COMPREHENSIVE DAMAGE ASSESSMENT AND ANALYSIS OF DAMAGE MECHANISMS FROM HURRICANE HARVEY

By

SARA WENGROWSKI

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Jie Gong

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ABSTRACT OF THE THESIS

Comprehensive Damage Assessment and Analysis of Damage Mechanisms from Hurricane Harvey

By SARA WENGROWSKI

Thesis Director:

Jie Gong

A combination of mobile data collection and new damage assessment methods with spatial analysis and machine learning algorithms were used to correlate structural characteristics with damage and iterate upon damage assessment protocols for further development. More specifically, data was collected using a mobile scanning vehicle, reducing volunteer exposure to the harsh post-disaster environment, collecting high volumes of panoramic and LiDAR imagery in a relatively short period of time. This new data collection method was deployed in Texas during Hurricane Harvey. Among many datasets collected by this method, the dataset used in this study consisted of almost purely wind-caused damage from Hurricane Harvey to 553 homes in southeast Texas. A damage assessment methodology was created, combining lessons learned and protocols from previous studies, to increase efficiency and include more external public sources of data for better damage analysis. Statistical analysis was combined with spatial analysis revealing structural components which can be expected to reduce or increase damage from single-hazard wind damage. Spatial analysis indicated that damage rating was related to peak wind speed and explanatory regression revealed that the most significant variables to classification were: Age, Latitude, Metal Roofs, Distance to Coast, Total Area, Asphalt Roofs, Wood Siding, Stucco Siding, Two Story Buildings, and Building Value. Machine Learning classifiers were used improve the efficiency of damage assessments by indicating the multicollinearity and the feature importance of each variable. The variables with the highest feature importance include: Distance to Coast, Longitude, Single-Family, Age, Total Area, Wind Speed, and Single Story. These variables should be prioritized in future studies, while variables with low feature importance, such as Grade Level Entry, Intersecting or Overlapping Roofs, 10/12 Roof Pitch, Commercial uses, and Vinyl Siding, should be reconsidered in future damage assessments.

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Chapter 1: Research Background

As coastal communities grow, the implications from hurricanes will affect large populations of people. Coastal communities are growing faster than non-coastal communities; about one in six people lives in a coastal county along the Gulf and Atlantic coasts in the United States (Friedland, 2012). These people carry a higher risk of being affected by tropical cyclones based on their location. Wealthier individuals are increasingly moving towards the coast, meaning that higher-valued property will be at risk to future natural disasters (Pielke, 2008). Between 2000 and 2004, the average cost for weather-related natural disasters was between $94 and $130 billion, globally. The average annual damage from hurricanes in the United States is about $10 billion (Pielke, 2008). At the forefront of these damages are residential properties which were often designed at lower engineering standards than those of critical infrastructures.

Designing stronger and more resilient residential homes is a topic that has been studied for decades. Yet, in recent hurricane events, we still saw the destruction of tens of thousands of residential properties. Consequently, for the vast majority of structural failures in recent hurricanes, current scientific knowledge is still inadequate and imprecise enough to specify with sufficient confidence why exactly an individual building performed as it did. Post-hurricane investigations identify factors that enhance or reduce damage. Often various stakeholders isolate single factors such as construction material (e.g., wood vs concrete or asphalt shingle vs metal roofing), laying the ground for blame, but we lack understanding as to what extent these various factors interplay in deciding the final damage state, nor do we know to what extent the combination of known factors explain the high variability in building performance in hurricane-impacted communities.

In the following, I briefly review known hurricane damage mechanisms, major damage assessment methodologies, and damage assessment analysis methods to highlight the advantages and limitations of each method with the hope to set the ground for my own research quests.

1.1 Hurricane Damage to Residential Structures

Hurricane damage is often measured by the damage to residential structures so the combination of population movement and settlement towards coastal communities and expected impacts from climate change, predicting damage to residential structures is imperative towards protecting future lives and property (Burger, 2015; Friedland, 2012). Coastal communities are growing faster than non-coastal communities; about one in six people lives in a coastal county along the Gulf and Atlantic coasts in the United States (Friedland, 2012). These people carry a higher risk of being affected by tropical cyclones based on their location. Wealthier individuals are increasingly moving towards the coast, meaning that higher-valued property will be at risk to future natural disasters (Pielke, 2008). The average annual damage from hurricanes in the United States is about $10 billion (Pielke, 2008).

By understanding the factors which impact hurricane damage to residential structures communities, decision makers, and individuals can make better decisions to protect themselves and their assets from destruction caused by future hurricanes. Hurricane damage has been linked to failure of structural elements, natural systems, social unpreparedness, and interdependencies between them (Adger, 2005; Burger, 2015; Kousky, 2014; Pielke, 2008; Shults, 2017). The impacts of a hurricane can be influential long after the initial tropical cyclone, by building more resilient communities the post-storm recovery may be reduced in scale and quicker (Hyder, 2017; Logan, 2016; Mastaglio 2018; Shults, 2017; Walton, 2018; World Health Organization, 2013).

1.2 Hurricane Damage Mechanisms

The Saffir Simpson scale predicts damage based on the wind speed over the duration of one minute at an elevation of about ten meters (Eamon, 2017). Although the Saffir-Simpson scale is used widely to describe the severity of a hurricane to the public, tropical cyclones can cause varying degrees of damage based on factors which are not captured by this scale. The most common damage mechanisms are: flooding, wind, debris, or any combination of them. Single-hazard events result in damage from one of the damage mechanisms, whereas multi-hazard events have damage from any combination of two or more damage mechanisms. Damage from multi-hazard events is not the linear combination of single-hazard damage, making damage prediction more difficult (Klima, 2012).

1.2.1 Flooding & Surge Damage Mechanisms

Because an estimated 10% of the world's population lives on the less than 2% of global land which is under 10 m elevation, it is important for coastal communities to understand risks of flooding (Burger, 2015). There are three primary means of flooding: storm surge, astronomical tides, and flooding from torrential rainfall.

Storm surge, especially in combination with tidal flooding, and wave action can pose a substantial threat to communities and the environment (Eamon, 2017). Storm surges vary greatly depending on the local bathymetry, thus may not be the most effective method of communicating potential hurricane threats. It is important to consider the impact of storm surged, though, because flooding resulting from storm surge has killed more people in the United States than all other hurricane-related threats combined, since 1900 (Blake, 2007).

Single hazard storm surge destruction was found on the Bolivar Peninsula in Texas during Hurricane Ike in 2008. Wave action also amplified damage caused by the storm surge, in this example. A study was conducted on permanent wood-framed homes, using satellite imagery and aerial photos, used to determine if homes were still standing after Hurricane Ike (Kennedy et. al, 2011). Building elevation, in this case, was the primary indicator of damage in areas with large waves. The elevation difference between homes that were and were not damaged was as little as 0.5 feet. In areas with smaller waves, well-built homes at lower elevations also survived. Homes immediately adjacent to the Gulf of Mexico generally failed because of widespread erosion, causing foundation failure (Kennedy et. al, 2011).

Astronomical tides can produce regular issues in some low-lying areas from the combined effects of the rotation of the Earth and the gravitational forces of the moon. Storm tides are the combined flooding level of astronomical tides and storm surge, producing more damage than storm surge alone.

Tidal flooding combined with storm surge amplified the damage from Superstorm Sandy in parts of New York and New Jersey in October 2012 (Baquero-Duran, 2015; Burger, 2015; Hatzikyriakou, 2015; Lin, 2016; Sharkey, 2016; Xian, 2015). The factors which influenced the damage to structures from Superstorm Sandy include: distance to the coast, elevation on structure above ground (the higher the structure, the less damage sustained, in general), and the age of the home (Xian, 2015). Most of the surge damage from Sandy was generated near the shore and on the ocean-facing side of a structure. Foundations and exterior walls were particularly vulnerable to this form of damage (Xian, 2015). Soil scour and foundation-separation from structure were common methods of failure for structures from surge. Closed-foundations faced significant damage and exterior walls were susceptible to surge loads and impact from debris in the water (Baquero-Duran, 2015; Hatzikyriakou, 2015). Debris is often shielded by neighboring structures, so the success rate of a neighboring structure plays an important role in the damage sustained by an individual structure. Most exterior walls failed from hydrostatic loading from Superstorm Sandy than from impact loads from debris (Hatzikyriakou, 2015).

Large and slow-moving tropical cyclones, like Hurricane Harvey in Southeast Texas, produce the most significant precipitation-related flooding. Since 1980, hurricanes in the Gulf of Mexico produced an estimated 20% more event precipitation, and the probability of extreme rainfall caused from tropical cyclones is expected to increase in the future (Wang, 2018). Hurricane Harvey is best known for the damage it caused in the Houston area from sever rainfall, about 51.88 inches of rain over a five-day period, setting a record for the continental United States (Kluger, 2017). In the greater Houston area, more than 70 fatalities were reported and over 100,000 homes were affected. More than 10,000 rescues were conducted by professional and volunteer rescuers (Sebastian, 2017).

Structural failures from flooding result in damage to foundations and lower members of structures. Although the location of flooding may be highly related to the distance from the coast and the amount of precipitation in an area, failure of structures is not easy to predict (Blake, 2007; Kennedy et. al, 2011; Xian, 2015). Complex geo-technical mechanisms, causing soil scour and other foundation failure, impact the amount of damage sustained by a structure.

1.2.2 Wind Damage Mechanism

There is significant variability in wind-caused damage, some of which is expected to be produced from small-scale tornadoes and eyewall mesovorticies (Wurman, 2018). Mesovorticies are small rotational features, sometimes occurring on the eyewall of an intense tropical cyclone, which have higher wind speeds than other parts of the storm. The complex nature of the wind patterns on a tropical cyclone can result in uncertainty in damage prediction.

Hurricane Andrew's destruction in some locations was single-hazard wind damage, causing structural damage to roofs, roof shingles, and roof sheathing. Roof type played a role in the damage; hip-shaped roofs were less likely to sustain damage than gable roofs (Crandell, 1998; Egnew, 2018; van de Lindt, 2007). Damage to two-story homes was greater than that of single-story homes. There was also a correlation between more severe damage and the loss of a window or door (Crandell, 1998). Single-hazard wind damage was also found from Superstorm Sandy in New Jersey and New York. The attributes which had the most direct relationship with the damage were: the distance from the berm of the sand dunes to the dune crest, the number of stories, the front door elevation, and the dune type (Xuan, 2016). The building envelope plays a very vital role in protecting a structure from wind damage (Norman, 2010).

Tornados can be analyzed to further understand single-hazard wind damage. Multinomial logistic regression models related damage levels with common building attributes, such as the year built, the living area, appraised value, and the number of stories, as well as non-physical attributes such as estimated peak wind speed for the 2011 Joplin, MO tornado (Egnew, 2018). Newer homes, counterintuitively, had increased likelihood of damage (Egnew, 2018). A hypothesis for the relationship between new homes and damage is that there is a lack of code enforcement and a deterioration of construction quality in more recent decades (De Silva et. al 2008). Homes with lower value per area also had higher frequencies of tornado damage. The number of stories a home had also had a weak correlation with damage. Peak wind speed, although an estimate, was strongly correlated with wind damage (Egnew, 2018).

Wind damage primarily originates at the roofline, but wind damage is very stochastic making it challenging to estimate and predict.

1.2.3 Debris Damage Mechanism

Both high speed winds and moving water can act as a medium for debris to travel through. Debris is difficult to predict because of its stochastic nature, but there are factors which may impact probability to debris damage. Debris can be shielded by neighboring structures but can also be created by nearby neighboring structures (Hatzikyriakou, 2015). Debris can cause extremely high loading to concentrated areas, resulting in high rates of damage where debris is present.

1.2.4 Multi-Hazard Damage

The most common forms of hurricane damage consist of multiple hurricane hazards, though poorly understood. Structural damage caused by multi-hazard Hurricane Katrina in 2005 resulted in about 130,000 homes in Mississippi sustaining complete destruction or severe damage. The primary cause of component damage was tied to the failure of connections. Although high winds primarily damaged roofs and exterior structural components, storm surge and wave action posed a larger threat because the magnitude of the loading was much higher than wind loading (Eamon, 2017). Hurricane Katrina's damage was more present in pre-cast concrete, light-framed wood structures, and bridges, whereas there was minimal structural damage to reinforced concrete, steel frames, and heavy timber (Eamon, 2017). Hurricane Katrina produced non-structural damage to facades and interior partitions, as well (Eamon, 2017). In most cases, multi-hazard damage is influenced more by flooding and storm surge than wind, but also can aggregate the damage caused by high winds. To best prevent damage from multi-hazard events, homeowners should: seal all openings from wind and water, reinforce all windows and doors by using shutters or plywood, by implementing impact resistant glass, by using wind-rated and impact tested doors, and by bracing the garage, making sure that the exterior frame is secure, and through improvements to the roof such as roof straps, ring-shank nails for roof decking, sealed and storm-resistant shingles, and flashing on roof when the slope changes (Lankford, 2018).

1.3 Past Damage Measurement

Damage ratings and economic losses are sometimes valued by the number of claims that FEMA receives, but most often by the amount of structural damage estimated from a hurricane. Damage assessments estimate structural damage through questionnaires that diagnose whether a structure is safe, what the overall damage is, and/or damage to individual components. Damage can be measured in a damage assessment using a binary scale, discrete ratings, and/or continuous percentages. In the past, damage assessments were surveys conducted by volunteers and structural professionals on-site.

A disadvantage of on-site surveys is that areas affected by natural disasters may have poor access routes, limited power, and scarce resources. These surveys must be conducted soon after a storm before re-construction efforts take place, this way accurate damage values are estimated, so there is little prior notice. The recovery begins almost immediately after a hurricane strikes, and damage may look altered after re-build begins. For example, tarps over roofs cover the amount of damage to a roof. Towns with higher income tend to rehabilitate quicker than towns with lower income (Baquero-Duran, 2015). The quantity of on-site damage assessments is directly related to the number of volunteering assessors and their allotted time in a damage zone. The conditions for an assessor are not ideal and the process of assessing damaged property can be long and tedious. The use of less manual damage assessment techniques, such as using LiDAR or aerial surveys could remedy the disadvantageous nature of on-site assessments (Hatzikyriakou, 2015). Further inputting information from the physical damage assessment forms into a database is a tedious and time-consuming process which can introduce new errors into the data. Online forms can be used, if the internet is accessible on-location.

There is no universal damage assessment, and the lack of consistency in assessments can result in damage estimates that carry uncertainty. A system known as the

ATC-45 was created in 2004 to estimate the overall damage of a structure and subsequent components using ratings: “Minor/None,” “Moderate,” and “Severe” (ATC, 2004). This rating system is used to understand if a building is safe to enter. ATC-45 had the goal of determining whether a structure is safe to enter, but component-level damage is not recorded (ATC, 2004). Categorical rating systems, such as ATC-45, can be easy to collect, but do not yield much information for further analysis.

The United States Department of Housing and Urban Development also evaluated the damage resulting from Hurricane Andrew in 1992, based on a percentage scale of damage to certain structural components (U.S. Department of Housing and Urban Development, 1993). These ratings systems are not completely comprehensive and have not been adopted globally. The benefit of a percentage scale is that data is complete, but assessments which are comprised entirely of continuous scales can contain bias depending on the assessor and take much longer to quantify.

Damage assessments rarely consider damage to the interior of a structure, and water and wind intrusion into a structure can cause considerable damage. In cases where the interior of a structure is considered in damage assessments, the damage is calculated based on empirical functions based on envelope damage or decided through expert opinion (Pita, 2012). To record damage information about the inside of a structure, assessors must expose themselves to potential hazards, longer damage assessments, and may require permission to enter a structure.

Although there is no universal damage assessment, most assessments share some characteristics in common. Structural damage assessments generally contain questions about the location of a structure, the address, the condition of the envelope of the home, such as the roof, walls, and foundation, as well as questions about the materials used during the construction. An ideal assessment would also contain information about the overall physical appearance of the structure, pre-storm information, aerial photography of the structure, and exterior aspects of the structure (Norman, 2010). An assessment created by students from Princeton University included structural damage to the entire structure, a weighted sum of damage to each level of the building, and construction cost estimate to each structural component with damage (Owensby, 2013).

Resulting from the lack of consistency of damage assessments, communities may be underestimating the risk and damage associated with hurricanes and other natural disasters. For example, FEMA has historically underestimated the risk to structures near the shore when compared to structures further inland to storm surge (Xian, 2015). The National Oceanic and Atmospheric Administration's National Climatic Data Center releases a Weather/Climate Disaster report, and this report converts insured losses to total direct losses which can result in an underestimation of average damage and loss from hurricanes (Smith, 2013). Being that risk perception is a major component of the evacuation decision process, it is important for risk and damage to be communicated with as much certainty as possible.

1.4 Data-Science Analysis Approach

Damage assessments have, in previous studies, been analyzed using machine learning classifiers, text mining, statistical analysis, fragility curves, logistic regression, visual analysis after projecting data onto a map, and any combination of the mentioned methods (Crandell, 1998; Hatzikyriakou, 2015; Owensby, 2013; Salazar, 2015; van

Verseveld, 2015; Xuan, 2016). All these analysis techniques have their limitations, though.

Fragility curves are probability distributions representing the conditional probability that a structure will sustain or exceed damage at a given wind speed, modeled as lognormal distributions with two parameters, mean and variance (Subramanian, 2013). HAZUS utilizes fragility curves to estimate damage, but additional variables can be useful in improving the accuracy (Subramanian, 2013). Fragility curves can be useful for estimating damage, but they have their limitations because they only represent probabilistic distributions which do not simultaneously link multiple variables at once. Physical models also have their constraints. They are useful in holistically understanding damage to a specific structure but cannot be applied to other structures.

Machine learning models which combine classification trees and logistic regression had relatively high accuracy (75.2%) when predicting damage caused by Hurricane Ike at a scale of one-kilometer blocks (Salazar, 2015). Though accuracy of predictions is high, this study did not analyze structures at the scale of a single-structure. The benefit of single-structure analysis is that specific methods and materials in construction can be individually analyzed, and the data can be aggregated to any scale. Also, the combination of classification trees and logistic regression had a high accuracy value, but the training dataset used in was very large (Salazar, 2015). This study, in contrast, does not have access to a large dataset with single-hazard wind damage, so the combination of the specified machine learning models may not be as effective.

Vulnerability of structures from Superstorm Sandy in New Jersey were assessed using a combination of statistical models, fragility curves, and logistic regression models.

Statistical analysis was used as the primary means of determining significance of each building parameter (Hatzikyriakou, 2015). Component-based vulnerability curves were then made to predict component failure for a calculated vulnerability parameter. This combination of analysis methods underestimated damage in some areas and overestimated damage in other areas (Hatzikyriakou, 2015). This analysis was done primarily to predict damage caused by storm surge and flooding, which tends to be less stochastic than wind damage.

Linear regression was also used to predict degree of damage and loss ratio, given some parameters from a damage assessment in Ortley Beach, NJ from Superstorm Sandy (Owensby, 2013). The accuracy of this regression analysis was not very high, but it may have been a result of the relatively small dataset, the low number of input variables, and because the relationship between damage and independent variables tends not to be linear in nature, therefore a linear regression would not be the ideal method for analyzing this type of data (Owensby, 2013).

The rough set data mining theory was used to explore variable significance contributing to hurricane damage from Superstorm Sandy in New York and New Jersey (Xuan, 2016). Benefits of using this theory include: that it can be applied to incomplete datasets, datasets with variables which carry multicollinearity, and can reduce bias which is inherent in damage assessments based on the assessor. This study had a limited sample size of 74 homes, and low damage rates among studied homes. This analysis was also conducted on a single-hazard surge event, where damage tends to be less stochastic than that of wind damage, because it is highly correlated distance to the coast (Xuan, 2016).

The primary goal of this study was to understand the dominant factors which influence the survival of structures but did not indicate the intensity of damage (Xuan, 2016).

Some machine learning models, such as the Bayesian Belief Network (BBN), require significant damage data, which this project does not have access to (van Verseveld, 2015). The benefit of the BBN is that it can predict using several variables which are combined, producing probabilistic predictions which include uncertainty (van Verseveld, 2015). Similar benefits are found in other machine learning models and combinations of other machine learning approaches (Salazar, 2015).

Both spatial analysis and machine learning algorithms were used in this study to collect further information on factors impacting damage and to analyze the results of the damage assessment. The analysis of homes in this study are at an individual scale, so this data can be aggregated to any scale.

Spatial statistics and tools were used to identify variables that were missing from the damage assessment, as well as better understand the relationship space and scale has on pre- and post-storm variables. The Cluster and Outlier (Anselin Local Moran's I) tool and the Exploratory Regression tool in ArcMap were applied to the dataset to better understand the spatial component of the data and to describe the variable significance, relationship, and adjusted R^2 value of dependent and independent variables (ESRI, 2018).

Supervised machine learning classifiers were optimized to predict damage to the entire structure and to individual structural components. The machine learning classifiers were used to build a correlation matrix and feature importance, which can be applied to improve future damage assessments.

1.5 Research Objectives

Given the above identified challenges in reducing hurricane damages to residential structures and research gaps in understanding hurricane damage mechanisms, this study has several research objectives.

The first objective is to test the feasibility of using remotely sensed imagery, including airborne and street-level imagery and other publicly available data sets such as Zillow, to conduct detailed damage assessment.

The second objective is to test whether a new damage assessment protocol can be developed based on the above data sources to provide robust pre- and post-storm datasets. In particular, this study applies information from public datasets to increase the quantity of pre-storm structural data, such as building location, age, area, and value. By implementing information that was previously collected, the time and resources used on each damage assessment is reduced.

The third objective is to use the unique data sets compiled using the above approach to identify dominant factors contributing to hurricane damage to residential structures. The study used a dataset with almost exclusive wind-damage, which eliminates the cross-contaminations by flood-induced damages.

The fourth objective is to test whether data science-based approaches can be used to develop hurricane damage models for residential structures. For this research, data analysis includes a combination of simple statistical analysis, data visualization, statistical analysis, and an optimization of machine learning classifiers. By combining methods of data analysis used in previous studies, data analysis is expected to be more accurate and reduce limitations of previous studies.

The final objective is to identify building typologies or construction practices that have performed poorly during hurricane winds.

To realize these research objectives, a unique data set collected from a heavily damage community during Hurricane Harvey is used. The details and uniqueness of this community and date assets are summarized in the following box:

Key Allegro during Hurricane Harvey

About 88% of the U.S.'s major hurricanes have hit either Texas or Florida (Jarrell et al., 2001). The projected average sea-level rise in Texas is expected to be 2.1 feet, and this increased sea-level is expected to amplify the impacts of hurricanes in this area (Kopp et. al 2014). The most notable hurricane to have hit southeast Texas was Hurricane Harvey in August 2017. Hurricane Harvey was the first major hurricane, category 3 and above, since Hurricane Wilma, in 2005, to make landfall in the United States and is now tied with Hurricane Katrina as the most expensive hurricane in American history (Huber, 2018).

Hurricane Harvey made landfall near Rockport, Texas on August 25th, 2017 as a Category 4 hurricane on the Saffir-Simpson scale. Harvey's maximum sustained wind speed was approximately 212 km/hour (Sebastian, 2017). Though Harvey's damage in the Houston area was unprecedented, it produced widespread damage in the Southeast Texas coastal area. Hurricane Harvey caused an estimated 300,000 homes to lose power and over 500,000 people to seek federal aid for damage from FEMA (Hyder, 2017; Kluger, 2017). An estimated 45,000 people sought refuge in shelters from the storm, which was originally predicted to be a category 1 or 2 hurricane with maximum rainfall of about 25 inches (Kluger, 2017). Over 45 schools suffered water damage, out of the total 350 schools in the area. There was no mandatory, large-scale evacuation ordered before or during Hurricane Harvey (Sebastian, 2017). In 2010, it was stated that the most serious threat to Texas residents from a tropical cyclone was serious flooding, and Hurricane Harvey proved that this was a major risk (Roth, 2010). Hurricane Harvey made a second landfall near the Texas-Louisiana boarder after causing extensive damage to the Texas coast (Sebastian, 2017).

Damage assessments in this study focused on two communities which fall within Aransas County in Texas, in the greater area of Hurricane Harvey's landfall. Near Port Aransas in Aransas County, the peak wind gusts of 212 km/hour were reported and the total water levels exceeded 2 meters over their normal levels. Around the Aransas Wildlife Refuge, the storm tide reached about 12 feet (Sebastian, 2017).

The study area utilized in analysis was comprised of the entirety of Key Allegro, a neighborhood located in Rockport, Texas. Key Allegro is very close to the location of Hurricane Harvey's landfall, but surprisingly did not sustain damage as severe as its neighboring communities. Key Allegro is of interest for this study because the damage from Hurricane Harvey was almost entirely caused by single-hazard wind damage. Key Allegro was purchased and developed in 1962, so homes in this area have a relatively uniform age (Jasinski, 2010). The oldest homes in Key Allegro were 57 years old in 2017, less than the length of two 30-year mortgages (Zillow, n.d.). Homes build around the same time are assumed to have similar building codes and regulations. Homeowners in this area are also wealthier than surrounding communities; the median household income in Key Allegro was $131,389 in 2017, compared to the median household income in Rockport of $57,958 (American Community Survey, 2017). The high median household income can be associated with high-value, upscale homes with luxury features, construction methods, and building materials.

1.6 Research Contributions

The combination of new data collection and damage assessment methods with spatial analysis and machine learning algorithms were used to correlate structural characteristics with damage and iterate upon damage assessment protocols for further development. Advances in data collection improved conditions and reduced on-site time for damage assessor volunteers. Damage assessment was performed completely off-site, utilizing data collected from a mobile scanning vehicle, previously collected data, and external data from Google Maps, Google Streetview, NOAA aerial imagery, Zillow, Geocodio, and ArcMap (ESRI, 2018; Geocodio, 2019; Google, n.d.; Google Streetview, n.d.; Guo, 2017; Kijewski-Correa, 2018; NOAA NGS, 2017; Vickery, 2017; Zillow, n.d.). Both pre- and post-storm information was collected for a comprehensive picture of factors influencing single-hazard wind hurricane damage. The damage assessment implements protocols and lessons learned from previous studies.

Once the dataset was compiled, spatial analysis was applied. The spatial analysis was the primary method for understanding the significance and relationship of building components with damage (ESRI, 2018). The spatial analysis indicated that age, wind speed, roof and wall cover determined the extent of most. This analysis also indicated that resiliency can be improved by implementing reinforced exterior roof and wall covering. Larger, more valuable homes, which tended to be close to the coast, had lower rates of damage- this could be a result of more-expensive building materials and construction practices on luxury structures.

Machine learning algorithms showed dependence between certain variables as well as variable importance of predicting damage. Both analyses can be used to iterate upon the current damage assessment, reducing the number of features, therefore reducing time of assessment while preserving the robustness of the dataset. Future assessments should keep questions about distance to coast, location, building use, age, area, wind speed and other environmental factors, and number of stories. By reducing information about entry level and reducing the number of roof pitch, roof shape, and wall covering options in the damage assessment, time and other resources may be re-allocated for further analysis.

1.7 Organizational Overview

Chapter 2 includes the research methods in this study. Methods of collecting damage data, conceptualizing the damage assessment, compiling the Hurricane Harvey dataset for Key Allegro, and proposed analysis approaches are included in Chapter 2. Chapter 3 discusses the results of the damage assessment, spatial analysis, and machine learning classifiers with their respective implications. Chapter 3 also includes an examination of international building codes and the impact that, if applied, newer building codes would have had on Hurricane Harvey damage in Key Allegro. Chapter 3 will conclude with limitations of this study and future research opportunities. Chapter 4 summarizes the main points, findings, and conclusions of this study.

Chapter 2: Research Methods

In this chapter, I discuss the methodology of this study, including data collection, data archiving, damage assessment, data analysis, iterative improvement of damage assessment, and the ideal community improvement (**Figure 1**). To collect the pre- and post-hurricane data, a mobile scanning vehicle collected imagery and spatial data – which was archived into the Rutgers-Harvey Portal, discussed in **Section 2.1** (Guo, 2017). Additional post-disaster data collected by Kijewski-Correa, et. al was used in this study (Kijewski-Correa, 2018). Other public and private datasets were utilized for further data collection, including Google Maps, Google Street View, NOAA aerial imagery, Zillow, and Geocodio (ESRI, 2018; Geocodio, 2019; Google, n.d.; Google Streetview, n.d.; Guo, 2017; Kijewski-Correa, 2018; NOAA NGS, 2017; Vickery, 2017; Zillow, n.d.). Data fell into three categories: imagery, building attributes, and geospatial attributes. Imagery information is assessed and converted to pre- and post-storm building attribute information. All this data is then input into the damage assessment, discussed in detail in **Section 2.2** and **Section 2.3**. The damage assessments were then analyzed in three ways: simple statistical analysis, spatial analysis, and machine learning analysis. Information gathered from the data analysis can inform future decisions on damage assessment methodology and building more resilient communities.

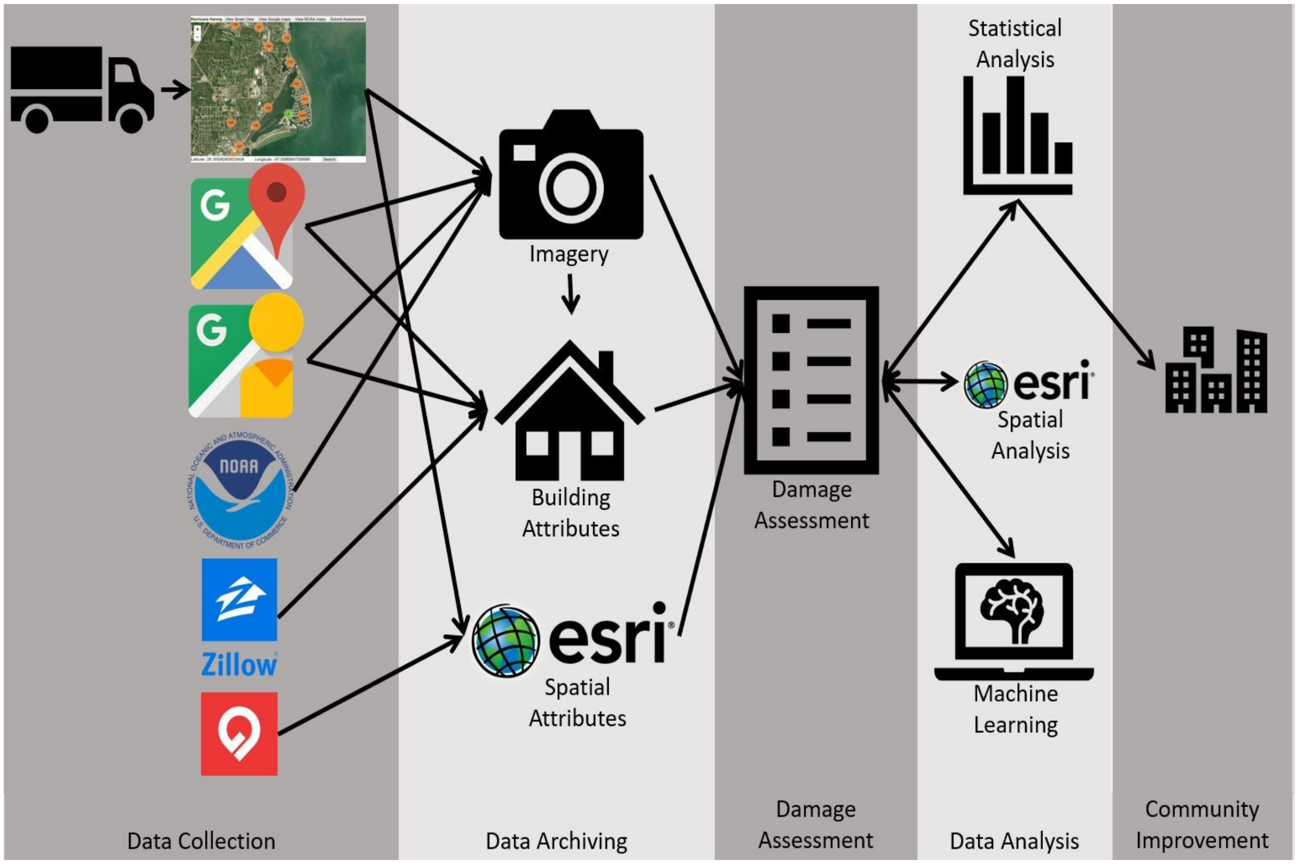

Figure 1: Overview of study methods, including data collection, data archiving, damage assessment, data analysis, damage assessment improvement iteration, and community improvement.

2.1 Damage Data Collection and Archiving

Students from Rutgers University, accompanied by students from Princeton University and University of Texas at Austin, collected data in Port Aransas and Rockport, Texas. The volunteers utilized a mobile scanning vehicle, three days after the Hurricane Harvey, to document damage to residential structures caused by the storm. The mobile scanning device combined GPS ensembled equipment with a 360-degree panoramic camera and LiDAR scanners. Over 60,000 panoramic photos were taken during the reconnaissance effort (Guo, 2017; Rutgers Magazine, 2018). The photos taken during this exploration period were compiled and geo-located on a map, then linked with a pre-storm google street map and NOAA aerial photos from the post-storm study areas

(Guo, 2017; NOAA NGS, 2017). The data compilation, geo-coding, and links were provided at the Rutgers-Iris Hurricane Harvey Portal (Guo, 2017). The portal allows the public to access imagery collected from the mobile scanning vehicle. The imagery is also linked to Google Street View, Google Maps, NOAA imagery, and the damage assessment in this study (**Figure 2** & **Figure 3**) (Google, n.d.; Google Streetview, n.d.; Guo, 2017; NOAA NGS, 2017).

The mobile scanning vehicle is beneficial in several ways. The damage assessment process can be conducted after the initial survey, so assessors are not exposed to the harsh environment of a post-disaster area for a long period of time. The mobile scanning vehicle requires fewer volunteers to be on-site, reducing the need for a high volume of volunteers, especially when post-disaster assessments must be done very shortly after a natural disaster. The mobile scanning vehicle can utilize generators when power and resources are scares. The scanning vehicle is also beneficial to a team struggling with post-disaster resource limitations, allowing a survey team to cover large swaths of land without leaving the vehicle and in a shorter period than more traditional methods of damage assessment. Once data is collected by the surveyors, utilizing the mobile scanning vehicle, data is processed, then structures are manually assessed off-site.

