This Figure shows a positive relationship which means that as the maximum sustained wind speed increases, the ratio also increases. The intercept, also called the starting value, of -0.135 means that when the wind speed is 0 m/s, the ratio is -0.135($/$). The slope, also called the rate of change, of 0.007 indicates that if the maximum sustained wind speed increases by 1 m/s, the ratio increases by 0.007($/$). The R-square of 0.016 signifies that this relationship can be explained with a 1.6% margin of variance. In addition, the P-value of 0.005 is less than 0.05, which represents that the relationship is significant.



- Intercept : -0.135
- Slope : 0.007
- R-square : 0.016
- P-value : 0.005

Figure 29. Scatter Plot of Ratio vs. Max. Sustained Wind Speed (m/s)

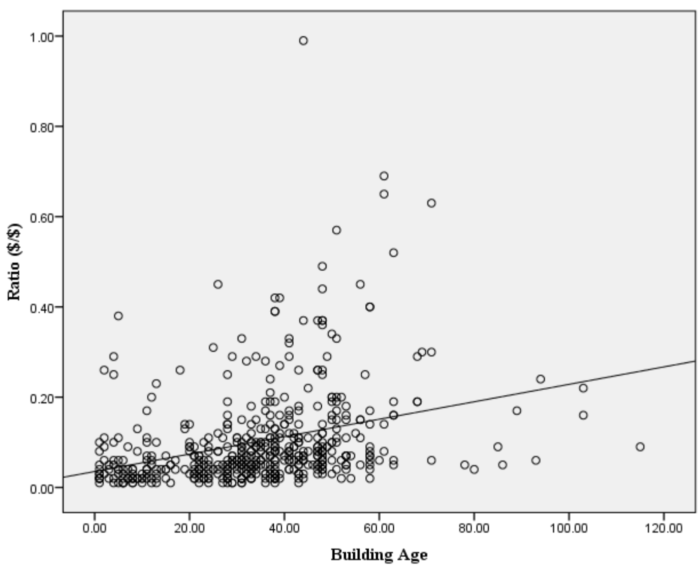
Figure 30 shows the ratio versus the right side of the hurricane track. The right side of the hurricane track is a dummy variable, represented by 0 or 1. If a building is located on the right side of the hurricane track, it is assigned the dummy variable 1. If a buildings is located on the left side of the hurricane track, it is assigned the dummy variable 0. The two variables have a positive relationship which reveals that the ratio increases if the building is located on the right side of the hurricane track. The intercept of 0.094 means that when the building is located on the left side of the hurricane track, the ratio is 0.094 ($/$). The slope of 0.029 indicates that if the building is located on the right side of the hurricane track, the ratio increases by 0.029($/$). The R-square of 0.013 signifies that this relationship can be explained with a 1.3% margin of variance. The P-value of 0.011 is less than 0.05, which shows that the two variables have a significant relationship.



- Intercept : 0.094
- Slope : 0.029
- R-square : 0.013
- P-value : 0.011

Figure 30. Scatter Plot of Ratio vs. the Right Side of the Hurricane Track

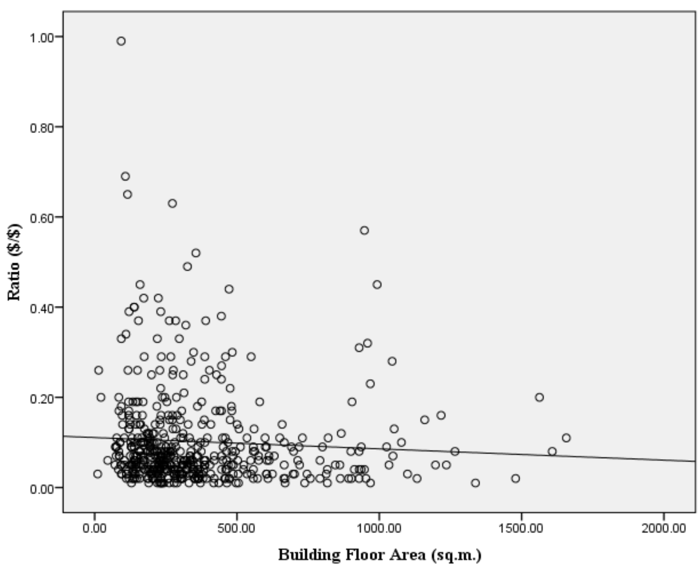
Figure 31 represents the relationship between the ratio and the building age. It shows a positive relationship which means that as the building age increases, the ratio increases. The intercept of 0.035 means that when the building age is 0, the ratio is 0.035 ($/$). The slope of 0.002 indicates that if the building age increases by 1, the ratio increases by 0.002($/$). The R-square of 0.100 explains that there is a 10% margin of variance in the relationship between the variables. The two variables have a significant relationship because the P-value of 0.000 is higher than 0.05.



