Impact of Flooding on Power System Restoration Following a Hurricane

by

Grant Robert Cruse

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This thesis was presented

by

Grant Robert Cruse

It was defended on

July 8, 2020

and approved by

Alexis Kwasinski, Ph.D., Associate Professor, Department of Electrical and Computer Engineering

Masoud Barati, Ph.D., Assistant Professor, Department of Electrical and Computer Engineering

Brandon Grainger, Ph.D., Assistant Professor, Department of Electrical and Computer Engineering

Vaidyanathan Krishnamurthy, Ph.D., Research Associate, University of Texas at Austin

Katrina Kelly-Pitou, Ph.D., Economist and Energy Systems Strategist, SmithGroup

Thesis Advisor: Alexis Kwasinski, Ph.D., Associate Professor, Electrical and Computer Engineering

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Grant Cruse, M.S.

University of Pittsburgh, 2020

Historically, hurricanes have been a major cause of devastation and widespread power outages in many areas of the United States. Since the 1970s, several popular methods for estimating hurricane intensity have been developed, but these have tended to focus solely on the amount of damage and outages that can be expected rather than the amount of time that will be required to restore power. Additionally, these methods allow for the inclusion of only a small number of variables, such as wind speeds and storm surge. In Krishnamurthy's and Kwasinski's "Characterization of Power System Outages Caused by Hurricanes through Localized Intensity Indices," four metrics that describe the damage sustained by and the restoration times required for power systems that are affected by hurricanes were proposed as alternatives to the existing methods for estimating hurricane damage. These were maximum outage incidence, restoration times for 95% and 98% of the total number of outages, and average outage duration. Regression curves were generated by relating these indices to four variables that describe the intensity of the storms. The results showed that the generated curves fit the measured data very well, but they also seemed to suggest that there are other factors that may affect the metrics. In this work, three additional variables were included in the models to examine the impact of flooding on the metrics, particularly the amount of time that is required to restore outages. These were the flooded area in a county, the time until flood waters in a county receded, and the total area flooded by the hurricane.

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Nomenclature

Symbol	Description
a	Regression Coefficient (Not Part of Basis Function)
A_F	Area in a County Flooded by a Hurricane
A_S	Area Affected by a Hurricane
A_{TF}	Total Area Flooded by a Hurricane
B	Basis Function
c	Regression Coefficient
f	Regression Function
H	Storm Surge Height
i	Particular County
j	Particular Observation of a Regression Variable
k	Particular Regression Coefficient
ℓ	Total Number of Regression Coefficients
$LTCII$	Base Form of Local Tropical Cyclone Intensity Index
$LTCII_{AOD}$	Intensity Index for Average Outage Duration
$LTCII_{MOI}$	Intensity Index for Maximum Outage Incidence
$LTCII_{Tr}$	Intensity Index for Restoration Times

Symbol	Description
m	Total Number of Observations
n	Total Number of Regression Variables
p	Regression Coefficient (Part of Basis Function)
r	Residual
${R_0}^2$	Ordinary Coefficient of Determination
R^2	Adjusted Coefficient of Determination
S_f	Sum of Squared Residuals
$S_{\bar{y}}$	Total Sum of Squared Errors
T_F	Time Until Flood Waters Receded
T_S	Time Under Storm Conditions
τ	Subscript for Type of Restoration Time (Either 95% or 98%)
V	Maximum One-Minute Sustained Wind Speed
x	Independent Variable for Regression Analysis
X	Generic Hurricane Action
y	Dependent Variable for Regression Analysis
$\bar{y}$	Average Value of Dependent Variable Data
0	Subscript Indicating Reference Value of a Hurricane Action

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1.0 Introduction

Flooding due to the storm surge and rainfall from a hurricane has historically been shown to be a major cause of damage and loss of life [1]. In addition to these devastating effects, flooding has caused major delays during the power system restoration process that immediately follows a hurricane event because flood waters affect the accessibility of many areas, especially when the flooding impedes movement across major highway systems [2].

In order to quantify the impact that flooding has on the amount of time required for restoration, the statistical models contained in [3] were updated to account for the extent of flooding that was experienced in various counties or parishes in the United States following a hurricane. The models previously related four variables, which were storm surge height, maximum sustained wind speed, time under storm conditions, and area on land affected by the hurricane, to four outage metrics: maximum outage incidence, 95% and 98% restoration times, and average outage duration. Regression curves were generated to graphically show these relationships, and the results from [3] showed that these curves were adequate representations of the measured data. However, they also seemed to suggest that there are other factors that may affect the metrics.

Therefore, the purpose of this work was to achieve two goals. The first was to introduce new variables that quantify the effects of flooding so that the previous regression curves could be improved, and the second, based on the results, was to draw conclusions about how flooding affects the restoration process. Three additional variables were included in the models from [3] to examine the impact of flooding on the metrics, particularly the restoration times and the average outage duration.

1.1 Electric Utility Outage Restoration Process

When weather disturbances with thunderstorms occur over an ocean, a tropical cyclone can form if water temperatures are warm enough and wind speed and direction remain constant in the atmosphere. If the wind speeds caused by the cyclone continue to increase, the storm could be classified as a hurricane, which indicates that there is a strong expectation that the storm will cause a significant amount of damage if it reaches land. The main hazards associated with hurricanes are wind speeds, rainfall, and storm surge, which is when water is pushed inland by the hurricane, and these can cause severe damage to a power system and lead to a large number of outages [4].

Although storms can vary in size and intensity, electric utilities tend to follow the same basic steps when restoring outages for any given storm event. The first of these is to perform damage assessments and make repairs to any essential equipment located at power generation plants. This step is given the highest priority because these sites are the primary sources of power production for the systems. The next steps in the process are to send crews to repair damaged or fallen transmission lines and essential equipment located at individual substations so that power can be properly supplied to local distribution systems. With power readily available for distribution, the crews then restore outages for sites that are deemed to be essential to the safety and health of the communities. These include hospitals, police and fire stations, and sanitation and communication facilities. Finally, the crews work to restore power to the other customers, starting with large service areas and concluding with isolated outages [5]. A summary of these steps is shown in Figure 1.1.

In the case of hurricane events, the property damage and the number of outages experienced is likely to be severe when compared to events of a weaker intensity. Because of this, utilities

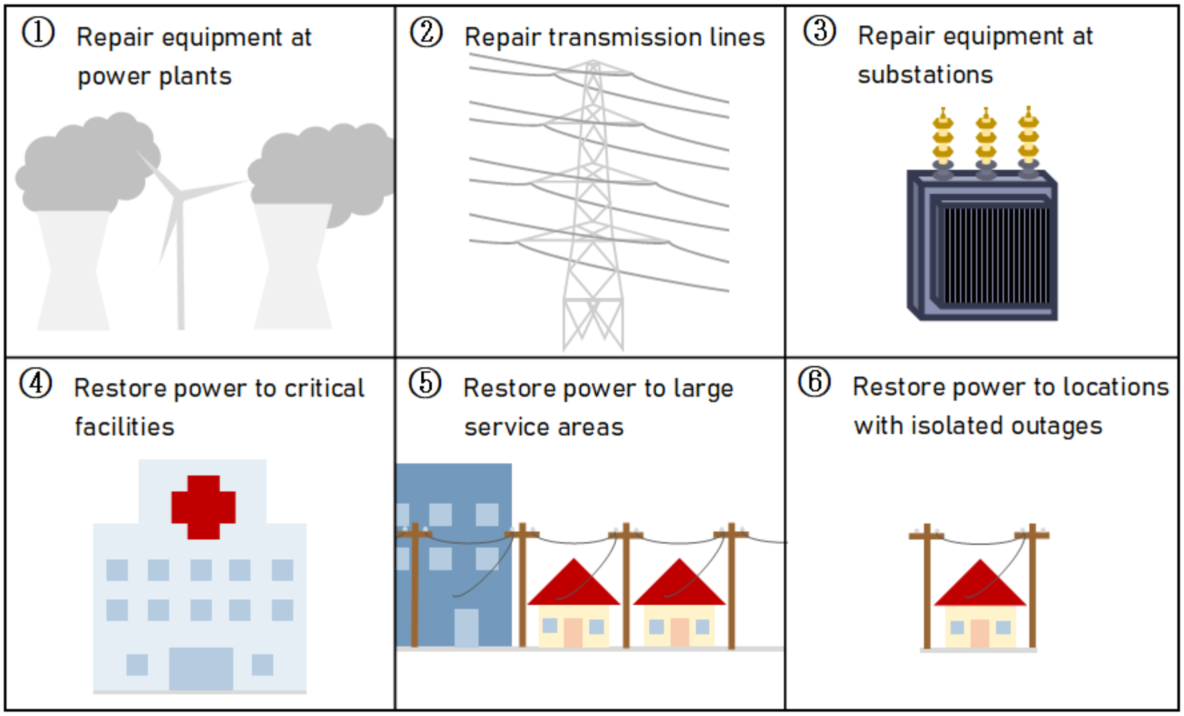


Figure 1.1 Steps Taken for Outage Restoration [5]

often request help from other entities such as local contractors or employees from its service centers. Additionally, utilities sometimes form mutual assistance groups with one another, where one company will provide aid for another when requested [6]. In order to provide assistance, workers from utilities in the group may have to travel long distances to reach the affected area.

Flooding can have significant effects on outage restoration. Most often, the flooding that is experienced after a hurricane event causes delays in the completion of each of the steps of the process. First, vehicles used by deployment crews can be easily subjected to sliding or floating instability even when water levels are low [7], and, as a result, when flood waters cover major highway systems, the crews may be unable to reach certain areas for extended periods of time. Additionally, flood waters can also deposit large amounts of debris on roads, which can further delay restoration [2].

1.2 Issues with Determining Hurricane Intensity

The most commonly used system for quantifying hurricane intensity has been the Saffir-Simpson Hurricane Wind Scale (SSHWS), which was created by Herbert Saffir, who wanted to provide a simple way to estimate the amount of property damage that can be expected from a hurricane. He divided it into five categories that are determined based on the one-minute sustained wind speed that can be measured for a given hurricane, where category-1 is the weakest and category-5 is the strongest. Saffir submitted the scale to the National Hurricane Center (NHC), and the director at that time, Robert Simpson, added estimations for the expected range of pressure and storm surge height that could be expected for each category [8]. When the scale is used by the NHC and other organizations or individuals, the wind speed measurements are the only parameter used to determine the category of the hurricane. The Saffir-Simpson scale with wind speed and storm surge height ranges is shown in Table 1.1.

Table 1.1 Original Saffir-Simpson Hurricane Scale [8], [9]

Classification	Wind Speed (miles per hour)	Storm Surge Height (feet)
Tropical Depression	< 39	< 1.2
Tropical Storm	39–73	< 1.2
Category-1	74–95	4–5
Category-2	96–110	6–8
Category-3	111–129	9–12
Category-4	130–156	13–18
Category-5	> 156	> 19

Despite the fact that the scale in Table 1.1 is simple to apply to any given tropical cyclone, it does have several issues with the implications of the categories. First, the wind speed ranges for each category are relatively large while the number of available categories is small, so the scale may not provide an accurate depiction of the intensity of the storm. For example, a change of one mile per hour could result in a change of category, which implies a large increase in intensity when, in reality, the change was much less significant [8]. Another issue is that storm surge predictions based on the scale have historically tended to be erroneous, particularly with many recent hurricanes. For example, Hurricanes Katrina and Ike were designated as category-3 and -2 storms respectively while their storm surge heights were more reflective of category-4 or -5 storms [3]. Because of this trend, the storm surge estimates were eventually removed from the scale [9]. Finally, the scale can be beneficial for advisory warnings and damage predictions, but it does not directly provide estimates for the amount of time required for the restoration process that follows the storm event.

Many other methods for determining hurricane intensity have been proposed since the creation of the SSHWS, such as the Hurricane Surge Index [8], Hurricane Hazard Index [8], and other, more complex models and statistical analyses [3]. However, each of these tends to provide information on a large geographical scale that is not suitable for accurate estimations of power system outages and the planning of outage restoration. Therefore, the objective of [3] was to provide a simple approach to estimate the potential effects of hurricanes on smaller geographic areas by integrating additional hurricane actions in addition to wind speed so that power grid planners could perform reliable risk assessments.