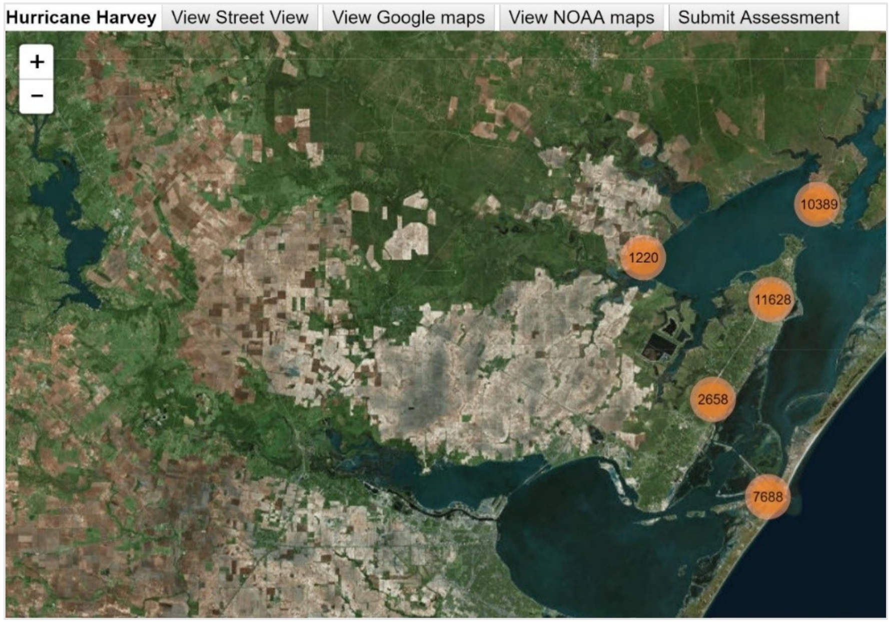

Figure 2: Snapshot of the Rutgers-Iris Hurricane Harvey Portal zoomed to see Rockport, Texas. The circles indicate the number of panoramic photos collected in each area (Guo, 2017)

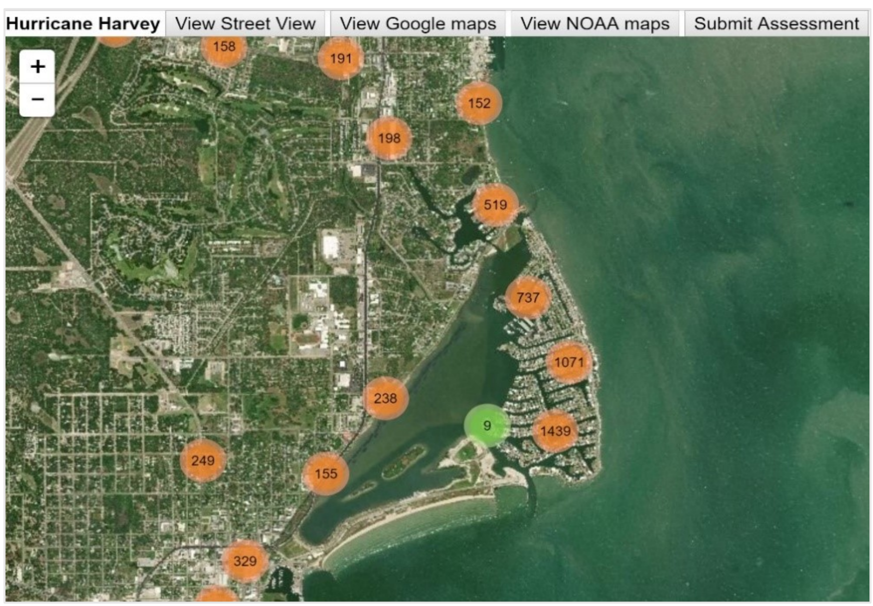

Figure 3: Snapshot of the Rutgers-Iris Hurricane Harvey Portal, zoomed to Key Allegro. Notice the links at the top of the page, which lead visitors to Google Street View, Google Maps, NOAA aerial imagery, and Damage Assessment form (Guo, 2017).

2.2 Damage Assessment Protocols

Though there are a few different damage assessment methodologies, as described in **Chapter 1**, a combination of different protocols was used in this study with the aim of optimizing time and detail of assessment data. Like the ATC-45, this assessment utilizes a categorical method of measuring overall building damage (ATC, 2004). Both the Princeton assessment and the HUD assessment utilize percentages to measure damage to a structure, this study incorporates this rating scale into data measurement, as well (Owensby, 2013; U.S. Department of Housing and Urban Development, 1993). The damage assessment in this study also applies some recommendations from Hudson (2010). The combination of previous studies is intended to reduce the amount of time required to conduct a damage assessment without reducing quality of data.

Pre-storm information such as building attributes, home value, square footage of the homes, location of home, distance to the coast, position in the peak wind fiend and year built were collected through use of Google Maps aerial imagery, Google Maps Street View, ArcMap, NOAA and Zillow, combined with imagery collected by Rutgers University (**Figure 1**) (ESRI, 2018; Geocodio, 2019; Google, n.d.; Google Streetview, n.d.; Guo, 2017; Kijewski-Correa, 2018; NOAA NGS, 2017; Vickery, 2017; Zillow, n.d.). Zillow provided information about home age, home value in July 2017, just before Hurricane Harvey, and the square footage of each home, when applicable (**Figure 4** & **Figure 5**) (Zillow, n.d.).

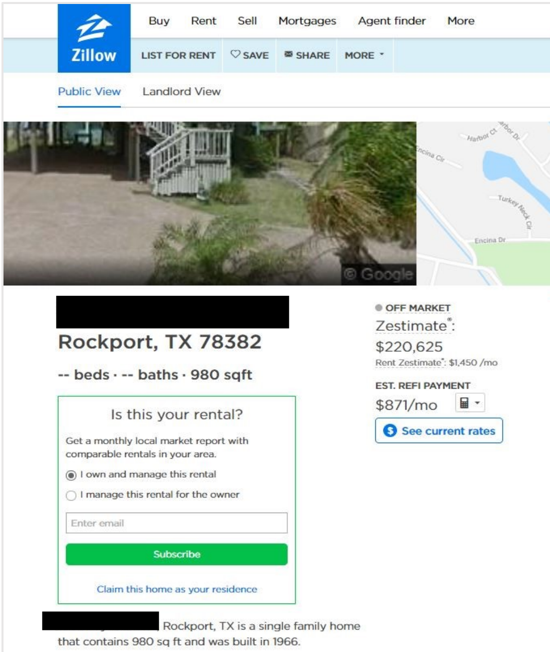

Figure 4: Screenshot of Zillow website. Includes, but is not limited to, home age, home area, home value history (Zillow, n.d.).

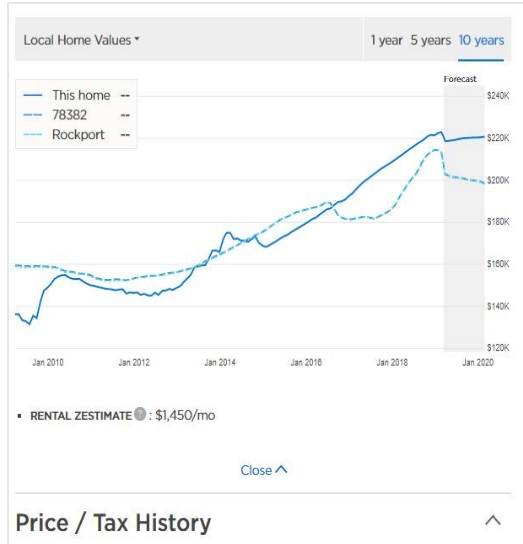

Figure 5: Screenshot of home value history from Zillow (Zillow, n.d.).

Assessors were expected to reference the Rutgers-Iris Hurricane Harvey Portal imagery, Google Maps aerial imagery and Google Street view to collect information about pre-storm features, such as location, number of stories, entry level, roof shape, roof slope, roof cover material, wall cover material, the percentage of openings, presence of a garage, entry door, full-sized windows, and ventilators, whether the structure was elevated and how the structure was elevated, and information about the presence of balconies, porches, and window protection (**Figure 6** & **Figure 7**) (Google, n.d.; Google Streetview, n.d.; Guo, 2017).

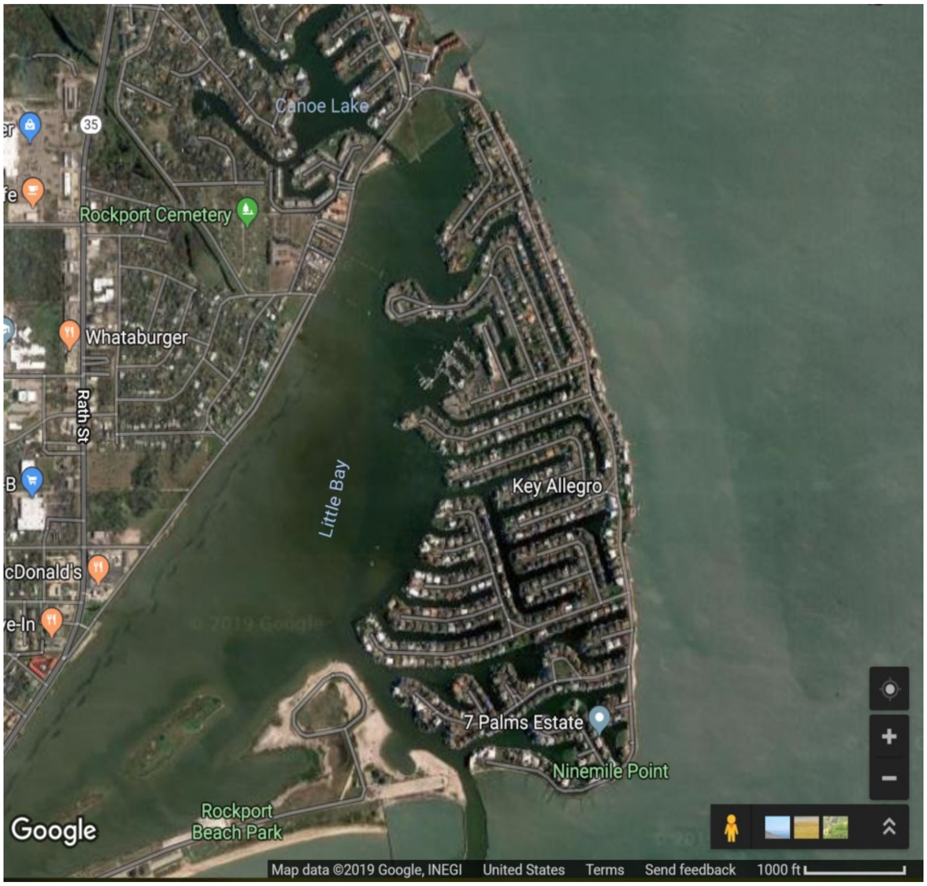

Figure 6: Snapshot of Google Maps Imagery (Google, n.d.).

Figure 7: Google Street View imagery example (Google Streetview, n.d.).

ArcMap, in combination with Geocodio, was used to locate assessed buildings for mapping purposes. Esri ArcMap tools were also used to better understand pre- and post-storm spatial characteristics, which are discussed in further detail in **Section 2.4** (ESRI, 2018; Geocodio, 2019). A complete list of all pre-storm physical building attributes and non-physical building attributes in **Table 1** and **Table 2**, respectively.

Post-storm data was collected by using aerial imagery published by the National Oceanographic and Atmospheric administration after Hurricane Harvey (**Figure 8**), combined with the street view imagery collected by the mobile assessment vehicle (**Figure 9**) (Guo, 2017; NOAA NGS, 2017).

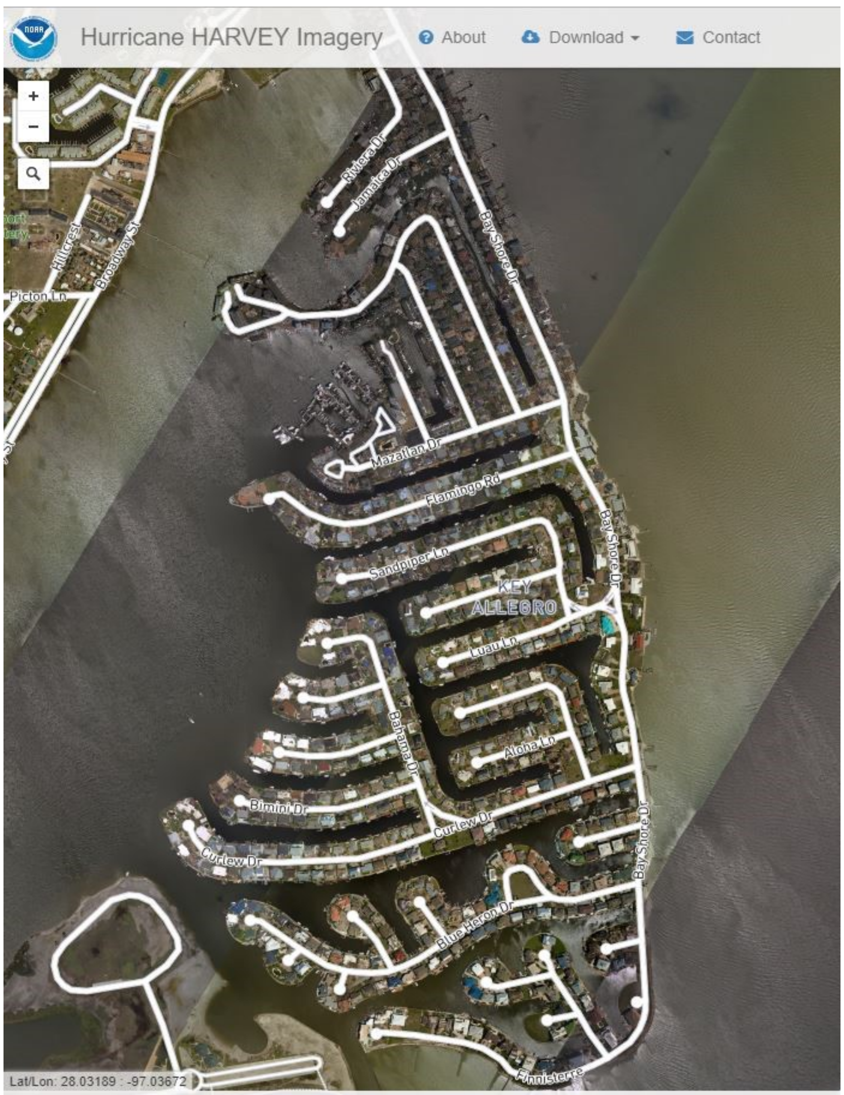

Figure 8: Example of NOAA post-Hurricane Harvey imagery of Key Allegro (NOAA NGS, 2017).

Figure 9: Example of panoramic imagery collected by the mobile scanning vehicle (Guo, 2017).

Assessors had the ability to assign a numerical value to the entire building's damage, the damage mechanism (i.e. flooding, surge, wind, debris, or a combination), percentage value to roof cover damage, roof sheathing damage, roof framing damage, wall cover damage, wall sheathing damage, wall framing damage, window damage, and the presence of damage to the entry door, patio door, and garage door. The use of percentage associated with damage is intended to reduce the subjective nature of the damage assessment process. A complete list of all post-storm damage measurements is listed in **Table 3**.

Table 1: Physical Building Attributes used for this study.

Physical Pre-storm Building Attributes:
Building Use (Commercial, Single Family, Multi-Family)
Total Area
Number of Stories (One, Two, Three Story, & Split Level)
Entry Level (Grade Level, Level One)

Attached Garage
Attached Balcony
Roof Shape (Hip, Box Gable, Open Gable, Dutch Gable, Flat, Hip and Valley, Intersecting, Cross Hipped, Combination)
Roof Covering (Asphalt Shingles, Wooden Shingles, Metal Roof, Clay Tile, Concrete Tile, Tar)
Roof Pitch (12/12, 10/12, 8/12, 6/12, 4/12, 2/12, Unknown Pitch)
Hurricane Clips (Yes, No, Unknown)
Wood Framed Roof
Wall Cover (Vinyl, Stucco, Wood, Other)
Opening Types (Entry Door, Garage Door, Full-Sized Windows, Ventilators)
Percent Openings
Window/Door Shutters or Panels
Elevated
Elevation Styles (Partially Elevated, Wet-Proofed, Dry-Proofed)

Table 2: Non-Physical Building Attributes used for this study.

Non-Physical Pre-storm Building Attributes:
Address
Latitude/Longitude
Building Value
Age
Distance to Coast

The damage assessor manually inputted information, using a Google Form as the platform for the assessment. Google Forms was chosen for its user-friendliness and ease of conversion to a spreadsheet format. The Google Form platform was eventually replaced with a simple spreadsheet to reduce the time it took to fill-out an assessment, and to increase the number of binary variables. For multiple-choice questions in excel, with multiple answers, Google Forms classified data differently based on the order of the answers. For the purposes of this project, that type of classification was not necessary. Some questions, originally multiple choice in Google Forms, were converted to a binary response in the spreadsheet, this choice was made for easier data processing. Future uses of this damage assessment should be conducted in Google Forms, because continual improvements to the form has been done throughout the completion of this project. See Appendix for full damage assessment form.

Table 3: All Post-Storm Damage Measurements used in this study.

Post-Storm Measurements:
Damage Rating (0 None, 1 Minor, 2 Moderate, 3 Major, 4 Destroyed)
Damage Mechanism (Flooding, Surge, Wind, Debris)
Safe to Use (Yes/No)
Roof Cover Damage (0-10)
Roof Sheathing Damage (0-10)
Roof Framing Damage (0-10)
Wall Cover Damage (0-10)
Wall Sheathing Damage (0-10)
Wall Framing Damage (0-10)
Window Damage
Patio Door Damage
Garage Door Damage
Entry Door Damage

An overview of the relationship between the attributes in the damage assessment with resistance methods, loads, and failure is show in **Figure 10**. Damage assessment attributes were also sub-categorized within their respective categories. Resistance methods include non-physical, external, and internal building attributes. The categories of loads include hazard loads, loads attributed to location, and features impacting the aerodynamics. There were four types of failure measured by the damage assessment: structural, roof, wall, and opening failure.

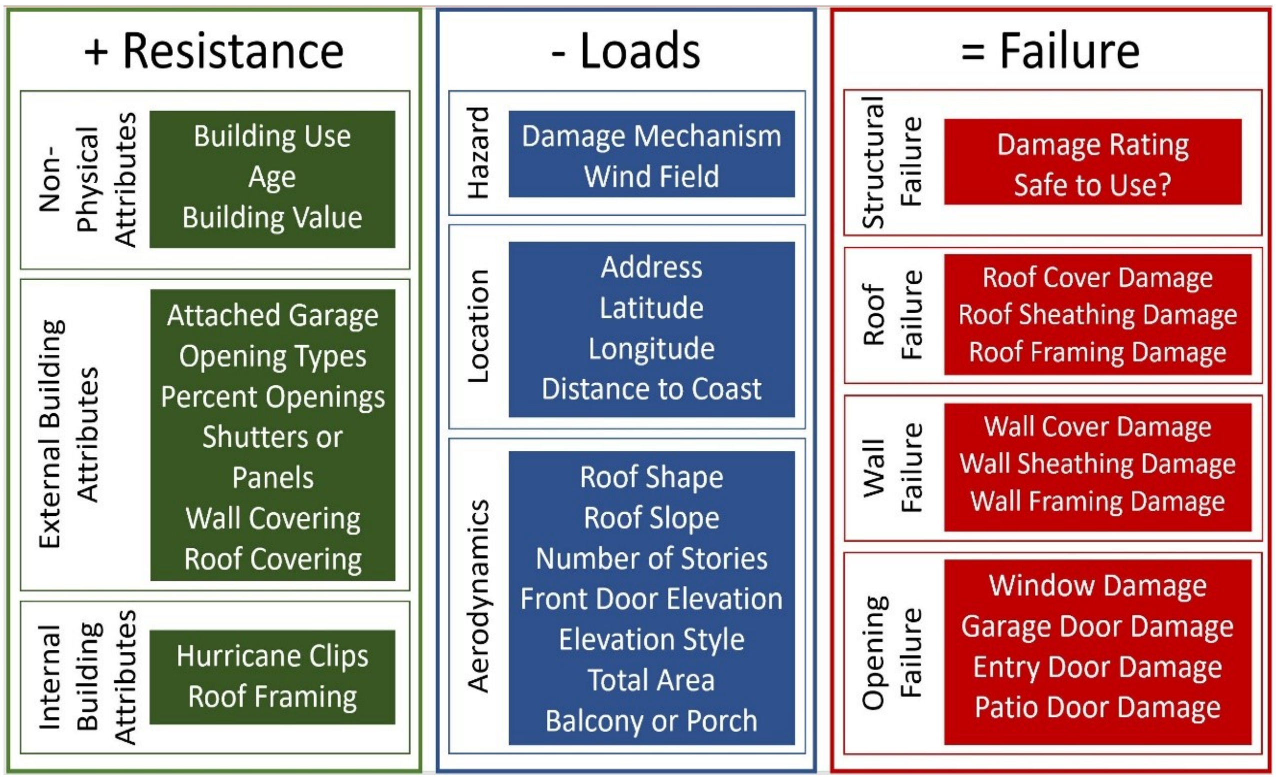

Figure 10: Illustrative summary of various factors found in the damage assessment and their contribution to different failure probabilities.

The scale of this study focuses on the individual level of homes, though this scale carries uncertainty of naturally stochastic wind currents and other stochastic factors affecting the wind resistive capacity of structures (Salazar, 2015). The benefits, though, of the individual structure approach is that is gives a better idea of the probability of damage to a specific home, the model is based on structures that share similar components and characteristics, and so future studies can aggregate the individual structure scale to any larger scale (Salazar, 2015).

2.2.1 Damage Assessment Example

In this section, an example damage assessment will be performed for a home in Key Allegro. The Damage Assessment can be found, in the form of a Google Form, at https://goo.gl/forms/olxUkhY4gyevWCJU2. Once a home is chosen for assessment, the assessor is expected to locate the home from the Rutgers-Iris Hurricane Harvey Portal, Google Maps, NOAA Hurricane Harvey Imagery, Zillow, and Google Street View (**Figure 11**) (ESRI, 2018; Geocodio, 2019; Google, n.d.; Google Streetview, n.d.; Guo, 2017; Kijewski-Correa, 2018; NOAA NGS, 2017; Vickery, 2017; Zillow, n.d.).

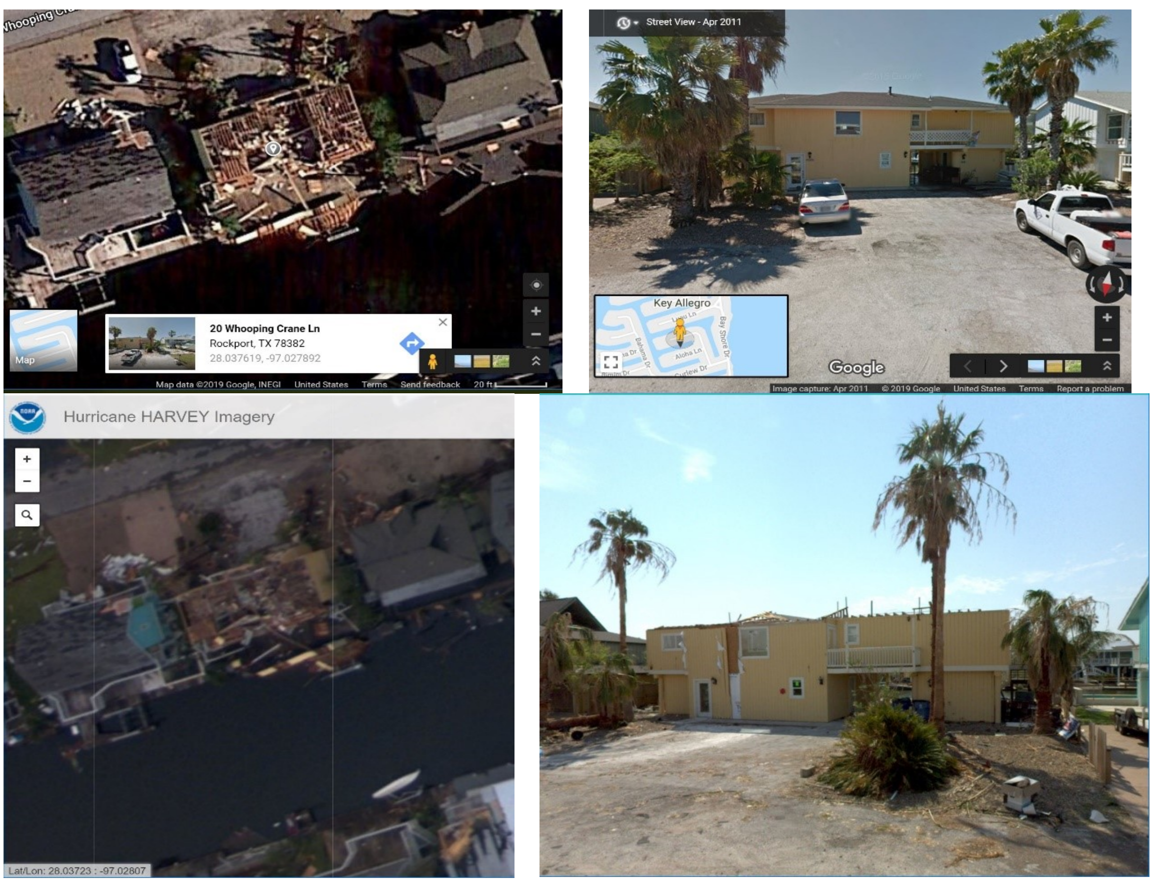

Figure 11: Example of a single home being located on Google Maps (top left), Google Street View (top right), NOAA Hurricane Harvey Imagery (bottom left), and Rutgers-Iris Hurricane Harvey Portal (bottom right) (Google, n.d.; Google Streetview, n.d.; Guo, 2017; NOAA NGS, 2017).

The initial questions in the Damage Assessment form refer to the location of the home and photos of the home, if applicable (**Figure 12**). Google Maps can be the primary reference for this section, though Geocodio was used to identify the latitude and longitude of all homes for data analysis purposes (Google, n.d.; Geocodio, 2019).

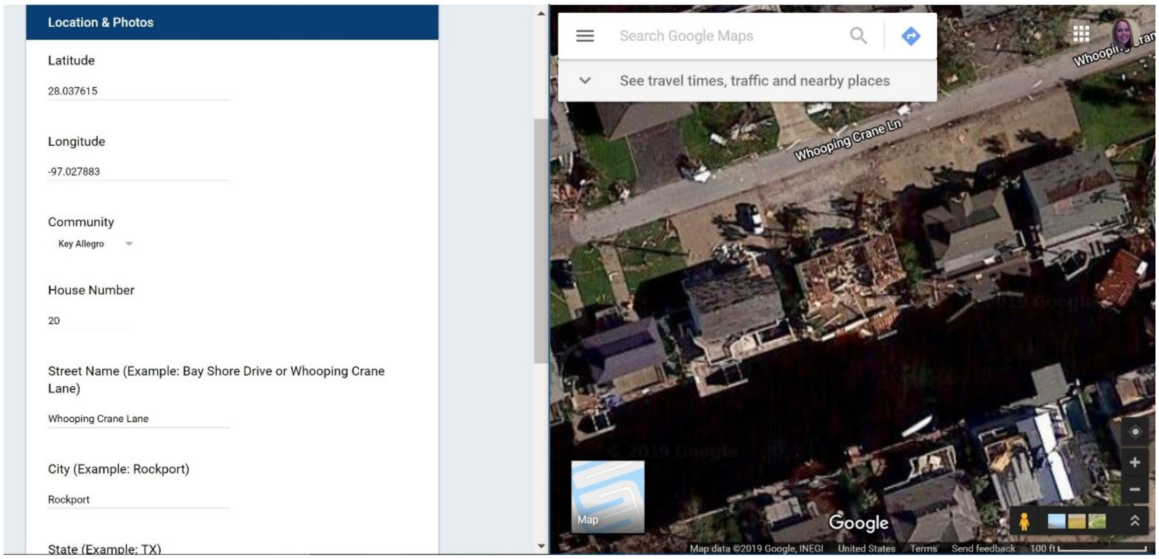

Figure 12: Example of the location and photos portion of study damage assessment, filled-out using Google Maps.

The next section of the damage assessment, *Building Basics*, includes questions about the building use, the age, building value in July 2017, Total Area. Zillow should be the primary reference for these questions (**Figure 13**) (Zillow, n.d.). *Building Basics* also asks about the number of stories, entry level, attached garage, and balcony or porch. To answer these questions, a combination of the Rutgers-Iris Hurricane Harvey Portal and Google Street View imagery should be used (**Figure 14**) (Guo, 2017).

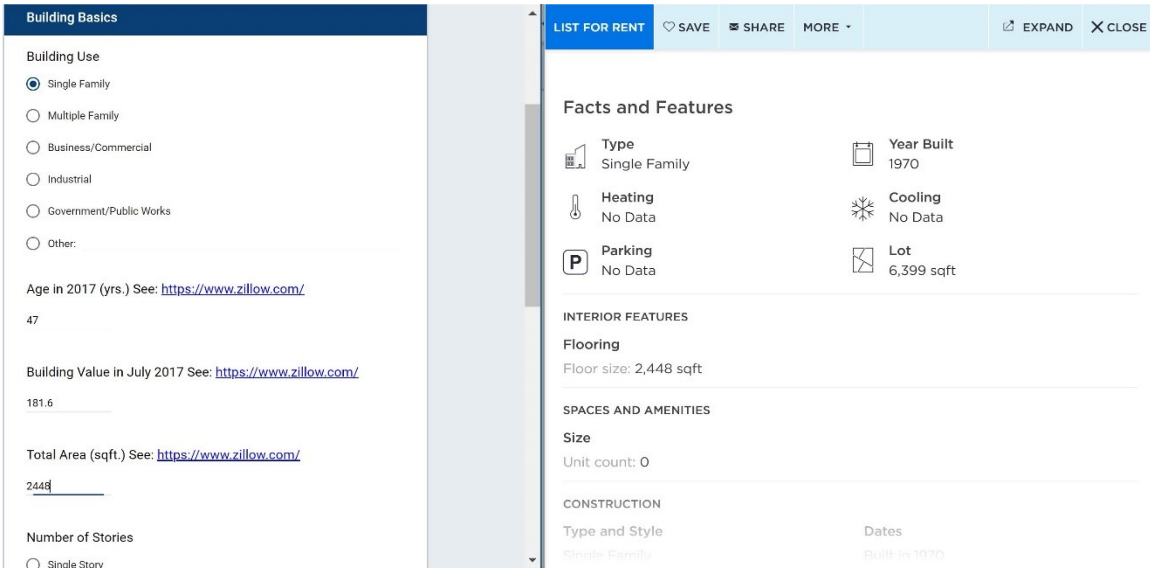

Figure 13: Example of the "Building Basics" portion of the Damage Assessment, using Zillow to answer questions about building use, age, value, and area (Zillow, n.d.).

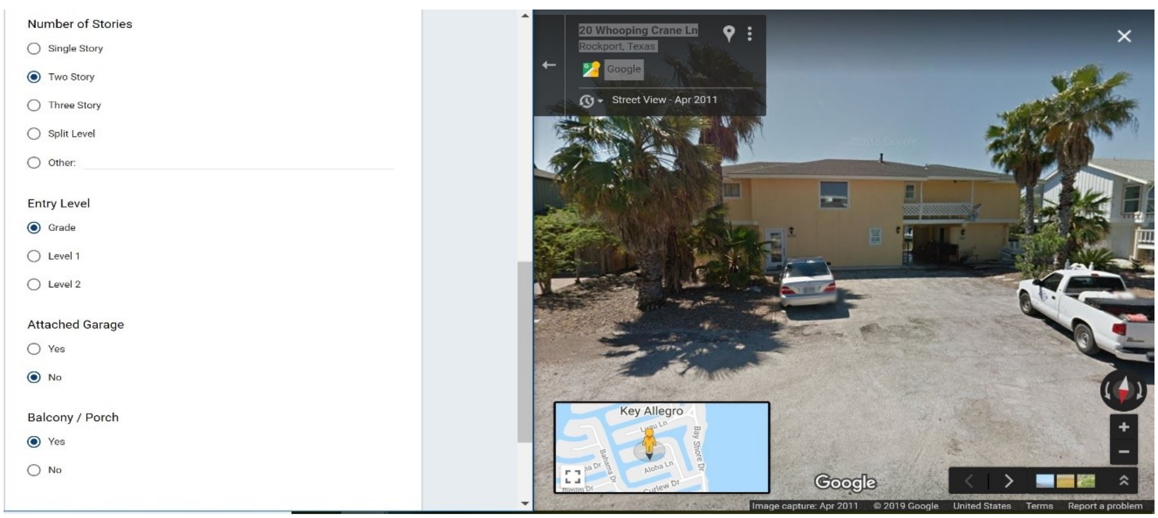

Figure 14: Example of the "Building Basics" portion of the Damage Assessment, using Google Street View to answer questions about the pre-storm building attributes (Guo, 2017).

More questions about the building enveloped are asked in the next sections. A combination of Google Maps, Google Street View, and the Rutgers-Iris Hurricane Harvey Portal can be used to answer questions about: roof shape, roof covering, roof slope, roof framing material, hurricane clips, wall framing, wall covering, opening types, percent of openings, shutters or panels, elevation and elevation methods (Google, n.d.; Google Streetview, n.d.; Guo, 2017).

The final sections in the damage assessment are about the amount of damage that the home may have sustained during the natural disaster: damage rating, damage mechanism, usability, roof damage, wall damage, and opening damage. The Rutgers-Iris Hurricane Harvey Portal is most useful during this section (**Figure 15**, **Figure 17**, & **Figure 18**), though NOAA post-storm imagery is also useful in determining damage, especially roof damage (**Figure 16**) (Guo, 2017; NOAA NGS, 2017).

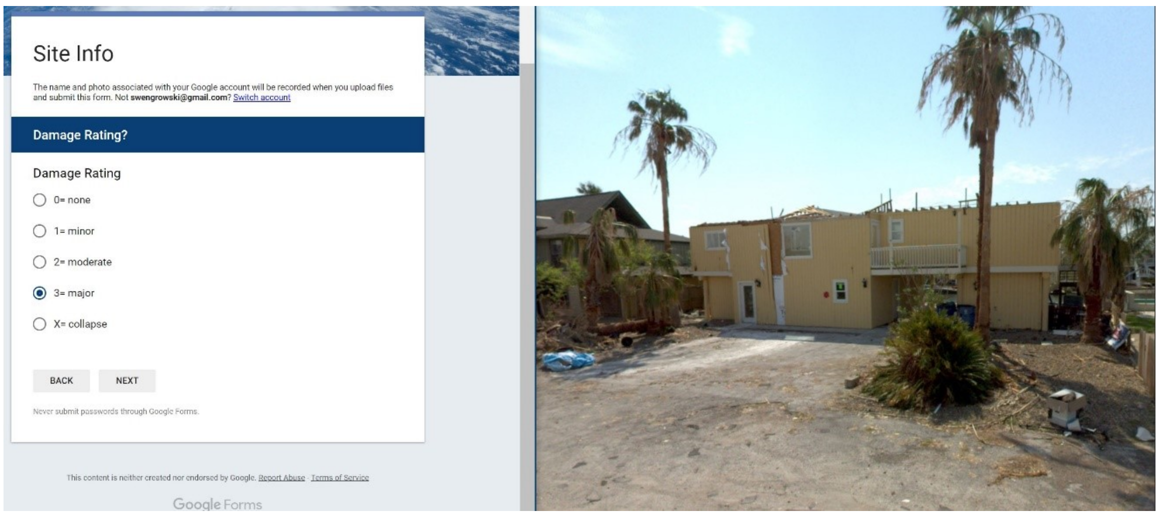

Figure 15: Damage Rating in the damage assessment can be based on the Rutgers-Iris Hurricane Harvey Portal, as in this example (Guo, 2017).