- Intercept : 0.035
- Slope : 0.002
- R-square : 0.100
- P-value : 0.000

Figure 31. Scatter Plot of Ratio vs. Building Age

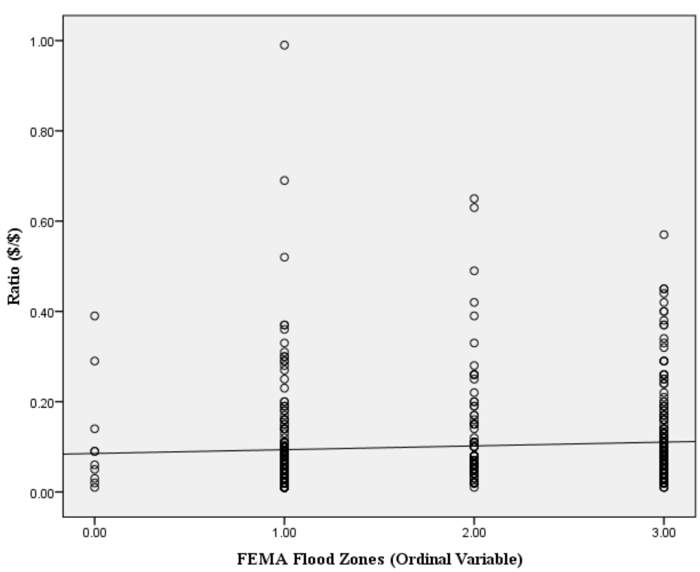
The relationship between the ratio versus the building floor area is illustrated in Figure 32. The scatter plot displays a negative relationship which indicates that as the building floor area increases, the ratio decreases. The intercept of 0.111 represents that when the building floor area is 0, the ratio is 0.111 ($/$). The slope of -2.504E-5 implies that if the building floor area increases by 1 m^2, the ratio decreases by -2.504E-5($/$). The R-square of 0.004 signifies that this relationship can be explained with a 0.4% margin of variance. The P-value of 0.173 is higher than 0.05 which confirms that the two variables do not have a significant relationship.



- Intercept : 0.111
- Slope : -2.504E-5
- R-square : 0.004
- P-value : 0.173

Figure 32. Scatter Plot of Ratio vs. Building Floor Area (m^2)

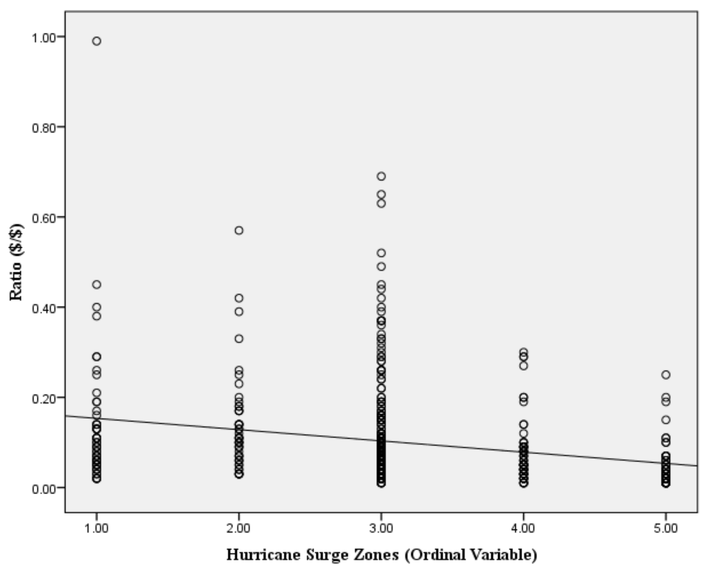
Figure 33 shows the ratio versus the FEMA flood zones. The FEMA flood zones are represented by ordinal variables ranging from 0 to 3. The variable 0 means that the zone is unregistered. The variable 1 signifies that the area is categorized in the FEMA flood zone X. The variable 2 signifies that the area is categorized in the FEMA flood zone X500. The variable 3 signifies that the area is categorized in the FEMA flood zone A. The two variables have a positive relationship which reveals that as the FEMA flood zone number increases, the ratio increases. The intercept of 0.085 means that when the building is located in the unregistered zone, the ratio is 0.085 ($/$). The slope of 0.008 indicates that if the FEMA flood zone number increases by 1, the ratio increases by 0.008 ($/$). The R-square of 0.005 illustrates that there is a 0.5% margin of variance in the relationship between the variables. The P-value of 0.109 is higher than 0.05 which reveals that the relationship is not significant.



- Intercept : 0.085
- Slope : 0.008
- R-square : 0.005
- P-value : 0.109

Figure 33. Scatter Plot of Ratio vs. FEMA Flood Zones

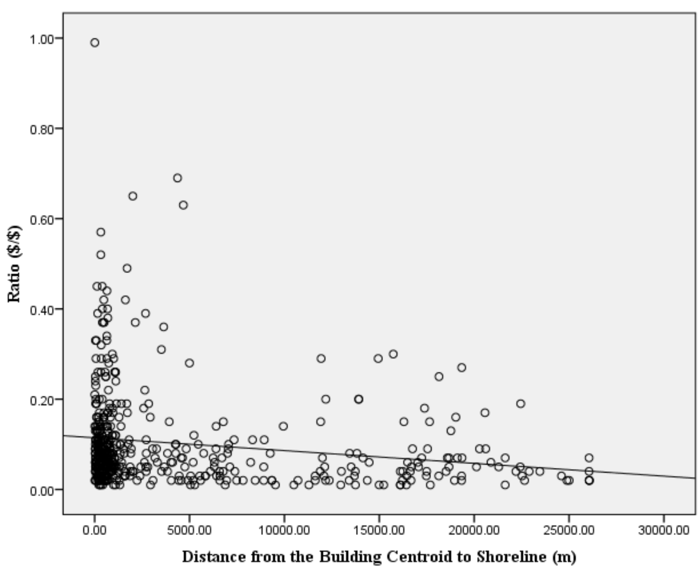
The relationship between the ratio and the hurricane surge zones are illustrated in Figure 34. The hurricane surge zones are represented by ordinal variables ranging from 0 to 5. The scatter plot shows a negative relationship which means that as the hurricane surge zone number increases, the ratio decreases. The intercept of 0.178 represents that when the hurricane surge zone is 0, the ratio is 0.178 ($/$). The slope of -0.025 implies that if the hurricane surge zone number increases by 1, the ratio decreases by 0.025($/$). The R-square of 0.058 signifies that this relationship can be explained with a 5.8% margin of variance. The P-value of 0.000 is less than 0.05, which verifies that the two variables have a significant relationship.