In [3], nonlinear regression analyses were used to create sets of equations and curves that could be used as alternatives to the existing methods for predicting hurricane damage and expected restoration times that are more suited for power grid planning. The results of these analyses indicated that the proposed alternatives were promising, but they also seemed to suggest that there were additional hurricane actions that were not being considered, particularly with the restoration times and the average outage durations. This work proposes that an important factor that was not included in [3] was the effects that flooding has on the restoration process. In this work, the models were updated to include three additional variables that quantify different aspects of the flooding that is experienced following a hurricane event.

2.0 Nonlinear Regression Analysis

In this work, nonlinear regression analyses were used to determine the relationships between the outage metrics and the hurricane actions that were mentioned in Chapter 1.0. The primary goal of these analyses, in the context of this work, is to determine the curves that best fit the measured outage metric data. Unlike linear regression, there is not a closed-form expression for nonlinear regression for determining the best fit of a given data, so computer algorithms are commonly used to complete the analysis.

2.1 Regression Functions

Regression analysis is the process of determining the relationships between one or more independent variables, denoted as $x_1, x_2, \ldots x_n$, where n is the number of variables, and a dependent variable of interest, denoted as y. All variables involved in the analysis are comprised of several observations for the quantity that they represent [10]. For example, consider the variables listed in Table 2.1. This model consists of one independent variable, x, and a dependent variable, y, and several measurements of y were recorded for different values of x. In general, the relationship between independent and dependent variables can be expressed as

$$y \sim f(\vec{x}, \vec{c}) \tag{2.1}$$

where $\vec{x}$ is the vector of all independent variables, f is the regression function that approximates y, and $\vec{c}$ is the vector of all coefficients that are necessary for f to be the best fit for y [10].

When creating a model for a regression analysis, the first step is to determine the function f. This can be achieved by plotting the observations of y against the observations of $\vec{x}$ and noting the distribution of the data points. For the variables listed in Table 2.1, the distribution can be seen in Figure 2.1. It appears to resemble a quadratic relationship, so, for this example, a good choice for the regression function would be

$$y \sim f(x, \vec{c}) = c_2 x^2 + c_1 x + c_0 \tag{2.2}$$

Table 2.1 Example Data

Observation Number	Observation of x	Observation of y
1	1.31	2.55
2	3.01	11.53
3	3.43	22.06
4	2.21	4.91
5	0.11	4.12
6	4.4	33.86
7	0.9	6.75

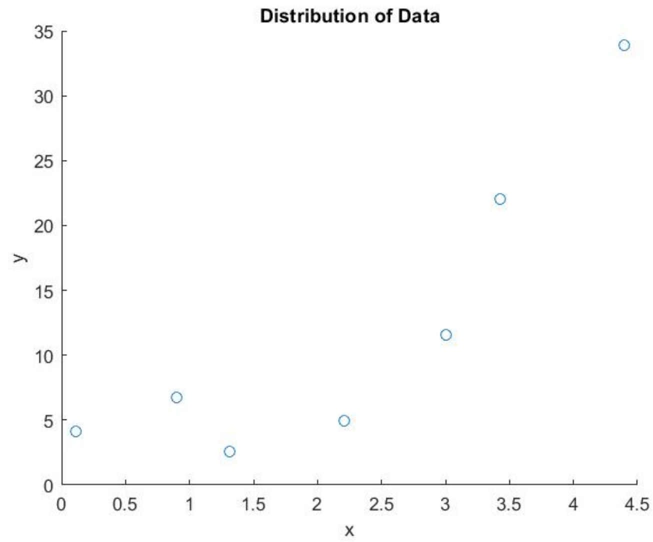


Figure 2.1 Plot of Example Data

2.2 Basis Functions

In the example from the preceding section, only one independent variable was considered. However, in many applications, several independent variables may affect the distribution of the dependent variable, and their inclusion makes the model more complex. So, for two or more components in $\vec{x}$, the selection of a regression function becomes more difficult. Also, as more independent variables are included in the regression model, their relationships with the dependent variable become more complicated and are not always apparent.

A method for systematically determining the relationships involves the use of basis functions that consist of different combinations of the independent variables [11]. Many different types of basis functions exist, but, in this work, polynomial basis functions were used exclusively and will be the focus of the following discussion. The general equation for these functions could potentially consist of the summation of all independent variables and all possible combinations of the products of the variables raised to all integer exponents. In order to limit the number of terms to a finite amount, the highest polynomial exponent is restricted to a certain value, and some combinations may be excluded. As an example, consider a polynomial basis function that consists of two independent variables, x_1 and x_2, and is limited to powers of 2. The function could have the following form:

$$B(\vec{x},\vec{p}) = p_1x_1 + p_2x_2 + p_3x_1x_2 + p_4{x_1}^2 + p_5{x_2}^2 + p_6x_1{x_2}^2 + p_7{x_1}^2x_2 + p_8{x_1}^2{x_2}^2 \tag{2.3}$$

where $\vec{p}$ is the vector of coefficients to be determined through the regression analysis and is a subset of $\vec{c}$. In general, the dependent variable may not be characterized by all of the terms shown in (2.3) because it may be affected more by particular independent variables than others, and the inclusion of more terms could increase the regression errors [3].

When a basis function is used with a regression function, (2.1) takes the following form:

$$y \sim f(B, \vec{a}) \tag{2.4}$$

where $\vec{a}$ consists of all coefficients in $\vec{c}$ that are not contained in $\vec{p}$. If the example from Section 2.1 is altered so that there are two independent variables, but the distribution is still expected to follow a quadratic relationship, then the basis function of (2.3) can be used, and the regression function would be

$$y \sim f(\vec{x}, \vec{c}) = f(B, \vec{a}) = a_2 B^2 + a_1 B + a_0 \tag{2.5}$$

2.3 Coefficient Estimation

The basic form of a nonlinear regression function can be determined by examining the distribution of the recorded data points, but the coefficients must be determined through algorithmic estimation methods. One of the most common of these methods and the one implemented in this work is estimation using nonlinear least squares.

2.3.1 Method of Nonlinear Least Squares

The goal of the method of nonlinear least squares is to obtain estimates for the values of each of the coefficients in the regression function that will allow the function to be the best prediction for the dependent variable of interest [12]. For the following, consider that m is the total number of observations used with the variables, j is a particular observation, ℓ is the total number of coefficients used in the regression function, and k is a particular coefficient. The error between the dependent variable of interest and the approximation of that variable obtained from the regression function for a particular observation is called a residual, and, if a basis function is used, these are given by

$$r_j = y_j - f(\vec{x}_j, \vec{c}) = y_j - f(B_j, \vec{a}) = y_j - f(p_1 x_{1j} + p_2 x_{2j} + \cdots, \vec{a}) \tag{2.6}$$

The best estimations of the coefficients are those that minimize the sum of the squares of the residuals, S_f [12], which is formulated as

$$S_f = \sum_{j=1}^{m} {r_j}^2 \tag{2.7}$$

A geometric interpretation of residuals can be seen in Figure 2.2, which uses the data from Table 2.1. In this sense, a residual is the distance between an individual data point and a given regression curve. So, the curve that provides the best fit for the data is the one in which the sum of the squares of these distances is the smallest possible. In the figure, the formulation of the residual for the seventh observations of *x* and *y* from Table 2.1 is shown.

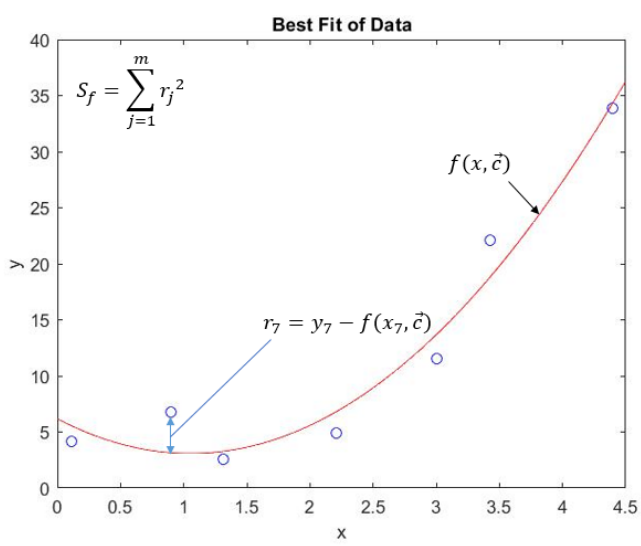


Figure 2.2 Geometric Interpretation of a Sum of Squared Errors

Mathematically, the sum is minimized when its gradient is equal to zero:

$$\frac{\partial S_f}{\partial c_k} = 2\sum_{j=1}^{m} r_j \frac{\partial r_j}{\partial c_k} = 0 \qquad (k = 1,2, \ldots \ell) \tag{2.8}$$

Because residuals are functions of both the independent variables and the coefficients, (2.8) lacks a closed-form solution for any observation. Therefore, algorithmic methods must be utilized to determine the best estimates [12]. Initial guess values must be provided for the coefficients, and these are iteratively refined until the gradients are as close to zero as is allowed by the algorithm.

2.3.2 Coefficient of Determination

When estimates of the coefficients are obtained using the method of nonlinear least squares, it is then possible to plot the regression curve that best fits the measured data. In order to quantify how well the curve represents the data, a figure of merit known as the coefficient of determination is commonly used [10]. This metric compares the sum of squared errors that is calculated from (2.7) to the sum of the squared errors that would be obtained if the average value of the data was used as the fitting curve instead of a regression curve. The average value of the data is

$$\bar{y} = \frac{1}{m}\sum_{j=1}^{m} y_j \tag{2.9}$$

and the total sum of squared errors between the data and its average is

$$S_{\bar{y}} = \sum_{j=1}^{m} \left(y_j - \bar{y}\right)^2 \tag{2.10}$$

A geometric interpretation of these errors is shown in Figure 2.3. Again, the data from Table 2.1 is used, and the formulation of the error between the third observation and the average is shown.

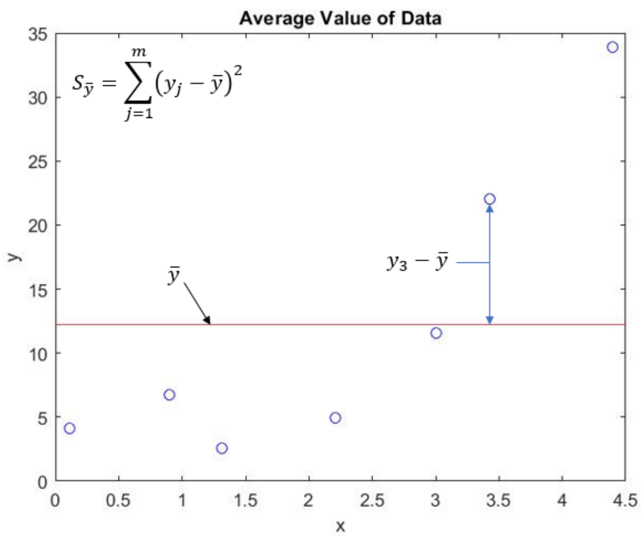


Figure 2.3 Geometric Interpretation of a Total Sum of Squared Errors

The ordinary coefficient of determination [10] is

$$R_0^{\ 2} = 1 - \frac{S_f}{S_{\bar{y}}} \tag{2.11}$$

The maximum value of the coefficient is 1, which indicates that the generated regression curve is an exact fit for the data. As stated in Section 2.3.1, the goal of the method of nonlinear least squares is to minimize S_f. So, based on (2.11), the method provides the highest $R_0^{\ 2}$ value possible for the data.