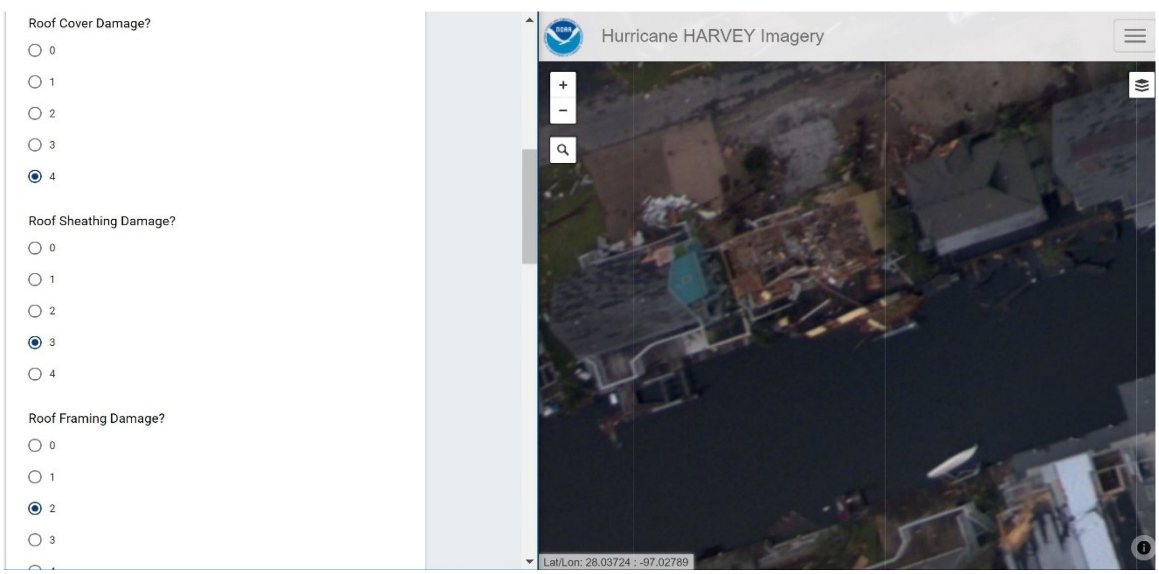

Figure 16: Example of Roof Damage Ratings, using NOAA post-storm aerial imagery (NOAA NGS, 2017).

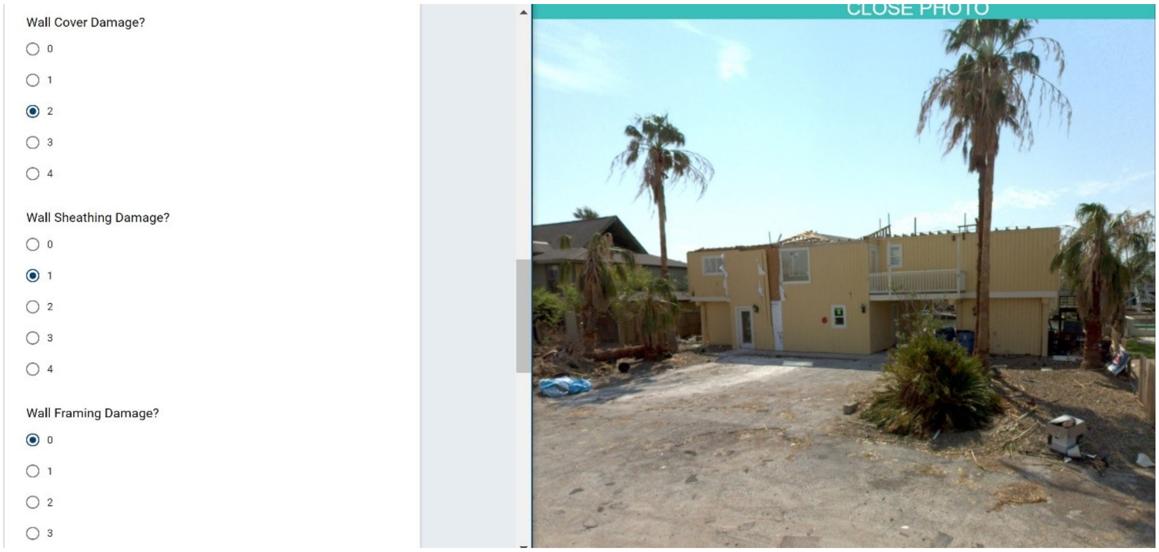

Figure 17: Wall damage was determined from imagery collected by Rutgers' mobile scanning vehicle (Guo, 2017).

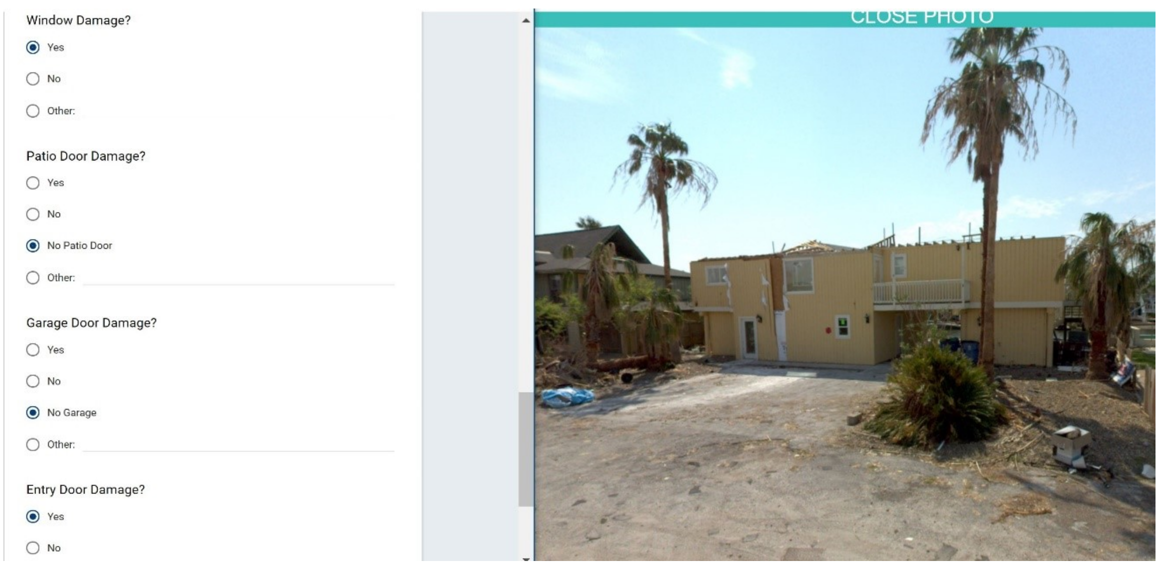

Figure 18: Damage to openings also used Rutgers-Iris Hurricane Harvey and Rutgers mobile scanning vehicle imagery, as in this example (Guo, 2017).

2.3 Data Compilation

Most raw data used in this study came in the form of panoramic imagery from the mobile scanning vehicle during the on-site data collection process (Guo, 2017). Other raw data was compiled from Zillow's database, Google Maps, Google Streetview, and NOAA aerial photography (Google Maps, n.d.; Google Streetview, n.d.; NOAA NGS, 2017; Zillow, n.d.).

Imagery was analyzed by a damage assessor, then converted to the damage assessment format – including pre- and post-storm information in **Table 1**, **Table 2**, and **Table 3**. Some data was missing after collection, mostly because of missing data in the Zillow database (Zillow, n.d.). To remedy the missing data, for proper analysis using machine learning algorithms, the missing values were filled with the average value for each respective attribute. Missing values were found in the following attributes: home value in July 2017, home age, and total area (sq. ft.). The average values for each attribute were $655,011, 39 years old (as of 2018), and 2580 square feet, respectively.

After primary classification, using machine learning algorithms, the accuracy of classifiers which predict damage on a scale from 0-10 (0-100%) was low. These values were converted to discrete categorical values, shown in **Table 4**, the goal of this conversion was to improve accuracy of classifiers by reducing the number of possible classes.

Table 4: Conversion from 0-10 scale to discrete rating, used to increase accuracy of machine learning algorithms.

Original 0-10 Scale Value(s)	New Categorical Values
0	0
1-3	1
3-6	2

6-9	3
10	4

To further improve the accuracy of the dataset, the information was imported into ArcGIS for spatial analysis. Before importing the data, it was geocoded, using the Geocodio batch geocoding process in the WGS 1984 coordinate system (Geocodio, 2019). Variables such as, wind speed and distance to coastline were added to each attribute (ESRI, 2018; Vickery, 2017). These spatial characteristics have, in previous studies, been attributed to hurricane damage (Hatzikyriakou, 2015; Xuan, 2016). Geospatial analysis can also be achieved using tools in ArcGIS, which will be further discussed in **Section 2.4.2** and **Chapter 3** (ESRI, 2018).

2.4 Analysis

2.4.1 Statistical Analysis

Simple statistical analysis was performed on the data to get an idea of major patterns. Mean, median, mode, range, and histograms were made for all pre-storm attributes.

2.4.2 Spatial Analysis

Spatial analysis can give a better understanding of data, especially with data that has a spatial component. Creating visuals using spatial components of the dataset can better communicate information, especially to the public and decision makers. ArcMap was used to add spatial components to this data, including the latitude, longitude, and distance to coastline. Some statistical analyses were projected onto maps of Key Allegro, for visualizing clusters or other spatial patterns of the data.

Aside from pure visualization of data, spatial tools in ArcMap can be used to further understand clustering and outlier patters, as well as spatial regression. The exploratory regression analysis was created following the "Spatial Statistics: Simple Ways to Do More with Your Data" technical workshop by Lauren Bennett and Flora Vale. The technical workshop advises practitioners to utilize the "Exploratory Regression" tool in ArcMap, which tries combinations of variables to best describe a dependent variable using a properly specified model framework. This tool will iterate from one to, up to, five variables at once, providing information about each variable (Bennett, 2017, ESRI, 2018).

When this dataset was fed into the "Exploratory Regression" tool in ArcMap, with damage rating as a dependent variable, and all pre-storm data as the explanatory variables, there was no passing model, but there was information about variables with the highest adjusted R^2 values and a summary of variable significance. The results of the spatial statistics, clustering and outlier analysis, and exploratory regression will be further discussed in **Chapter 3** (ESRI, 2018).

2.4.3 Machine Learning Classifiers

Machine Learning approaches are useful in understanding which variables are most important to a model, which can be used to further improve predictions (Subramanian, 2013; Salazar, 2015).

Machine Learning approaches used in damage science fall into two main methods: regression and classification. Regression models have a dependent variable that is continuous, whereas classifiers have dependent variables which are discrete categories.

In the case of predicting damage, based on a discrete scale, a classifier will be used to place data into different predicted classes. For example, if damage states fall into categories, such as “no damage”, “minor”, “moderator”, “major”, and “destroyed”, then a classifier will be used to predict which category a dataset is most likely to be found (**Figure 19**).

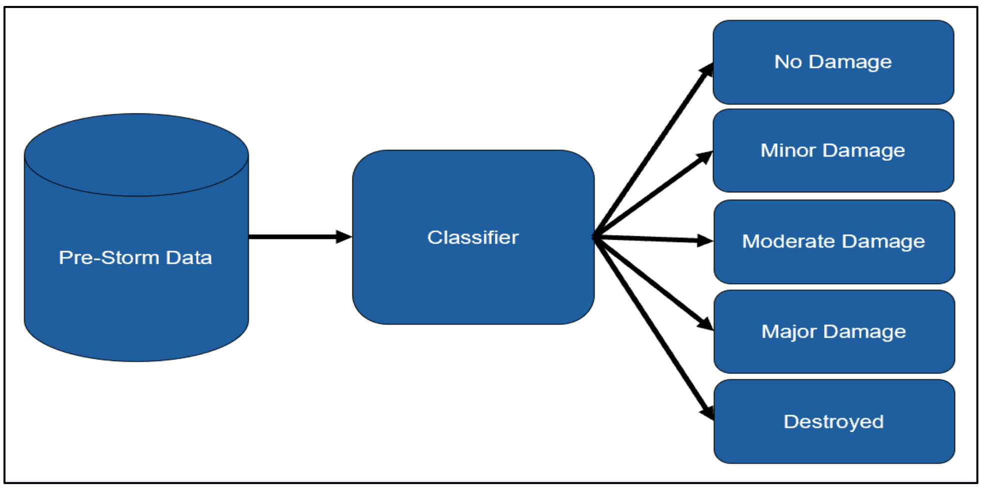

Figure 19: Overview of the classification process from pre-storm data to post-storm Damage Rating.

Classifiers can also be unsupervised or supervised. In the case of an unsupervised model, the correct ‘classes’ are not known for the dataset. The machine learning algorithms are expected to classify data through clustering or other means of classifying. Pre-storm information and post-storm measurements are used to train the data, in this study, so a supervised machine learning classifier is used. When building a supervised machine learning model, some percentage of the dataset is given to the model, in combination with the proper classes. Once the model is built, testing data is fed into the classifier, and asked to predict the class of each data point. The predictions are then validated using the correct class prediction, producing an accuracy value for the classifier. **Figure 20** illustrates the process of building and testing a supervised machine learning classifier.

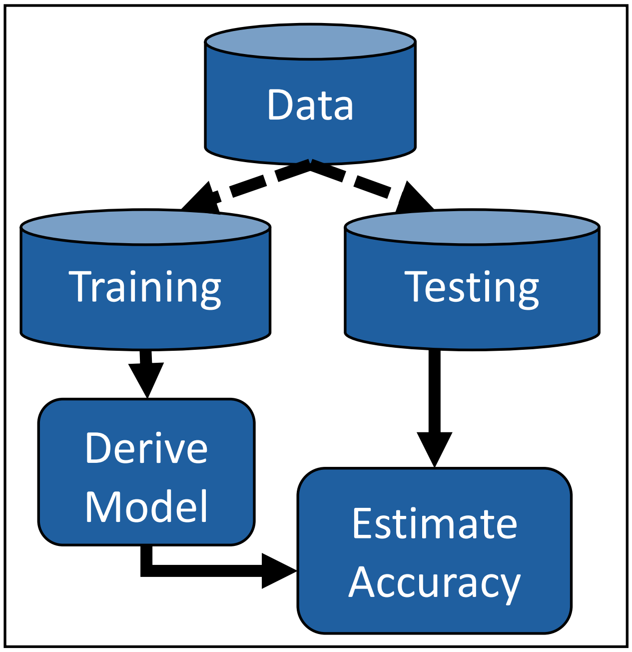

Figure 20: Process of building and validating Machine Learning Classifiers.

Pre-storm data (**Table 1** and **Table 2**) was input into classifiers, which classified a number of damage outputs, in **Table 3**. 70% of the pre-storm data was used as training data and the remaining 30% was used to validate the model and understand accuracy. For each post-storm prediction, five classifiers were compared and the one with the highest accuracy value was used for further analysis. The classifiers were as follows: Support Vector Machine (SVM), Decision Tree Classifier using Gini impurity to create nodes, Decision Tree Classifier using entropy to create nodes, Random Forest Classifier using Gini to create nodes, and a Random Forest Classifier using entropy to create nodes. By optimizing the mentioned classifiers by accuracy, we can combine these predictions to form a better understanding of damage predictions in the future.

The Support Vector Machine (SVM) classifier can be understood as plotting a dataset onto a n-dimensional coordinate system, where n is equal to the number of independent variables. After the data is plotted, the SVM classifier attempts to create a (n-1)-dimensional plane separating the data into classes, the plane which has the largest gap between data in different classes is the one used by the model after it is trained.

The Decision Tree Classifier can also be visualized using an n-dimensional coordinate system, where n represents the number of independent variables. The decision tree draws a series of (n-1)-dimensional planes between datapoints based on questions which sub-divide the data. For example, in this dataset, a decision tree classifier may separate data by asking if the structure is single family. It would then draw a plane which ideally would divide the data into two distinct groups where all the members of one group are single family structures and all the members of the other group would not be single family structures. The Decision Tree Classifier would continue to ask questions, grouping the data until either data in each group are of a single class or some criteria is met. The Decision Tree Classifier decides which questions to ask by using a measure of uncertainty, this study utilizes Gini impurity and entropy. Basically, both Gini impurity and entropy measure the amount of information gained by asking one question or another. These values help the classifier when and what to ask to separate the data into the purest classes.

The Random Forest Classifier used in this study runs a Decision Tree Classifier onto sub-sets of the training data, then creates an aggregated model using prediction information from each Decision Tree Classifier. Both Gini impurity and entropy were also applied to the Random Forest Classifier.

These machine learning classifiers were used to build a correlation matrix, which describes how independent or dependent different variables are. The classifiers were also used to understand feature importance. The variable importance does not necessarily show the magnitude nor the direction of the relationship these variables have with damage, unlike the exploratory regression, but it does tell us which variables were most important in creating the classifiers. Knowing the importance of each variable in building a classifier can help to make the damage assessment process more streamlined and efficient in the future. Feature importance is not a function of an SVM classifier, so the classifiers used to get feature importance were limited to the decision tree and random forest classifiers. Both the correlation matrix and the results of variable importance will be further discussed in **Chapter 3**.

Chapter 3: Results & Discussion

3.1 Damage Assessment Efficiency Analysis

Previous studies have not mentioned the time taken to perform a single damage assessment. If the damage assessment in this study takes the same amount of time as a standard on-site damage assessment, this study would remain superior because of the ideal conditions to assessors. The amount of information collected for each damage assessment is also an important part of the damage assessment's efficiency. Some assessments may be collecting less information, therefore taking less time to collect. A goal of this study is to optimize the amount of data collected while reducing the time of assessment as much as possible.

The average damage assessment in this study takes about 10 minutes to fill-out, collecting a total of 74 different variables. Some questions in the assessment are designed to collect multiple variables at once, with 50 questions total in the damage assessment (including photo uploads). The average damage assessment question collects information on 1.48 variables, taking approximately 12 seconds per questions. 553 homes were analyzed during this study, totaling over 92 hours of assessment conducted.

A hybrid method of assessment may be considered in future studies, combining off-site assessment with external sources and on-site assessment. On-site assessors can collect post-storm damage information, such as damage rating, wall damage, and opening damage. NOAA aerial imagery should remain the main source for roof damage. Pre-storm and building attribute information can be collected by off-site assessors, using this damage assessment methodology. The benefit of a Google Form platform for assessment is that on- and off-site assessments can be conducted simultaneously, assuming on-site access to internet ,furthering increasing efficiency. If an on-site assessor can answer questions about damage, about 10 questions, this will reduce the amount of time per assessment by approximately 2 minutes per assessment, if on- and off-site assessors are working on the same home. If this method of assessment was used in this study, off-site damage assessments would have taken over 18 hours less time for the entire study area.

Damage assessments require continual improvement to be at their highest efficiency. The results of this study, primarily from machine learning classifiers, can be used to specify potential areas of further improvement.

Figure 21: Location of all surveyed homes in this study, Key Allegro, Rockport, Texas.

3.2 Descriptive Analysis and Results

Over 1,000 homes were assessed between Key Allegro and nearby community, Holiday Beach. 553 structures were used during analysis, found in **Figure 21** (Kijewski-Correa, 2018). Of the analyzed homes, 551 were single-family residential structures and 2 were used for commercial purposes. Most homes were single level, and all structures were wood framed. The average home value was approximately $655,000 in July 2017, just before Hurricane Harvey struck (**Figure 22**). The most expensive home in the study area was $3.2 million in July 2017 (Zillow, n.d.).

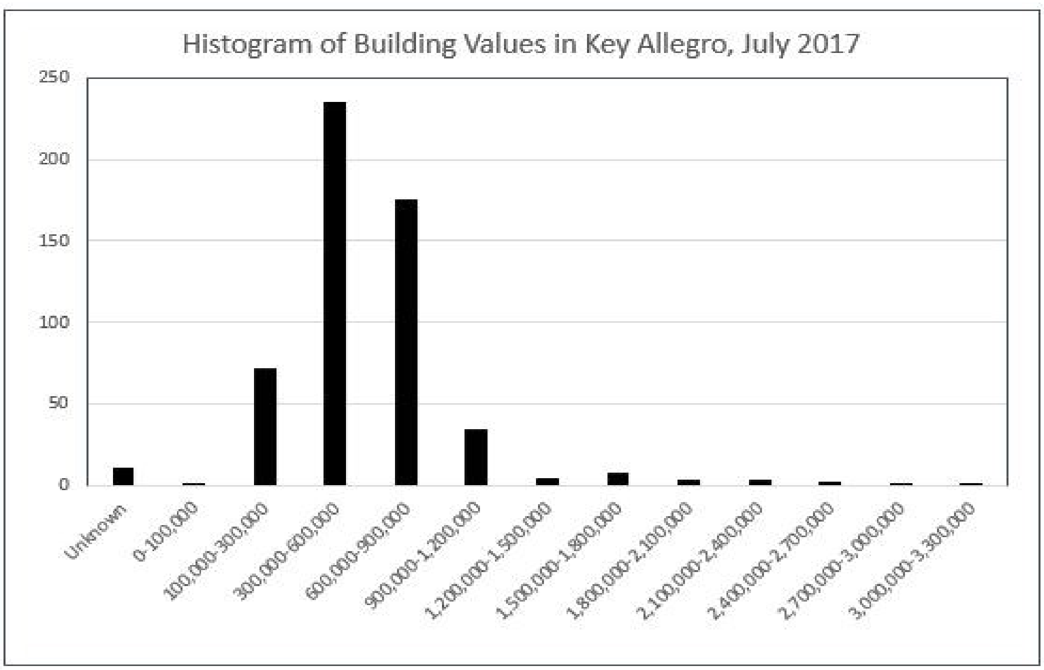

Figure 22: Histogram of building values in Key Allegro in July 2017, before Hurricane Harvey struck the area (Zillow, 2018).

The average age of the assessed homes was 42 years old, as of 2018 (Zillow, n.d.). Development on Key Allegro began in 1962, so the age of all homes on Key Allegro cannot exceed 57 years old (Jasinski, 2010). The relatively short time period that homes were developed in this area assures that building codes and regulations remain relatively similar. The distribution of home-age can be found in a chart in **Figure 23** (Zillow, n.d.).

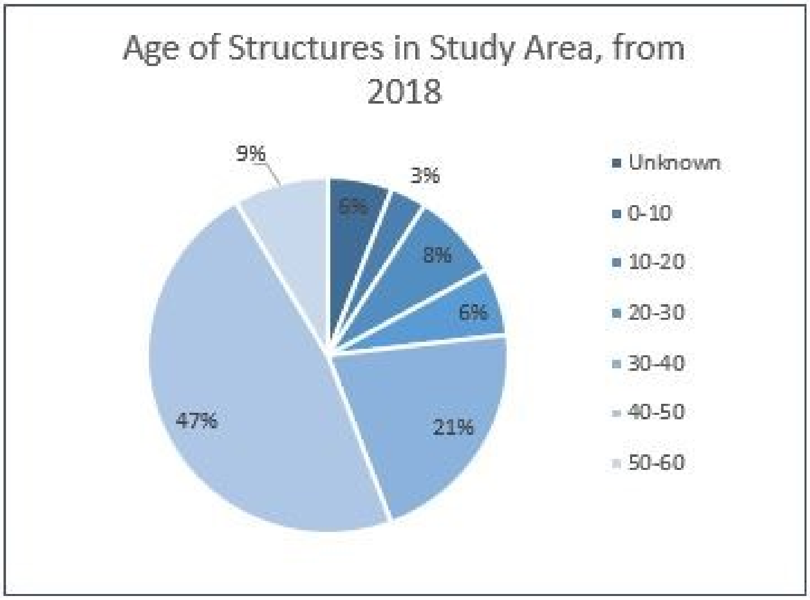

Figure 23: Chart of the age of homes in study area, as of 2018 (Zillow, 2018).

The area of a home influences the amount of damage that it will receive, this is evident during tornados and hurricanes alike (Egnew, 2018). The average area of the homes in the study area was 2580 square feet, with a range between 454 and 8942 square feet (Zillow, n.d.). **Figure 24** illustrates the distribution of building area in the study region.

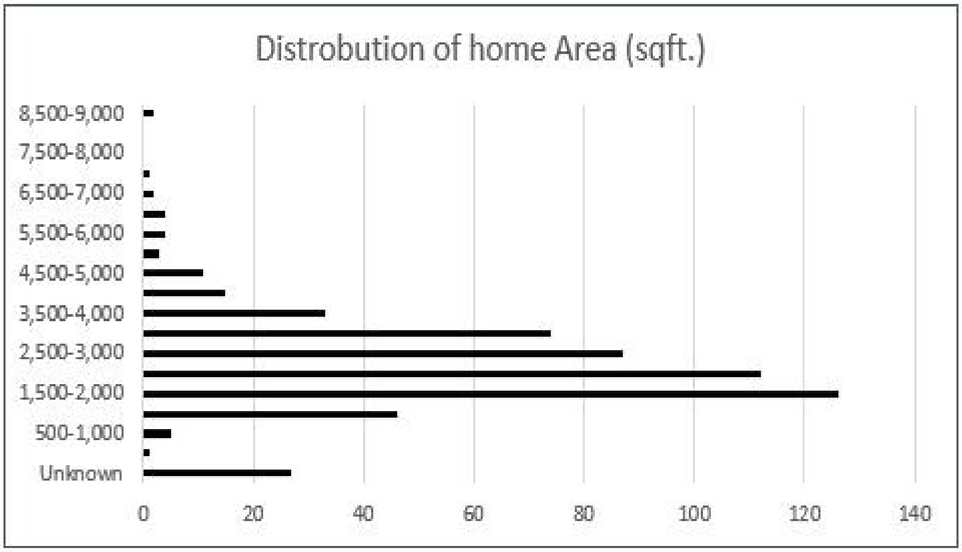

Figure 24: Histogram of home area (sq. ft.) in study region.

Roof shape is can impact damage, especially when the damage mechanism is wind (Crandell, 1998). Examples of common roof shapes are shown in Error! Reference source not found.**Figure 25**, **Figure 26**, and **Figure 27**. Roof shapes vary in this study, with the highest frequency in combination and hip roofs (**Figure 28**). Combination roofs exhibit characteristic shapes of multiple roofs at once.

Figure 25: Example of Intersecting or Overlapping roof shape in Key Allegro.

Figure 26: Example of Dutch gable shaped roof in Key Allegro.

Figure 27: Example of a Combination roof shape in Key Allegro.

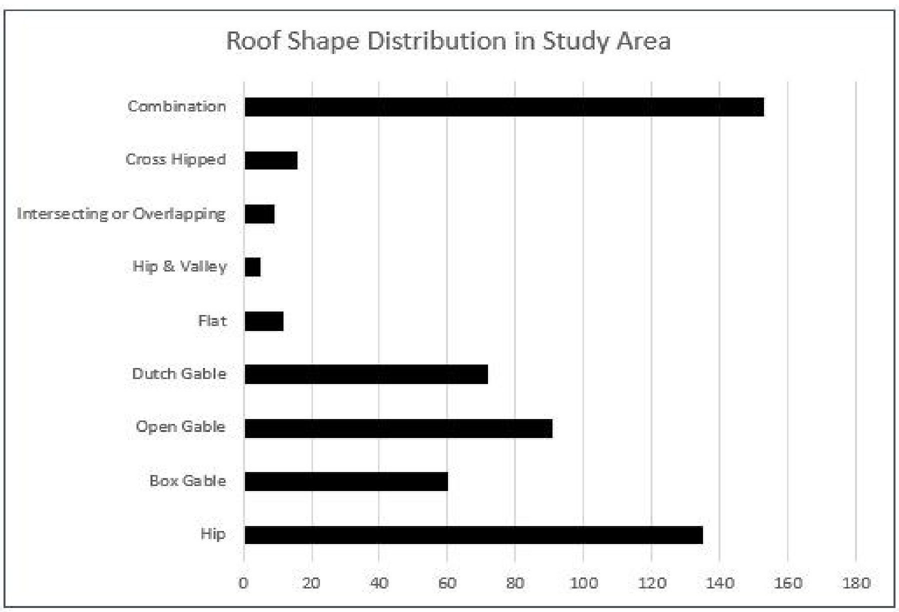

Figure 28: Roof shape distribution in study region.

In addition to the roof shape, information about the roof slope was collected during the damage assessment process. Roof slope was not measured using the LiDAR imagery which was collected during the damage survey, and instead was estimated using the panoramic photos collected during the damage survey period. Most homes had a slope of either 6/12 or 4/12 (**Figure 29**).

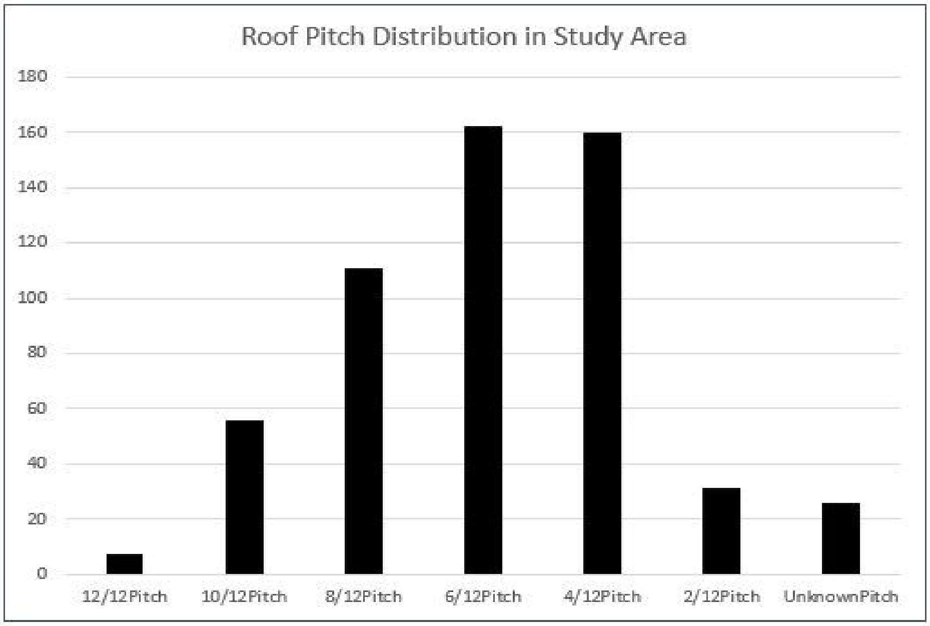

Figure 29: Roof pitch distribution in study region.

The roof and wall covering can be the first line in defense against damage during a hurricane. Most structures in Key Allegro had asphalt shingles as roof cover (**Figure 30**). Most homes utilized wood for siding, whether in panels or shingles (**Figure 31**). Wooden siding is a common wall covering in other coastal towns.

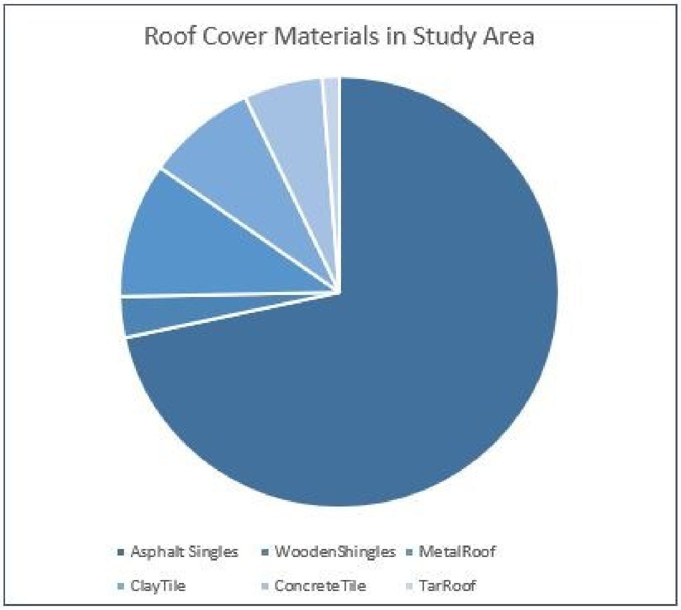

Figure 30: Roof cover materials in study area.

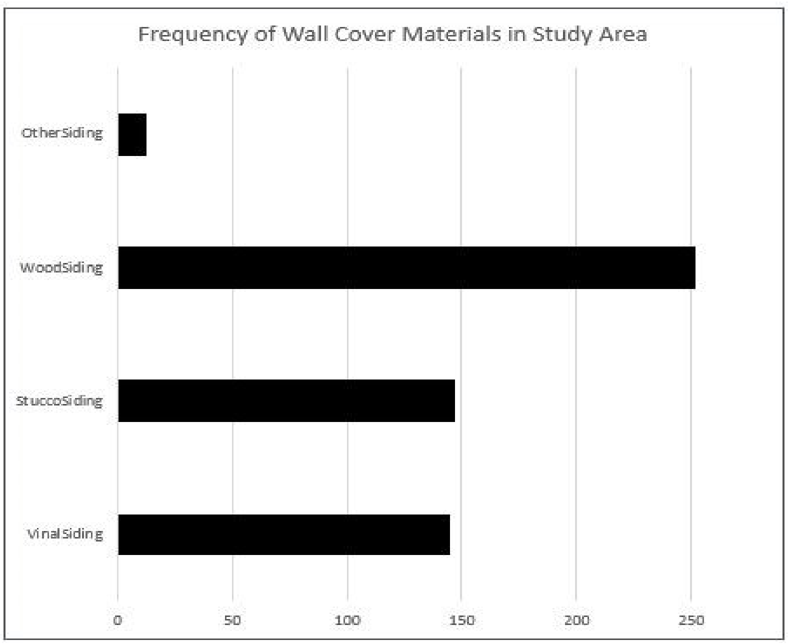

Figure 31: Wall cover materials in study area.

Wind damage during Hurricane Andrew illustrated the relationship between damage to openings and overall damage to a structure (Crandell, 1998; Egnew, 2018). To better understand the relationships between openings and hurricane damage, the damage assessment in this study measured the percentage of openings, see **Figure 32**, on a structure and whether specific opening types are present.

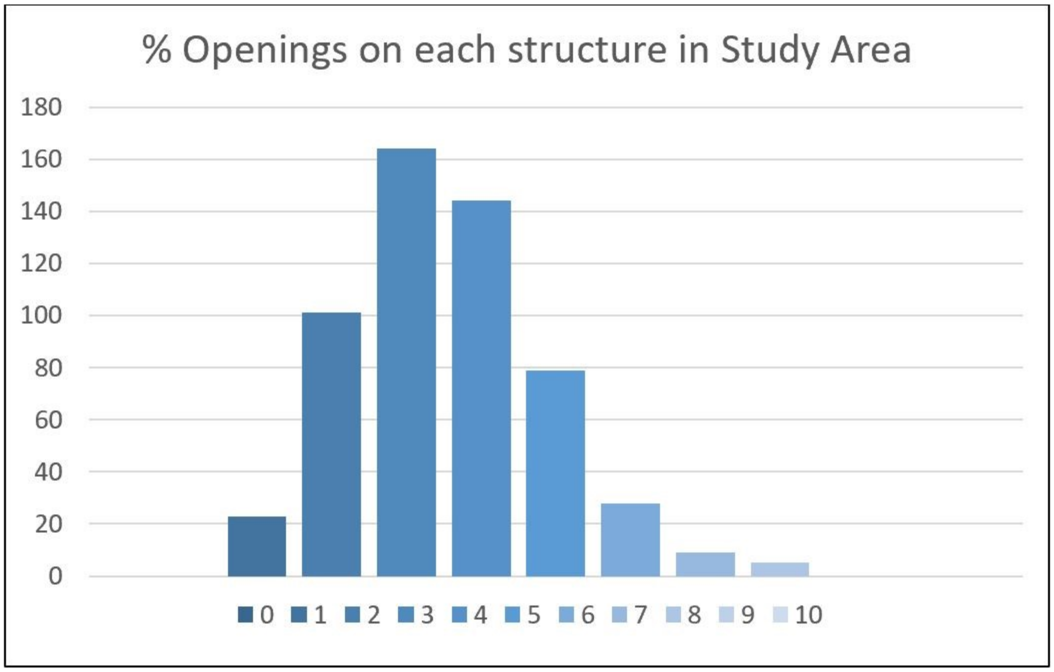

Figure 32: Distribution of the percentage of openings on each structure in the study region.