- Intercept : 0.178
- Slope : -0.025
- R-square : 0.058
- P-value : 0.000

Figure 34. Scatter Plot of Ratio vs. Hurricane Surge Zones

Figure 35 represents the relationship between the ratio and the distance from the property centroid to the shoreline. This shows a negative relationship which means that as the distance from the property centroid to the shoreline increases, the ratio decreases. The intercept of 0.114 means that when the distance from the property centroid to the shoreline is 0, the ratio is 0.114 ($/$). The slope of -2.829E-6 indicates that if the distance from the property centroid to the shoreline increases by 1 m, the ratio decreases by -2.829E-6($/$). The R-square of 0.029 explains that there is a 2.9% margin of variance in the relationship between the variables. The two variables have a significant relationship because the P-value of 0.000 is less than 0.05.



- Intercept : 0.114
- Slope : -2.829E-6
- R-square : 0.029
- P-value : 0.000

Figure 35. Scatter Plot of Ratio vs. Distance from the Property Centroid to Shoreline

5.3.2 Correlation Analysis

Table 18 shows the summary of the correlation results with the ratio and the continuous variables. A Pearson Correlation analysis was used to test the continuous variables. Each result shows the relationship between the two variables used in the test. The building floor area is the only variable that has an insignificant relationship with the ratio. 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 sign of the coefficients determine whether the relationship is positive or negative, and the coefficients indicate the amount of the linear relationship, with a range of +1 to -1.

Table 19 displays the summary of correlation results with the ratio and ordinal variables. Spearman's rho Correlation analysis was used to test the ordinal variables. Each result represents the relationship between two 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 sign of the coefficients determine whether the relationship is positive or negative, and the coefficients indicate the amount of the linear relationship, with a range of +1 to -1.

Table 18. Results of Pearson Correlation Analysis

		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).
*. Correlation is significant at the 0.05 level (2-tailed).

Table 19. Results of Spearman's Correlation Analysis

		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).
*. Correlation is significant at the 0.05 level (2-tailed).

5.3.3 Initial Multiple Regression Analysis and Checking Assumptions

The backward elimination method was used to find the best-fit regression model. Table 20 provides a summary of the initial ratio regression model. The model is statistically significant because the P-value of 0.000 is less than 0.05. The adjusted R-square of 0.198 verifies that the independent variables can explain the 19.8% variability of the ratio. Table 21 shows the coefficients of the initial ratio regression model. There are four significant variables (i.e., the right side of the hurricane track, building age, hurricane surge zones, and distance from the property centroid to shoreline). However, it was necessary to check the linear regression assumptions before making interpretations.

Table 20. Summary of Initial Ratio Regression Model

Model	**Sum of Squares**	**f**	**Mean Square**	**F**	**Sig.**	**R^2**	**Adj-R^2**
Regression	1.236	4	.309	31.853	.000	.205	.198
Residual	4.804	495	.010				
Total	6.040	499					

Table 21. Coefficients of Initial Ratio Regression Model

Model	β	Std. Error	Beta	Sig.	VIF
Constant	.089	.017		.000	
Hurricane Indicators					
Right side of hurricane track	.057	.012	.226	000	1.438
Built Environment Vulnerability Indicators					
Building age	.002	.000	.340	000	1.022
Geographical Vulnerability Indicators					
Hurricane surge zones	-.020	.005	-.195	000	1.685
Distance from shoreline	-2.419E-6	.000	-.146	.014	2.180

The Kolmogorov-Smirnov value was adopted to test for the normality of the residuals. In Table 22, the P-value of 0.000 is smaller than 0.05, which means that the residuals are not normally distributed. Moreover, in Figures 36 (a) and (b), the standardized residuals histogram and the Q-Q plot also shows that the initial model's residuals are not normally distributed.

The residual plot tests whether the residuals have the constant variance to check for homoscedasticity, as shown in Figure 37. The fan-shaped residuals plot determines that the residuals have a trend; there is no dispersion based on the regression line. This represents that the residuals' variance is not constant.