An issue with the interpretation of the metric calculated from (2.11) is that it monotonically increases with the number of independent variables that are included in the analysis. So, the value will continue to increase as more variables are introduced into the regression model regardless of whether the variables have any correlation with the data. A more accurate depiction of the goodness of the fit can be obtained from the adjusted coefficient of determination, which systematically reduces the value of the $R_0^{\ 2}$ to account for the number of variables that are used in the model [10]. The adjusted value can be calculated with

$$R^2 = 1 - \frac{(m-1)\left(1 - {R_0}^2\right)}{m-n-1} \tag{2.12}$$

All references to the coefficient of determination in Chapters 5.0 and 6.0 refer to the adjusted value.

2.3.3 Implementation with MATLAB

In this work, MATLAB was used to complete all regression analyses. The program contains various toolboxes that contain functions for nonlinear curve fitting, but the Statistics toolbox was used for the following two reasons:

1) It allowed for more complicated regression functions. As explained in Section 2.2, the inclusion of a basis function makes a regression function more complex, and the resulting expression may be too complicated for implementation with basic MATLAB regression functions such as fminsearch.
2) It automatically provided information such as the adjusted coefficient of determination and squared errors. Most toolboxes that allow for nonlinear curve fitting, such as the Symbolic and NAG toolboxes, require additional coding to obtain these values.

The function fitnlm was used from the Statistics toolbox. The MATLAB code used to obtain the regression curves for the outage metrics can be seen in Appendix A.

3.0 Definitions

Important definitions include those for each of the outage metrics and hurricane actions that were mentioned previously as well as for three additional actions that are introduced in this work. Some definitions associated with floods are discussed first in order to provide context for the values used and decisions made that appear throughout the text.

3.1 Flooding

3.1.1 Classifications

Hurricane flooding is commonly classified into two categories that differ in causes and duration. The most common of the two, coastal flooding, is primarily due to storm surge, where a hurricane's winds force ocean water onto land areas along the coast. The severity of this flooding varies depending on many factors such as the size, wind strength, and speed of the storm, and it has historically been a leading cause of damage and loss of life during a hurricane event [13]. Additional causes of coastal flooding include rainfall and river discharge [1], but the effects of these during a hurricane event are typically much less apparent than that of storm surge.

The second category is inland flooding and is usually the result of heavy precipitation [1]. This type can be further divided into two subcategories, which are fluvial and pluvial flooding. Fluvial flooding, or river flooding, occurs when a river's water level rises above its banks due to excessive rainfall. Pluvial flooding, or surface water flooding, occurs when rainfall produces a flood independently from bodies of water. A common cause of this is the accumulation of rainfall on hillsides or other elevated terrain that cannot effectively absorb the amount of water flowing on them. If there are few obstacles to impede the flow of water, it will quickly accumulate in flatter areas and produce flooding. Pluvial flooding can also occur when rainfall causes the water in drainage systems to overflow onto streets [13]. Although coastal flooding has been historically more widespread than inland flooding during a hurricane event, there are several examples of storms included in this work where inland flooding was more extensive.

One of the major observed differences between the two categories is that, in general, inland flood waters tend to recede at a slower rate when compared to coastal flood waters due to the differences in topography [14]. The pathways that allow water to return to its sources tend to be more widespread for coastal flooding due to its close proximity to expansive bodies of water, and, as a result, the water may recede much more quickly. Additionally, for the case of pluvial flooding, there may not be any significant pathways if the flooded area is not near a river or stream.

3.1.2 Annual Exceedance Probability

In order to quantify the risk associated with floods and their effects, hydrologists have developed statistical methods to describe the occurrence of floods in different areas. One of the most widely used practices is the classification of flood levels based on an annual exceedance probability (AEP), which is the percent chance that a flood of a certain magnitude will be equaled or exceeded in any given year [15]. For example, a 10-percent AEP flood has a 10 percent chance of occurring each year.

In the United States, the AEP flood stages for different areas throughout the country are determined by examining the peak streamflow measurements that are recorded each year at various hydrologic monitoring stations near the sites [15]. These are operated by the United States Geological Survey (USGS) [16], and they typically record aspects of a river, stream, lake, or sea such as discharge or height of water. As more data is collected each year, the accuracy of the AEP flood stages increases, but this also implies that the defined values for the magnitude of these floods could change from year to year [15].

The United States government uses 1-percent AEP flood stages to determine costs for its National Flood Insurance Program, and, as a result, this has been the most widely used AEP for flood-related applications. Historically, it has been more common to use amounts of time, called recurrence intervals, rather than AEPs when describing floods. A 1-percent AEP flood correlates to a 100-year flood recurrence interval, and the interval can be interpreted in the following way: a 100-year flood has a 1 in 100, or 1 percent, chance of occurring in a single year [15].

3.2 Outage Metrics and Hurricane Actions

The work presented in [3] defined four metrics that quantify the effects that a hurricane can have on the power system in a county and the amount of time that deployment teams will need to restore power. The metrics can be calculated based on the measurements of hurricane actions that reflect the intensity of a hurricane.

3.2.1 Outage Metrics

The outage metrics reflect how a hurricane affected the power system in an area of interest, and, in the context of regression analysis, they are analogous to the dependent variable y that was discussed in Chapter 2.0. They were derived from indices listed in IEEE 859 [17], and measurements for each of them were determined by examining outage data provided by various electric utilities that were recorded at regular intervals during a hurricane event. The metrics are defined as

1) *Maximum Outage Incidence*: the fraction of electricity customers in a county that lost power.

2-3) *Restoration Times*: the times, in days, needed to restore 95% and 98% of the total number of outages in a county since those outages first peaked. These particular percentages were selected because they are commonly reported by electric utilities as a measure of progress made during the restoration period. Additionally, these values account for the fact that, in the case of widespread devastation, some reported outages may not be able to be restored if infrastructure has been destroyed.

4) *Average Outage Duration*: the average amount of time, in days, that was needed to restore a single outage in a county. Although this metric is similar to the restoration times, it accounts for the fact that a small percentage of the outages may take much longer to restore and may not be reflective of the majority of the progress that was made by utilities.

3.2.2 Hurricane Actions

The hurricane actions reflect the intensity of a hurricane that affected an area of interest, and they were used to obtain the independent variables used in the regression analyses. The four hurricane actions presented in [3] are defined as

1) *Storm Surge Height*, H_i: the height of the water, in feet, that a hurricane forced inland in county i. It was measured with respect to a reference value, H_0, that was considered to be equal to 4 feet and is a typical minimum height of water for a category-1 storm. Measurements for this

action were obtained by using storm surge modelling programs or from storm surge contour maps compiled by the National Oceanic and Atmospheric Administration (NOAA).

2) *Maximum One Minute Sustained Wind Speed,* V_i: the maximum wind speed, in miles per hour, measured at 10 meters above the Earth's surface in county *i* during a one minute interval. These measurements were obtained from NHC storm reports or from wind fields produced for NOAA's H*Wind dataset. This action was measured with respect to a reference value, V_0, which is 39 miles per hour. This reference was selected because, as shown in Table 1.1, it is the minimum wind speed for the tropical storm classification of the SSHWS, and, when it is attained, conditions become unsafe for repair crews.

3) *Time Under Storm Conditions,* T_{Si}: the duration of time, in hours, that a county *i* experienced at least tropical storm wind speeds. It is measured with respect to a reference value, T_{S0}, which is 12 hours and was determined based on observations made during field assessments. Measurements for this action were obtained from wind fields produced for NOAA's H*Wind dataset.

4) *Area Affected by Hurricane,* A_{Si}: The total area of land, in square miles, across all applicable counties that experienced at least tropical storm wind speeds. It was measured with respect to a reference value, A_{S0}, which is 35,342 square miles and is defined as the amount of area that is expected to be swept by a category-1 hurricane. Measurements for this action were obtained by analyzing the data contained in wind fields from NOAA's H*Wind dataset.

In this work, three additional actions that represent the effects of flooding were included in the regression analyses. The sources of information and the methods used to obtain data for these variables are discussed in Chapter 4.0. The actions are defined as

5) *Area Flooded by Hurricane, A_{Fi}*: the area of land, in square miles, within county *i* that experienced coastal or inland flooding. Because the area of one county can be significantly different from the area in another county, the reference value for this action, A_{F0}, was different for each location. For coastal flooding, the expected area in the county that would be flooded by a category-1 hurricane was used as the reference, and, for inland flooding, the area of land that is part of a 1-percent AEP floodplain was used as the reference.
6) *Time Until Flood Waters Receded, T_{Fi}*: the duration of time, in days, that a county *i* experienced flooding. Because of the differences between coastal and inland flooding that were summarized in Section 3.1.1, the reference value for this action, T_{F0}, was considered to be three days for coastal flooding and five days for inland flooding. These values were selected based on observations made during field assessments.
7) *Total Area Flooded by Hurricane, A_{TFi}*: the total area of land, in square miles, across all applicable counties that experienced coastal or inland flooding. While A_{Fi} is representative of mobility within a county, A_{TFi} is representative of the accessibility of a county. As discussed in Section 1.1, personnel commonly travel to a county to aid in the restoration of the power system, and this action serves to quantify the difficulty that out-of-county teams may have when trying to enter a certain location. The reference value for this action, A_{TF0}, was different for each hurricane used in the analyses and was determined using the same criteria that was used with A_{F0}.

For the analyses presented in [3] and in this work, the independent variables that were used to form a basis function were defined as

$$X = \frac{X_i}{X_0} \tag{3.1}$$

where X can be any one of H, V, T_S, A_S, A_F, T_F, or A_{TF}, and the subscripts i and 0 indicate the measured value of X in a county and the reference value of the measurement, respectively.

4.0 Data Collection for Flooding

The two types of flood data that were collected for each of the hurricanes were the area on land that was flooded and the amount of time that passed until the flood waters receded. This chapter first discusses the magnitude of the damage and flooding experienced for each of the hurricanes considered and then highlights the sources of the data and the steps that were taken to calculate the flooding actions from these data.

4.1 Overview of Hurricanes Considered

Data from eight hurricanes from the 2004, 2005, and 2008 Atlantic hurricane seasons were used in the regression analyses. Each of these storms made landfall in the mainland United States in or near either Florida, Louisiana, or Texas, and counties or parishes from these states comprise the study regions for the analyses. A description of the damage and flooding associated with each of the hurricanes is presented below, and maps of the study regions with hurricane tracks can be seen in Figures 4.1 and 4.2.

1) *Charley, 2004*: Hurricane Charley made landfall in southwestern Florida as a category-4 hurricane. The storm was notable for its intense winds [18], and several counties experienced a maximum outage incidence of 80 percent or higher. Despite the powerful winds, flooding was restricted to the coasts, where it receded at a fast rate when compared to other storms considered in this work.

2) *Ivan, 2004*: This storm made landfall west of Florida and affected counties in the northwest part of the state where it was classified as a category-3 hurricane and caused a significant amount of storm surge [19]. As a result, the flooding associated with this storm mainly affected the coast.

3) *Dennis, 2005*: Hurricane Dennis also made landfall in Florida, and, like Hurricane Charley, it did not cause widespread and prolonged flooding.

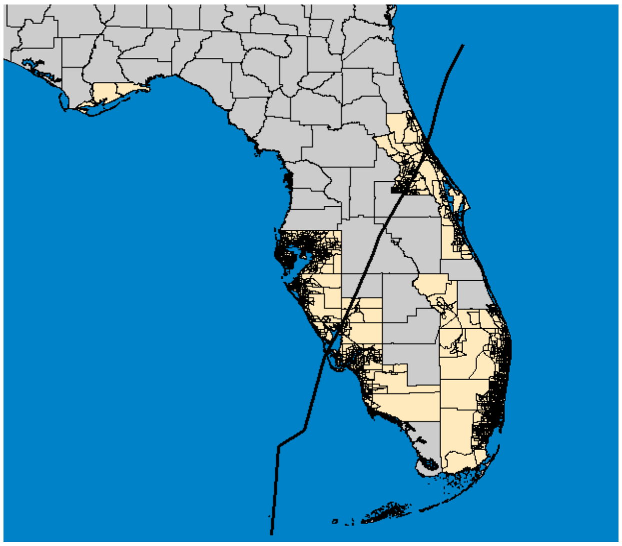
4) *Katrina, 2005*: This storm, considered one of the most devastating natural disasters to affect the United States, caused substantial amounts of flooding in Louisiana. In particular, Orleans, Plaquemines, and St. Bernard parishes were largely devastated by the amount and breadth of water. Furthermore, nearly 80 percent of the city of New Orleans was flooded with water that was nearly 20 feet in height [20].