Elevating a structure is a popular method of mitigating damage from flooding and storm surge. Past studies have indicated that elevating a structure can impact damage from hurricanes, and a goal of this study was to understand the relationship between wind damage and elevating a structure (Hatzikyriakou, 2015; Kennedy et. al, 2011; Norman, 2010; Xian, 2015; Xuan, 2016). The results of the damage assessment indicate that most homes in Key Allegro were not elevated (**Figure 33**).

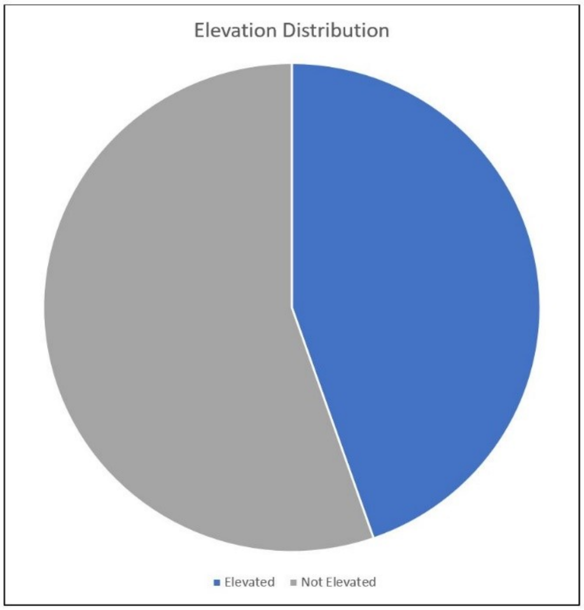

Figure 33: Distribution of elevated and not elevated homes in study region.

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Figure 34 illustrates the methods of elevation: either wet-proofed, dry-proofed, and/or partially elevated. Wet-proofed homes are elevated and have an opening below them, allowing water to pass easily though without added lateral hydraulic loading (**Figure 35**).

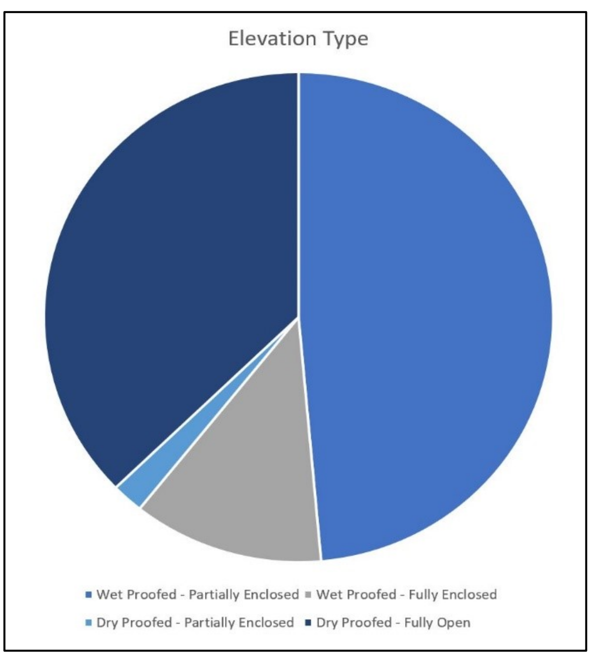

Figure 34: Breakdown of the elevation structure of homes that were elevated, in the study region.

Figure 35: Example of an elevated home using a wet-proofed method of elevation (Google Street View).

Wet-proofed homes have a large pocket below the home, which could potentially lead to complex uplift forces during high velocity wind events. Homes that are partially elevated have a portion that is fully enclosed and a portion that is completely open. This partially-elevated- wet-proofed style is popular in the community of Key Allegro, where there is a walkthrough from the street to the lagoons behind most homes (**Figure 36**). Of the homes that were elevated, most homes were wet-proofed.

Figure 36: Example of an elevated home that is wet-proofed but has a portion that is enclosed (Google Street View).

Dry-proofing is an elevation method where the foundation is entirely enclosed, and the space is considered non-livable (**Figure 37**). Many dry-proofed homes use this area as a garage. Dry proofed homes are still elevated, so the building height could be detrimental to wind damage, but this could serve to be a good way to balance protection from wind and surge damage because the enclosure may reduce complex wind patterns and uplift forces. For a home to have dry-proofing and partially enclosed, most of the structure is fully enclosed. In these rare cases, there are small openings below the structure where there is an elevated deck, elevated main entrance, or there is a small garage opening that is not enclose though the remaining parts of the home are enclosed (**Figure 38**).

In contrast to the benefits for surge and flooding damage, elevated structures, especially those that are elevated using the wet-proof method, may cause complicated and/or uplift wind patterns. Elevated homes can be expected to have higher heights than non-elevated homes, which could result in more wind damage, as well.

Figure 37: Example of a home that is elevated using the dry-proofing method (Google Street View).

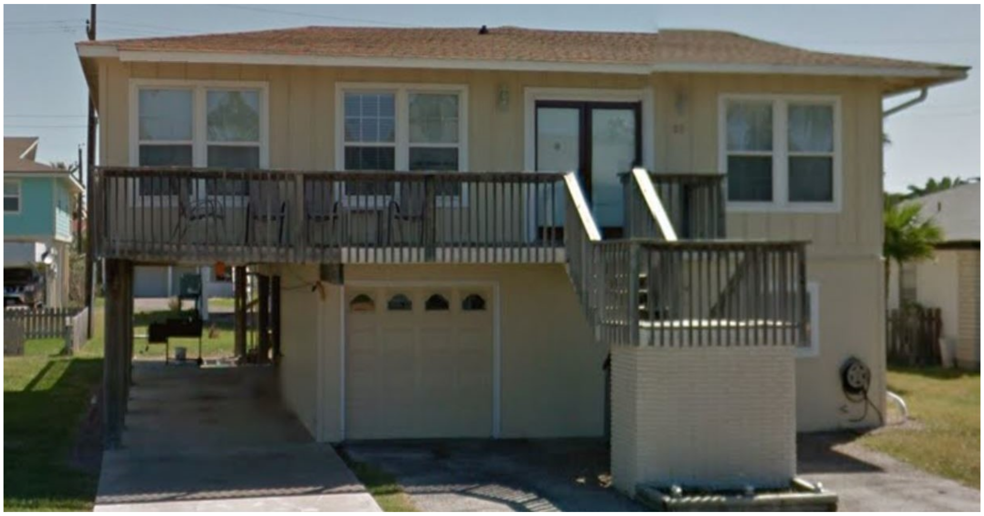

Figure 38: Example of a home which is elevated using a dry-proofed method, though there is a portion which is not fully enclosed (Google Street View).

3.3 Spatial Analysis and Results

To further understand the relationship between the data and space, some variables were projected onto maps in ArcMap (**Figure 39**, **Figure 40**, and **Figure 41**). **Figure 39** shows that highest concentration of high home values is found on the southernmost tip of Key Allegro (ESRI, 2018; Zillow, n.d.). These home values seem to be related to the home area and home age because high-area homes and newer homes appear to be concentrated on the southernmost tip of Key Allegro (**Figure 40** & **Figure 41**).

Figure 39: Map of building value distribution in study area (Zillow, n.d.).

Figure 40: Map of the distribution of home area (sq. ft.) in study region (Zillow, n.d.).

Figure 41: Map of the distribution of home-ages in study area, as of 2018 (Zillow, n.d.).

ArcMap was used to add spatial components to the data, including the latitude, longitude, and distance to coastline (**Figure 42**) (ESRI, 2018).

Figure 42: Distance to the coastline for all homes in the study area, with a line used to identify the shoreline (ESRI, 2018).

Using the ArcMap "Cluster and Outlier Analysis (Anselin Local Moran's I)" spatial statistics tool, showing the clustering and outliers of the damage rating variable, the resulting map is shown below (**Figure 43**) (ESRI, 2018). There is a cluster of high damage toward the northernmost tip of the island and a cluster of low damage towards the southernmost tip of the island. Outliers of low damage can be found near the northern portion of the island, and outliers of high damage can also be found near the southern portion of Key Allegro.

The "High-High Cluster" indicates statistically significant clusters of high values, or higher damage; "Low-Low Cluster" indicated statistically significant clusters of low values, low damage. Similarly, "High-Low" and "Low-High" clusters indicate outliers in which high values are surrounded by low values, and outliers in which low values are surrounded by high values, respectively (**Table 5**). There are more clusters of low values damage ratings on the southern portion of the island, whereas the northern portion of Key Allegro has more clustering of high damage ratings. The clustering of higher damage near the northern portion of the community, may be of concern. Higher damage may lead to more debris, and the only point of entry into Key Allegro via the northernmost tip could be impacted by the debris.

Table 5: Breakdown of results from Cluster and Outlier Analysis.

	High	**Low**
High	Statistically significant clusters of high damage	Low value outliers which are surrounded by high values of damage
Low	High value outliers which are surrounded by low values of damage	Statistically significant clusters of low damage values

Figure 43: Map of study area using the ArcMap Cluster and Outlier Analysis (Anselin Local Moran's I) spatial statistics tool (ESRI, 2018).

The wind field of Hurricane Harvey plays an important role of the spatial relationships between variables (Vickery, 2017). First by converting the wind field grid data to a raster file, using the IDW Interpolation tool in ArcMap, then converting the IDW raster file into a contour field, we have usable data to visualize the impact of wind on the study area and the greater region (**Figure 44** & **Figure 45**) (ESRI, 2018; Vickery, 2017).

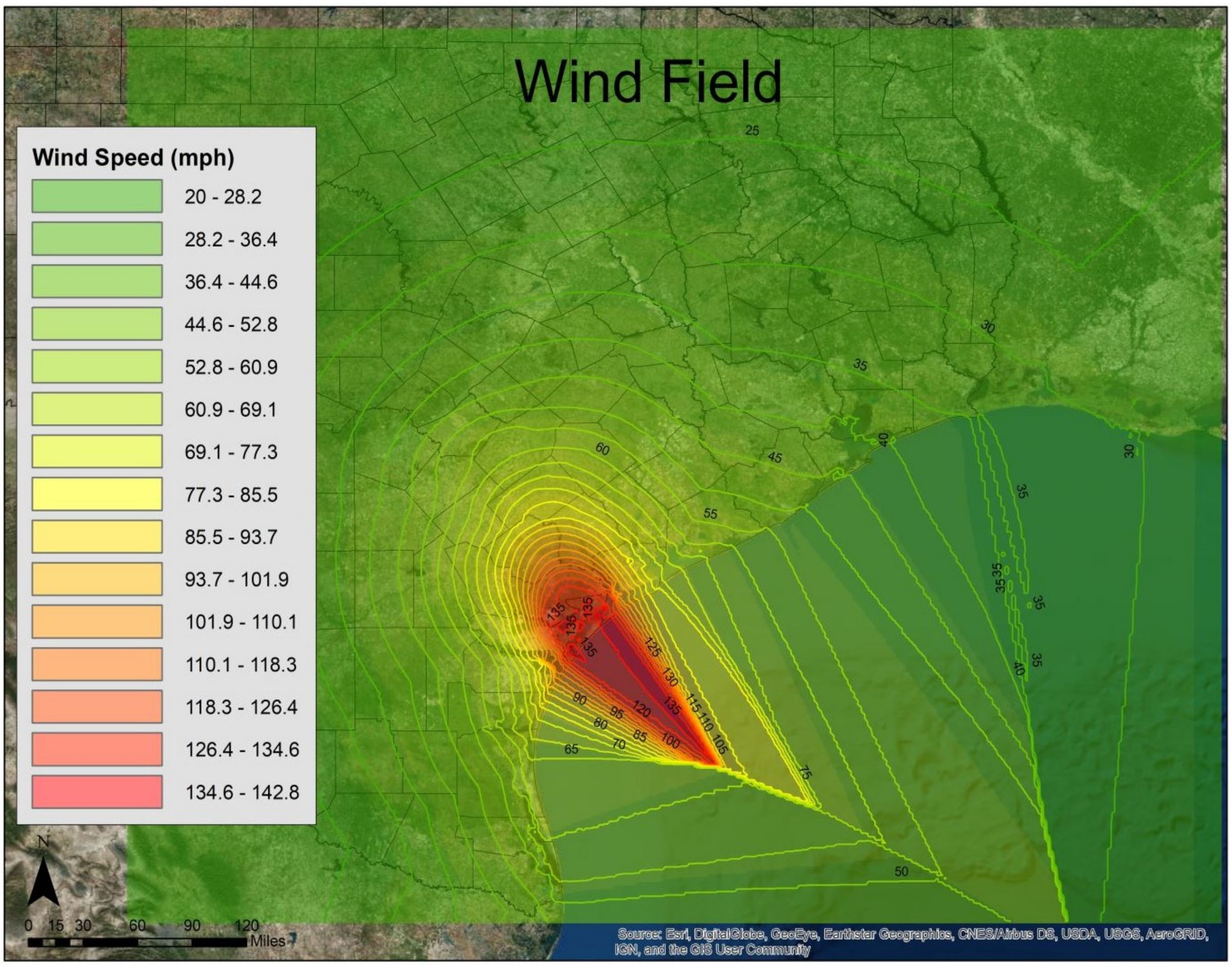

Figure 44: Map of greater Texas coast overlaid with Hurricane Harvey (Vickery, 2017).

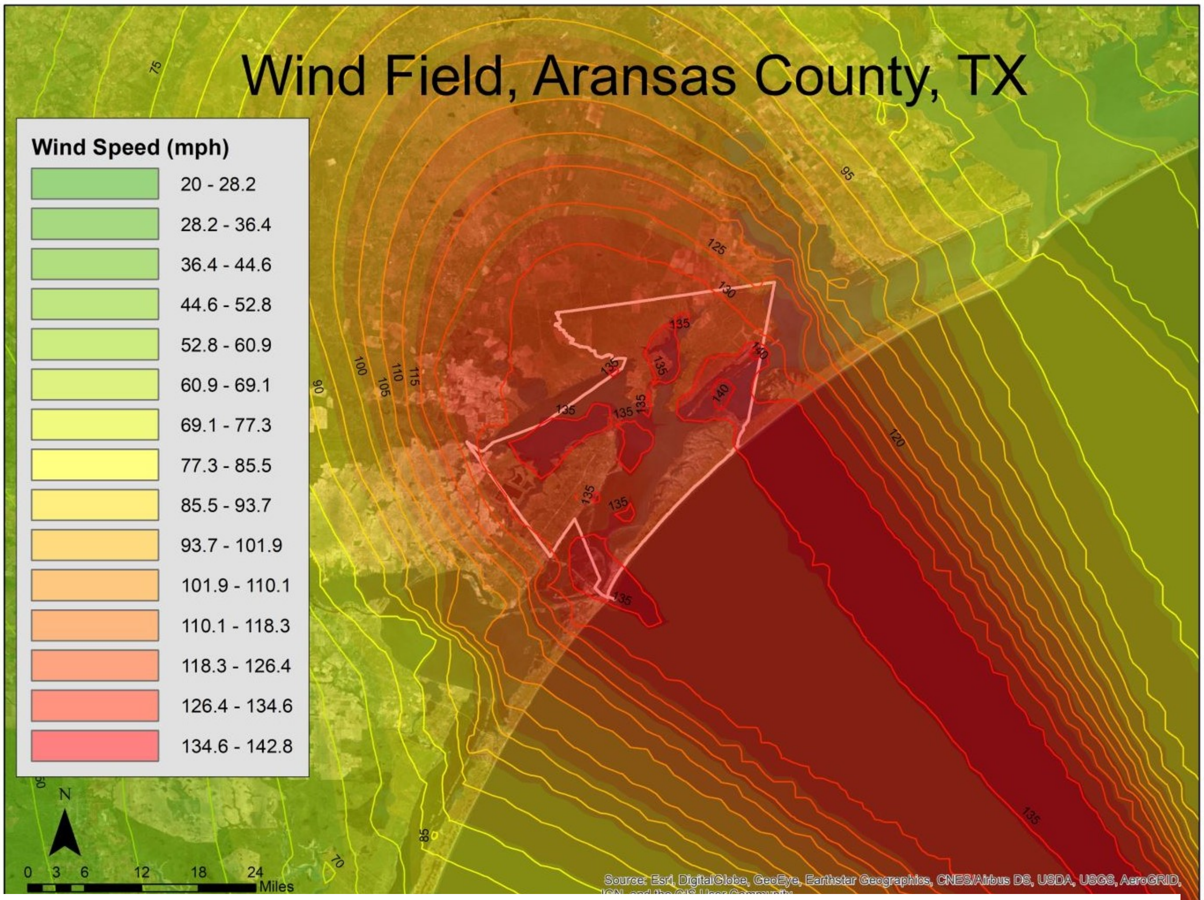

Figure 45: Map of greater Aransas County, TX overlaid with Hurricane Harvey wind field (Vickery, 2017).

After overlaying the clustering analysis onto the wind fields, it is apparent that higher velocity winds swept through the northern portion of the island, and the southern portion of the island found slightly smaller wind speeds (**Figure 46**) (Vickery, 2017). This same phenomenon is reflected when the wind field is overlaid with the damage ratings (**Figure 47**) (ESRI, 2017; Vickery, 2017). Wind speed appears to have been highly correlated with damage in this area during Hurricane Harvey.

Figure 46: Key Allegro damage ratings overlaid with Hurricane Harvey wind field. Note the damage ratings are higher on northern portion of the community, where wind speed was higher during Hurricane Harvey (ESRI, 2018; Vickery, 2017).

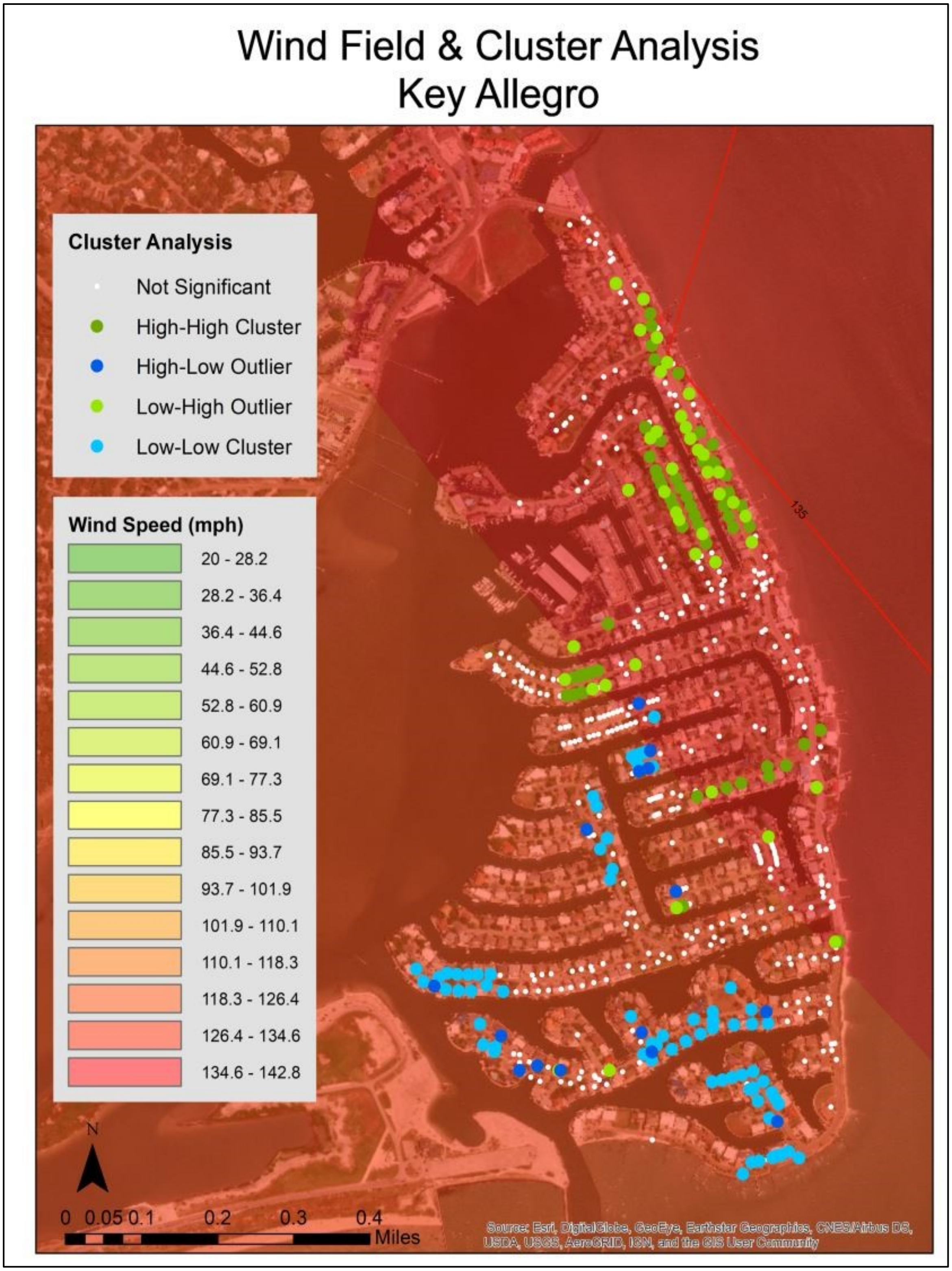

Figure 47: Key Allegro damage rating ArcMap Cluster and Outlier analysis (Anselin Local Moran's I) overlaid with Hurricane Harvey wind field (ESRI, 2018; Vickery, 2017).

The exploratory regression analysis was created following the "Spatial Statistics: Simple Ways to Do More with Your Data" technical workshop by Lauren Bennett and Flora Vale. The technical workshop advises practitioners to utilize the "Exploratory Regression" tool in ArcMap, which tries combinations of variables to best describe a dependent variable using a properly specified model framework. This tool will iterate from one to, up to, five variables at once, providing information about each independent variable and the relationship with the chosen dependent variable (Bennett, 2017).

When this dataset was fed into the "Exploratory Regression" tool in ArcMap, with damage rating as a dependent variable, and all pre-storm data as the explanatory variables, there was no passing model, but there was information about variables with the highest adjusted R^2 values, variable significance, and relationships between the independent and dependent variables (**Table 6**) (ESRI, 2017). Variable significance is used by this tool to describe the proportion of times where the variable was statistically significant. The relationship, whether positive or negative, is also measured. Variables which are strong predictors of the dependent variable will be consistently significant and the relationship will be stable. For example, the age of the home is a strong predictor because it was significant 100% of the time and had a positive relationship with building damage 100% of the time. Other significant variables include: latitude, metal roofs, distance to ocean, and total home area (**Figure 48**). All variables not included in **Figure 48** were not significant with Damage Rating used as the dependent variable. The latitude may be particularly significant because the wind field is shows stronger winds on the northern portion of the island, as previously discussed.

Table 6: Independent variables used in exploratory regression, including their respective variable type and the resulting % significance, % positive, and % negative (ESRI, 2018).

Variable	Variable Type	% Significant	%Negative	%Positive
Age	Numerical - Continuous	100	0	100
Latitude	Numerical - Continuous	99.99	0	100
Metal Roof Cover	Categorial - Binary	99.98	100	0
Distance to Coast	Numerical - Continuous	99.54	100	0
Total Area	Numerical - Continuous	95.93	100	0
Asphalt Roof Cover	Categorial - Binary	94.27	0.11	99.89
Wood Siding Wall Cover	Categorial - Binary	93.08	0	100
Stucco Siding Wall Cover	Categorial - Binary	88.7	99.52	0.48
Two Story	Categorial - Binary	86.4	100	0
Building Value	Numerical - Continuous	85.08	99.56	0.44
Single Story	Categorial - Binary	79.15	100	0
Grade Level Entry	Categorial - Binary	77.58	0	100
Level One Entry	Categorial - Binary	77.58	0	100
Elevated	Categorial - Binary	67.63	3.98	96.02
Open Gable Roof Shape	Categorial - Binary	66.06	0	100
Wet-proofed Foundation	Categorial - Binary	59.21	0.06	99.94
2/12 Roof Pitch	Categorial - Binary	53.79	0	100
Attached Garage	Categorial - Binary	44.06	100	0
Combination Roof Shape	Categorial - Binary	36.52	100	0
Garage Door	Categorial - Binary	19.43	91.73	8.27
Concrete Tile Roof Cover	Categorial - Binary	17.17	0.71	99.29
Unknown Roof Pitch	Categorial - Binary	11.83	99.96	0.04
Tar Roof Cover	Categorial - Binary	11.81	97.63	2.37
Partially Elevated	Categorial - Binary	9.16	47.68	52.32
Dry-proofed Foundation	Categorial - Binary	4.7	32.98	67.02
Clay Tile Roof Cover	Categorial - Binary	4.67	65.93	34.07
Vinyl Siding Wall Cover	Categorial - Binary	4.15	70.25	29.75
Balcony or Porch	Categorial - Binary	0.8	93.78	6.22
8/12 Roof Pitch	Categorial - Binary	0.27	99.99	0.01
Dutch Gable Roof Shape	Categorial - Binary	0.2	97.56	2.44
Hip Roof Shape	Categorial - Binary	0.11	75.17	24.83
Cross Hipped Roof Shape	Categorial - Binary	0.1	0	100
Entry Door	Categorial - Binary	0.01	100	0
Hip and Valley Roof Shape	Categorial - Binary	0	99.49	0.51
12/12 Roof Pitch	Categorial - Binary	0	100	0
Flat Roof Shape	Categorial - Binary	0	5.37	94.63
Split Level	Categorial - Binary	0	6.22	93.78

Three Story	Categorial - Binary	0	16.98	83.02
Box Gable Roof Shape	Categorial - Binary	0	17.88	82.12
Intersection Roof Shape	Categorial - Binary	0	97.17	2.83
Wooden Shingles Roof Cover	Categorial - Binary	0	94.52	5.47
10/12 Roof Pitch	Categorial - Binary	0	48.05	51.95
6/12 Roof Pitch	Categorial - Binary	0	1.29	98.71
4/12 Roof Pitch	Categorial - Binary	0	12.96	87.04
Hurricane Clips	Categorial - Binary	0	4.23	95.77
Unknown Hurricane Clips	Categorial - Binary	0	95.77	4.23
Other Siding Wall Cover	Categorial - Binary	0	99.97	0.03
Full-sized Windows	Categorial - Binary	0	32.07	67.93
Ventilators	Categorial - Binary	0	0	100
Percent Openings	Numerical - Discrete	0	89.91	10.09
Shutters or Panels	Categorial - Binary	0	0.47	99.53

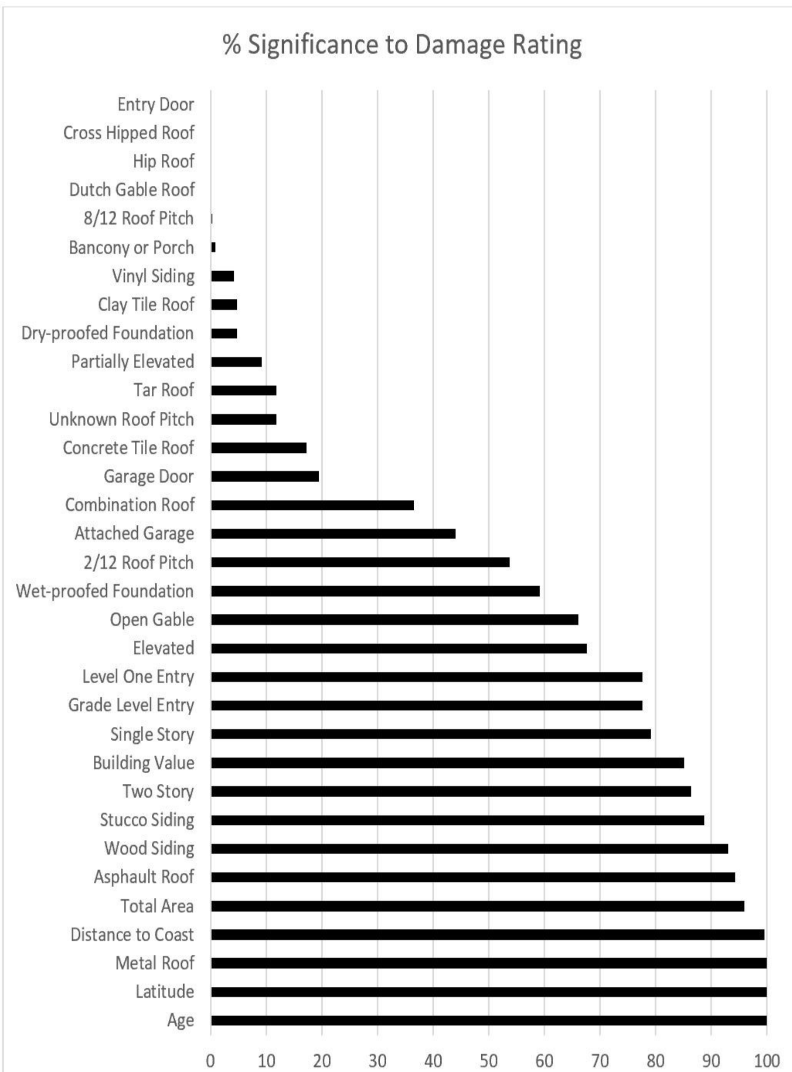

Figure 48: Significance to Damage Rating according to Exploratory Regression in ArcMap.

With the goal of understanding the relationship between categories of pre-storm variables and the damage rating, the exploratory regression tool was run, using the damage rating as the dependent variable (ESRI, 2018). **Figure 49** illustrates all explanatory variables and their relationship with damage rating. During the explanatory regression, variables are not always either positive or negative, so the tool provides information about the percentage of time that each variable is either positive or negative. High consistency of the relationship with damage rating can show the stability of the variable.

Positive relationships with damage rating would suggest that presence of this variable would lead to higher levels of damage. Variables which consistently had a positive relationship with damage rating included: Age, Latitude, Wooden Siding, Grade Level Entry, Level One Entry, Open Gable roof shape, 2/12 Roof Pitch, Cross-Hipped Roof, Ventilators, Wet-Proofed Foundation, Asphalt Roof covering material, Shutters or Panels covering the windows and/or other openings, Concrete Tile roof covering material, 6/12 Roof pitch, and Elevated foundation.

These results indicate that the older homes received higher rates of damage. This confirms the results of previous studies (Owensby, 2013; Xian, 2015). Latitude may be highly related to wind speed in this study, so these results would suggest that homes with higher latitude, closer to the northernmost tip of the island, had higher rates of damage. Wind speed is highly correlated with wind damage during tornados, as well (Egnew, 2018). Wooden siding, though popular in coastal communities, was not enough wall covering material to reduce overall structural damage. Both grade-level and level-one entry had a positive relationship with damage, indicating that the location of the entry door does not reduce damage sustained from a single-hazard wind hurricane. Entry level, in the past, was positively related to damage from storm surge (Xuan, 2016). Open-gable roof shapes had previously received less damage than hip roofs, but the results of this exploratory regression indicate that gable-roofs consistently resulted in more damage than hip roofs, which had a mostly negative relationship with overall damage (Crandell, 1998; Egnew, 2018). Although closed-foundations, i.e. dry-proofed elevated structures, performed positively during storm surge and flooding events, dry-proofed homes only performed slightly better than wet-proofed foundations in this study (Xian, 2016). Elevated structures, both wet- and dry-proofed, resulted in higher rates of damage than non-elevated structures. This is in direct disagreement with previous studies which indicated that elevated structures reduced damage from hurricanes, primarily in single-hazard flooding events (Kennedy et. al, 2011; Xian, 2015). Another variable of interest is that the presence of shutters/panels over openings resulted in higher rates of damage, this is counterintuitive because reinforcing openings has previously been suggested to reduce multi-hazard damage (Eamon, 2017).

Variables which have a consistently negative relationship with damage rating include: steep roof pitch, presence of an Entry Door, Combination Roof shape, presence of an Attached Garage, Single Story, Two Story, Total Area, Distance to Coast, Metal Roof, Building Value, Stucco Siding, and Hip and Valley Roof shape. When a variable has a negative relationship with overall damage, this indicates that the presence of this variable would result in lower rates of damage.

Only seven homes in the study area had a roof pitch of 12/12, so perhaps that size of the dataset may be skewing the relationship between steep roof pitch and overall damage. The same phenomena could be applied to the presence of an entry door and a garage door because most homes in Key Allegro have both an entry door and a garage door. The number of stories, both single and two-story, consistently had a negative relationship with damage rating. Previous studies have indicated that two story homes had a more positive relationship with wind damage than single stories (Crandell, 1998; Egnew, 2018; Xuan, 2016). Total area previously was positively related to damage, but this analysis suggested that home area had the opposite relationship with damage (Egnew, 2018). Distance to Coast, especially for multi-hazard hurricanes and single-hazard flooding events, has previously had a positive relationship with damage (Kennedy et. al, 2011; Xuan, 2015). This study, in contrast, suggested that distance to coast has a negative relationship with wind damage. Perhaps, distance to coast is indirectly proportional to wind damage in this community – which would explain this counterintuitive relationship with damage. Building value, confirming previous studies, had a negative relationship with building damage (Egnew, 2018).

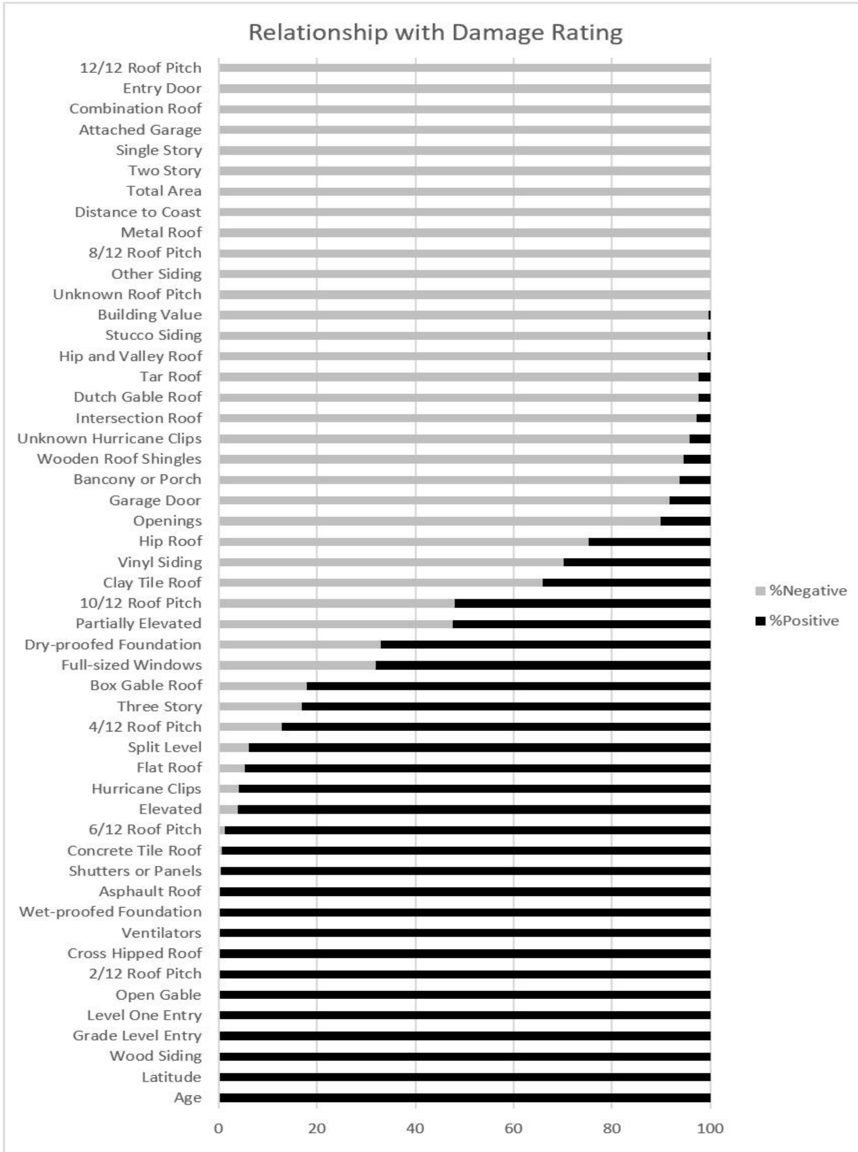

Figure 49: Illustrates the percentage of time, during the exploratory regression in ArcMap, where each explanatory variable has either a positive or negative relationship with the Damage Rating.