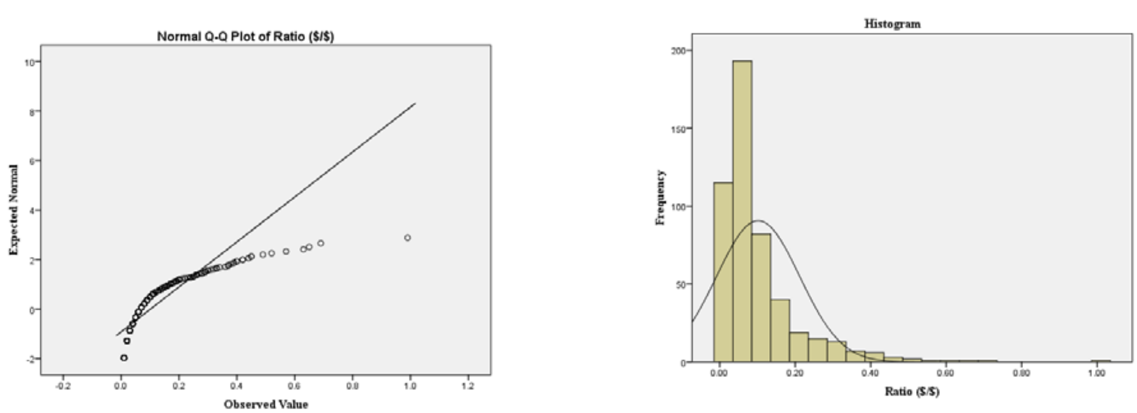
In summary, these results, the residuals analyses, and the test all confirm that the dependent variable needs a transformation.

Table 22. Test of Normality for Initial Ratio Regression Model

Tests of Normality

	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Ratio	.218	500	.000	.698	500	.000

a. Lilliefors Significance Correction



(a) (b)

Figure 36. Q-Q plot and Histogram of Residuals for Initial Ratio Regression Model

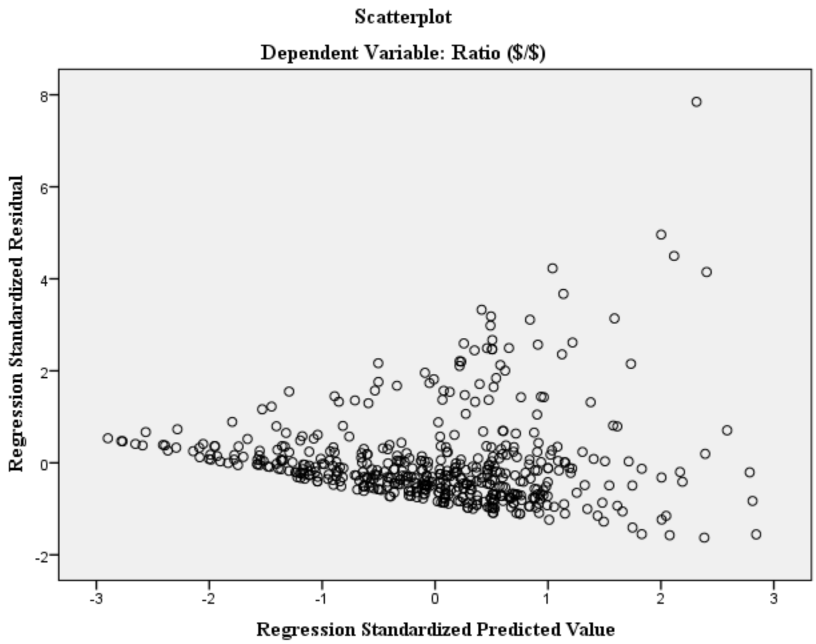


Figure 37. Residuals Plot for Initial Ratio Regression Model

5.3.4 Transformation of Dependent Variable

The ratio was transformed by a natural log. The transformed dependent variable is as follows:

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

After the log transformation of the dependent variable, the Kolmogorov-Smirnov value shows that the transformed model's residuals are normally distributed because the P-value of 0.200 is higher than 0.05, as seen in Table 23. Furthermore, the standardized residuals histogram and the Q-Q plot also show that the transformed model’s residuals are normally distributed, as shown in Figure 38.

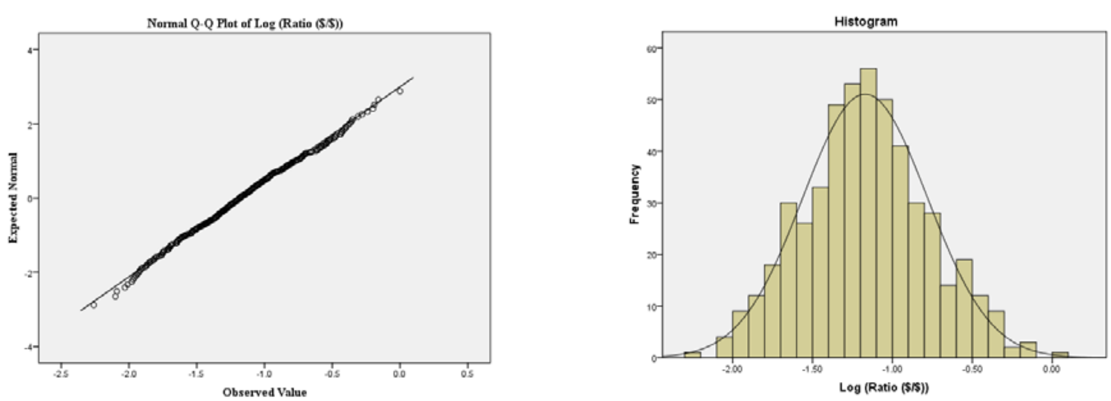
The residual plot checks the homoscedasticity, as shown in Figure 39. The residuals are randomly spread without any systematic patterns. This represents that the residuals’ variance is constant.

Table 23. Test of Normality for Transformed Ratio Regression Model

Tests of Normality

	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Log_Ratio	.028	500	.200*	.996	500	.323

a. Lilliefors Significance Correction
*. This is a lower bound of the true significance.