5) *Wilma, 2005*: Unlike the previous hurricanes, Hurricane Wilma predominantly caused inland flooding. It made landfall in southwestern Florida as a category-3 hurricane and continued east, causing widespread damage and flooding across the southern part of the state [21].

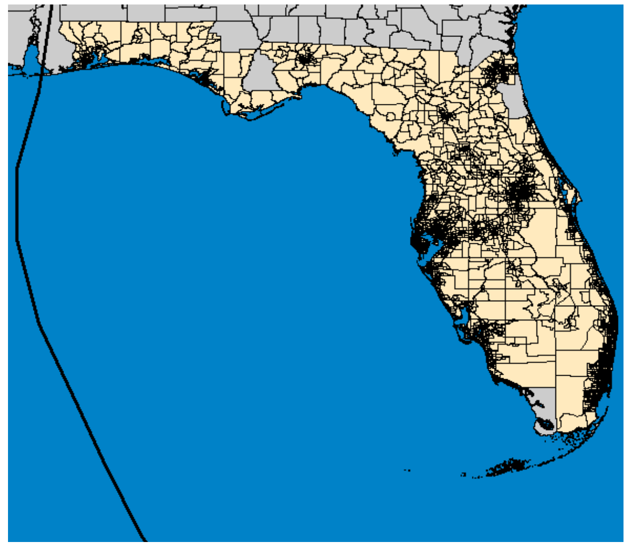
6) *Dolly, 2008*: Hurricane Dolly made landfall in Texas and affected counties in that state as well as parts of Mexico. It is unique among the storms considered because the amount of flooding that occurred in the study regions was very small and the flooding outside of the regions was significant. Because of this, the A_F variable was negligible for each of the counties considered, but the A_{TF} variable had a significant value.

7) *Gustav, 2008*: Hurricane Gustav made landfall as a category-2 storm in southeastern Louisiana [22]. It caused some coastal flooding in the immediate areas where it made landfall, but it caused much more inland flooding as it continued throughout the state.

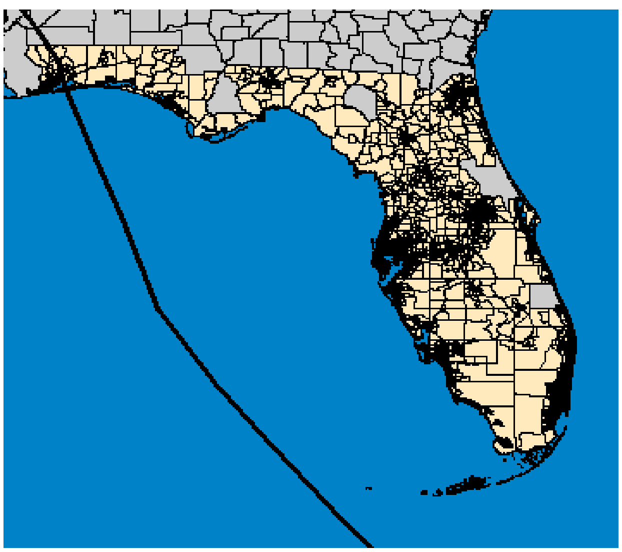
8) *Ike, 2008*: This storm, along with hurricane Katrina, was one of the costliest storms in United States history and caused extreme amounts of coastal flooding. It made landfall in southeastern Texas, but it also affected parishes in Louisiana [23].



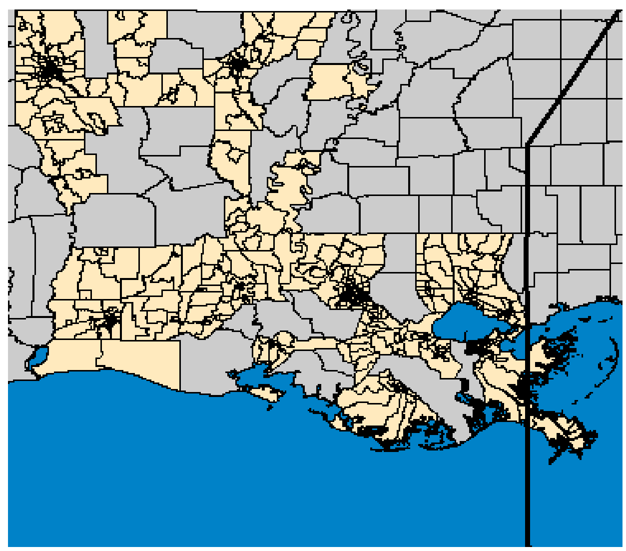
Charley, 2004



Ivan, 2004



Dennis, 2005

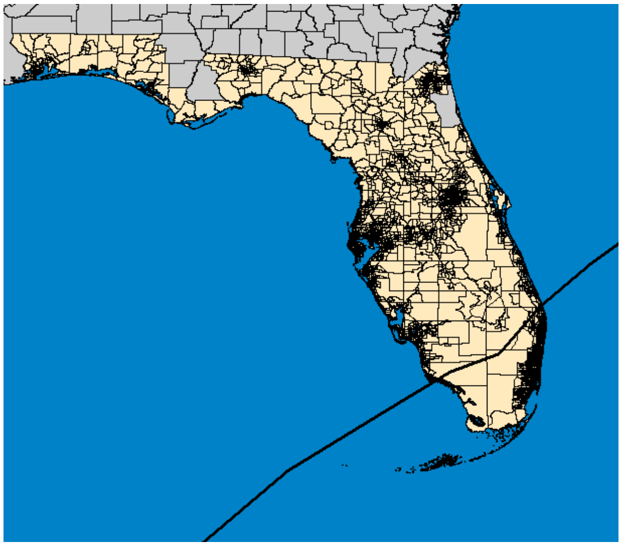


Katrina, 2005

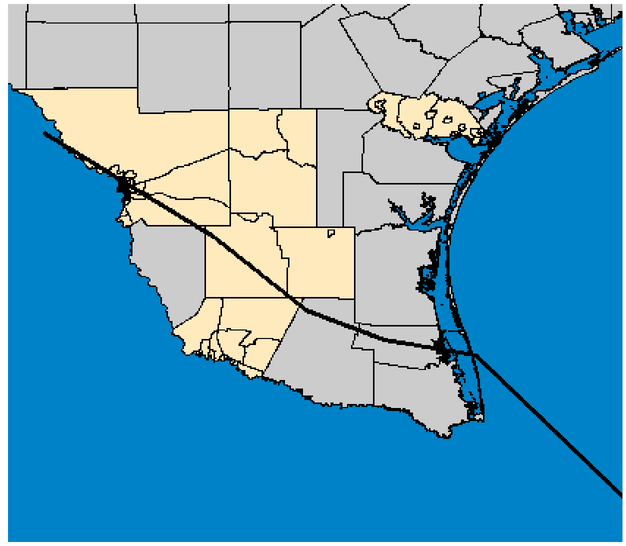
Counties or Parishes colored were part of the study regions used in the analyses.

Storm track for each hurricane is denoted by .

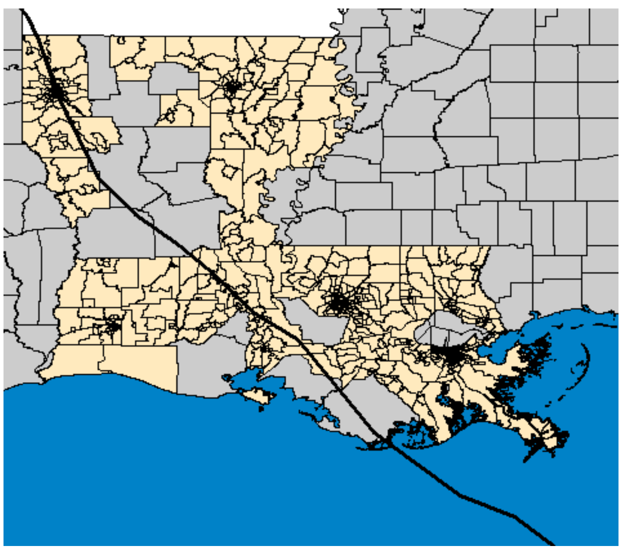
Figure 4.1 Storm Tracks and Study Regions, Part 1



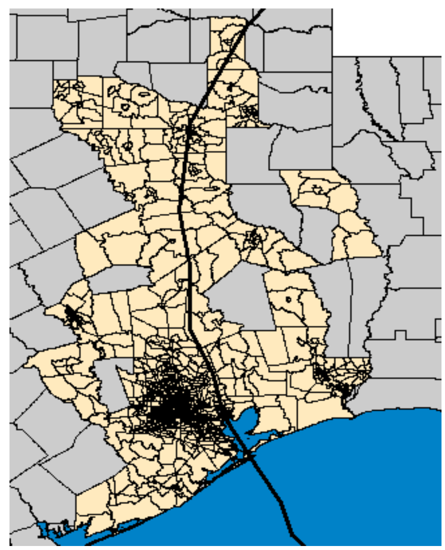
Wilma, 2005



Dolly, 2008



Gustav, 2008



Ike, 2008

Counties or Parishes colored were part of the study regions used in the analyses.

Storm track for each hurricane is denoted by .

Figure 4.2 Storm Tracks and Study Regions, Part 2

4.2 Flooding Areas

4.2.1 Hurricane Measurements

Several flood inundation maps prepared by the Federal Emergency Management Agency (FEMA) [24], [25], [26], the Dartmouth Flood Observatory [27], and the Harris County Flood Control District [28] were used to estimate the approximate area of land in each of the study regions that was flooded. The FEMA map for flooding in Santa Rosa County, Florida, following Hurricane Ivan is shown in Figure 4.3 as an example.

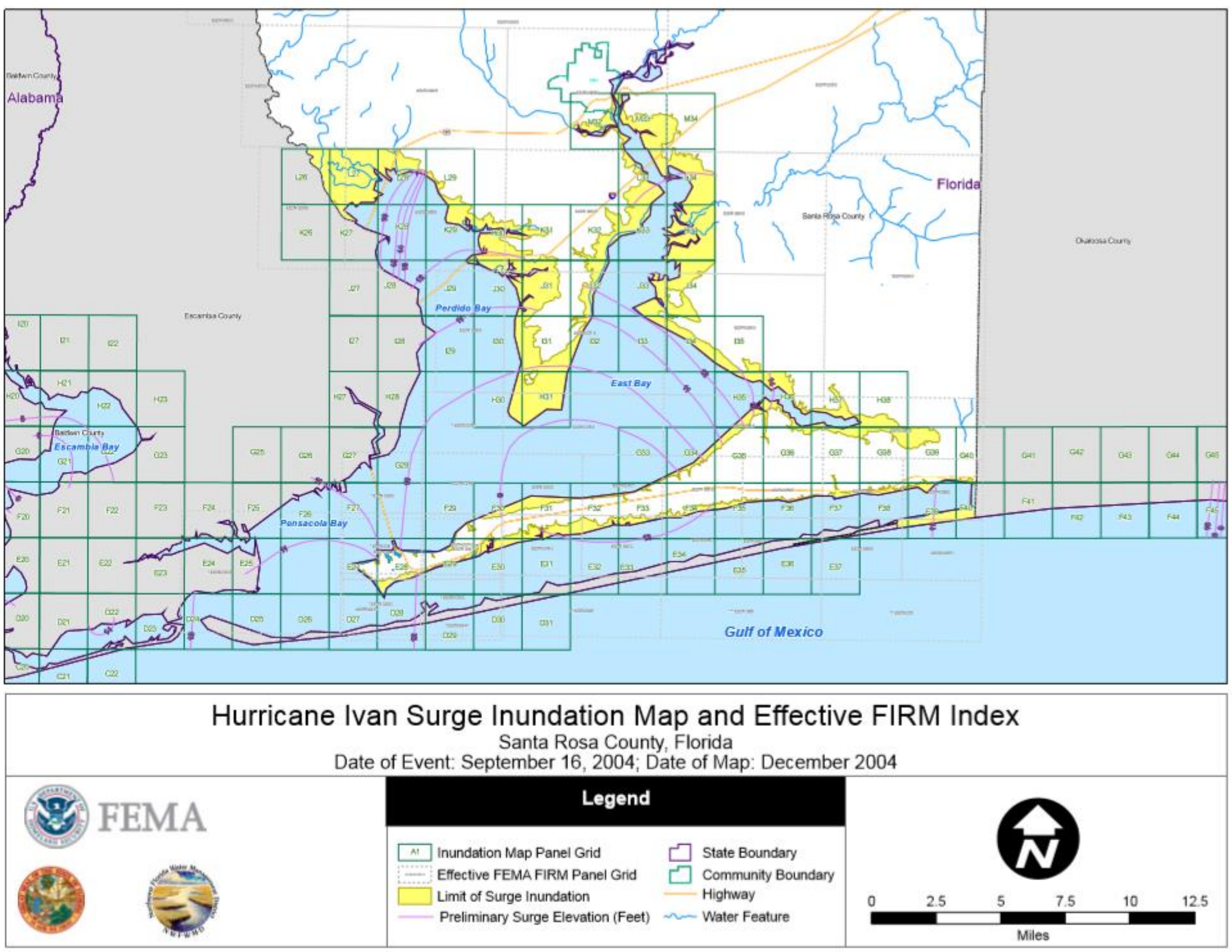


Figure 4.3 Hurricane Ivan Inundation Map for Santa Rosa County, Florida [25]