To combine the information gained from the % significance and relationship with damage rating, a prediction factor was calculated (**Figure 50**). The prediction factor indicates the strength of each variable to predict damage rating, by combining the significance and the stability of the variable with damage rating, either positive or negative. The prediction factor is calculated by:

*Prediction Factor = % Significant * (% Positive - % Negative)/100.*

The prediction factor ranges from 100 to -100, where a prediction factor of 100 would indicate a variable which was significant to damage rating 100% of the time and always positive. A prediction factor of -100 means that the variable was significant to predicting damage rating 100% of the time but had a consistently negative relationship with damage rating. Where the absolute value of a prediction factor is high, these variables are strong predictors – meaning they are highly significant and have a consistent relationship with damage rating. Strong predictors of damage rating include: age, latitude, asphalt roof covering, wood siding, grade level and level one entry, open gable roof shape, and elevation, all having a positive relationship with damage rating. Highly significant variables with consistently negative relationships with damage rating include: metal roof covering material, distance to coast, total area, stucco siding, two story homes, and building value. After normalizing the prediction factor by the number of samples in each feature, the variables with the strongest prediction are: age, latitude, and asphalt roof covering with positive relationships with damage rating; distance to coast, total area, and building value with a negative relationship with damage rating (**Figure 51**).

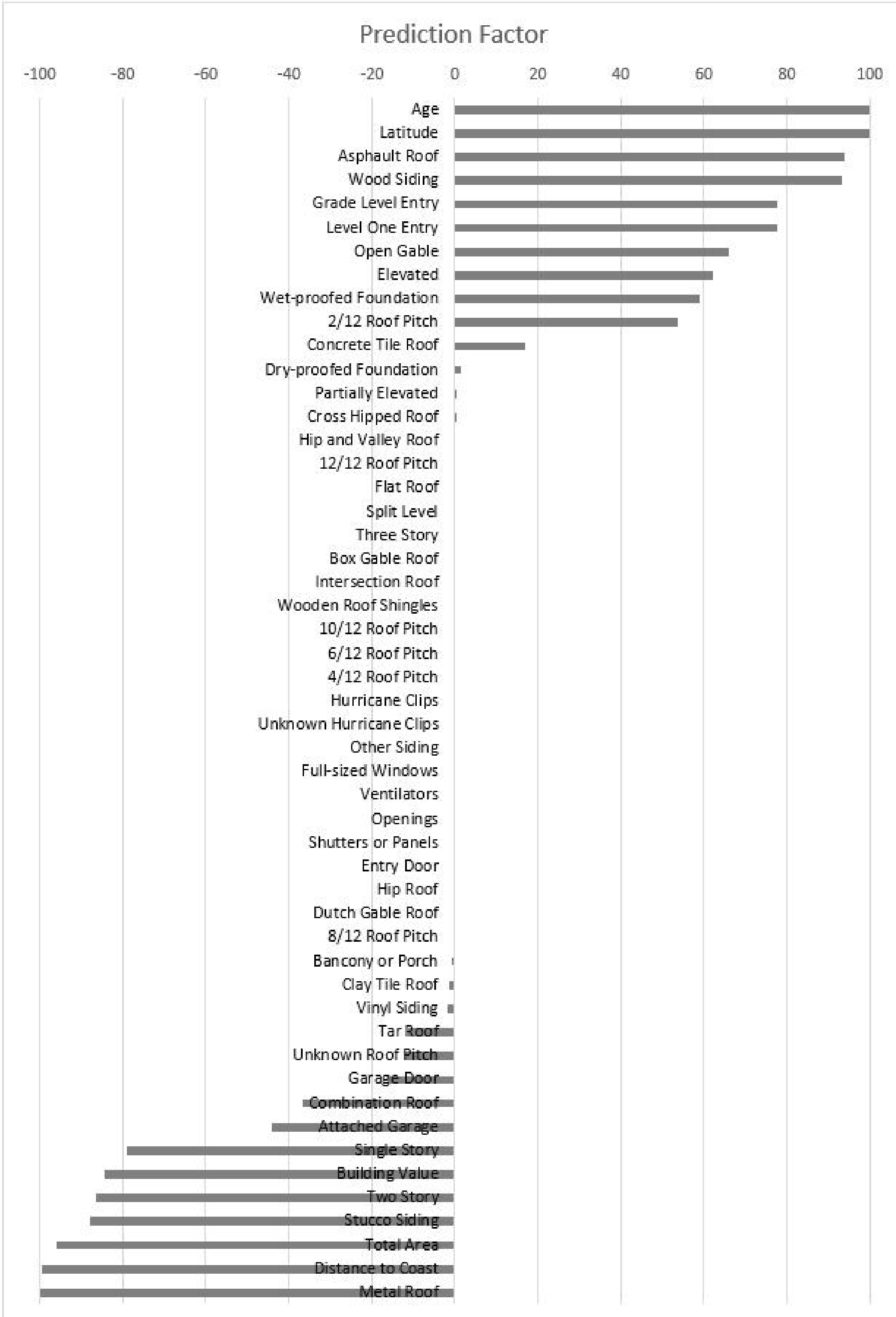

Figure 50: Prediction factor combines the variable significance and the consistency of the relationship with damage rating. Variables where the absolute value of the prediction factor are high are strong predictors of damage rating.

Figure 51: Distribution of the prediction factor, after being normalized by the number of samples in each feature.

The Explanatory Regression tool also pointed out the frequency of “perfect multicollinearity” in this dataset, or correlation between explanatory variables (ESRI, 2018). Variables with the highest Variance Influence Factor (VIF) values, one measure of multicollinearity, include: Single Story, Two Story, Asphalt shingles, Metal roof covering, vinyl siding, stucco siding, and wood siding (**Figure 52**). For perfectly independent explanatory variables, the VIF value would be 1 – although some are close to 1, no pre-storm explanatory variables in this dataset are perfectly independent. More information about multi-collinearity will be discussed in **Section 3.4**.

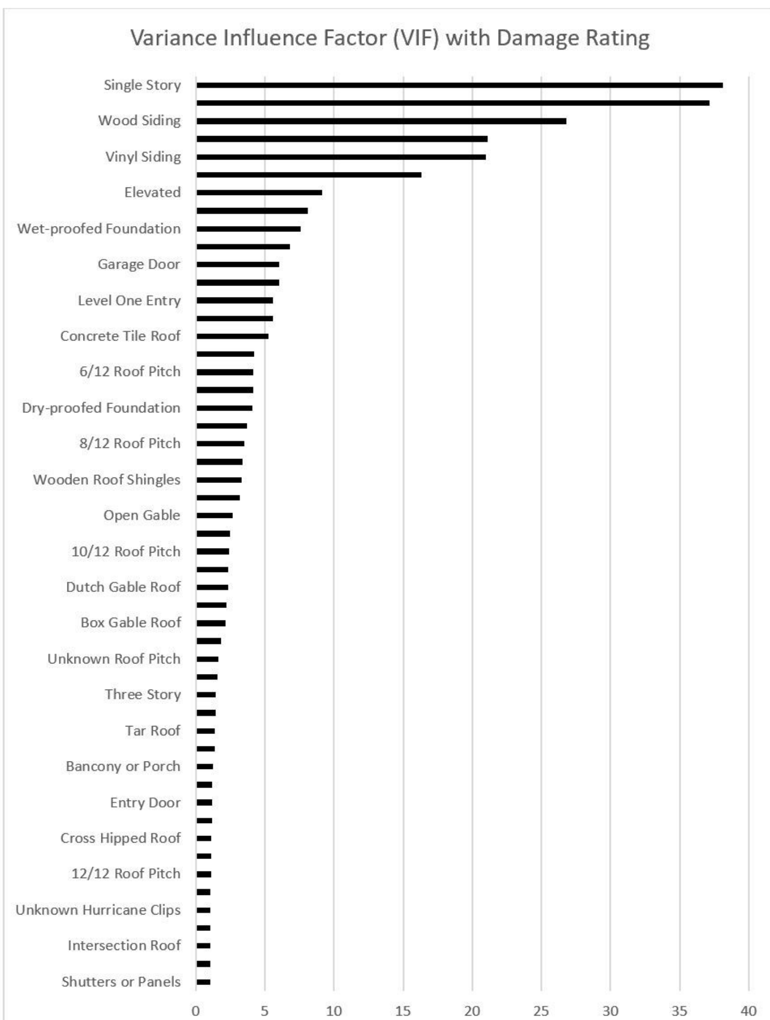

Figure 52: Variable Influence Factor (VIF), which measures multi-collinearity, for each variable when predicting Damage Rating.

The following categories of variables were chosen for further analysis: number of stories, roof shape, roof covering, roof pitch, wall covering, elevation and type of elevation, and openings. For each of these categories of variables, an explanatory regression was run. The damage rating was used as the dependent variable and the independent variables were all the variables that fell into the respective category. No properly specified models were produced by these exploratory regressions, but other important information was gathered.

In the case of number of stories, both single and two story were significant most of the time, having a positive and negative relationship with damage rating 100% of the time, respectfully (**Figure 53**). It is intuitive to believe that the height of the home is negatively correlated with damage, primarily wind damage. Counter to this belief, three story homes are almost as likely to have a positive relationship as a negative relationship to damage rating (**Figure 54**). This may be caused by higher quality building materials, more wind protection, or different roof profiles on these taller and larger homes.

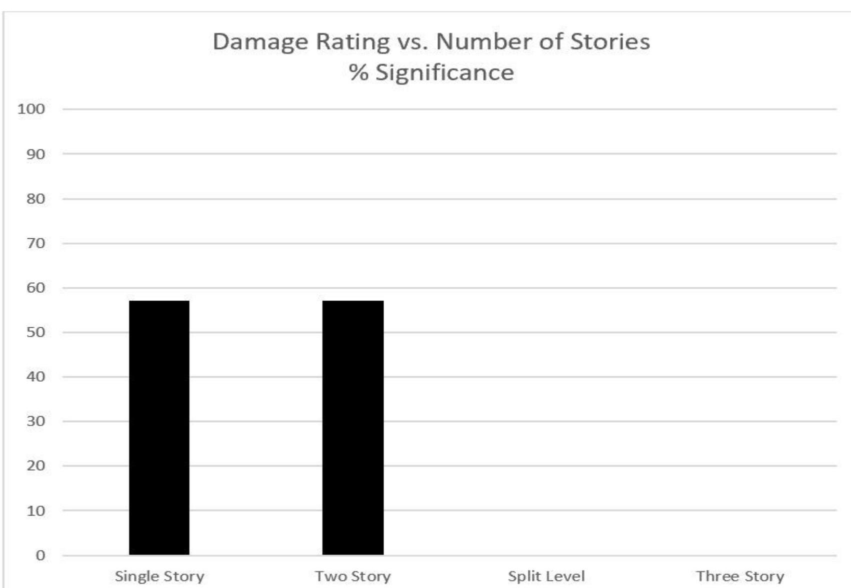

Figure 53: Significance of variables from exploratory regression with Number of Stories as independent variables and Damage Rating as the dependent variable.

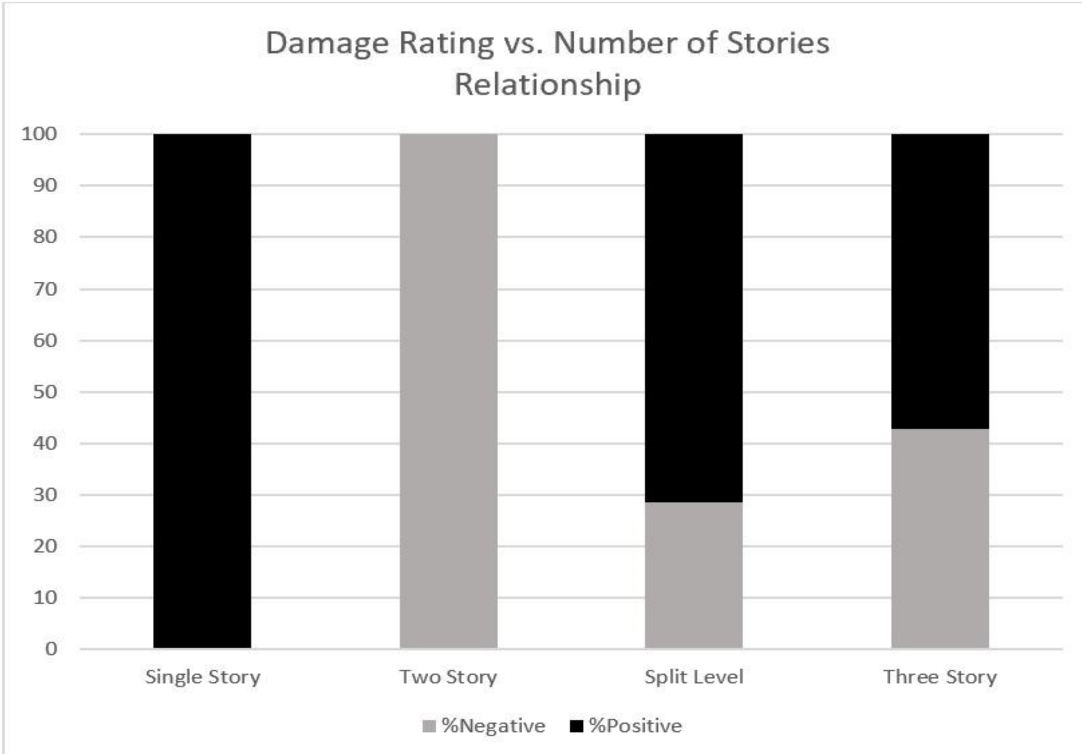

Figure 54: Relationship, whether positive or negative, of Number of Stories with Damage Rating.

Exploratory regression of roof shape indicated a relatively high significance between open gable roofs and damage rating (**Figure 55**), consistently having a positive relationship (**Figure 56**). Previous studies have indicated that hip roofs are more likely to sustain damage than gable roofs, but the results of this analysis show that open gable roofs had higher rates of damage and more significance than hip roofs for the damage rating (Crandell, 1998; Egnew, 2018).

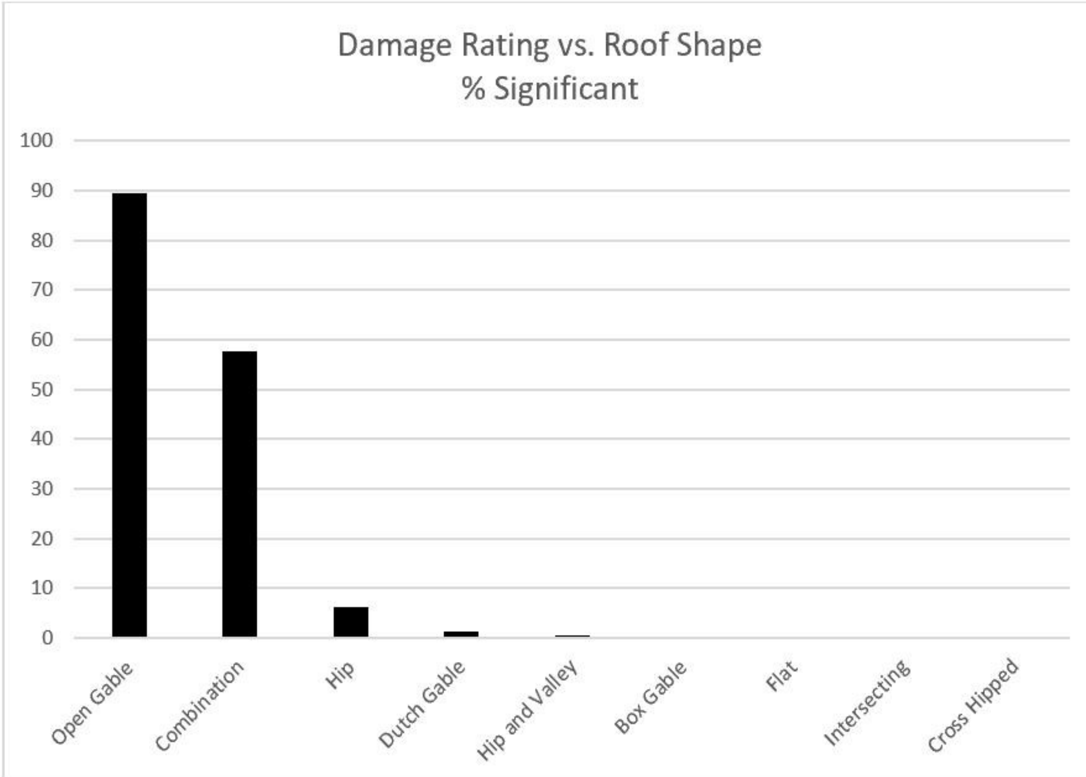

Figure 55: Significance of Roof Shape variables in exploratory regression, when predicting Damage Rating.

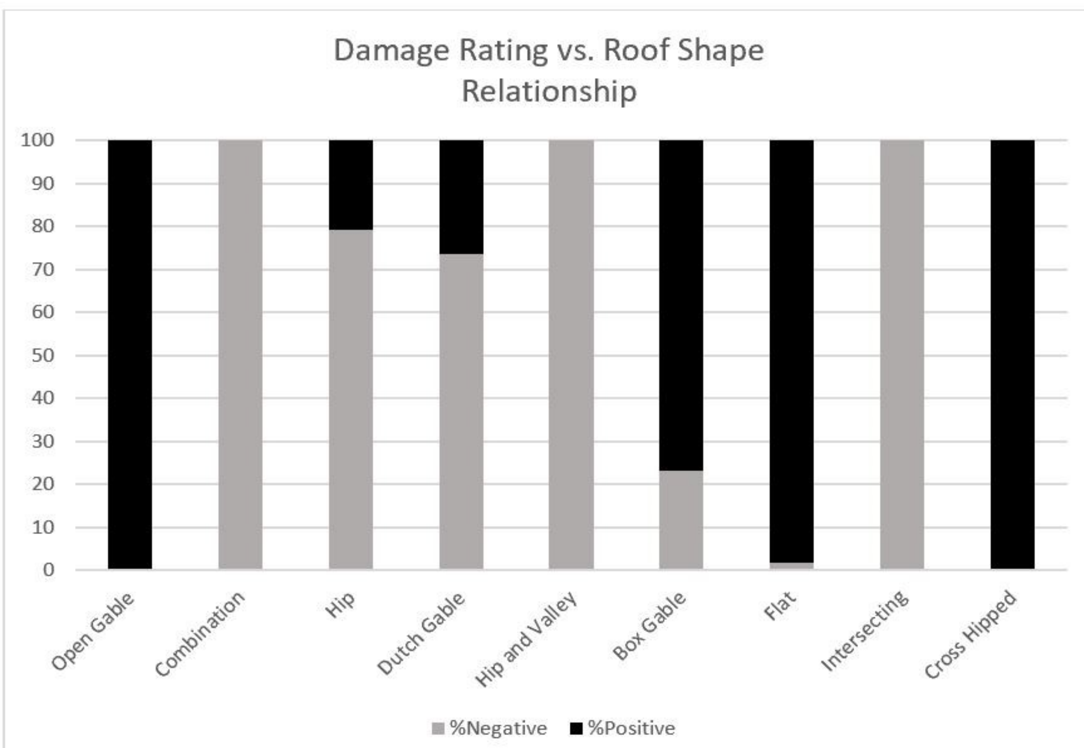

Figure 56: Relationship of Roof Shape variables with Damage Rating.

In terms of roof covering material, all roof cover types were significant aside from wooden shingles and tar roofs (**Figure 57**). Metal roof covering had a negative relationship with damage rating and a high significance, meaning that homeowners should be encouraged to utilize metal roofs to protect damage from wind (**Figure 58**). Metal roofs may be beneficial as a protection measure against wind damage because, unlike tiled or shingled roofs, metal roofs are a solid component. Asphalt shingles, in contrast, have a high significance but a positive relationship with damage rating.

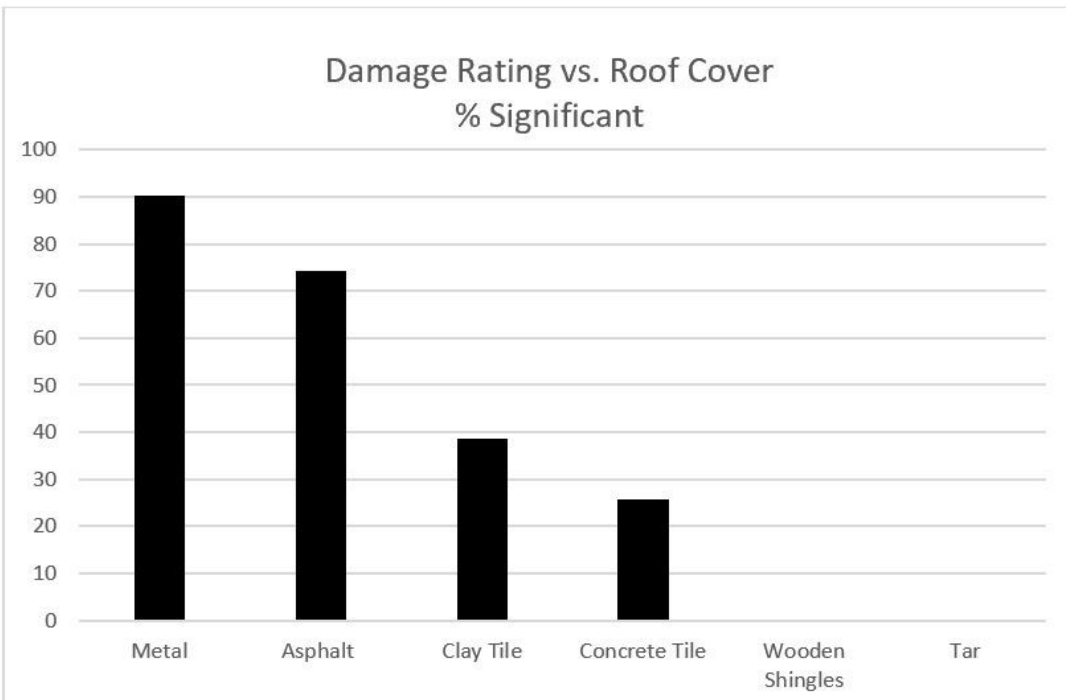

Figure 57: Variable significance of Roof Cover, for exploratory regression of Damage Rating.

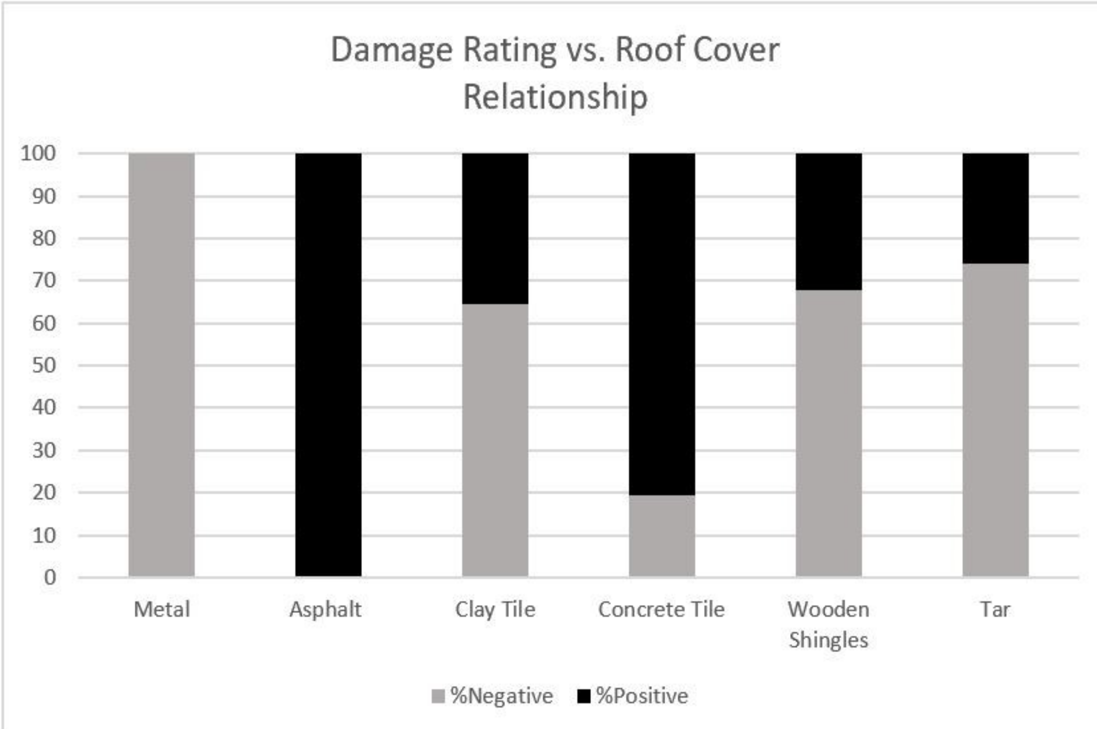

Figure 58: Relationship between Roof Cover variables and Damage Rating during exploratory regression.

Very shallow roof pitch had the highest significance with damage rating during exploratory regression (**Figure 59**). The roof pitch is expected to have a positive relationship with damage, because more steep roofs are expected to have more lateral loading from wind. Contrary to this expectation, and with very high significance, roofs with a 2/12 pitch have a consistently positive relationship with damage rating. Although, much less significant, roofs with a pitch of 8/12 most often have a negative relationship with damage rating. Factors outside of the roof pitch could explain these counterintuitive relationships between roof pitch and damage rating (**Figure 60**).

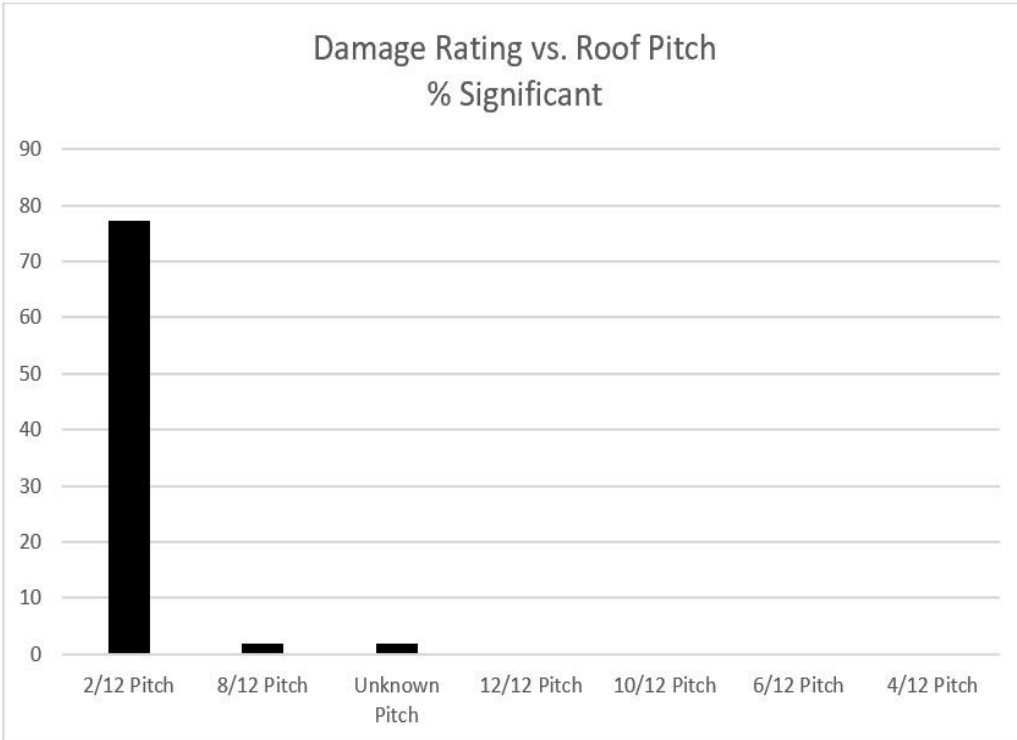

Figure 59: Significance of Roof Pitch with Damage Rating during exploratory regression analysis.

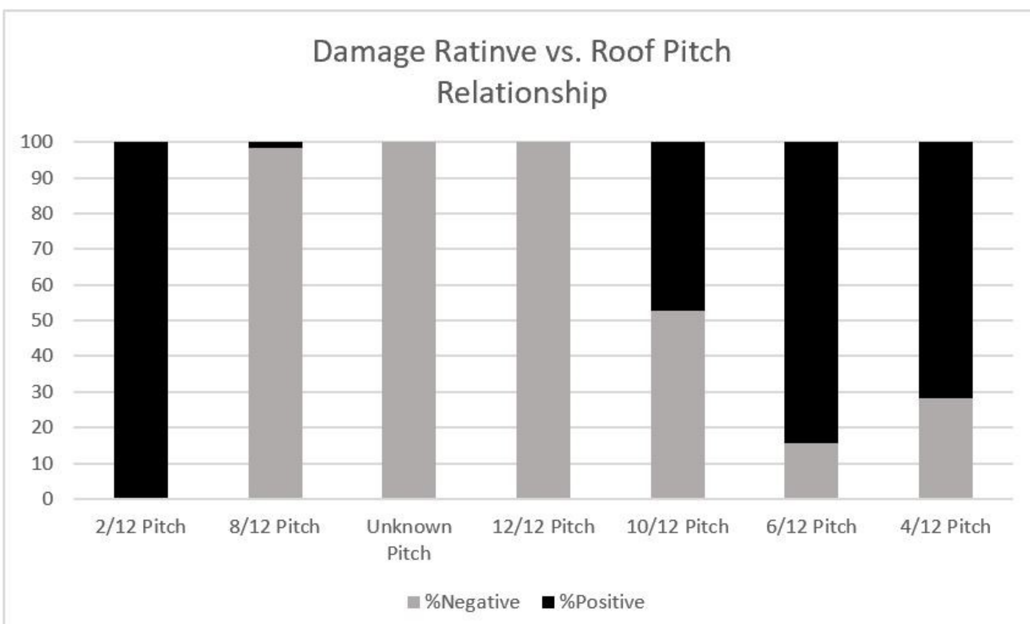

Figure 60: Relationship between Roof Pitch and Damage Rating.

Wall covering should mirror results of roof cover; wall coverings that have larger or more solid components are expected to perform better than smaller components when it comes to the impacts of wind damage (**Figure 61** & **Figure 62**). Stucco has very high significance, but it did not always have a negative relationship with damage; instead two-thirds of the time the relationship was negative, and the remaining homes indicated that stucco siding led to more damage. More consistently, wood siding has a high relative significance and always had a positive relationship with damage. In this area, much like many coastal communities, wood siding is a popular building attribute, but it may cause higher rates of wind damage during similar natural disasters.

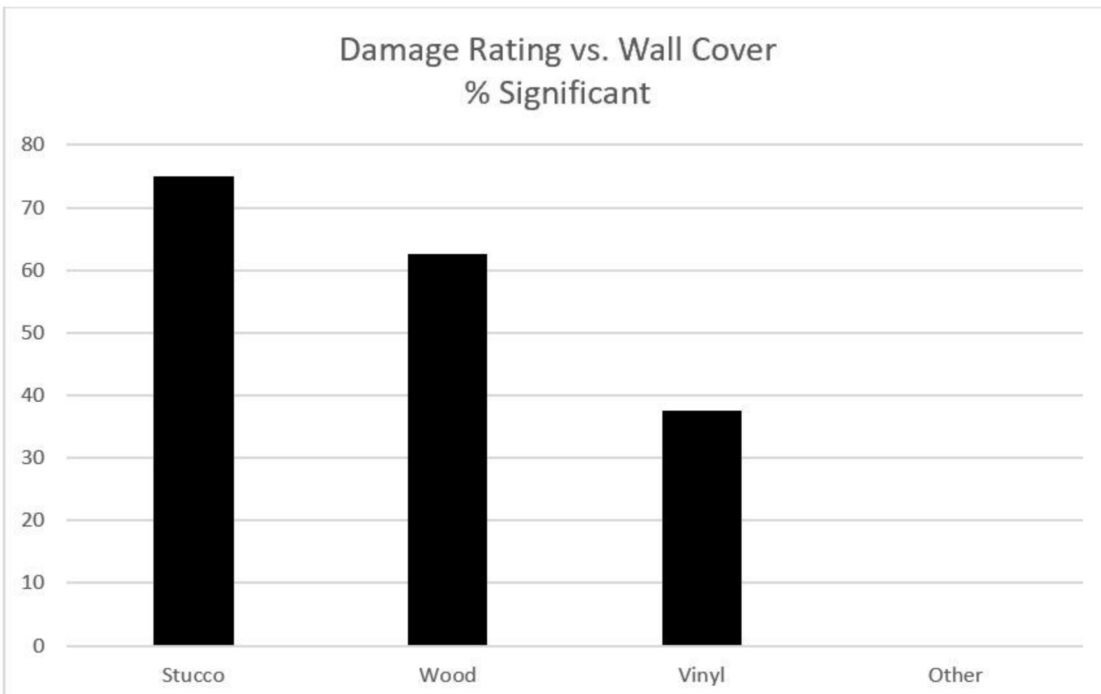

Figure 61: Percent significant during exploratory regression of Wall Covering materials to Damage Rating.

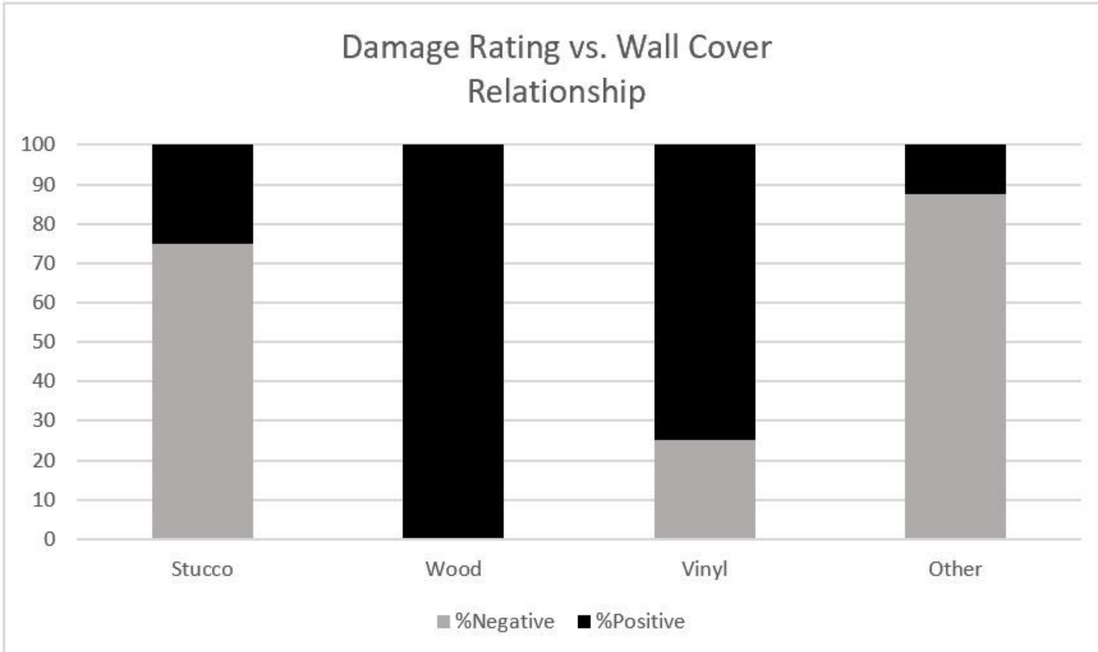

Figure 62: Relationship of Wall Covering Materials with Damage Rating.