(a) (b)

Figure 38. Q-Q plot and Histogram of Residuals for Transformed Ratio Regression Model

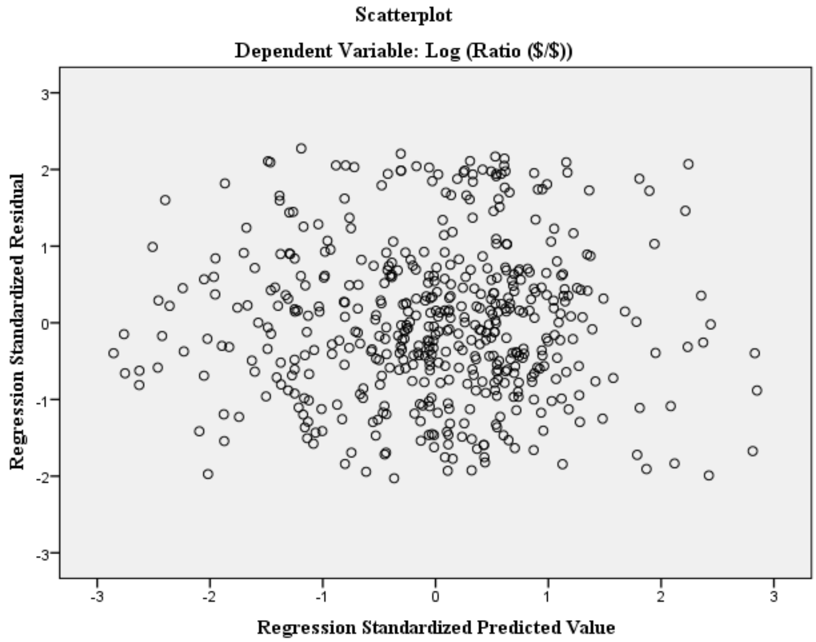


Figure 39. Residuals Plot for Transformed Ratio Regression Model

5.3.5 Multiple Linear Regression Analysis

The backward elimination method was utilized to find the best-fit regression model. Table 24 provides a summary of the transformed ratio regression model. The model is statistically significant because the P-value of 0.000 is less than 0.05. This means that the independent variables and the dependent variable have a significant linear relationship. Also, the null hypothesis which states that there is no linear relationship between the independent variables and the dependent variable can be rejected. Therefore, the multiple linear regression model is able to predict the transformed dependent variable.

The adjusted R-square 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 building property to shoreline). However, this study does not address that the rest of the variability, 66.3%, could be explained by unidentified variables.

Table 24. Summary of 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 25 shows the summary of coefficients for the transformed ratio regression model. The four significant predictors – (1) the right side of the hurricane track, (2) the building age, (3) the hurricane surge zone, and (4) the distance from the property centroid to the shoreline - were identified to predict the transformed ratio. The FEMA flood zones, maximum sustained wind speed, and building floor area were eliminated because the P-value was higher than 0.10. The range of the Variance Inflation Factor

(VIF) was from 1.022 to 2.180. These values verify that the individual predictors have no serious multicollinearity.

The beta coefficients, also called standardized coefficients, ranged from 0 to 1 and were used to determine which independent variables have a significant influence on the ratio when the variables have different units. Following the amount of the coefficients, the rank is in sequence: (1) building age, (2) hurricane surge zone, (3) right side of the hurricane track, and (4) distance from property centroid to the shoreline.

Table 25. Coefficients of Transformed Ratio Regression Model

Model	β	Std. Error	Beta	Sig.	VIF
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

Based on the coefficients, a multiple linear regression model was created with four significant predictors to predict the transformed ratio, as shown in Equations (7) and (8). The models can explain the 34.3% variability of the transformed dependent variable.

$$\text{Log}\left(\text{Predicted Ratio}\left(\frac{\$}{\$}\right)\right) = -1.167 + (\text{Side\_Right} * 0.200) + (\text{Age} * 0.010) + (\text{Surge\_Zones} * -0.112) + (\text{Dist\_Shore} * -8.605\text{E}-6) \quad (7)$$

$$\text{Predicted Ratio}\left(\frac{\$}{\$}\right) = e^{-1.167 + (\text{Side\_Right} * 0.200) + (\text{Age} * 0.010) + (\text{Surge\_Zones} * -0.112) + (\text{Dist\_Shore} * -8.605\text{E}-6)} \quad (8)$$

Based on Equation (7), the interpretations of the coefficients in the regression model are as follows:

1. $\widehat{\beta_1}$ is 0.200 which implies that if the building is located on the right side of the hurricane track, the log transformed ratio increases by 20.
2. $\widehat{\beta_2}$ is 0.010 which implies that if the building age increases by 1, the log transformed ratio increases by 1.
3. $\widehat{\beta_3}$ is -0.112 which implies that if the hurricane surge zone number increases by 1, the log transformed ratio decreases by -11.2.

4. $\widehat{\beta_4}$ is -8.605E-6 which implies that if the distance from the property centroid to the shoreline increases by 1 m, the log transformed ratio decreases by 0.0008605.