In order to obtain the measurements for the amount of land that was flooded, the ImageJ image processing software was used to filter the map images and calculate the number of square pixels that contain flooding. The filtered Santa Rosa County map that was obtained with ImageJ is shown in Figure 4.4. As shown in the figure, after the filtering settings were adjusted, the flooded portions of Figure 4.3 were the only part of the map that remained.

Figure 4.4 Extracting the Flooded Area

After filtering the maps, ImageJ was then used to calculate the area in square pixels. This was converted to square inches by using the resolution of the map image and then to square miles by using the map's scale. The area conversions for each of the counties in Florida that experienced major flooding due to Hurricane Ivan are summarized in the red portion of Table 4.1. The total area measurements used to determine the A_{TF} variable for each hurricane were obtained using a similar procedure.

4.2.2 Reference Measurements

The reference area measurements for each county were obtained using the process that was described in the previous section, but screenshots of an interactive United States flooding map created by ArcGIS [29] were used instead of the storm inundation maps. The map's settings could be adjusted so that the average flooding for each of the five main hurricane categories shown in Table 1.1 or the average 1-percent AEP flood zones were shown. For cases when the main type of flooding in a county from a hurricane was coastal flooding, the settings were adjusted so that the average flooding due to category-1 hurricanes was shown, and, when the main type was inland flooding, the settings were adjusted so that the 1-percent AEP flooding was shown. The screenshot used to obtain the reference area for Santa Rosa County, Florida, is shown in Figure 4.5. Because the flooding shown in Figure 4.3 was restricted to the coast, the settings used for the screenshot are for the average flooding from category-1 hurricanes.

In order to accurately determine the flooded area in square miles from the screenshots, county borders were superimposed over the images and resized to match the resolution of the screenshots so that flooding outside of the county could be excluded, and scales that corresponded to the dimensions of the borders were added so that the area in square pixels could be converted. The screenshot for Santa Rosa County with the added scale and the screenshot after filtering are shown in Figure 4.6a and b respectively.

The reference area conversions for each of the counties in Florida that experienced major flooding due to Hurricane Ivan are summarized in the blue portion of Table 4.1. After both A_{Fi} and A_{F0} were determined for all counties, the independent variable A_F was calculated for each location by using (3.1), and these values are shown in the farthest right column of Table 4.1.

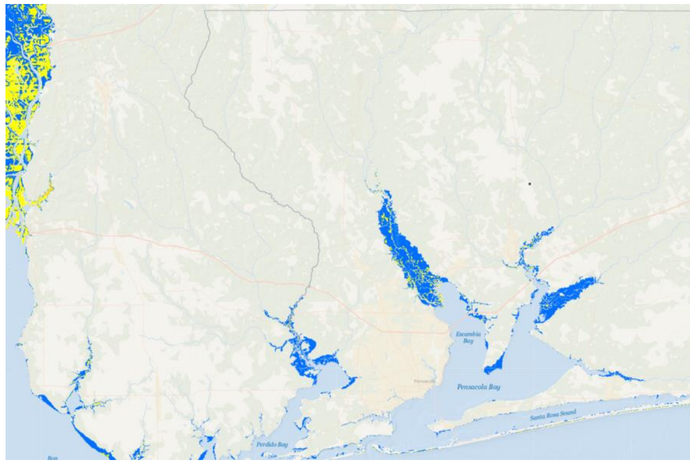
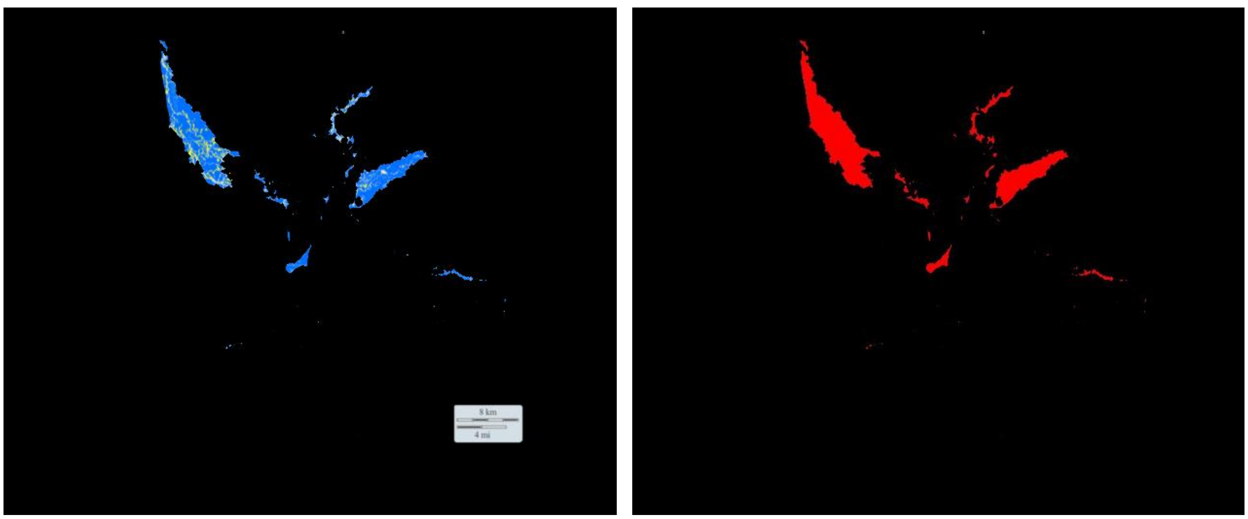


Figure 4.5 Screenshot Used to Obtain Santa Rosa County Reference Area [29]



(a) Screenshot with Scale **(b) Filtered Screenshot**

Figure 4.6 Extracting the Reference Area

Table 4.1 Calculation of A_F for Hurricane Ivan

	Hurricane Measurement				Reference Measurement				
County, i	**Area (px^2)**	**Resolution (px/in)**	**Scale (mi/in)**	**Area, A_{Fi} (mi^2)**	**Area (px^2)**	**Resolution (px/in)**	**Scale (mi/in)**	**Area, A_{F0} (mi^2)**	**A_F**
Escambia	17,171	108	6.15	55.7	2,009	151.8	12	12.6	4.42
Okaloosa	8,441	114	4.8	15	696	151.8	6.1	1.13	13.2
Santa Rosa	27,194	114	5.71	68.7	5,805	151.8	9.85	24.4	2.81

4.3 Flood Receding Times

Receding time data for the study regions were obtained by examining hydrographs created from data recorded by USGS monitoring stations [16]. As discussed in Section 3.1.2, these stations collect measurements for gauge height and discharge, and changes in these data were used to identify the duration of flooding during hurricane events. The discharge hydrograph used for Okaloosa County, Florida, during Hurricane Ivan is shown in Figure 4.7. A list of all stations used to obtain the receding time data can be seen in Appendix B. In several parishes affected by Hurricane Katrina, none of the stations had available data from the time period of the storm, so estimates reported in the storm report prepared by the NHC [20] were used.

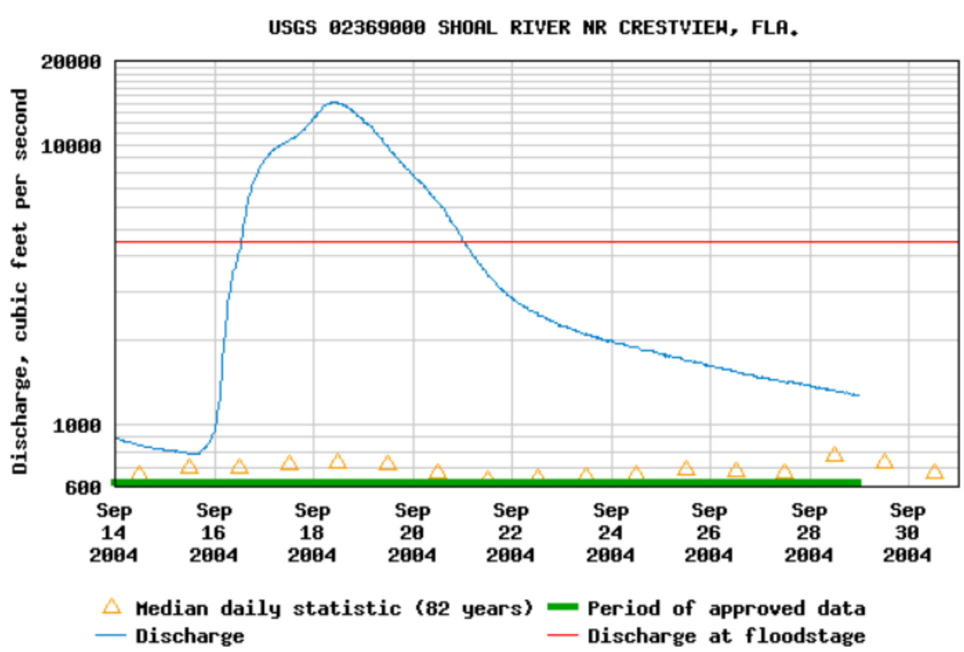


Figure 4.7 Hydrograph Used for Okaloosa County, Florida [16]

Some monitoring stations have a designated level of gauge height or discharge that indicates that the body of water is likely experiencing flooding conditions. This level is known as the flood stage, and it is indicated by a red line as shown in Figure 4.7. To determine the receding times from the hydrographs, the date when the measured data first exceeded the flood stage and the date when the data decreased below the flood stage were determined, and the amount of time between these two dates was used. For cases where a flood stage was not provided by a station, the date that the magnitude of the measurements began to greatly increase and the date when the magnitude decreased to a new normal condition were identified, and the time between these two dates was used instead.

In the example plot of Figure 4.7, the discharge began to increase substantially on September 15, 2004, which is when Hurricane Ivan made landfall in Florida. Midway through September 16, the discharge rose above the flood stage, and flooding conditions were experienced until September 21. So, based on the latter two dates, the flood receding time for Okaloosa County was determined to be approximately 4.5 days. The reference value for this measurement was 3 days because the flooding was predominantly restricted to the coast, so the independent variable T_F was calculated from (3.1) to be 1.5 for this case.