Whether a home is elevated, especially in coastal communities, impacts expected damage to a home during a hurricane, especially when storm surge is a dominant damage mechanism (Hatzikyriakou, 2015; Kennedy et. al, 2011; Norman, 2010; Xian, 2015; Xuan, 2016). As expected, the exploratory regression tool gives highest significance on the Boolean variable indicating elevation (**Figure 63**). Elevation had a positive relationship with damage 100% of the time. Wet-proofed homes had high significance and a positive relationship with damage rating. Dry-proofed elevation structure had a more negative relationship than the wet-proofed method of elevation (**Figure 64**). Although this relationship was *mostly* negative, it is not always negative. The most beneficial elevation structure, though the least significant in this group, are dry-proofed foundation types. Two thirds of the time this foundation type had a negative relationship with damage rating, whereas one third of the time the relationship was positive. If a homeowner in this area were to be exposed to a similar storm, the elevation, the more closed the foundation (whether partially elevated or dry proofed) will lead to lower rates and intensities of damage.

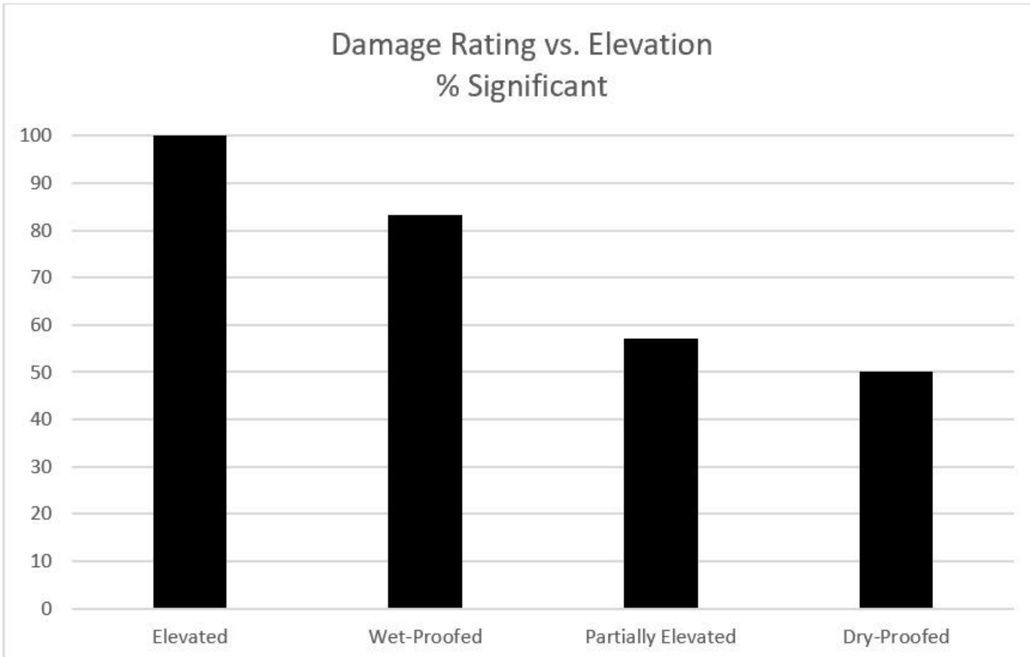

Figure 63: Binary elevation and Elevation Types and their significance in predicting Damage Rating in exploratory regression.

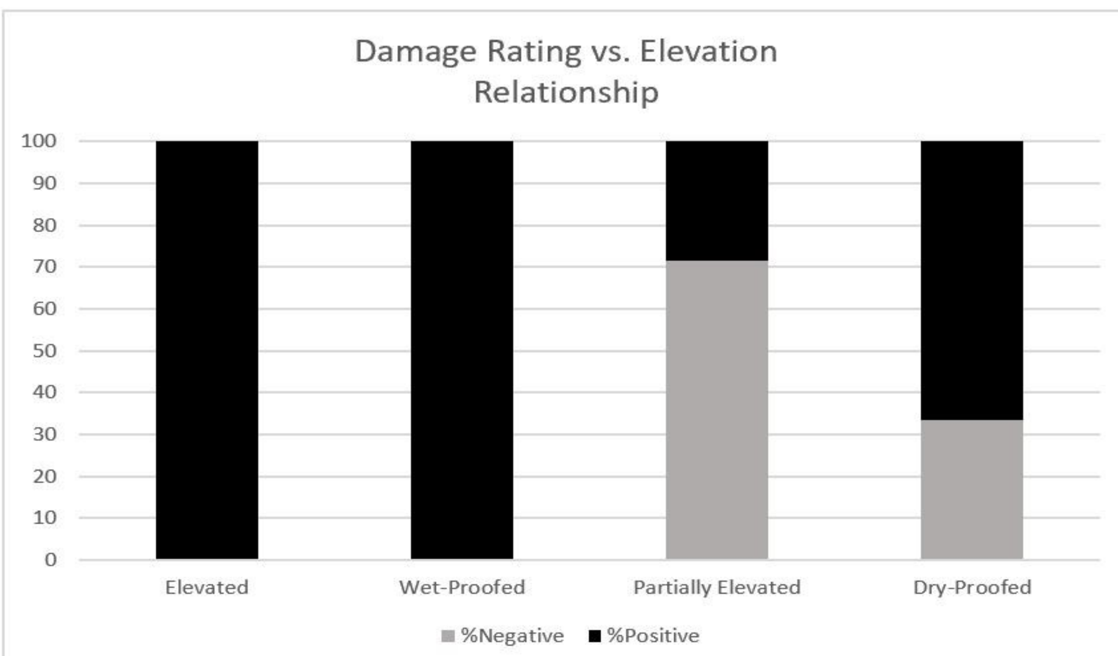

Figure 64: Relationship between binary elevation and Elevation Types with Damage Rating in exploratory regression.

The last category of specific analysis is of the relationship between openings and damage rating, this includes the percentage of openings and Boolean indicators of an entry door, garage door, full-sized windows, and ventilators. Wind has a habit of finding or creating openings on a structure, eventually causing lift or intrusion (Pita, 2012). Surprisingly, many of these attributes, including percentage of openings, have no significance in the exploratory regression (**Figure 65**). The attached garage was consistently significant and had a negative relationship with damage rating (**Figure 66**).

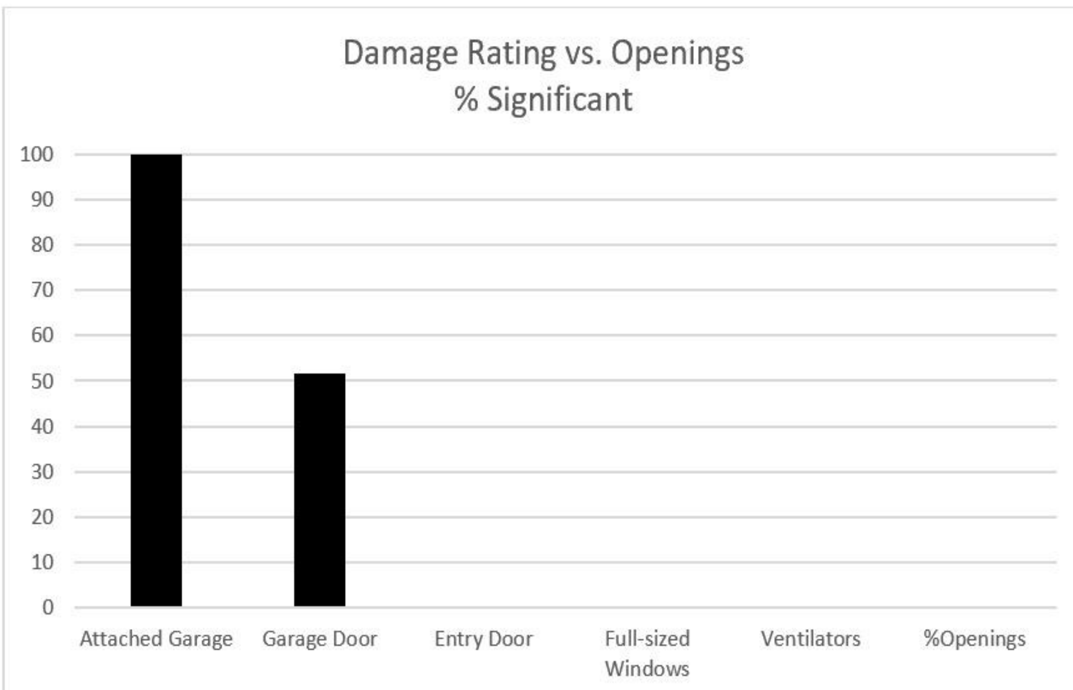

Figure 65: Significance of Opening Types with Damage Rating.

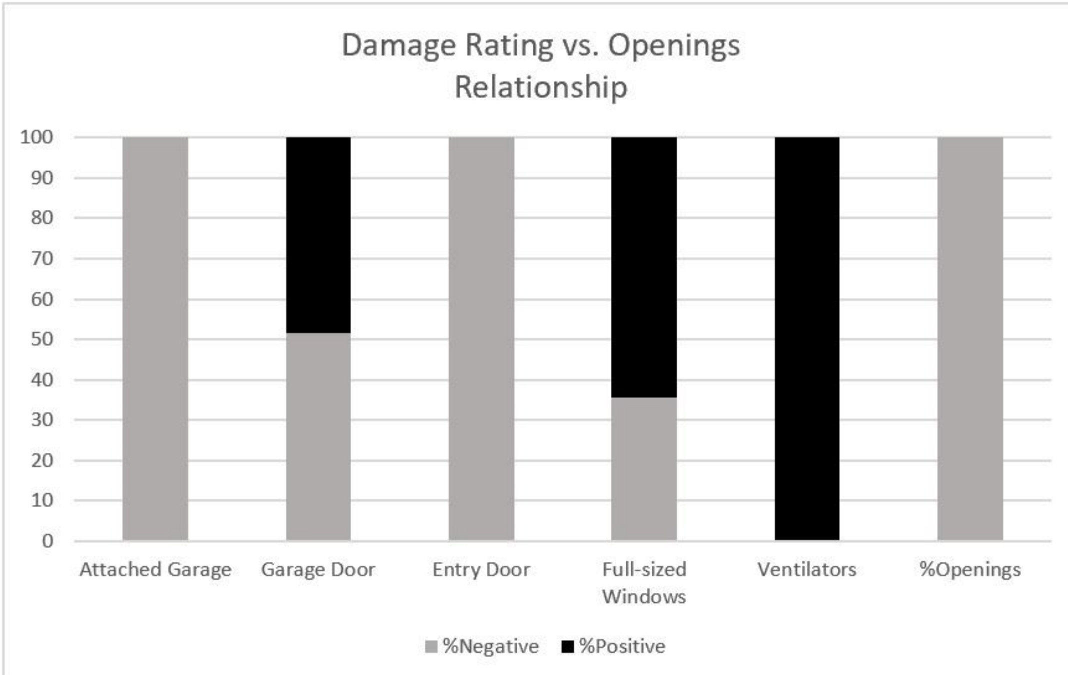

Figure 66: Relationship of Opening Types with Damage Rating.

To better understand the damage mechanisms leading to the damage rating, an Exploratory Regression was done using post-storm damage variables as the independent variables and the damage rating as the dependent variable. This analysis showed that, for this storm in this area, Boolean wind damage, roof cover damage percentage, roof framing damage percentage, wall cover damage percentage and Boolean debris damage were the most significant variables describing the damage rating of the entire home. The significance of these variables indicate that the storm caused damage primarily through roof failure from high wind loads.

3.4 Data Science based Analysis and Results

Classifiers can be used to create correlation matrixes, which give information about the independencies and dependencies of explanatory, of input, variables. **Figure 67** is the correlation matrix between all explanatory variables in this study. In blue are variables that have a negative correlation with each other, and red indicates variables with a positive correlation. All variables have a perfect, positive correlation with themselves, as shown by the red line crossing through the correlation matrix.

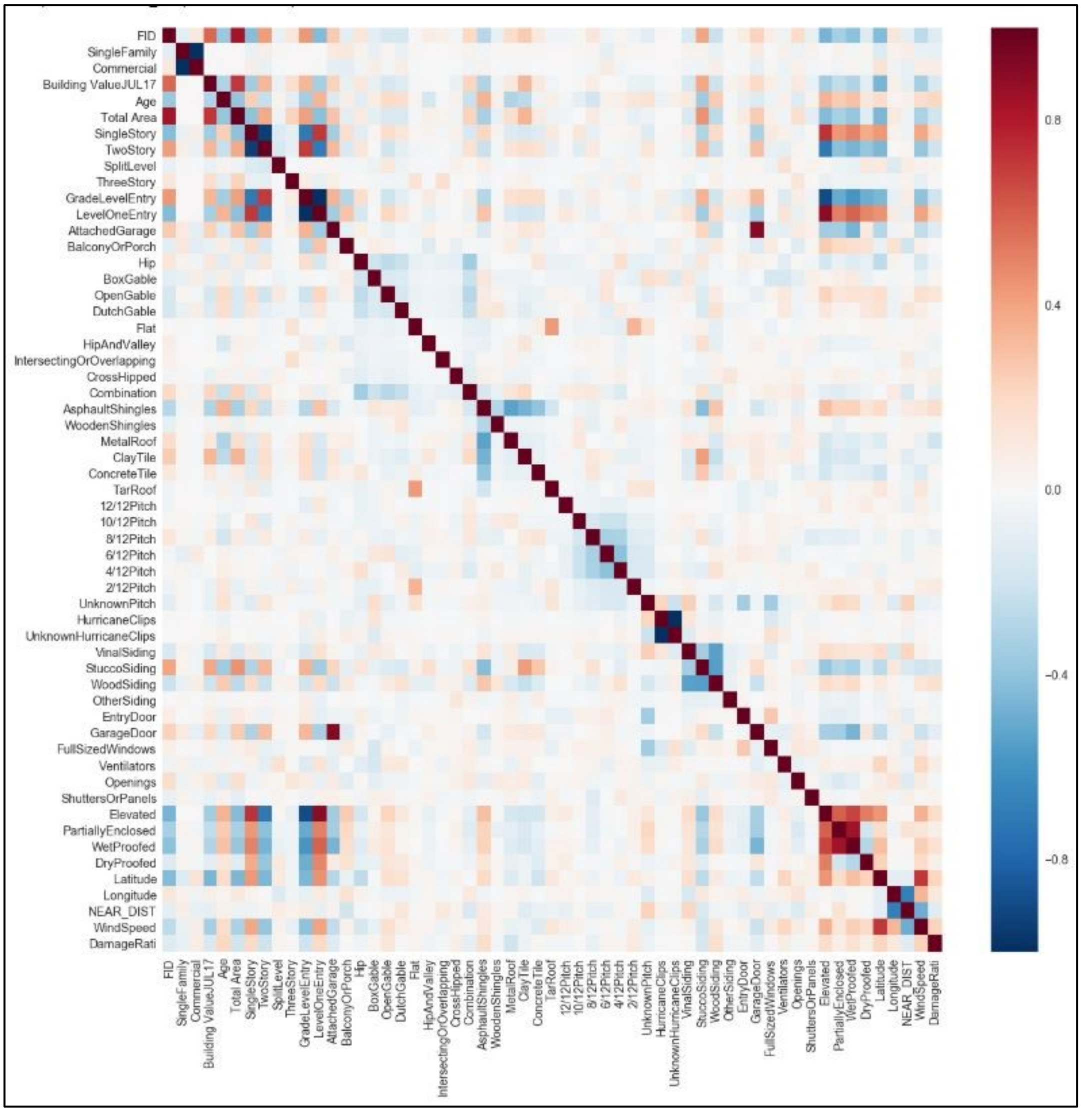

Figure 67: Correlation matrix from machine learning algorithms of all explanatory variables in this study.

There is relatively high multicollinearity between: Single Family and Commercial Structures, Single and Two Story, Grade and Level One Entry and Number of Stories, Hurricane Clips and Unknown Hurricane Clips, Wall Covering Types, Elevation and Elevation Types with Entry Level and Number of Stories, and Location with Distance to

Coast. All the variables with high multicollinearity fall in locations where one might expect them. For examples, in this dataset, if a home was not used as a single-family structure then it was used as a commercial structure – which is shown from the correlation matrix.

The classifiers also produced a feature importance factor. The variable importance does not necessarily show the magnitude nor the direction of the relationship these variables have with damage, unlike the exploratory regression, but it does tell us which variables were most important in creating the classifiers. Knowing the importance of each variable in building a classifier can help to make the damage assessment process more streamlined and efficient in the future. Feature importance is not a function of an SVM classifier, so the classifiers used to get feature importance were limited to the decision tree and random forest classifiers.

Figure 68 shows an aggregated picture of the variable’s importance's for an aggregation of all the different damage scenarios, see **Table 3**. The variables with the highest importance are: Distance to Coast, Longitude, Single Family Homes, Age, Total Area, Wind Speed, and Single Story (**Table 7**). These variables were mostly found using the spatial analyst tools in ArcMap and in Zillow’s databases. This information can help to improve future damage assessments, illustrating the importance of post-processing and virtual data collection.

Table 7: Explanatory variables used in the classifications with their respective variable type. Overall feature importance indicates the feature importance when predicting all damage scenarios.

Variable	Variable Type	Overall Variable Significance
Distance to Coast	Numerical - Continuous	2.382215201
Longitude	Numerical - Continuous	1.671635939

Single Family	Categorical - Binary	1.418693595
Age	Numerical - Continuous	1.292280779
Total Area	Numerical - Continuous	1.292209262
Wind Speed	Numerical - Continuous	1.101484053
Single Story	Categorical - Binary	0.86354205
Shutters or Panels	Categorical - Binary	0.309753847
Clay Tile Roof Cover	Categorical - Binary	0.290896522
Dutch Gable Roof Shape	Categorical - Binary	0.219384793
Split Level	Categorical - Binary	0.217191219
Wood Wall Siding	Categorical - Binary	0.212195319
2/12 Roof Pitch	Categorical - Binary	0.201871158
Asphalt Shingles Roof Cover	Categorical - Binary	0.184678167
Wooden Shingles Roof Cover	Categorical - Binary	0.176740021
4/12 Roof Pitch	Categorical - Binary	0.173888646
Percent Openings	Numerical - Discrete	0.170386203
Partially Enclosed Foundation	Categorical - Binary	0.16823294
Balcony or Porch	Categorical - Binary	0.164293464
Two Story	Categorical - Binary	0.151153096
Garage Door	Categorical - Binary	0.141774471
Latitude	Numerical - Continuous	0.139573308
Flat Roof Shape	Categorical - Binary	0.133898687
Other Siding Wall Cover	Categorical - Binary	0.128584979
Elevated	Categorical - Binary	0.121261959
Attached Garage	Categorical - Binary	0.12095177
Full-Sized Windows	Categorical - Binary	0.115895909
6/12 Roof Pitch	Categorical - Binary	0.112395733
Open Gable Roof Shape	Categorical - Binary	0.108210772
Wet-Proofed Foundation	Categorical - Binary	0.099784037
Dry-Proofed Foundation	Categorical - Binary	0.097701878
Unknown Roof Pitch	Categorical - Binary	0.097582432
Combination Roof Shape	Categorical - Binary	0.095443909
Stucco Siding Wall Cover	Categorical - Binary	0.09543365
Box Gable Roof Shape	Categorical - Binary	0.092297822
8/12 Roof Pitch	Categorical - Binary	0.08985484
Hip Roof Shape	Categorical - Binary	0.089465311
Level One Entry	Categorical - Binary	0.074515556
Metal Roof Cover	Categorical - Binary	0.069668542
Three Story	Categorical - Binary	0.049547502
Hip & Valley Roof Shape	Categorical - Binary	0.041852949
Hurricane Clips	Categorical - Binary	0.041730015
Entry Door	Categorical - Binary	0.04046085
Concrete Tile Roof Cover	Categorical - Binary	0.02794139
Tar Roof Cover	Categorical - Binary	0.02066302
12/12 Roof Pitch	Categorical - Binary	0.018236598
Cross Hipped Roof Shape	Categorical - Binary	0.015258822

Ventilators	Categorical - Binary	0.015253934
Unknown Hurricane Clips	Categorical - Binary	0.014978474
Building Value JUL17	Numerical - Continuous	0.014107745
Vinyl Siding Wall Cover	Categorical - Binary	0.01235482
Commercial	Categorical - Binary	0.006849936
10/12 Roof Pitch	Categorical - Binary	0.006288668
Intersecting or Overlapping Roof Shape	Categorical - Binary	0.00590367
Grade Level Entry	Categorical - Binary	0

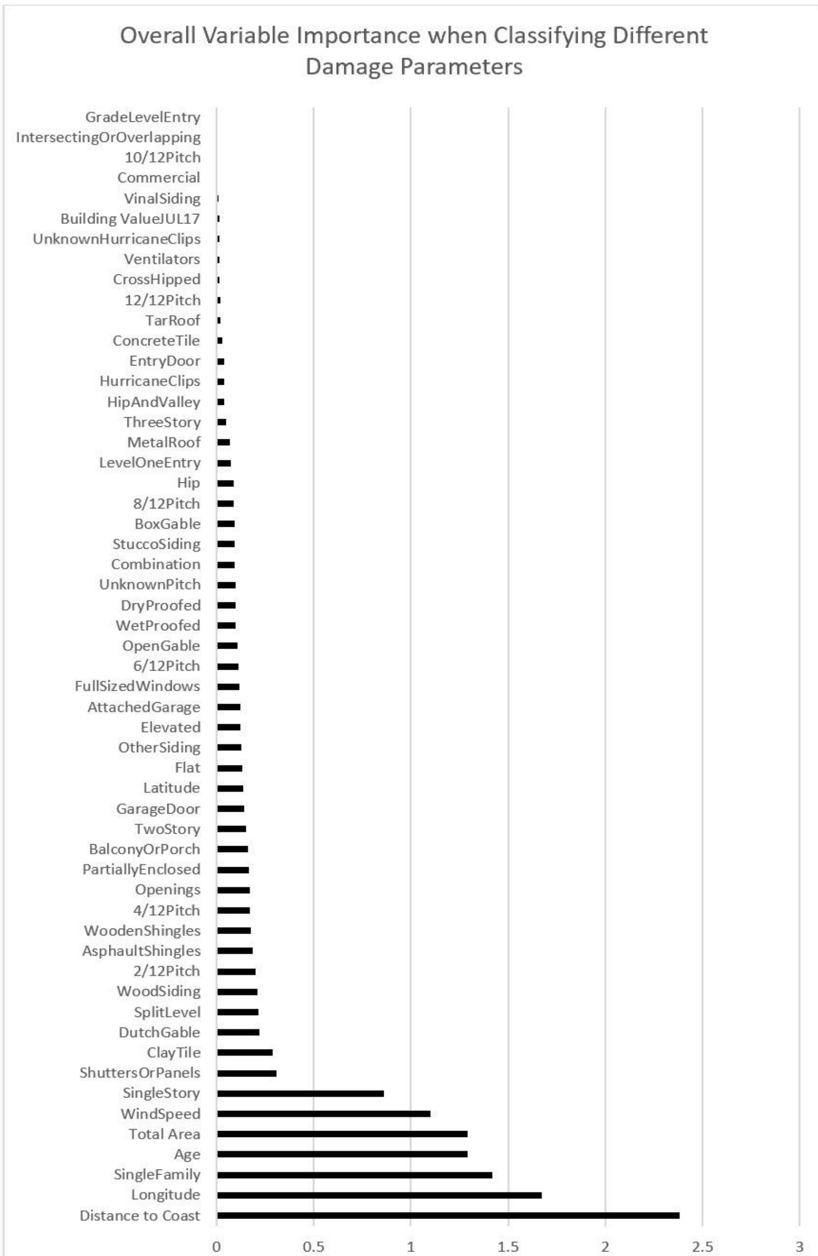

Figure 68: Aggregation of variable importance for all post-storm measurements, using decision tree and random forest machine learning algorithms.

The feature importance, when predicting the Damage Rating, utilized a Decision Tree Classifier with Gini impurity (**Figure 69**). The accuracy of this classifier was 45.8%. Although the accuracy is quite low, it is expected because of the stochastic nature of wind-damage and the number of predictions (0-4). Most important features to this classifier were: Longitude, Distance to Coast, & Age.

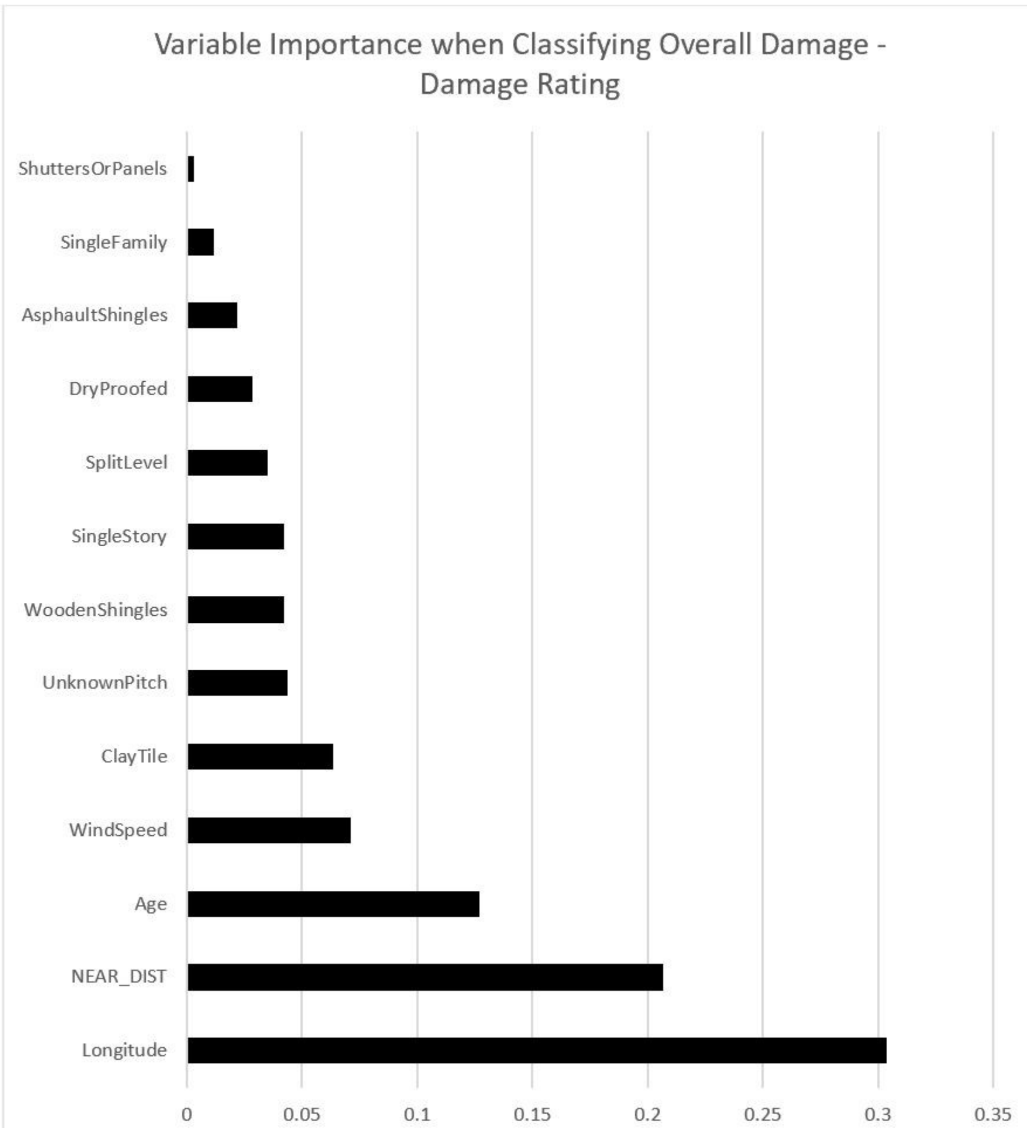

Figure 69: Variable importance when predicting the damage rating using the Decision Tree Classifier with Gini impurity.

To understand the relationship between whether the structure is “Safe to Use?” and all explanatory variables, feature importance was applied to the classifier (**Figure 70**). The classifier which had the highest accuracy was a Decision Tree Classifier which used entropy and had an accuracy of 88.55%. Most important features to this classifier were: Age & Distance to Coast. For damage assessments with the goal of understanding whether a home is safe to enter, such as the ATC-45 scale, both the Age and the Distance to the Coast should be added to the assessment (ATC, 2004).

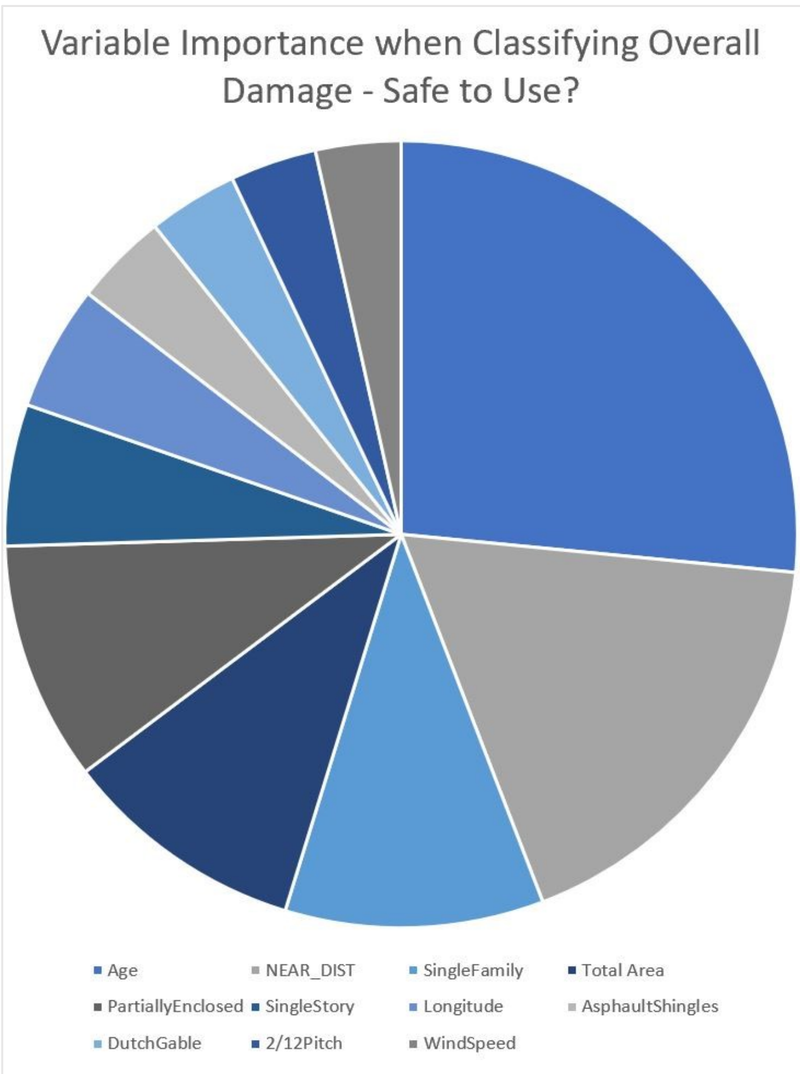

Figure 70: Variable importance when classifying whether a structure is "Safe to Use?", using a Decision Tree classifier which used entropy to build branches.

Feature importance when classifying if wind was the damage mechanism, for buildings that received damage, optimized accuracy to 77.1% using a Decision Tree Classifier with entropy to build branches (**Figure 71**). The variables with the highest importance when building this classifier were: Total Area, Clay Tiles, Single Story, and Distance to Coast.

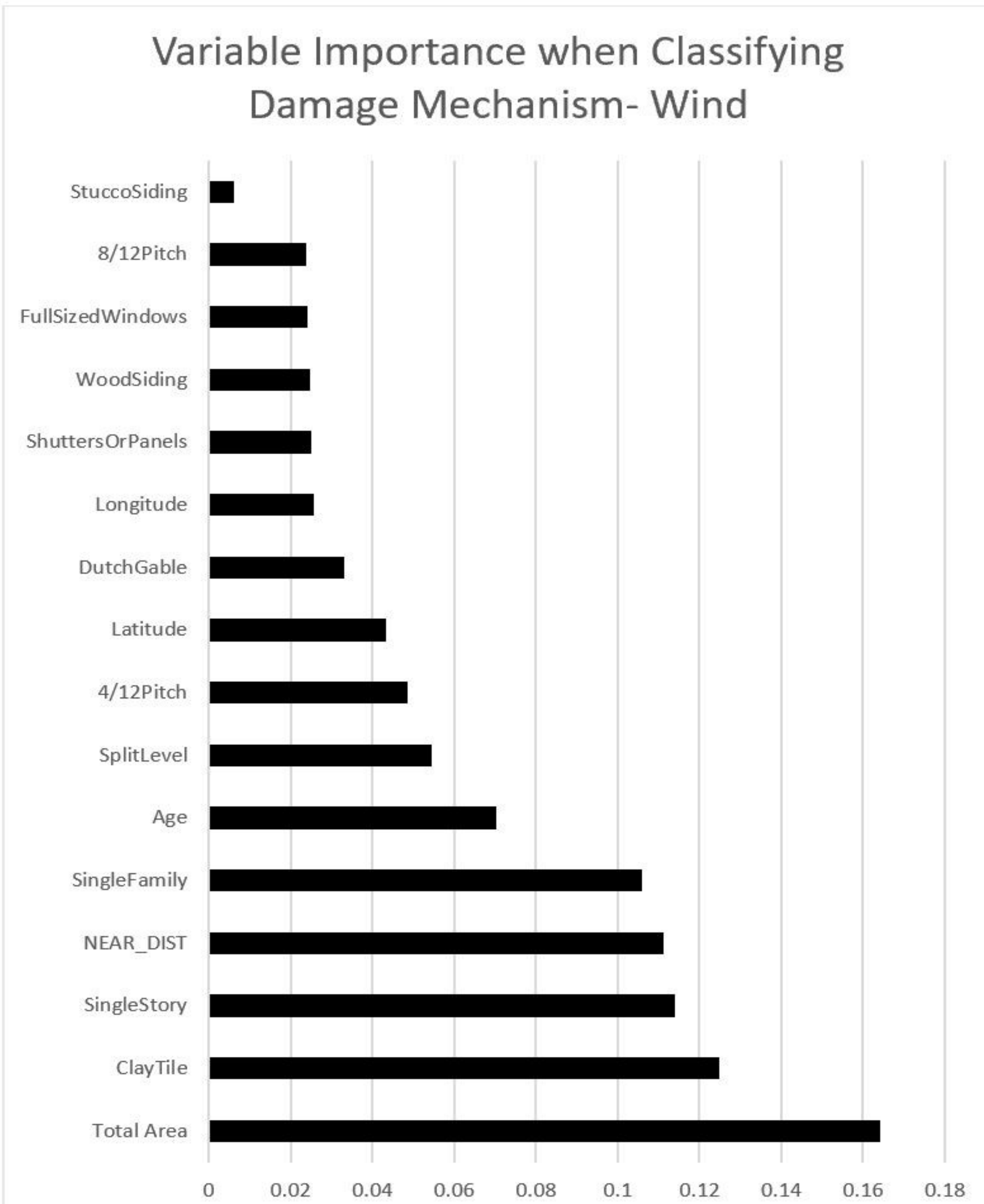

Figure 71: Variable importance when classifying, on damaged homes, if the damage mechanism was wind.