5.4 Discussion

5.4.1 Comparison between the Two Models

In both models, multiple linear regression analysis was adopted to predict the TWIA claim payout and the ratio and establish the multiple linear regression models. In turn, the models were used to determine the magnitude and identify the significant indicators. Natural log transformation was used to transform the dependent variables for abnormal distribution and uneven variance. The two models for the claim payout and ratio violated the linear regression assumptions, the normality, and the homoscedasticity. This was confirmed by following the standardized residuals histograms, the Q-Q plots, and the residual scatter plots. Hence, the dependent variables were transformed as follows:

$$\text{Transformed PDL} = \text{Log (TWIA claim payout (\$))}$$

$$\text{Transformed Ratio} = \text{Log}\left(\frac{\text{TWIA claim payout(\$)}}{\text{Building appraised value (\$)}}\right)$$

After the log transformation of the dependent variables, the regression models were seen to be significant because the P-values from the ANOVA table are less than

0.05. Moreover, the standardized residuals histograms, the Q-Q plots, and the residual scatter plots demonstrate that the transformed model's residuals are normally distributed and the residuals' variance is constant. Hence, these results prove that the data's robustness and the multiple linear regression models are statistically significant to test the hypotheses of this study.

On the other hand, the models have different significant predictors and adjusted R-squares. The TWIA claim payout regression has seven significant predicators: maximum sustained wind speed, the right side of the hurricane track, building age, building floor area, appraised value of the building, hurricane surge zone, and distance from the property centroid to the shoreline. The model's adjusted R-square is 0.401, which indicates that 40.1% of the variability in the transformed dependent variable can be explained by the significant variables. The ratio regression has four significant predicators: the right side of the hurricane track, building age, hurricane surge zone, and distance from the property centroid to the shoreline. The model's adjusted R-square is 0.337, which indicates that 33.7% of the variability in the transformed dependent variable can be explained by the significant predictors.

5.4.2 Validity of the Two Models

In this study, the backward elimination method was utilized to find the best-fit multiple linear regression model and to identify the significant predicators. In The TWIA claim payout regression, seven indicators were seen to be significant as predicators of the transformed dependent variable. The range of the Variance Inflation Factor (VIF), from1.130 to 2.208, also confirms that the individual predictors have no serious multicollinearity. The model's adjusted R-square of 0.401 indicates that the transformed dependent variable can be explained with 40.1% of variability by the significant independent variables. Figure 40 shows a scatter plot of the actual log-transformed TWIA claim payout versus the predicted log TWIA claim payout.

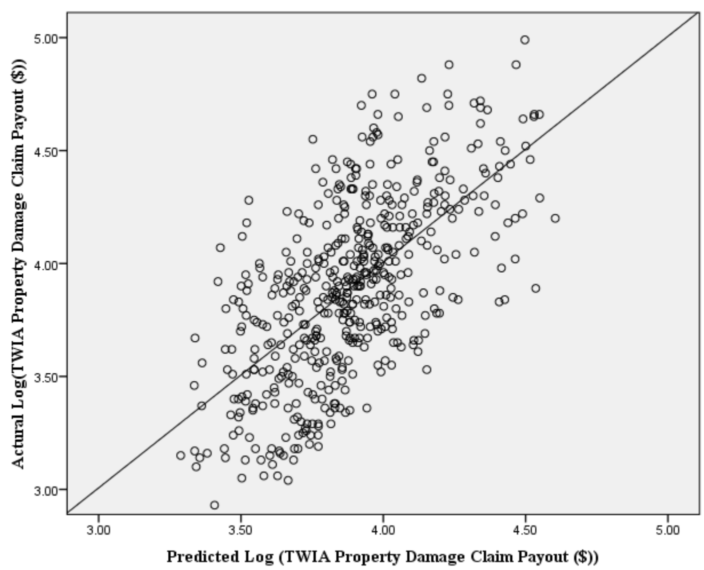


Figure 40. Actual vs. Predicted Log TWIA Claim Payout ($)

In the ratio regression, four indicators were seen to be significant as predicators for the transformed dependent variable. The range of the Variance Inflation Factor (VIF), from 1.022 to 2.180, verifies that the individual predictors have no serious multicollinearity. The model's adjusted R-square, 0.337, indicates that the transformed dependent variable can be explained with 33.7% of variability by the significant independent variables. Figure 41 shows a scatter plot of the actual log-transformed ratio versus the predicted log ratio.

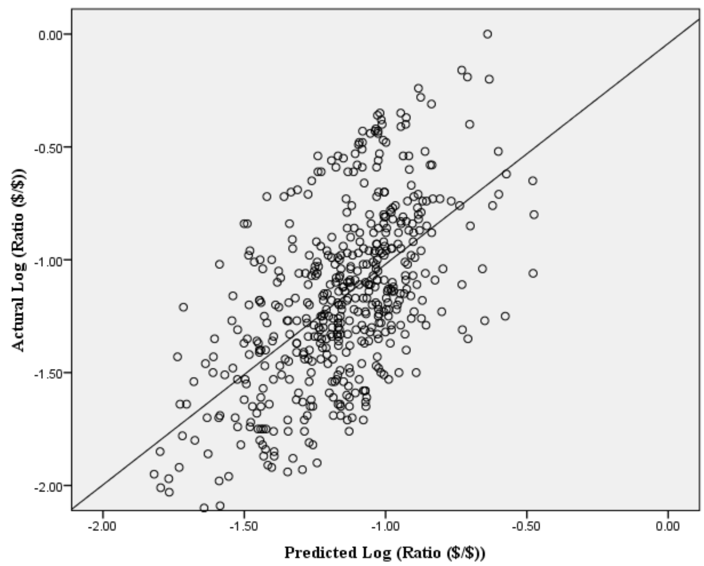


Figure 41. Actual vs. Predicted Log Ratio ($/$)

6. CONCLUSIONS

With growing public awareness of hurricane danger and with tremendous demands for damage analysis, many researchers have conducted studies to develop hurricane damage prediction methods. However, to date there has been no comprehensive research directed towards identifying the relationships among vulnerabilities, hurricanes, and the economic loss of individual commercial buildings. To fill this gap, this research has identified vulnerability indicators and hurricane indicators, developed metrics to measure the influence of economic losses from hurricanes, and visualized the spatial distribution of vulnerability to evaluate overall hurricane damage.