5.0 Results from Previous Work

The basis function for the regression analyses that was used in [3] was constructed as the following response surface model:

$$\begin{aligned} LTCII = p_1 H + p_2 V + p_3 T_S + p_4 A_S + p_5 HV + \cdots + p_{20} H^2 V^2 {T_S}^2 {A_S}^2 \\ + p_{21} HV^2 T_S A_S + p_{22} HV{T_S}^2 A_S + p_{23} H^2 V^2 + p_{24} H^2 V^2 T_S \end{aligned} \tag{5.1}$$

where *LTCII* is called the local tropical cyclone intensity index, and p_1, p_2, ... p_{24} are the coefficients that would be found through the regression analyses. Each of the four outage metrics have different forms of (5.1), and the following naming conventions will be used: $LTCII_{MOI}$ for maximum outage incidence, $LTCII_{Tr\tau}$ for the restoration times where τ can be either 95 or 98, and $LTCII_{AOD}$ for average outage duration. As stated in Section 2.2, an outage metric may not be characterized by all of the terms shown in (5.1).

5.1 Estimation of Coefficients

5.1.1 Maximum Outage Incidence

The following regression function was proposed as a general fit for the outage incidence based on the distribution of the data points:

$$f_1(LTCII_{MOI}, \vec{a}) = \frac{1}{1 + e^{-a_1[\ln(LTCII_{MOI}) - a_2]}} \tag{5.2}$$

The coefficients a_1, a_2, and p_1, p_2, ... p_{24} were found by minimizing the sum of squared residuals determined from (2.7), and the results showed that $\vec{a}$ = [a_2, a_1] = [5.8, 2.6], and

$$LTCII_{MOI} = 111V + 120HV + 107VA_S + 15HVA_S + 359V^2T_S \tag{5.3}$$

For this curve, the R^2 was found to be 0.8.

5.1.2 Restoration Times

The times taken to restore 95% and 98% of the peak number of outages were predicted to follow a third order polynomial form:

$$f_2(LTCII_{Tr\tau}, \vec{a}) = a_3 LTCII_{Tr\tau}{}^3 + a_2 LTCII_{Tr\tau}{}^2 + a_1 LTCII_{Tr\tau} + a_0 \tag{5.4}$$

The analysis results indicated that, for 95% restoration, [a_3, a_2, a_1, a_0] = [0, 0.009, 0.2, 0], and

$$LTCII_{Tr95} = 14V + 2T_SA_S + 2V^2T_S \tag{5.5}$$

For 98% restoration, [a_3, a_2, a_1, a_0] = [0, 0.00983, 0.2, 0.137], and

$$LTCII_{Tr98} = 15V + 2VT_S + T_SA_S \tag{5.6}$$

For both curves, the R^2 was 0.65.

Some data points obtained for Hurricane Katrina were excluded from the analyses performed for these two metrics. The restoration period following this storm was notable for taking much longer than the other storms considered in this work, due in part to the unprecedented amount of damage in several of the parishes as well as the fact that Hurricane Rita impacted some of the same areas less than a month later [30]. Because of these abnormalities, the points likely do not provide an accurate portrayal of how utilities will respond to a hurricane of this magnitude, and, as a result, they were not considered.

5.1.3 Average Outage Duration

This metric was predicted to follow the same cubic polynomial form as the restoration times:

$$f_2(LTCII_{AOD}, \vec{a}) = a_3 {LTCII_{AOD}}^3 + a_2 {LTCII_{AOD}}^2 + a_1 LTCII_{AOD} + a_0 \qquad (5.7)$$

The polynomial constants were found to be [a_3, a_2, a_1, a_0] = [0, 0, 0.28, 0], and

$$LTCII_{AOD} = 3V + 4VA_S + 4V^2T_S \qquad (5.8)$$

For this curve, the R^2 was 0.51. The outage duration points that correspond to the parishes excluded for Hurricane Katrina that were discussed for the restoration times were also excluded for this metric.

5.2 Regression Curves and Interpretations

The curves for each metric are the red traces in Figure 5.1, and the blue data points are the measured values for the metrics in a particular county or parish. The outage incidence curve had the highest R^2 value of the four indices, and the presence of all four hurricane action variables in (5.3) indicated that each of these had a significant correlation with the outage data. This can be explained by the fact that the actions quantify different aspects of the amount of damage that was sustained by the power system. For example, storm surge and wind speeds are major causes of power outages during a hurricane event, so these two variables were expected to have a strong influence on the $LTCII_{MOI}$. Additionally, the area affected by the hurricane and the time under storm conditions are reflective of the number of outages that can be expected because a larger area and longer time make it much more likely for outages to occur, so these were also expected to be highly correlated with the outage incidence.

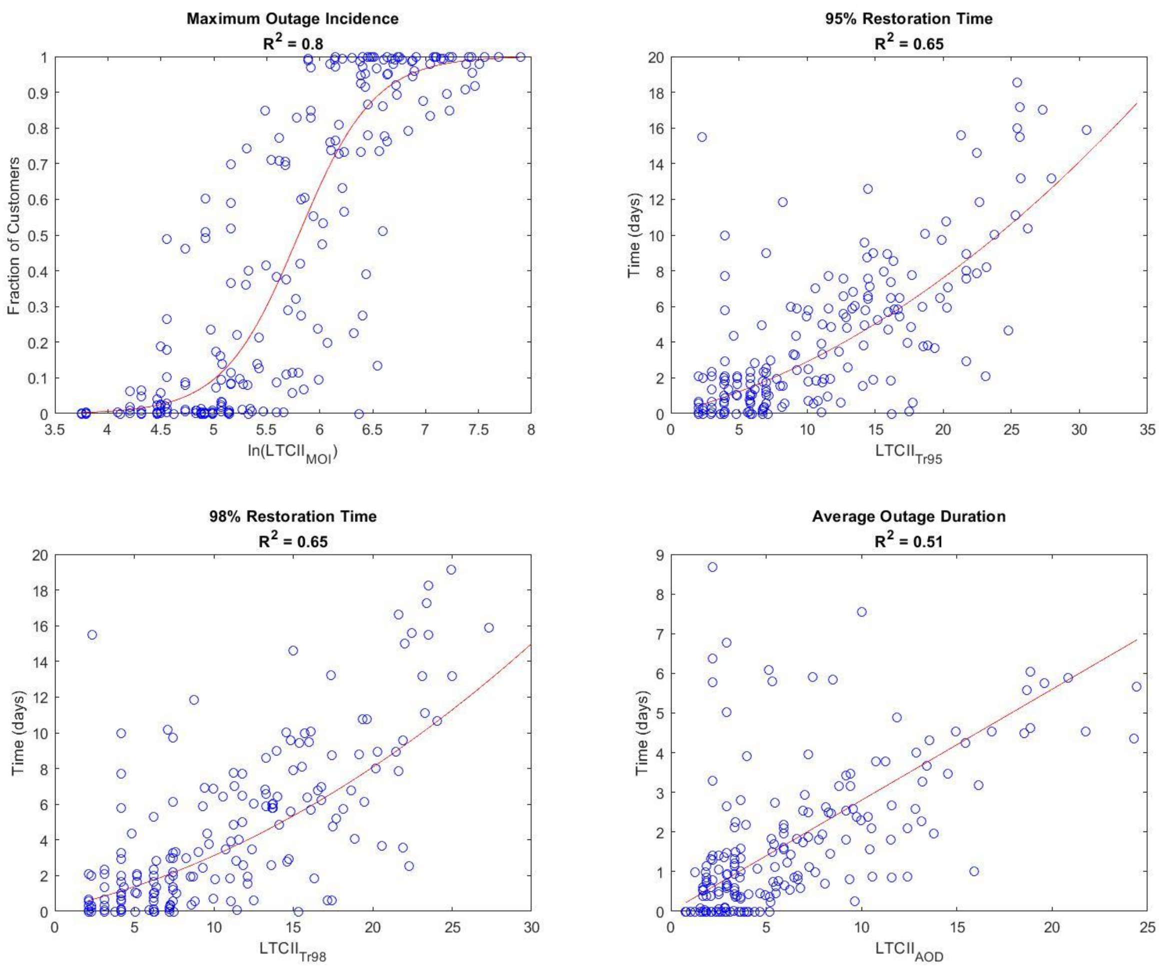


Figure 5.1 Original Regression Curves

Unlike the outage incidence, each of the four hurricane actions did not have a high correlation with the restoration times and average outage duration. In particular, none of the terms in (5.5), (5.6), or (5.8) had a dependence on storm surge height, and this is likely because this action is more reflective of damage caused to the power system rather than delays experienced during the restoration process. Conversely, the three remaining variables were each shown to have a significant influence on these three metrics. For the area affected by the hurricane and the time under storm conditions, these variables can be interpreted as being representative of the amount of area that could require restoration and an amount of time that must be delayed until repair crews can begin to restore outages.

The R^2 values for the restoration times and average outage duration were significantly smaller than that of the outage incidence, which could be due to a variety of reasons. One possibility is that there are additional factors that were not considered in the regression analyses summarized in the previous section that have a significant correlation with the metrics. For this work, delays due to the flooding that is associated with hurricanes were proposed as one of these factors, and the results of the regression analyses with these considerations are summarized in the following chapter.

6.0 Incorporation of Flooding

In the preceding chapter, the regression curve for the maximum outage incidence had the highest correlation to its measured data with a R^2 of 0.8 while the curves for the restoration times and average outage duration were not as well-fitted to their corresponding data. The three flood actions that were defined in Section 3.2.2 were incorporated into the existing models in order to identify whether flooding considerations could improve the R^2 values of these metrics. The same regression curve forms shown in (5.2), (5.4), and (5.7) were used in the regression analyses, and each of the coefficients were recalculated to identify any changes in the characterization of the outage metrics.

The basis function used for the analyses had the following form:

$$\begin{aligned} LTCII &= p_1 H + p_2 V + p_3 T_S + p_4 A_S + p_5 A_F + p_6 T_F + p_7 A_{TF} + p_8 HV + p_9 HT_S \\ &\quad + \cdots + p_{25} A_S A_{TF} + p_{26} A_F T_F + p_{27} A_F A_{TF} + p_{28} T_F A_{TF} \end{aligned} \tag{6.1}$$

As stated in Section 2.2, an outage metric may not be characterized by all of the terms shown in (6.1), and their inclusion could increase the regression errors, which could decrease the value of the R^2. Because of this, it was necessary to identify the terms that had little impact on the dependent variable and remove them from the regression model. In MATLAB, this was achieved by first completing a regression analysis with all 28 terms shown in (6.1), identifying the terms that had negligible coefficients, then completing the analysis again and repeating the process until all of the remaining terms were shown to have a significant impact on the characterization of the metric. The MATLAB code used to complete the analyses can be seen in Appendix A.

6.1 Estimation of Coefficients

6.1.1 Maximum Outage Incidence

When each of the flooding variables were included in the basis function for the outage incidence, the R^2 for the updated curve decreased from the previous value of 0.8 that was recorded in [3]. Based on the discussion of the adjusted coefficient of determination from Section 2.3.2, this suggested that the additional variables were not significantly correlated with the outage data. The reason for the unimproved nonlinear fit can be explained by the fact that outage incidence is characterized primarily by damaging actions such as the storm surge and wind speed rather than the flood actions, which have a greater association with the delays in restoration following the damage to the power system. For practical applications, the outage incidence curve shown in Figure 5.1 should still be used to obtain the best outage prediction possible from the included data.