When classifying whether there was surge damage or debris damage, on homes that were damaged, the classifiers were optimized to a Decision Tree using Gini index and Random Forest using Gini index, respectively (**Figure 72** & **Figure 73**). The surge classifier had an accuracy of 100% and the debris accuracy was 92.2%. Because both surge damage and debris were so rare in this dataset, the classifiers which were most accurate predicted that there was no debris nor surge damage at all.

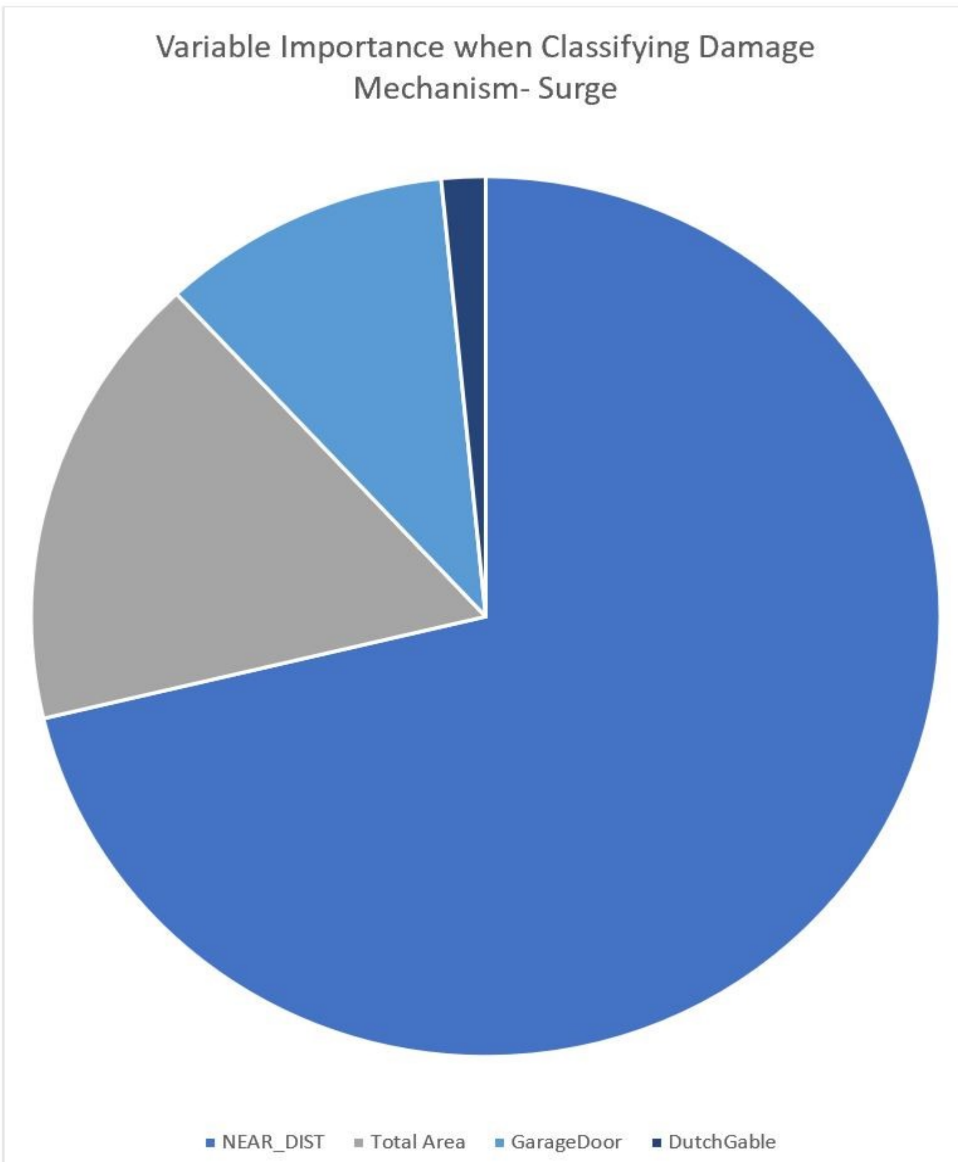

Figure 72: Variable importance when classifying the damage mechanism of storm surge.

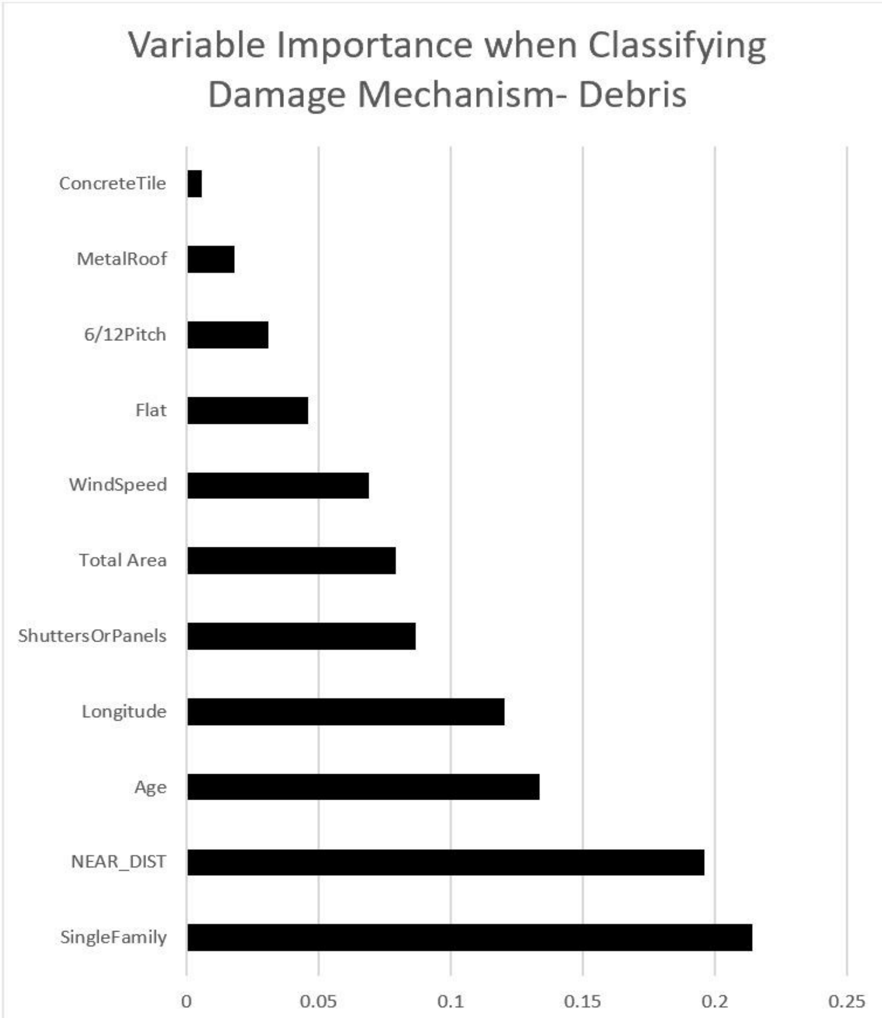

Figure 73: Variable importance when classifying debris as the damage mechanism.

Roof damage classification was broken-down by damage to the roof covering, roof sheathing, and roof framing materials. To classify roof cover, a Random Forest classifier was used, with the Gini index. The accuracy of this classifier was 35.5%, and the most important explanatory variables were: Single Family, Wind Speed, Distance to Coast, and Total Area (**Figure 74**). The roof sheathing classifier was a Gini index Decision Tree classifier, with an accuracy of 56% (**Figure 75**). The roof framing classifier had an optimized accuracy of 72.9%, using a Random Forest Gini-index classifier (**Figure 76**).

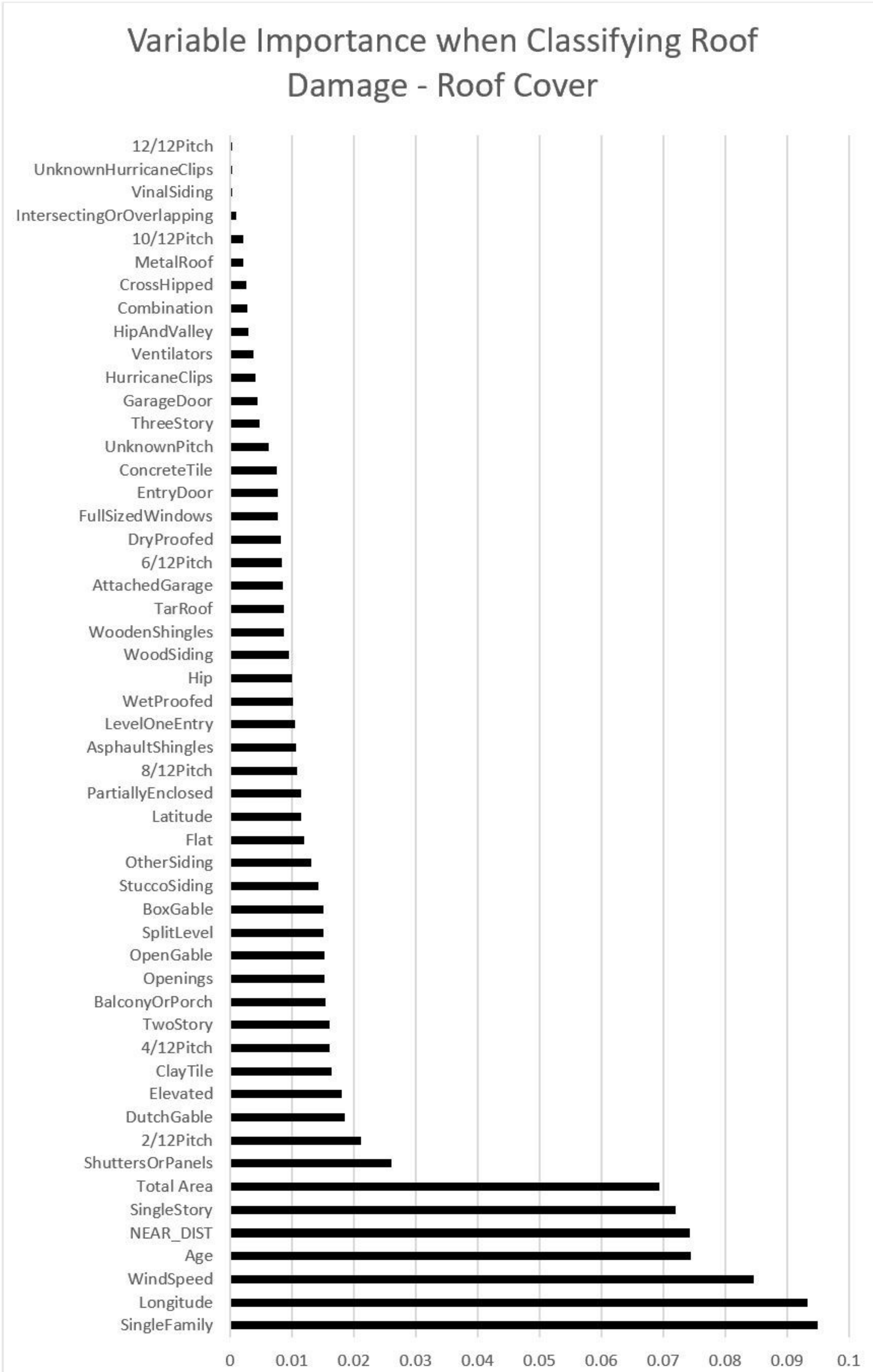

Figure 74: Variable importance when classifying roof cover damage.

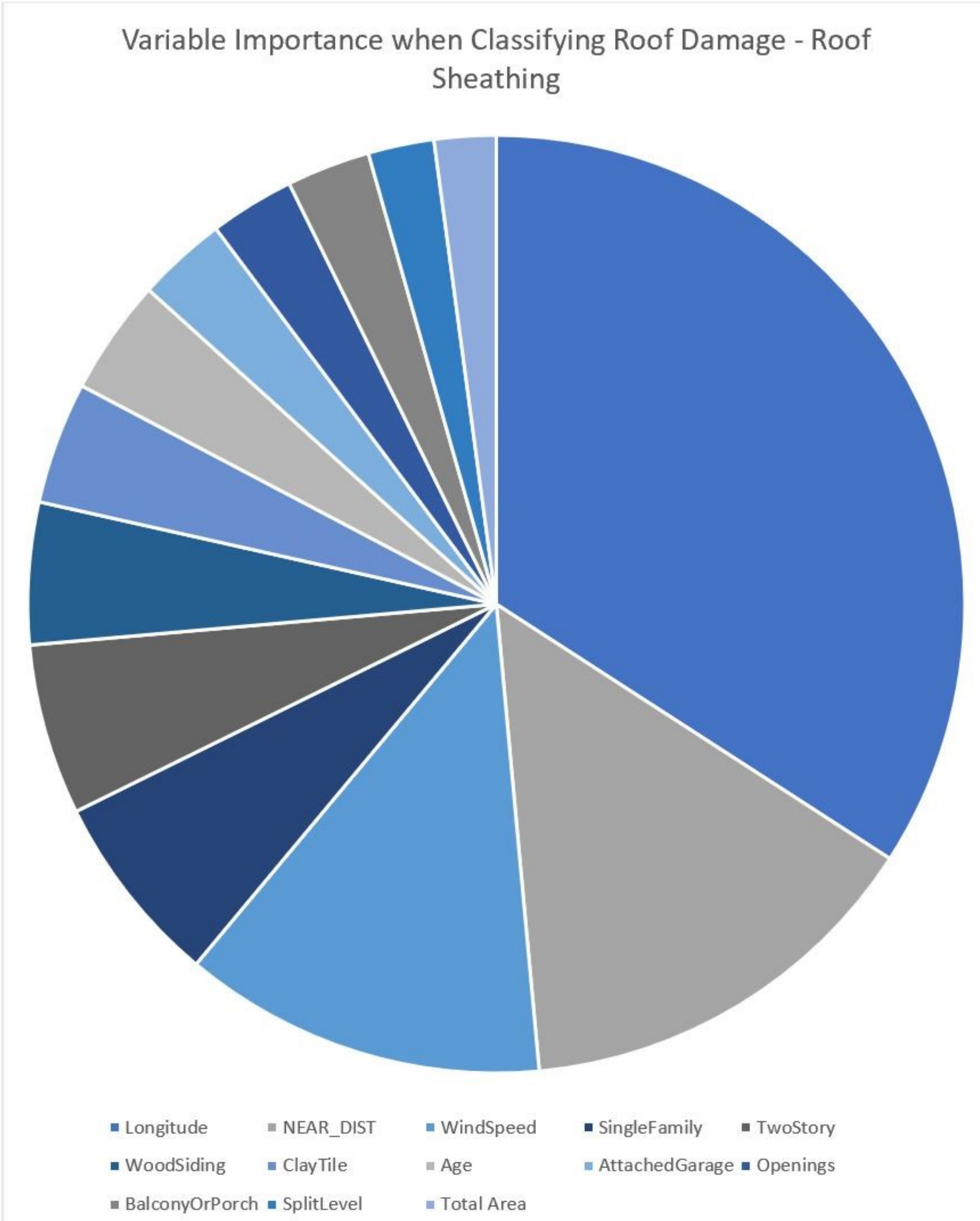

Figure 75: Variable importance when classifying roof sheathing damage.

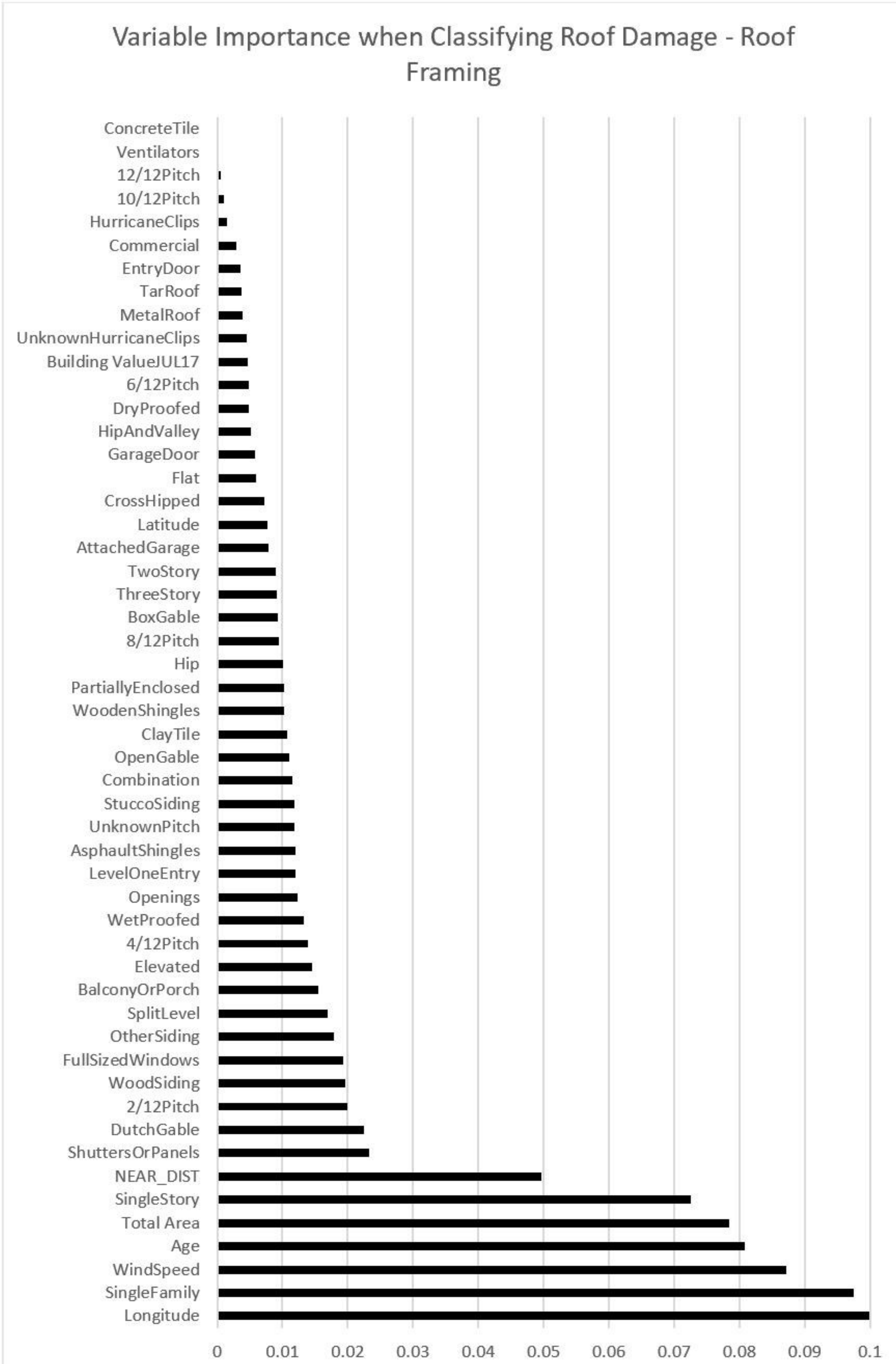

Figure 76: Variable importance when classifying roof framing damage.

Like roof damage, wall damage was also broken down by wall cover, sheathing, and framing damage. Wall cover damage was classified using a Decision Tree classifier, using Gini index. The accuracy of the wall-cover-damage classifier was 61.4%, and the most important variables were: distance to coast, total area, longitude, and wind speed (**Figure 77**). Based on the correlation matrix, the distance to the coast, longitude, and wind speed have high multicollinearity, this indicates the very high importance of wind speed on wall cover damage.

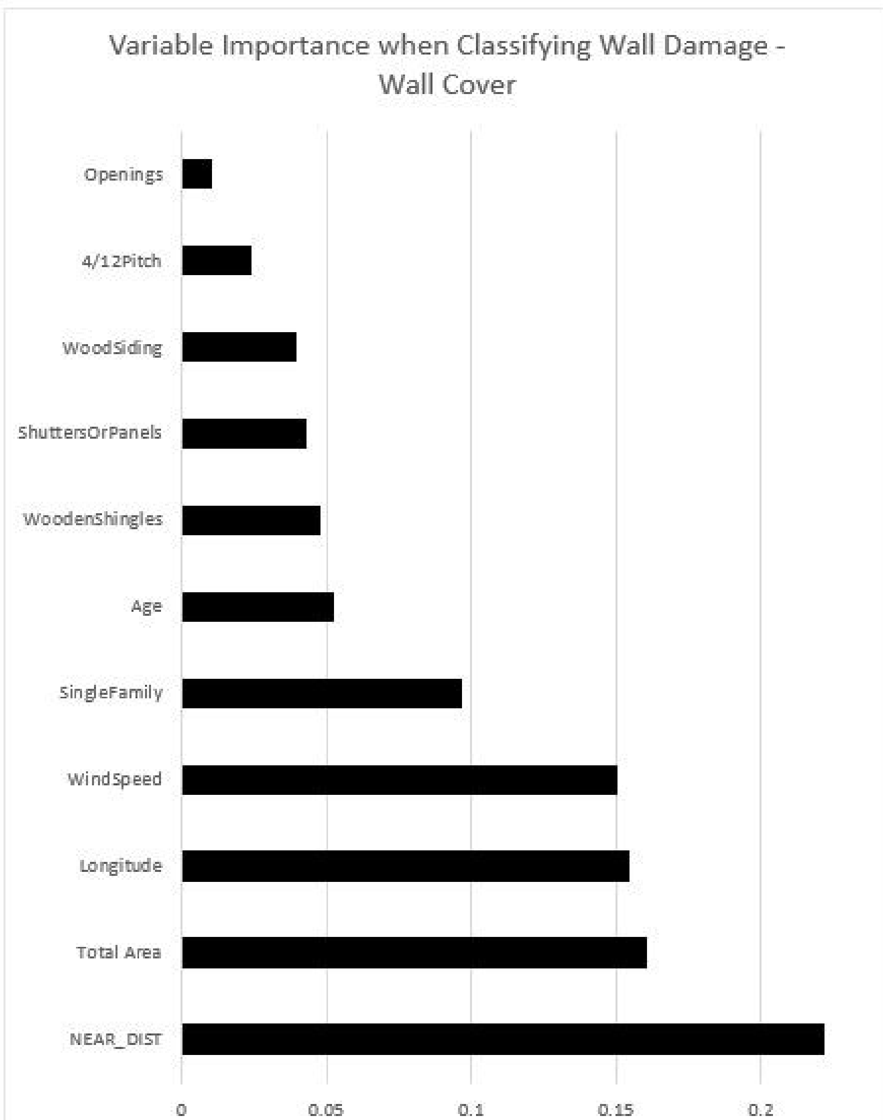

Figure 77: Variable Importance when classifying Wall Cover Material damage.

To classify wall sheathing damage, a Random Forest classifier was used, with Gini index. This classifier had an accuracy of 81.3% and the most important variables were Single Family use, longitude, wind speed, and age (**Figure 78**). Like wall cover damage, it appears that wall sheathing damage uses wind speed, and other related factors, to predict damage.

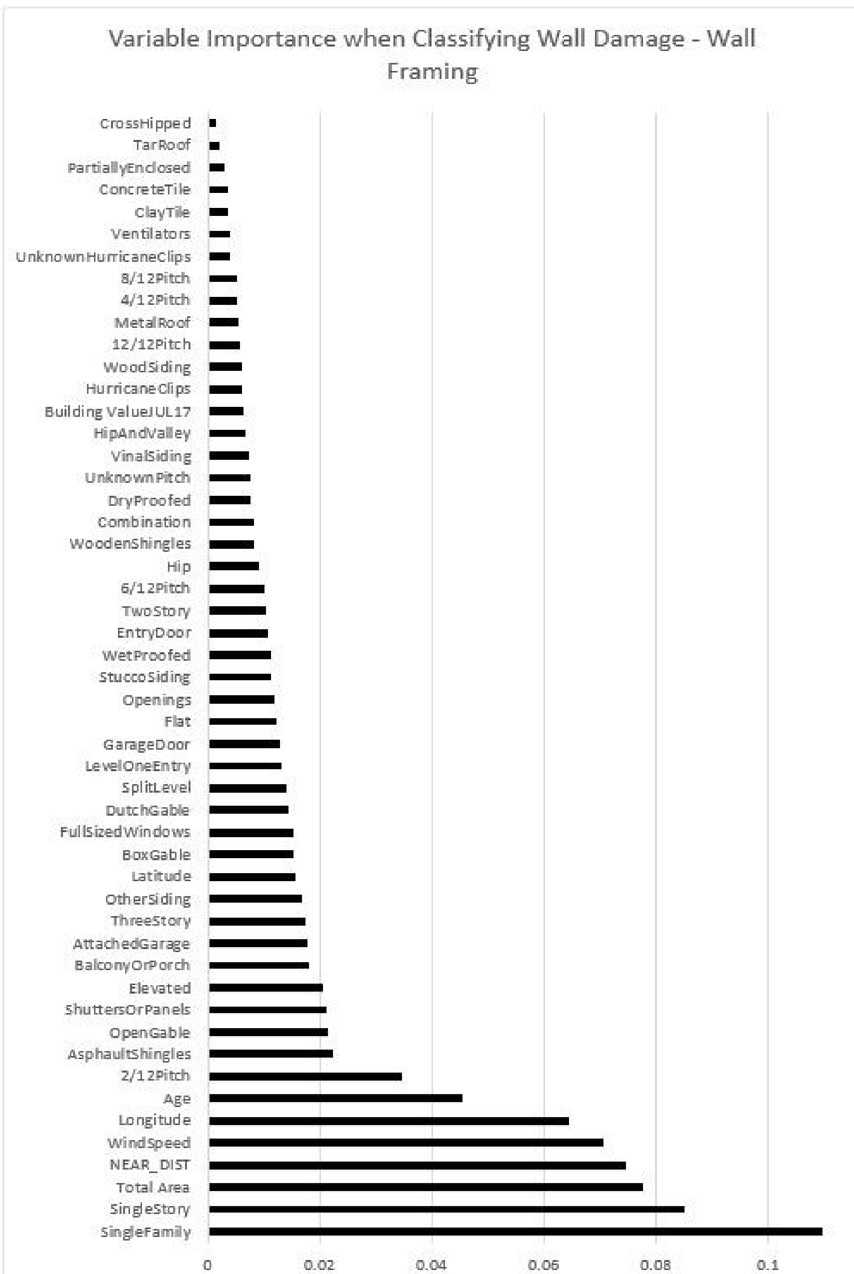

Figure 78: Variable Importance when classifying for Wall Sheathing damage.

Wall framing damage also was classified using a Gini-index, Random Forest classifier with an accuracy of 89.76%. The same variables which were most important for the wall sheathing classifier were also most important when classifying wall framing damage (**Figure 79**).

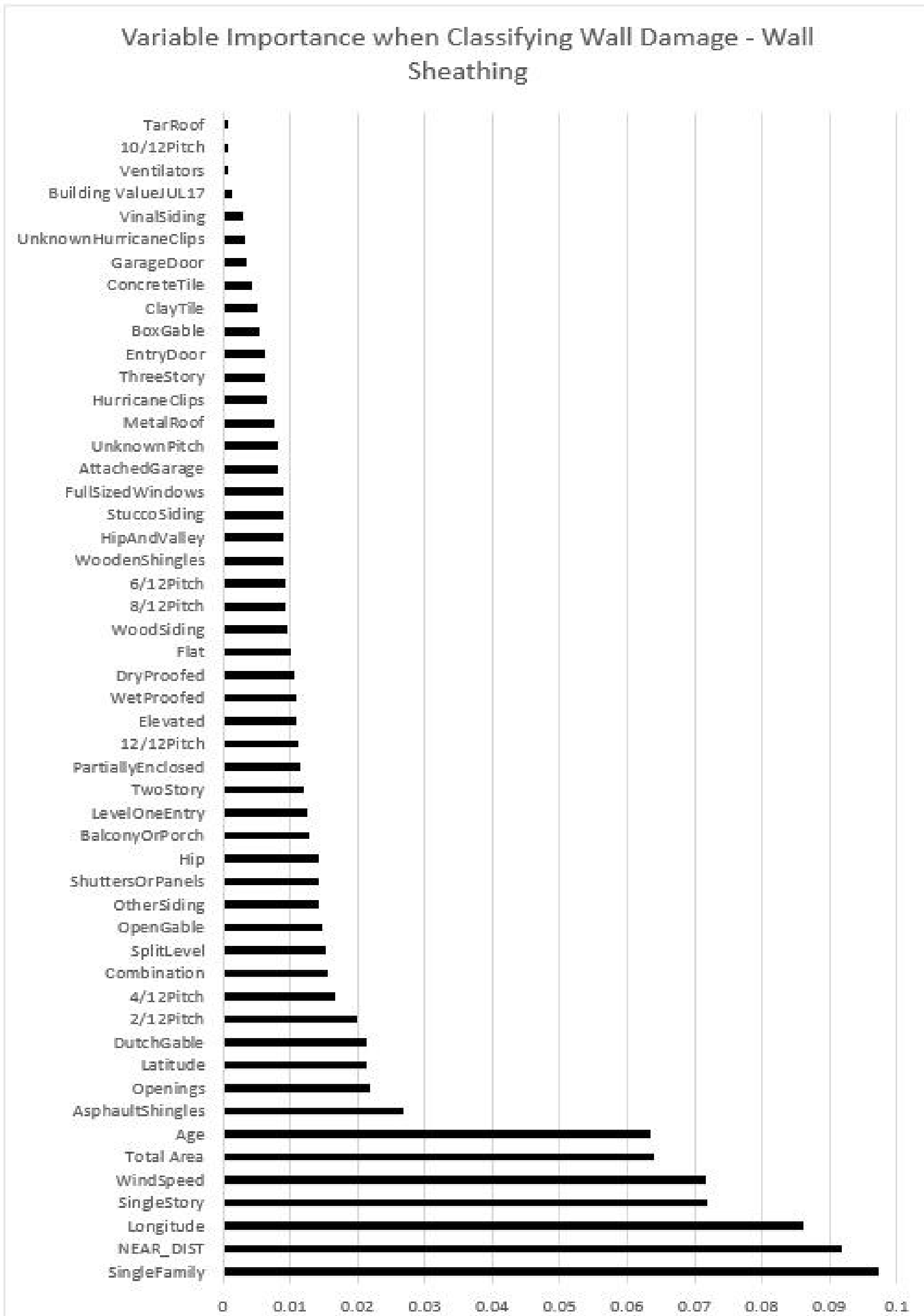

Figure 79: Variable Importance when classifying for Wall Framing damage.

The last series of damage measurements which were classified focused on damage to openings, including window damage, patio door damage, garage door damage, and entry door damage. Window damage was predicted using a Random Forest classifier, using Gini index to build branches. This classifier had an accuracy of 68.67%. The variables which were most important to window damage included, but were not limited to: single family use, longitude, age, and total area (**Figure 80**).

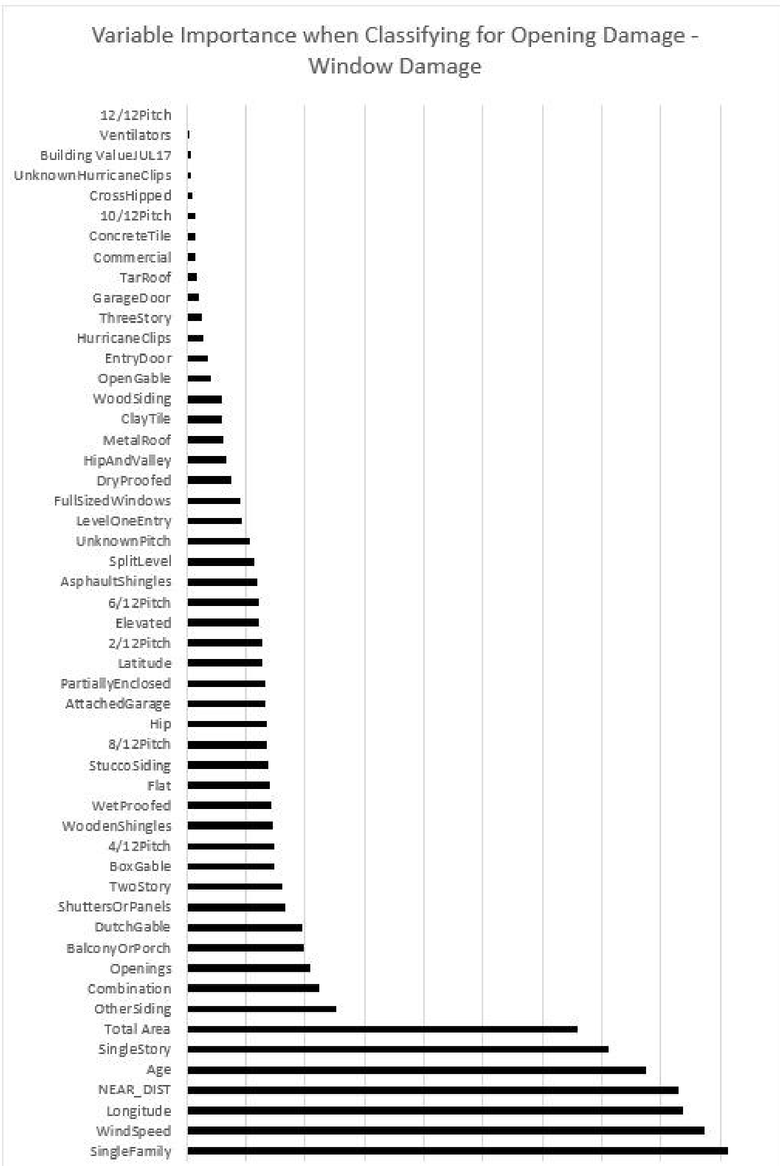

Figure 80: Variable Importance from Random Forest classifier, predicting window damage.

Variable importance of patio door damage indicates that the most important variables when classifying damage were: single family use, age, distance to coast, and total area (**Figure 81**). To classify patio door damage, an entropy-based Random Forest classifier was used, with an accuracy of 95.18%.