In this research, TWIA claim payouts from Hurricane Ike were used as the dependent variable to predict the actual financial damage and ratio and to decide the magnitude and significance of the indicators. Geographical vulnerability indicators, built environment vulnerability indicators, and hurricane indicators were used as independent variables.

The models and findings produced in this study could provide vital references for government agencies, emergency planners, and insurance companies seeking to predict hurricane damage. This research may help analyze damage and reduce financial loss. Moreover, this study defines hurricane-prone areas and the distribution of hurricane losses in an effort to reduce the perceived risks for residents who live in hurricane vulnerable areas.

6.1 Results and Interpretations

6.1.1 TWIA Claim Payout Record

This study considered improved commercial buildings in Texas coastal counties that had received insured claim payouts from the Texas Windstorm Insurance Association (TWIA) resulting from Hurricane Ike. The observational unit ranged from 17 August 2008 to 22 February 2012.

According to the claim payout records, the total claim payout was $450,518,330 and the total number of claims was 4,150. Galveston County received the most damage from Hurricane Ike in both the dollar amount of damage ($255,333,818; 56.68%) and the number of claims (1,807; 43.54%). Therefore, we recognized from the distribution of the damages that Galveston county is the most hurricane-prone area in the Texas coastal counties.

6.1.2 Correlation Results

A Pearson Correlation analysis was conducted to check the correlation between the dependent variables and the continuous variables. The correlation results between the maximum sustained wind speed and the dependent variables are similar. In both cases, the wind speed and the dependent variables have positive relationships because the P-values are less than 0.05. However, the value of the correlation shows that the claim payout has a stronger correlation with the wind speed than the ratio. The distance from the property centroid to the shoreline has a similar correlation. The distance and the dependent variables have negative relationships because the P-values are less than 0.05.

Nevertheless, the value of the correlation shows that the claim payout is more negatively correlated with the distance than the ratio.

On the other hand, the building age is not significantly correlated with the claim payout, while the relationship with the ratio is positively significant. The building floor area also has different relationships among the dependent variables. The building floor area is positively correlated with the claim payout, while the relationship with the ratio is not significant. The appraised value of the building is positively correlated with the claim payout.

Spearman's rho Correlation analysis test was used to check the correlation between the dependent variables and ordinal variables. The correlations between the FEMA flood zones and the dependent variables have similar correlation results. In both cases, the FEMA flood zones have positive relationships because the P-values are less than 0.05. However, the value of the correlation representing the claim payout is more closely correlated with the FEMA flood zones than the ratio. The hurricane surge zones also have similar relationships with the dependent variables. The hurricane surge zones have negative relationships with the dependent variables because the P-values are less than 0.05. Nonetheless, the values of the correlations indicate that the ratio has a stronger negative correlation with the hurricane surge zones than the claim payout. However, The right side of the hurricane track is not statically correlated with the dependent variables because the P-value is larger than 0.05 in both cases.

In summary, in accordance with the correlation results, the claim payout increases as the maximum sustained wind speed, the building floor area, the appraised value of the building, and the FEMA flood zone number increases. Otherwise, the claim payout decreases as the distance from the property centroid to the shoreline and the hurricane surge zone number increases. The ratio increases as the maximum sustained wind speed, the building age, and the FEMA flood zone number increases. Meanwhile, the ratio decreases as the distance from the property centroid to the shoreline and the hurricane surge zone number increases.

6.1.3 Regression Models

In the TWIA claim payout prediction model, the model is statistically significant because the P-value of 0.000 is less than 0.05, which means that the independent variables could predict the TWIA claim payout. The adjusted R-square of 0.401 represents that the 40.1% of variability in the transformed dependent variable can be explained by the significant variables. Checking the P-values reveal seven significant variables: maximum sustained wind speed, the right side of the hurricane track, building age, building floor area, appraised value of the building, hurricane surge zone, and distance from the property centroid to the shoreline. In this phase, the FEMA flood zones were rejected due to the high P-value. Following the values of the standardized coefficients, the significant variables also measured the magnitude of the dependent variable. Therefore, the claim payout can be measured by using the prediction model, as follows:

$$\text{Log (Predicted TWIA Property Damage Claim Payout (\$))} = 2.973 + (\text{Wind\_Speed} * 0.019) + (\text{Side\_Right} * 0.100) + (\text{Age} * 0.007) + (\text{Area} * 2.522\text{E}-4) + (\text{Imp\_Value} * 1.526\text{E}-6) + (\text{Surge\_Zones} * -0.111) + (\text{Dist\_Shore} * -5.254\text{E}-6)$$

In the prediction model,

1. The maximum sustained wind speed has a positive relationship with the TWIA claim payout, which means that if the maximum sustained wind speed increases, the claim payout increases. This result supports the results of the previous studies that wind speed is a significant indicator of hurricane damages and is useful for predicting hurricane damages (Burton 2010; Dunion et al. 2003; Powell and Houston 1998; Powell et al. 1998).
2. The right side of the hurricane track has a positive relationship with the TWIA claim payout, which means that if a building is located on the right side of the hurricane track, the claim payout increases. This result reinforces former studies that a building located on the right side of the hurricane track usually has more damage than one on the left side of the hurricane track, in the Northern Hemisphere (Keim et al. 2007; Noel et al. 1995), and confirms that the variable is a critical indicator for hurricane damage prediction.
3. Building age has a positive relationship with the TWIA claim payout, which means that if the building age increases, the claim payout also increases. This

result proves former study that the building age is a significant variable for predicting hurricane damage (Highfield et al. 2010).