6.1.2 Restoration Times

The cubic polynomial coefficients for 95% restoration were found to be [a_3, a_2, a_1, a_0] = [0.297, -3.18, 11.1, -7.82], and

$$\begin{aligned} LTCII_{Tr95} = {} & 0.92V + 2.8T_S + 0.84A_S - 3.4A_F + 5.2T_F - 0.82A_{TF} - 0.72HT_S \\ & + 1.6HA_{TF} + 4.3VA_F - 3.6VT_F + 0.62T_SA_S + 0.65T_ST_F \\ & - 0.5T_SA_{TF} + 1.1A_SA_F - 4.3A_ST_F - 0.99A_SA_{TF} - 2.8A_FA_{TF} \\ & + 3.3T_FA_{TF} \end{aligned} \tag{6.2}$$

For 98% restoration, the coefficients were [a_3, a_2, a_1, a_0] = [0.345, -3.88, 14.3, -12], and

$$
\begin{aligned}
LTCII_{Tr98} = {} & 3T_S + 1.7A_S + 2T_F - 0.93A_{TF} + 1.1HV - 1.1HT_S - 0.61HA_S \\
& + 2.1HA_{TF} + 1.8VA_F - 1.2VT_F + 0.66T_SA_S - 0.47T_SA_{TF} \\
& + 0.48A_SA_F - 1.9A_ST_F - 1.3A_SA_{TF} - 2.6A_FA_{TF} + 1.8T_FA_{TF}
\end{aligned} \tag{6.3}
$$

The majority of the terms in (6.2) and (6.3) have a dependence on at least one of the flood actions, which suggests that flooding does have a significant effect on the amount of time that is taken to restore outages. Additionally, the R^2 for 95% restoration increased from 0.65 to 0.72, and the R^2 for 98% restoration increased from 0.65 to 0.71, which further indicates that the curves are now better correlated with their measured data.

6.1.3 Average Outage Duration

The cubic polynomial coefficients were [a_3, a_2, a_1, a_0] = [0.0161, -0.358, 2.78, -4.28]. In Section 5.1.3, the results showed that the only coefficient that was not negligible was a_1, and, as a result, the outage duration curve in Figure 5.1 was linear. With the inclusion of the new data, the other three coefficients had a larger role in the characterization of the data points, and the curve then had the shape of a third order polynomial function. The basis function for the outage duration was

$$
\begin{aligned}
LTCII_{AOD} = {} & 4.4H - 1.9V - 1.9T_S + 6A_F - 4.1A_{TF} - 1.8HV - 3HA_S \\
& + 1.7HA_{TF} + 6.2VT_S + 6.1VA_S - 1.9VT_F - 1.8T_SA_S - 2.1T_ST_F \\
& - 1.1A_SA_F + 4.5A_ST_F + 2.7A_SA_{TF} - 4.5A_FA_{TF}
\end{aligned} \tag{6.4}
$$

The value of the R^2 increased from 0.51 to 0.69. The considerable improvement in the fit can be attributed partially to the fact that the excluded data points discussed in Section 5.1.3 were included in the analysis. As discussed in Section 3.2.1, the average outage duration accounts for the fact that a small percentage of the outages may take much longer to restore than others, and, because the excluded data points fit into this category, they were reinstated for this analysis.

6.2 Regression Curves and Interpretations

The majority of the terms in (6.2), (6.3), and (6.4) have a dependence on the flooding variables, which indicates that effects from flooding do have a significant impact on the amount of time that is required for the restoration process. The most commonly recurring flooding variable was A_{TF} while the least common was A_F. As stated in Section 3.2.2, A_{TF} is representative of the difficulty that out-of-county repair crews may face when trying to provide assistance in a county of interest, and, based on the results, this effect seemed to have the highest significance on the restoration process for each of the storms considered. The fact that T_F is more represented in the final equations than A_F indicates that, although flooded area in a county is an important factor, the time delay due to this flooding has a more significant role in characterizing the outage metrics.

The new 95% restoration time, 98% restoration time, and average outage duration curves are the red traces in Figure 6.1. Each of these follows the same basic shape: the amount of time required increases substantially in the lower and higher ranges of intensity and remains almost unchanged for the mid-range of intensity. This contrasts the corresponding curves in Figure 5.1, which each displayed a steady increase in time for all ranges of intensity, and this could indicate that certain ranges of flooding intensity do not significantly impact the amount of time required for restoration.

The largest errors between the data points and the curves occurred at lower values of each respective *LTCII*, where storm and flooding intensity were smaller, and damage was expected to

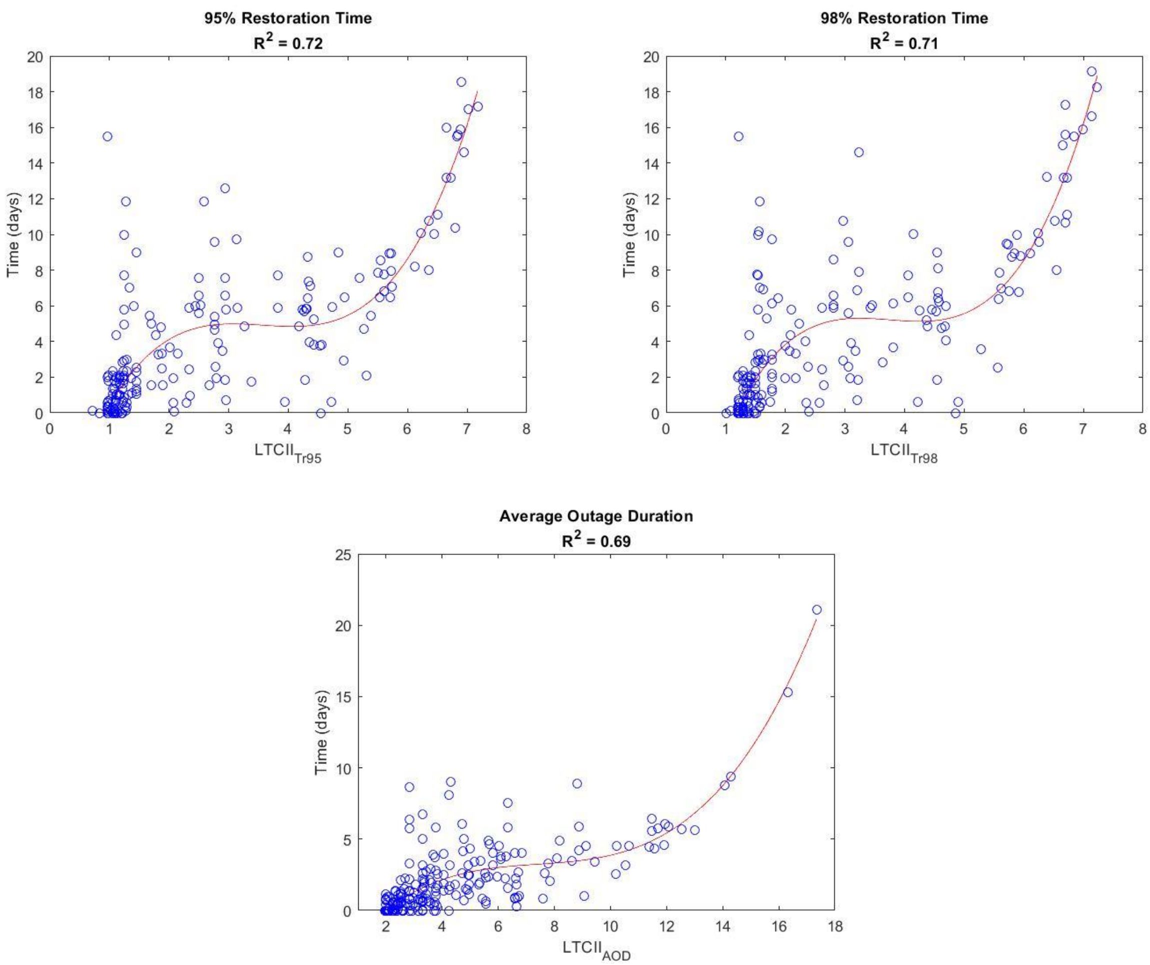


Figure 6.1 Updated Regression Curves

be less severe. In the majority of these cases, the affected areas were in regions where a storm's intensity diminished, that were on the edges of the wind-fields used to collect the wind speed data, or that did not have many USGS monitoring stations in which flood receding time data could be retrieved for the time period of the storm.

Despite the fact that the incorporation of flooding with the models improved the R^2 values for the restoration times and average outage duration, the values are still somewhat less than that of the outage incidence. The most likely cause of this is that a restoration period is affected not only by damaging actions and delays but also by factors that deal with human decisions such as the logistical strategies and restoration techniques that are employed by utilities [3]. Still, the updated models now appear to more accurately represent the measured data.

7.0 Future Work and Conclusion

Although the new regression curves are an improvement, there are still many aspects of the models that can be updated and more considerations that can be included. First, the models could possibly be improved by adding more terms to the *LTCII* of (6.1). For simplicity, the maximum number of terms that were included in this basis function was restricted to 28, and these consisted of each of the individual variables based on the seven hurricane actions and combinations of two of these variables. However, additional terms that could be analyzed include combinations that consist of more than two variables as well as squared variables and combinations of squared variables, similar to those seen in (5.1).

Additionally, the datasets can be expanded by including measurements from other storms that were not considered in this work. Several hurricanes have impacted the United States since 2008, and data for many of these, including Hurricanes Isaac and Sandy from 2012 and Harvey, Irma, and Maria from 2017 have been collected. The inclusion of these storms could lead to improvements with the R^2 values for the curves, or, at the very least, they could help to identify additional factors that have not been included in the models.

Other factors associated with hurricanes can be incorporated into the models to examine their impact on the outage metrics. One additional hurricane action that has been proposed is the amount of debris from wind and flooding that accumulates in a county, which causes further delays for restoration after flood waters have receded [2]. Finally, the results of [3] and this work showed that the average outage duration has the smallest R^2 of the four indices, so one area of focus for future work could be to identify and quantify other factors that may have a strong impact on this particular metric.

In this work, the statistical models introduced in [3] were updated to examine the impact of flooding on four metrics that characterize the damage sustained by and restoration times required for power systems when they are affected by hurricanes. Three additional variables, which are the flooded land area within a county or parish, the time until flood waters receded, and the total flooded area for a hurricane, were incorporated with the previous hurricane action variables. Regression analyses were used to obtain nonlinear fits for these metrics, and, based on the results, the three major conclusions were that

1) Hurricane flooding did not appear to substantially affect the number of outages that can be expected from a hurricane.
2) Hurricane flooding did have a significant impact on the amount of time that will be required to restore the outages.
3) The total land area flooded by a hurricane had the largest impact on the restoration times when compared to the other aspects of flooding that were considered. This seemed to suggest that the accessibility of an affected county should be an important consideration for a utility's restoration process.

The inclusion of the three flooding actions improved the R^2 values of the nonlinear fits for 95% and 98% restoration times and the average outage duration, so the generated regression curves were better correlated with the measured data that they represent. The results of the regression analyses suggest that coastal and inland flooding are important factors that must be considered when planning network deployment strategies and determining logistics for power outage restoration following a hurricane event.

Appendix A – MATLAB Script for Regression Analyses

To obtain the curves that were shown in Figure 6.1, a MATLAB script was created to complete regression analyses with the hurricane action and outage metric data. The program performed three major tasks: first, the hurricane action and outage metric data were read from a .xlsx file and stored in vector variables; then, the fitnlm function was used to complete the regression analysis; and, finally, the regression curve was plotted. Also, the program displayed a summary of the analysis in the MATLAB command window.