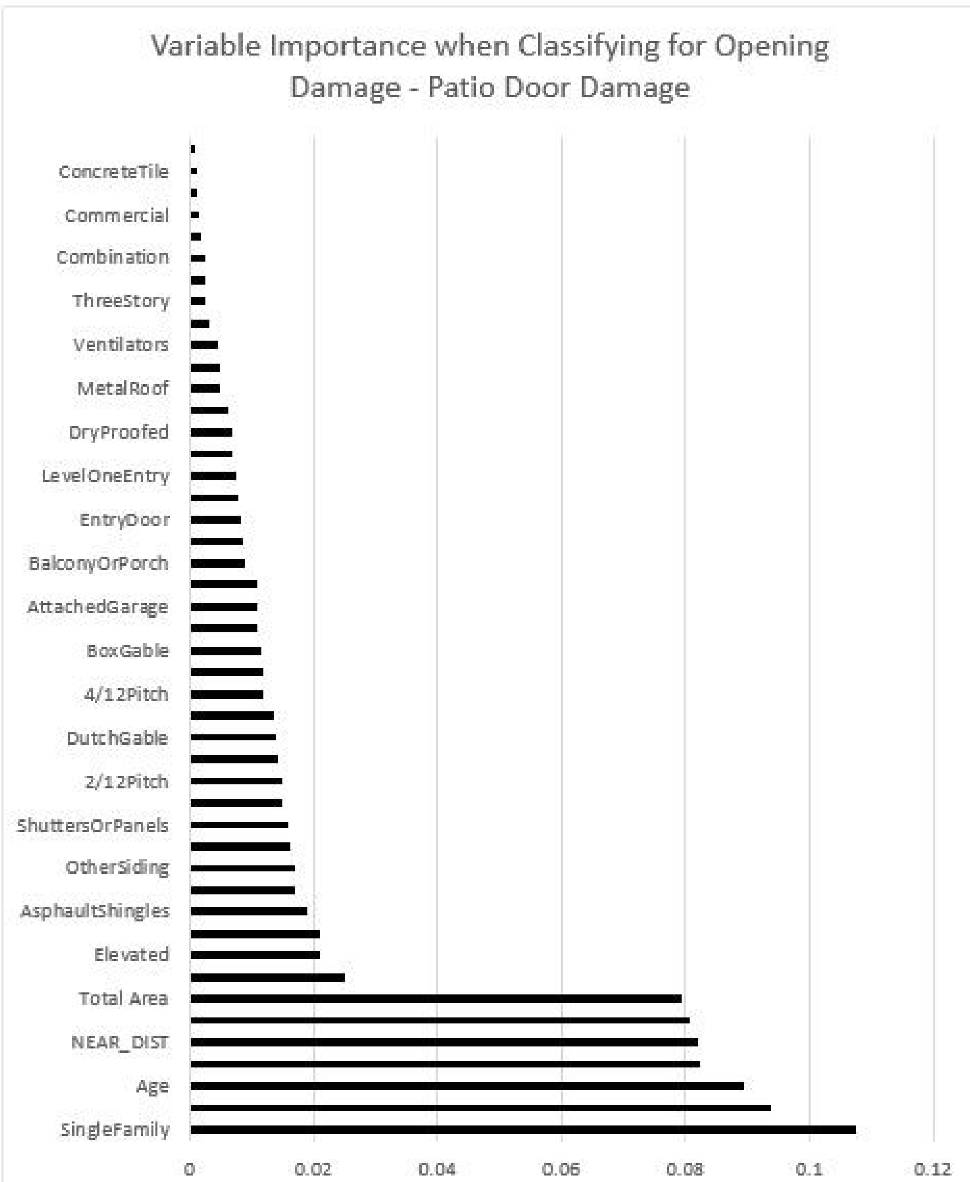

Figure 81: Variable Importance when predicting damage to a patio door.

A Random Forest classifier using entropy to build branches was used to predict damage to the garage door, when present. The accuracy of this classifier was 87.35% and the most important variables were: single family use, total area, age, and distance to coast (**Figure 82**).

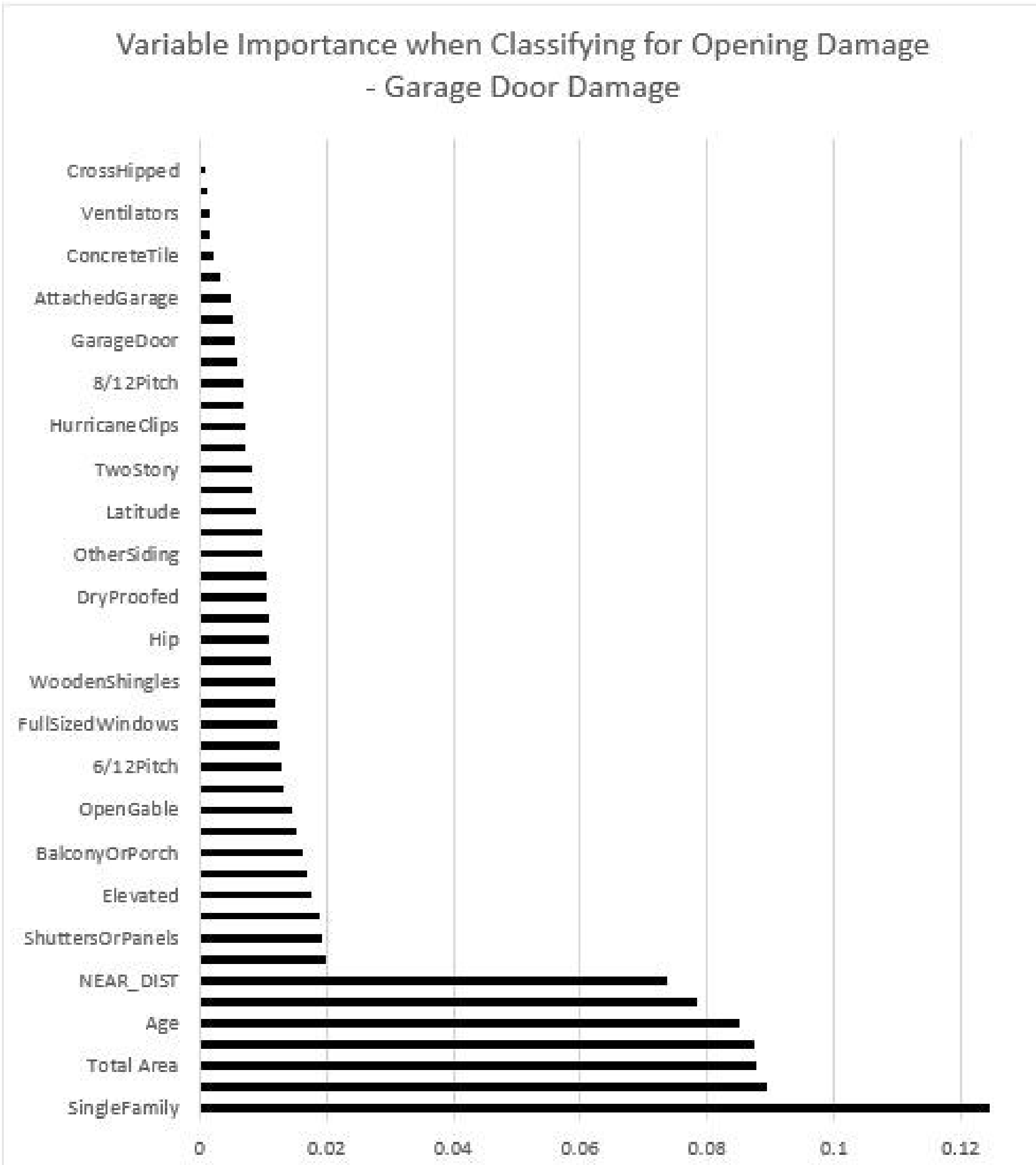

Figure 82: Variable Importance when predicting damage to a garage door.

The final classifier of damage was done on entry door damage, using a Random Forest classifier with entropy. Single story, age, longitude, and wind speed were among the most important variables to this classifier, whose accuracy was 88.55% (**Figure 83**).

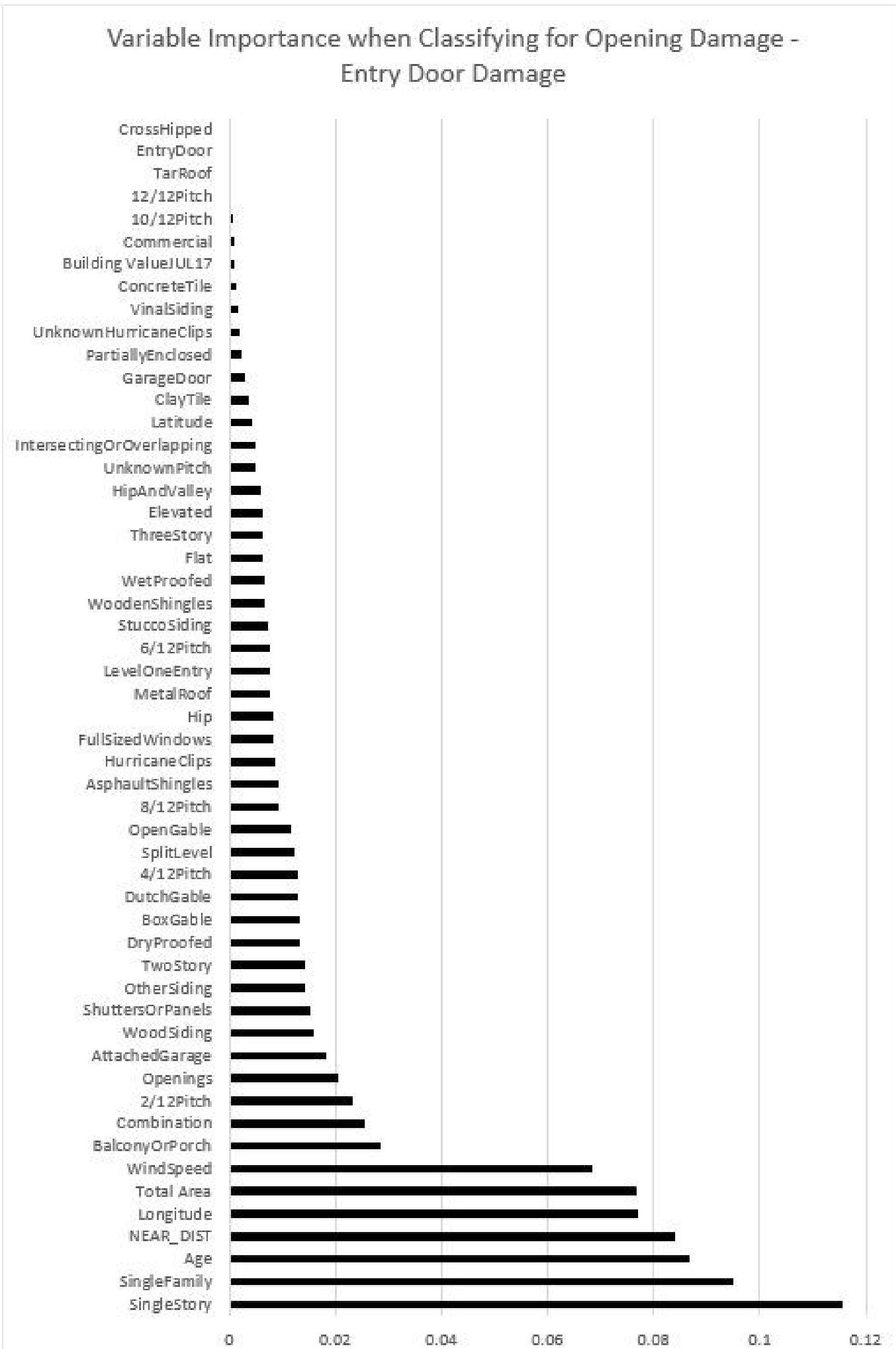

Figure 83: Variable Importance when classifying damage to the entry door.

3.5 Recommendations on Improvement

The results of analysis reveal two primary methods of further development: building communities more resilient through structural improvements, including building codes and zoning ordinances, and increasing efficiency of damage assessments without limiting data collection capacity.

Although some of the variables are difficult to alter without re-building a home entirely, such as home age, area, and location, community members in Key Allegro can rebuild their homes and community to be more resilient to similar storms in the future. Metal roof covering decreased overall damage, whereas asphalt roofs increased overall damage in this study area. Wood siding also received more damage than stucco siding. Buildings with higher value also had lower rates of damage- this may indicate that advanced building materials and construction techniques are beneficial in a hurricane. Wet-proofed, elevated foundations only performed slightly better than dry-proof, elevated and partially enclosed foundations.

Two methods for incorporating these findings into regular building practice is to change the local zoning ordinance or the international building code, if applicable. The City of Rockport adopted its Code of Ordinance in December 2018 and the Rockport Comprehensive/Master Plan is currently being updated with support from Texas A&M College of Architecture (Nira, 2018; Rockport City Charter, 2018). The Rockport Code of Ordinance has an article dedicated to Flood Damage Prevention, though it does not have an article on wind damage prevention (Rockport City Charter, 2018). The International Building Code also has a section of Flood-resistant Construction, though there is no such section for Wind-resistance (International Code Council, 2015). Because of the scale of reach of the Rockport City Comprehensive/Master Plan and the Code of Ordinance, it may be easier to alter than the much larger scale building code.

The International Building Code is updated and released every three years, the most recent edition having been released in 2018 (International Code Council, 2018). Hurricane Harvey struck the study area in 2017, so the most updated building code would have been 2015. The 2015 International Building Code includes subsections on Wind design within the Building Planning chapter (International Code Council, 2015, R301.2). The provisions of this code appear to be reliant on the wind exposure determined by the jurisdiction and the Ultimate Design Wind Speed Map, indicating that Rockport should design for wind speeds of 150 mph, indicating the 7% probability of wind speed exceedance in 50 years (International Code Council, 2015, Figure R301.2(4)A). The Code also suggests that structures be designed in accordance with the AF&PA *Wood Framed Construction Manual* (WFCM), ICC *Standard for Residential Construction in High-Wind Regions* (ICC 600), ASCE *Minimum Design Loads for Buildings and Other Structures* (ASCE 7), AISI *Standard for Cold-Formed Steel Framing—Prescriptive Method For One- and Two-Family Dwellings* (AISI S230), and the *International Building Code*(International Code Council, 2015, R301.2.1.1).

The 2015 International Building Code has subsections on compliance for "Wind resistance of asphalt shingles" and wind resistance for photovoltaic shingles (International Code Council, 2015, R905.2.4.1; International Code Council, 2015, R905.16.7). For photovoltaic shingles, there is a subsection on high-wind speed and the underlayment requirements. In areas exposed to winds of 140 mph or higher, such as Key Allegro during Hurricane Harvey, homes are required to install the underlayment with corrosion-resistance fasteners, in a specific pattern, with specific spacing (International Code Council, 2015, R905.16.4.2). Further wind protection requirements are related to the installation of photovoltaic systems, requiring panels or modules to be installed to resist the component and cladding loads (International Code Council, 2015, R907.2).

Changes made to the International Building Code in the 2018 version include updated wind speed maps and new wind speed terminology (International Code Council, 2018, 1609). For risk category II structures, including residential structure, a separate wind speed map was created, requiring Rockport to design for wind speed of 160 mph (International Code Council, 2018, Figure 1609.3(1)). Perhaps, if homes in Key Allegro were designed to the 2018 International Building Code standards, there would have been less damage to homes from single-hazard wind damage.

The next method for applying findings from this study would be to further iterate upon damage assessment protocols with the goal of reducing time of assessments, lessen the amount of time volunteers must spend on-site, and improve the overall data collected using the damage assessment. The machine learning classifiers can help to identify variables that can be most useful for future damage prediction. The results of the optimized machine learning classifiers in this study indicate that the features which were most useful for classification were: distance to coast, longitude, single-family use, age, total area, wind speed, and single story. Future damage assessments should therefore include questions about land topography, distance to coast, location, structural use, age, area, wind speed and other indicators of the hazard, and the number of stories. While the features with the lowest importance were: grade level entry, intersecting or overlapping roofs, 10/12 roof pitch, commercial uses, and vinyl Siding. Future damage assessments, according to these results, should reconsider using entry level, many specific roof shapes, specific roof slopes, uses that are not residential, or specific siding materials. Previous studies, in contrast, have indicated that some of these factors had very high correlation with damage (Crandell, 1998; Egnew, 2018; Xuan, 2016). This would indicate that future research should continuously be iterating on damage assessment methodology.

3.6 Limitations and Future Studies

This study was limited to the dataset, specifically chosen for the pure-nature of the damage mechanism. The dataset used in this study was limited to mostly single-story wood-framed residential structures, in relatively small numbers. The small size of the dataset may have limited the accuracy of the spatial and machine learning classifiers. Exploratory Regression in ArcMap was not run with all independent variables predicting all post-storm measurements. When using the exploratory regression tool with damage rating as the dependent variable and all pre-storm variables as the explanatory features, the exploratory regression tool took over 8 hours to process.

There are also limitations of relying on imagery for damage assessment, such as the presence of trees or dense shrubbery. In some cases, pre-storm imagery was taken during the growing season, so some buildings are covered by plants or shadows. This study relies heavily on imagery and data from external sources – so data relies on the continuation of this external data collection. For example, the United States federal government shut down during the data collection period, which resulted in limited access to NOAA aerial. For on-site team, collecting all necessary information, this would not have been a factor affecting their data. In the case of this study, each external source provides a significant amount of important information.

The questions asked in a damage assessment should continuously evolve based on the usefulness of that information. Because time and resources are often limited, optimizing the questions which are being asked while collecting all possible information will build the best dataset with the smallest amount of time. Results of the optimized Machine Learning classifiers, specifically feature importance, indicate that future damage assessments should prioritize distance to coast, latitude and longitude, building-use, age, area, wind speed, and number of stories. If time is constrained in future studies, these variables should consistently be included in assessments. Aside from altering the questions asked during the damage assessment, the assessment should be more automated. Ideally pre- and post-storm data collection and processing would be achieved using machine learning algorithms and computer vision application.

Future studies utilizing this damage assessment protocol, damage collection and assessment processes, should consider multi-hazard events in locations where multi-hazard damage was found. In addition to the data collected in this study, one may consider utilizing similar data collected in neighboring communities, to diversify the building styles, home value, and demographic population being affected. Although the amount of time taken to assess more buildings is longer, increasing the amount of homes in the dataset may improve accuracy. Larger datasets are ideal for statistical and machine learning accuracy, so combining datasets from past and future studies may improve the accuracy of results of similar analyses.

If time is not constrained, future studies may consider running exploratory regression to describe different damage scenarios, for example, to predict window damage, roof cover damage, etc. Data collected by the mobile scanning vehicle also included LiDAR data, which was not used in this study. LiDAR can be used to improve accuracy of damage assessment measurements, reducing inherent bias and inaccuracy of estimating pre- and post-storm values.

Hurricanes and other natural disasters have impact that goes far beyond structural implications. Future studies should consider the impacts of hurricanes on social, economic, and natural systems, along with the structural impacts. Improvements to any of these systems may affect others because they are highly interdependent.

Chapter 4: Conclusion

4.1 Conclusion

This study combines advances in post-hurricane data collection and damage assessment protocol with spatial analysis that links building attributes with single-hazard wind damage and machine learning classifiers which can be used to further improve damage assessments. The overall goal is to reduce time required to collect data, assess building damage, and improve analysis which will improve resiliency of communities from risks of future hurricanes and other natural disasters.

Through utilization of a mobile scanning vehicle to collect damage data, more comprehensive information can be collected, including panoramic photos, LiDAR, and aerial imagery. The mobile nature of this data collection reduces exposure to harsh post-disaster environments to volunteers, reduces required time and other resources to collect information, and decreases the number of volunteers to collect enough data. This method of data collection adds time to the post-processing activities, which include the damage assessment.

The damage assessment methodology combined suggestions from results of previous studies and the protocols employed by previous studies. This allowed the damage assessments in this study to reduce the amount of time taken to collect information without compromising the robustness of the data. This damage assessment utilized virtual and public datasets to provide pre-storm information, in combination with post-storm data collected by the mobile scanning vehicle.

553 structures were assessed and analyzed in Key Allegro, a community in Rockport, Texas, the location of the first landfall of Hurricane Harvey in the United States in July 2017. Homes in this community have a relatively consistent age, assumed to result in similar building codes, building materials, and construction practices. This data was also almost entirely pure single-hazard wind damage.

Clustering and Outlier spatial analysis indicated that damage rating was related to peak wind speed, indicating a cluster of high-value damage rating on the northernmost tip of the island. Explanatory regression, in ArcMap, also showed that the most significant variables were: Age, Latitude, Metal Roofs, Distance to Coast, Total Area, Asphalt Roofs, Wood Siding, Stucco Siding, Two Story Buildings, and Building Value. Age, Latitude, Asphalt Roof, and Wood Siding have consistently positive relationships with damage rating. These relationships are consistent with previous studies (Crandell, 1998; Eamon, 2017; Egnew 2018; Lankford, 2018; Xian, 2015). Variables with consistently negative relationships with damage rating include: Metal Roofs, Distance to Coast, Total Area, Stucco Siding, Two Story Buildings, and Building Value. Reinforced exterior facades, such as metal roofs and stucco siding have been related to lower rates of damage in the past (Lankford, 2018). Home value has also been negatively correlated with damage in the past (Egnew, 2018). In contrast to the exploratory regression results, though, distance to the coast and total home area have been positively correlated with damage in past studies (Egnew, 2018; Kennedy et. al, 2011; Xian, 2015). Similarly, two-story homes are expected to have more damage from wind, because of the high elevation, than single-story homes (Crandell, 1998; Egnew, 2018; Xuan, 2016). Inconsistencies with past studies may be related to the small size of the dataset or unintended dependencies between variables, such as the relationship between wind speed and distance to the coast.

The machine learning algorithms used in this study indicate that some variables in the damage assessment were not entirely independent and carried inherent multi-collinearity. Variables which are highly correlated can be removed, reducing the amount of time spent to conduct a damage assessment. Further improvements to the damage assessment protocol can be found through utilization of machine learning classifiers, optimized by accuracy when validated against a testing dataset, to understand the importance of each variable when classifying damage rating. The variables with the highest feature importance include: Distance to Coast, Longitude, Single-Family, Age, Total Area, Wind Speed, and Single Story. These variables should be prioritized in future studies, while variables with low feature importance, such as Grade Level Entry, Intersecting or Overlapping Roofs, 10/12 Roof Pitch, Commercial uses, and Vinyl Siding, should not be included in future damage assessments. By removing low-value questions in a damage assessment, the amount of time taken to assess homes is reduced and enough information is still collected in the process.

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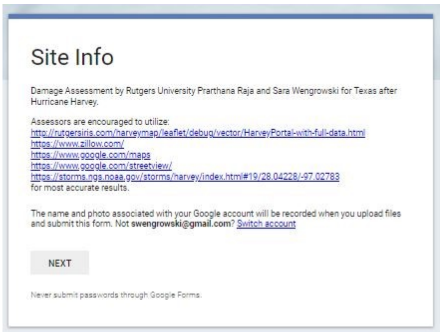
Appendix

Hurricane Harvey Damage Assessment Form



Site Info

Damage Assessment by Rutgers University Prarthana Raja and Sara Wengrowski for Texas after Hurricane Harvey.

Assessors are encouraged to utilize:
http://rutgersiris.com/harveymap/leaflet/debug/vector/HarveyPortal-with-full-data.html
https://www.zillow.com/
https://www.google.com/maps
https://www.google.com/streetview/
https://storms.ngs.noaa.gov/storms/harvey/index.html#19/28.04228/-97.02783
for most accurate results.

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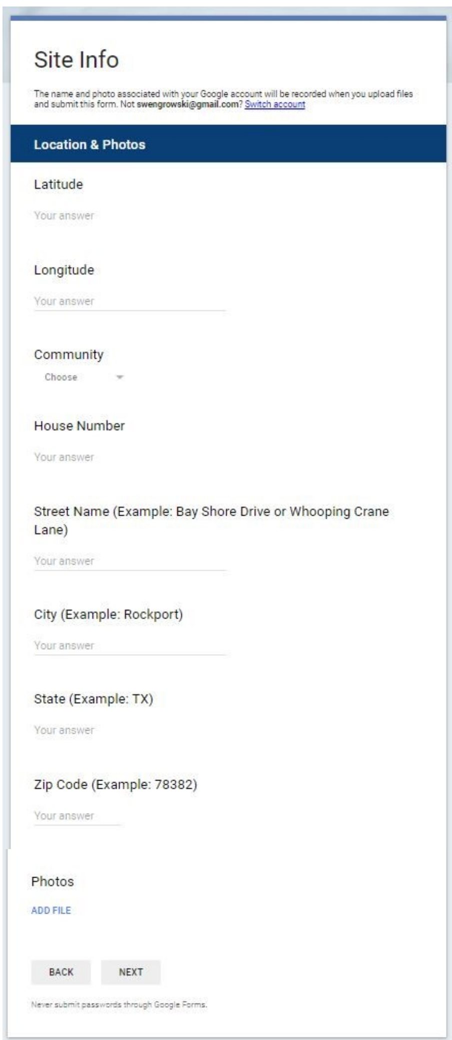

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Location & Photos

Latitude

Your answer

Longitude

Your answer

Community

Choose

House Number

Your answer

Street Name (Example: Bay Shore Drive or Whooping Crane Lane)

Your answer

City (Example: Rockport)

Your answer

State (Example: TX)

Your answer

Zip Code (Example: 78382)

Your answer

Photos

ADD FILE

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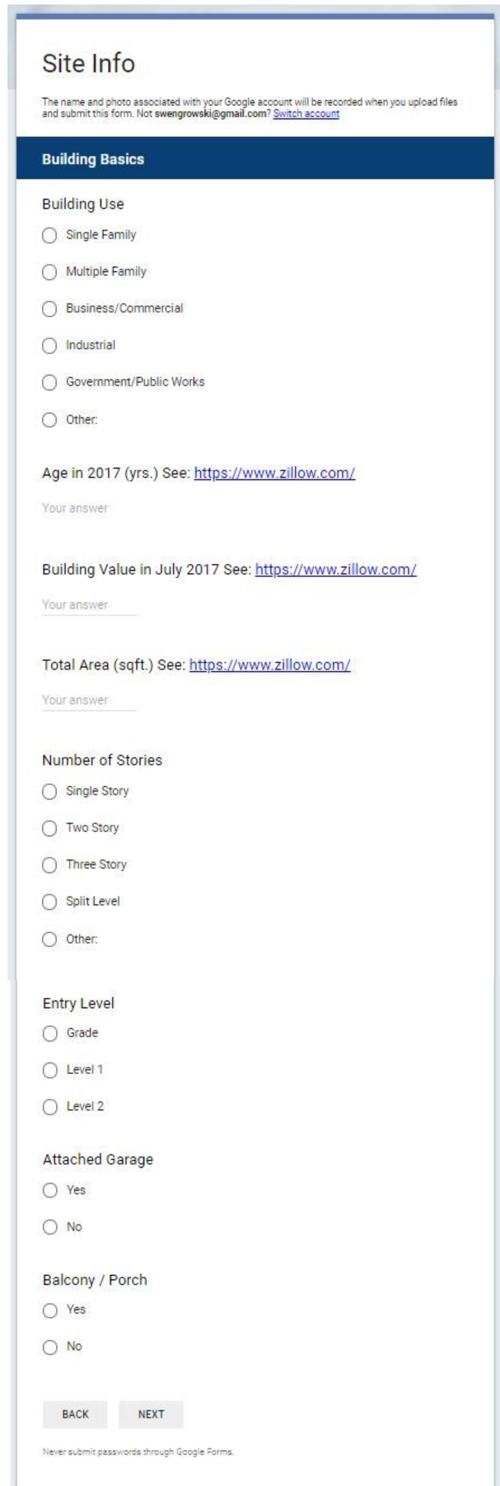

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Building Basics

Building Use

- Single Family
- Multiple Family
- Business/Commercial
- Industrial
- Government/Public Works
- Other:

Age in 2017 (yrs.) See: https://www.zillow.com/

Your answer

Building Value in July 2017 See: https://www.zillow.com/

Your answer

Total Area (sqft.) See: https://www.zillow.com/

Your answer

Number of Stories

- Single Story
- Two Story
- Three Story
- Split Level
- Other:

Entry Level

- Grade
- Level 1
- Level 2

Attached Garage

- Yes
- No

Balcony / Porch

- Yes
- No

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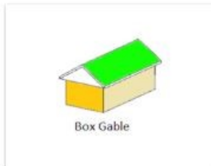
Building Envelope

Building envelope parameters

ROOF

Roof Shape

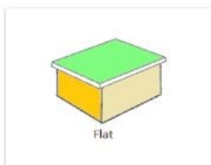
◯ Hip



◯ Box Gable

◯ Open Gable

◯ Dutch Gable



◯ Hip and Valley

◯ Intersecting

◯ Cross Hipped

◯ Combination

Roof Covering

◯ Asphalt Shingle

◯ Wooden Shingle

◯ Metal

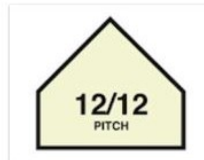
◯ Clay Tile

◯ Concrete Tile

◯ Tar Roof

◯ Slate

Roof Slope



◯ 12/12

◯ 10/12

◯ 8/12

◯ 6/12

◯ 4/12

◯ 2/12

◯ Flat Roof

Roof Framing

◯ Wood

◯ Metal Joist

◯ Structural Steel

◯ CF Steel

◯ CIP

◯ Other: ______

Hurricane Clips?

- ◯ Yes
- ◯ No
- ◯ Don't Know

WALL

Wall Framing

- ☐ Wood Framed
- ☐ Load Bearing Masonry
- ☐ Cold Form Steel
- ☐ Structural Steel
- ☐ Not Determinable
- ☐ Other:

Wall Cover

- ☐ Stucco
- ☐ Vinyl Siding
- ☐ Curtain Wall
- ☐ Brick Veneer
- ☐ Wood Siding
- ☐ Aluminium Siding
- ☐ Hardie Board
- ☐ Other:

OPENINGS

Entry Door?

- ◯ Yes
- ◯ No
- ◯ Don't Know

Garage Door?

- ◯ Yes
- ◯ No
- ◯ Don't Know

Full-Sized Windows?

- ◯ Yes
- ◯ No
- ◯ Don't Know

Ventilators?

- ◯ Yes
- ◯ No
- ◯ Don't Know

Percentages of openings ?

	0	1	2	3	4	5	6	7	8	9	10	
0 %	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	100%

Shutters/Panels?

- ◯ Yes
- ◯ No
- ◯ Don't Know

Elevated ?

- ◯ Yes
- ◯ No

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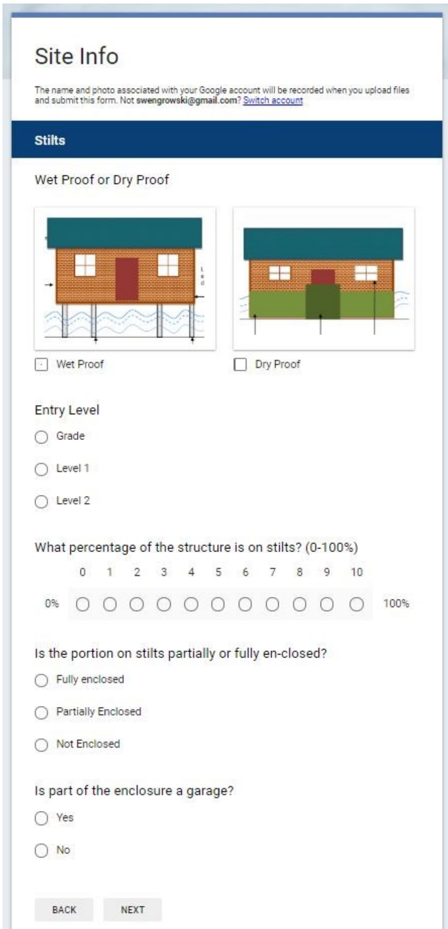

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Stilts

Wet Proof or Dry Proof

- [ ] Wet Proof
- [ ] Dry Proof

Entry Level

- ◯ Grade
- ◯ Level 1
- ◯ Level 2

What percentage of the structure is on stilts? (0-100%)

	0	1	2	3	4	5	6	7	8	9	10	
0%	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	100%

Is the portion on stilts partially or fully en-closed?

- ◯ Fully enclosed
- ◯ Partially Enclosed
- ◯ Not Enclosed

Is part of the enclosure a garage?

- ◯ Yes
- ◯ No

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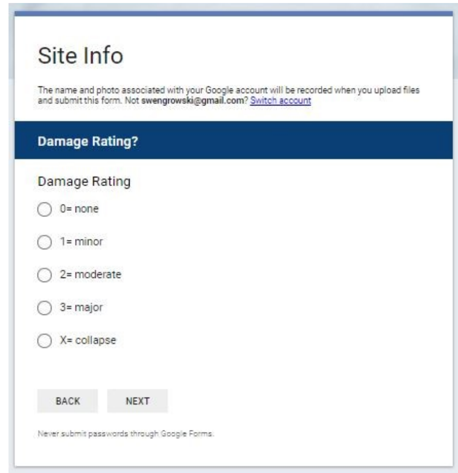

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Damage Rating?

Damage Rating

- ◯ 0= none
- ◯ 1= minor
- ◯ 2= moderate
- ◯ 3= major
- ◯ X= collapse

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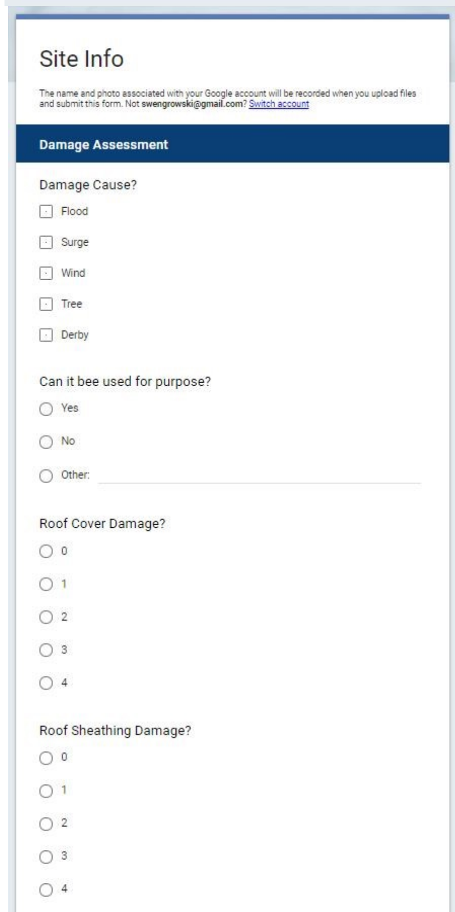

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Damage Assessment

Damage Cause?

- [ ] Flood
- [ ] Surge
- [ ] Wind
- [ ] Tree
- [ ] Derby

Can it bee used for purpose?

- ◯ Yes
- ◯ No
- ◯ Other:

Roof Cover Damage?

- ◯ 0
- ◯ 1
- ◯ 2
- ◯ 3
- ◯ 4

Roof Sheathing Damage?

- ◯ 0
- ◯ 1
- ◯ 2
- ◯ 3
- ◯ 4

Roof Framing Damage?

- ○ 0
- ○ 1
- ○ 2
- ○ 3
- ○ 4

Wall Cover Damage?

- ○ 0
- ○ 1
- ○ 2
- ○ 3
- ○ 4

Wall Sheathing Damage?

- ○ 0
- ○ 1
- ○ 2
- ○ 3
- ○ 4

Wall Framing Damage?

- ○ 0
- ○ 1
- ○ 2
- ○ 3
- ○ 4

Window Damage?

- ○ Yes
- ○ No
- ○ Other:

Patio Door Damage?

- ○ Yes
- ○ No
- ○ No Patio Door
- ○ Other: ____________

Garage Door Damage?

- ○ Yes
- ○ No
- ○ No Garage
- ○ Other: ____________

Entry Door Damage?

- ○ Yes
- ○ No
- ○ Other: ____________

BACK SUBMIT

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