4. Building floor area has a positive relationship with the TWIA claim payout, which means that if the building floor area increases, the claim payout increases. This result corroborates previos study which conclude that this variable is one of the indicators for measuring hurricane damage (Dehring and Halek 2006).
5. Appraised value of the building has a positive relationship with the TWIA claim payout, which means that if this value increases, the claim payout also increases. This result confirms that the appraised value of the building is a significant indictor in assessing the damage from hurricanes.
6. Hurricane surge zone has a negative relationship with the TWIA claim payout, which means that if the hurricane surge zone number increases, the claim payout decreases. This result verifies that the hurricane surge zone is a useful indicator for predicting hurricane damage.
7. Distance from the property centroid to the shoreline has a negative relationship with the TWIA claim payout, which means that if the distance increases, the claim payout decreases. This result confirms former study that the distance is related to the damage and is a significant variable for predicting hurricane damage (Highfield et al. 2010).

The ratio prediction model is statistically significant because the P-value of 0.000 is less than 0.05. This proves that the independent variables could predict the ratio. The adjusted R-square of 0.337 verifies that 33.7% of the variability in the transformed dependent variable can be explained by the significant predictors. Checking the P-values reveal four significant variables: the right side of the hurricane track, building age, hurricane surge zone, and distance from the property centroid to the shoreline. In this phase, the maximum sustained wind speed, FEMA flood zone, and building floor area were all rejected due to high P-values. Following the values of the standardized coefficients, the significant variables also measured the magnitude of the dependent variable. Therefore, the ratio can be measured by using the prediction model, as follows:

$$\text{Log}\left(\text{Predicted Ratio }\left(\frac{\text{TWIA Claim Payout (\$)}}{\text{Building Appraised Value (\$)}}\right)\right) = -1.167 + (\text{Side\_Right} * 0.200) + (\text{Age} * 0.010) + (\text{Surge\_Zones} * -0.112) + (\text{Dist\_Shore} * -8.605\text{E}-6)$$

In the prediction model,

1. The right side of the hurricane track has a positive relationship with the ratio, which means that if a building is located on the right side of the hurricane track, the ratio increases. This result reinforces former studies which found that a building located on the right side of the hurricane track usually has more damage than one located on the left side of the hurricane track, in the

Northern Hemisphere (Keim et al. 2007; Noel et al. 1995), and verifies that the variable is a critical indicator for hurricane damage prediction.

2. Building age has a positive relationship with the ratio, which means that if the building age increases, the ratio also increases. This result confirms former study that building age is a critical variable for predicting hurricane damage (Highfield et al. 2010).
3. Hurricane surge zone has a negative relationship with the ratio, which means that if the hurricane surge zone number increases, the ratio decreases. This result verifies that hurricane surge zones are a useful indicator for predicting hurricane damage.
4. Distance from the property centroid to the shoreline has a negative relationship with the ratio, which means that if the distance increases, the ratio decreases. This result confirms former study that the distance is related to the hurricane damage, and is a significant variable for predicting hurricane damage (Highfield et al. 2010).

In two prediction models, there are four common predictors:

1. Right side of the hurricane track
2. Building age
3. Hurricane surge zone
4. Distance from the property centroid to the shoreline

Maximum sustained wind speed and building floor area are insignificant predictors in the ratio model. Appraised value of the building is significant in the TWIA claim payout model.

On the other hand, the prediction models are both statistically significant. In addition, the ranks of the standardized and unstandardized coefficients and the magnitude of the standardized coefficients are similar, and the sign of the unstandardized coefficient is the same in each of the predictors. Besides, the results of this research are similar to those of previous studies. In summary, the TWIA claim payout and the ratio could be predicted by the significant predictors and the results here enhance those of previous studies. Additionally, the findings and models could be beneficial to public works and government agencies, emergency planners, and insurance companies in the field of hurricane damage prediction.

6.2 Recommendations

The adjusted R-square values of the claim payout and the ratio are 0.401 and 0.337, respectively, which means that the rest of the variability could be explained by some unidentified variables. Consequently, it would be valuable to come up with prospective indicators and make additions to find the best-fit regression model.

This study only considered improved commercial buildings in Texas coastal counties. The results and findings would likely be different with residential properties. Future studies will need to include residential properties to strengthen the results and findings. In addition, the hurricane damages considered were only those resulting from

Hurricane Ike. Therefore, it would be worthwhile to study various other categories of hurricanes in the future.

Moreover, using the developed methodology and indicators in this study, it should be possible to predict hurricane damage for other hurricane-prone areas such as Florida, South Carolina, North Carolina, Alabama, and Louisiana.

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