Appendix A.1 Script Template

```
% Script for Regression Analyses
% Grant Cruse
% Originally created May 2019, updated for flooding March 2020


% READ FROM EXCEL
H = readtable('C:\Users\Grant\Desktop\Research Assistant\V2.xlsx',
'Range','C1:C336'); % Storm Surge Height
V = readtable('C:\Users\Grant\Desktop\Research Assistant\V2.xlsx',
'Range','D1:D336'); % Wind Speed
T = readtable('C:\Users\Grant\Desktop\Research Assistant\V2.xlsx',
'Range','E1:E336'); % Time Under Storm Conditions
A = readtable('C:\Users\Grant\Desktop\Research Assistant\V2.xlsx',
'Range','F1:F336'); % Area Affected by Hurricane
AF = readtable('C:\Users\Grant\Desktop\Research Assistant\V2.xlsx',
'Range','G1:G336'); % Area in County Flooded by Hurricane
TF = readtable('C:\Users\Grant\Desktop\Research Assistant\V2.xlsx',
'Range','H1:H336'); % Time Until Flood Waters Receded
ATF = readtable('C:\Users\Grant\Desktop\Research Assistant\V2.xlsx',
'Range','I1:I336'); % Total Area Flooded by Hurricane
M = readtable('C:\Users\Grant\Desktop\Research Assistant\V2.xlsx',
'Range','M1:M336'); % Outage Metric
% M can be each outage metric. Change the column to access a different
% metric. J = Outage Incidence, K = 95%, L = 98%, and M = Outage Duration.
% So, in this example, outage duration is being plotted.
```

```
% CONVERT EXCEL DATA TO VECTORS
X = zeros(length(table2array(H)),7);
X(:,1) = table2array(H);
X(:,2) = table2array(V);
X(:,3) = table2array(T);
X(:,4) = table2array(A);
X(:,5) = table2array(AF);
X(:,6) = table2array(TF);
X(:,7) = table2array(ATF);
M = table2array(M);


% MODEL AND GUESSES
% The following is the LTCII with all terms shown:
% LTCII = p(5).*X(:,1) + p(6).*X(:,2) + p(7).*X(:,3) + p(8).*X(:,4) +
p(9).*X(:,5) + p(10).*X(:,1).*X(:,2) + p(11).*X(:,1).*X(:,3) +
p(12).*X(:,1).*X(:,4) + p(13).*X(:,1).*X(:,5) + p(14).*X(:,2).*X(:,3) +
p(15).*X(:,2).*X(:,4) + p(16).*X(:,2).*X(:,5) + p(17).*X(:,3).*X(:,4) +
p(18).*X(:,3).*X(:,5) + p(19).*X(:,4).*X(:,5) + p(20).*X(:,6) +
p(21).*X(:,1).*X(:,6) + p(22).*X(:,2).*X(:,6) + p(23).*X(:,3).*X(:,6) +
p(24).*X(:,4).*X(:,6) + p(25).*X(:,5).*X(:,6) + p(26).*X(:,7) +
p(27).*X(:,1).*X(:,7) + p(28).*X(:,2).*X(:,7) + p(29).*X(:,3).*X(:,7) +
p(30).*X(:,4).*X(:,7) + p(31).*X(:,5).*X(:,7) + p(32).*X(:,6).*X(:,7)
% Original LTCII consists of 28 terms. These are eventually reduced to the
% numbers seen in Chapter 6.0 after identifying and removing insignificant
% terms.

% Possible Forms for Regression Functions:
% f1 = 1./(1 + exp(-p(1).*(log(LTCII) - p(2)))); or f2 = p(1).*(LTCII).^3 +
p(2).*(LTCII).^2 + p(3).*(LTCII) + p(4);

% For this example, f2 is used because outage duration is being plotted.
f = @(p,X) p(1).*(p(5).*X(:,1) + p(6).*X(:,2) + p(7).*X(:,3) + p(8).*X(:,4) +
p(9).*X(:,5) + p(10).*X(:,1).*X(:,2) + p(11).*X(:,1).*X(:,3) +
p(12).*X(:,1).*X(:,4) + p(13).*X(:,1).*X(:,5) + p(14).*X(:,2).*X(:,3) +
p(15).*X(:,2).*X(:,4) + p(16).*X(:,2).*X(:,5) + p(17).*X(:,3).*X(:,4) +
p(18).*X(:,3).*X(:,5) + p(19).*X(:,4).*X(:,5) + p(20).*X(:,6) +
p(21).*X(:,1).*X(:,6) + p(22).*X(:,2).*X(:,6) + p(23).*X(:,3).*X(:,6) +
p(24).*X(:,4).*X(:,6) + p(25).*X(:,5).*X(:,6) + p(26).*X(:,7) +
p(27).*X(:,1).*X(:,7) + p(28).*X(:,2).*X(:,7) + p(29).*X(:,3).*X(:,7) +
p(30).*X(:,4).*X(:,7) + p(31).*X(:,5).*X(:,7) + p(32).*X(:,6).*X(:,7)).^3 +
p(2).*(p(5).*X(:,1) + p(6).*X(:,2) + p(7).*X(:,3) + p(8).*X(:,4) +
p(9).*X(:,5) + p(10).*X(:,1).*X(:,2) + p(11).*X(:,1).*X(:,3) +
p(12).*X(:,1).*X(:,4) + p(13).*X(:,1).*X(:,5) + p(14).*X(:,2).*X(:,3) +
p(15).*X(:,2).*X(:,4) + p(16).*X(:,2).*X(:,5) + p(17).*X(:,3).*X(:,4) +
p(18).*X(:,3).*X(:,5) + p(19).*X(:,4).*X(:,5) + p(20).*X(:,6) +
p(21).*X(:,1).*X(:,6) + p(22).*X(:,2).*X(:,6) + p(23).*X(:,3).*X(:,6) +
p(24).*X(:,4).*X(:,6) + p(25).*X(:,5).*X(:,6) + p(26).*X(:,7) +
p(27).*X(:,1).*X(:,7) + p(28).*X(:,2).*X(:,7) + p(29).*X(:,3).*X(:,7) +
p(30).*X(:,4).*X(:,7) + p(31).*X(:,5).*X(:,7) + p(32).*X(:,6).*X(:,7)).^2 +
p(3).*(p(5).*X(:,1) + p(6).*X(:,2) + p(7).*X(:,3) + p(8).*X(:,4) +
p(9).*X(:,5) + p(10).*X(:,1).*X(:,2) + p(11).*X(:,1).*X(:,3) +
p(12).*X(:,1).*X(:,4) + p(13).*X(:,1).*X(:,5) + p(14).*X(:,2).*X(:,3) +
p(15).*X(:,2).*X(:,4) + p(16).*X(:,2).*X(:,5) + p(17).*X(:,3).*X(:,4) +
p(18).*X(:,3).*X(:,5) + p(19).*X(:,4).*X(:,5) + p(20).*X(:,6) +
p(21).*X(:,1).*X(:,6) + p(22).*X(:,2).*X(:,6) + p(23).*X(:,3).*X(:,6) +
p(24).*X(:,4).*X(:,6) + p(25).*X(:,5).*X(:,6) + p(26).*X(:,7) +
```

```
p(27).*X(:,1).*X(:,7) + p(28).*X(:,2).*X(:,7) + p(29).*X(:,3).*X(:,7) +
p(30).*X(:,4).*X(:,7) + p(31).*X(:,5).*X(:,7) + p(32).*X(:,6).*X(:,7)) +
p(4);
% Initial guesses for the algorithm
pguess = [1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1];


% FIND COEFFICIENTS
mdl = fitnlm(X,M,f,psave) % Perform regression analysis and print results in
Command Window
p = mdl.Coefficients.Estimate; % Save coefficients in variable "p"


% PLOT DATA
L1 = p(5).*X(:,1) + p(6).*X(:,2) + p(7).*X(:,3) + p(8).*X(:,4) + p(9).*X(:,5)
+ p(10).*X(:,1).*X(:,2) + p(11).*X(:,1).*X(:,3) + p(12).*X(:,1).*X(:,4) +
p(13).*X(:,1).*X(:,5) + p(14).*X(:,2).*X(:,3) + p(15).*X(:,2).*X(:,4) +
p(16).*X(:,2).*X(:,5) + p(17).*X(:,3).*X(:,4) + p(18).*X(:,3).*X(:,5) +
p(19).*X(:,4).*X(:,5) + p(20).*X(:,6) + p(21).*X(:,1).*X(:,6) +
p(22).*X(:,2).*X(:,6) + p(23).*X(:,3).*X(:,6) + p(24).*X(:,4).*X(:,6) +
p(25).*X(:,5).*X(:,6) + p(26).*X(:,7) + p(27).*X(:,1).*X(:,7) +
p(28).*X(:,2).*X(:,7) + p(29).*X(:,3).*X(:,7) + p(30).*X(:,4).*X(:,7) +
p(31).*X(:,5).*X(:,7) + p(32).*X(:,6).*X(:,7); % Determine vector of all
LTCII values for each county using the estimated values of all coefficients
L = min(L1):.01:max(L1); % Create a vector over the range of all LTCII values
for plotting the curve
f = p(1).*L.^3 + p(2).*L.^2 + p(3).*L + p(4); % Calculate the values for the
regression curve

plot(L,f,'r') % Plot regression curve
hold on
scatter(L1,M,'blue') % Plot metric data points
xlabel('LTCII_A_O_D')
ylim([0,25])
ylabel('Time (days)')
title({'Average Outage Duration'},{'R^2 = 0.69'})
hold off
```

Appendix A.2 Sample Analysis Summary

After the fitnlm function was used to determine the values for each of the coefficients that provided the best fit for the desired metric, the program then displayed a summary of the analysis in the MATLAB command window. Several important results were listed, such as the values of each coefficient and the R^2 for the nonlinear fit. The text shown below is the summary that was obtained for the analysis with the average outage duration when the original 28 terms of $LTCII_{AOD}$ were reduced to the 17 terms shown in (6.4).

Estimated Coefficients:

	Estimate	SE	tStat	pValue
b1	0.016141	14.484	0.0011144	0.99911
b2	-0.35822	214.25	-0.001672	0.99867
b3	2.7831	831.93	0.0033453	0.99733
b4	-4.2785	3.6616	-1.1685	0.24349
b5	4.4229	1323.8	0.0033412	0.99734
b6	-1.8676	558.34	-0.0033449	0.99733
b7	-1.9337	577.54	-0.0033482	0.99733
b8	5.9989	1793.9	0.0033441	0.99733
b9	-1.8282	547.28	-0.0033405	0.99734
b10	-3.039	909.48	-0.0033415	0.99734
b11	6.1552	1841	0.0033435	0.99733
b12	6.1326	1834.7	0.0033426	0.99734
b13	-1.7536	525.19	-0.003339	0.99734
b14	-1.1363	339.29	-0.0033491	0.99733
b15	-1.9131	572.14	-0.0033438	0.99733

b16	-2.0721	619.85	-0.0033429	0.99733
b17	4.53	1354.9	0.0033434	0.99733
b18	-4.0518	1212.8	-0.0033409	0.99734
b19	1.7486	523.38	0.0033409	0.99734
b20	2.7163	813.05	0.0033409	0.99734
b21	-4.4842	1342	-0.0033414	0.99734

Number of observations: 335, Error degrees of freedom: 314

Root Mean Squared Error: 1.31

R-Squared: 0.711, Adjusted R-Squared 0.692

F-statistic vs. constant model: 38.5, p-value = 2.87e-72

Appendix B – List of USGS Monitoring Stations Used

Table B.1 List of USGS Monitoring Stations by State [16]

Station Number	County/Parish	Body of Water	Data Available
Florida			
02297310	De Soto	Horse Creek	Discharge
02369000	Okaloosa	Shoal River	Discharge
02370500	Santa Rosa	Big Coldwater Creek	Discharge
02376500	Escambia	Perdido River	Discharge
253044080555900	Monroe	EDEN 3	Gauge Height
Louisiana			
02492000	St. Tammany	Bogue Chitto River	Discharge
02492600	St. Tammany	Pearl River	Gauge Height/Discharge
073745257	Plaquemines	Crooked Bayou	Gauge Height
07375000	St. Tammany	Tchefuncte River	Discharge
07375500	Tangipahoa	Tangipahoa River	Discharge
07376500	Tangipahoa	Natalbany River	Discharge
07380200	Livingston	Amite River	Gauge Height
07380401	Ascension	Bayou Lafourche	Gauge Height/Discharge
07381000	Lafourche	Bayou Lafourche	Discharge
07381600	St. Mary	Lower Atchafalaya River	Gauge Height/Discharge
07385700	St. Martin	Bayou Teche	Gauge Height/Discharge
Texas			
08041780	Orange	Neches River	Gauge Height/Discharge
08042522	Jefferson	Taylor-Alligator Bayou	Gauge Height/Discharge
08067252	Chambers	Trinity River	Gauge Height
08076180	Harris	Garners Bayou	Gauge Height/Discharge
08077740	Galveston	La Marquee Levee	Gauge Height/Discharge
08079120	Brazoria	Old Brazos River	Gauge Height/Discharge

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