ASSESSMENT AND MODELING OF HURRICANE IMPACTS ON WATER QUALITY AND ITS SPATIOTEMPORAL DISTRIBUTION

By

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ABSTRACT

Hurricanes have affected the waters of the east coast of the United States throughout the region's history. These storms cause changes in water quality through mechanisms such as damage to infrastructure, excessive precipitation, and storm surges. We attempt to conduct a regional assessment of these changes in water quality through the study of 14 hurricanes. To reach our goal we collected water quality datasets for 815 stations from the USGS's Water-Quality Data for the Nation database, extracted a various range of contributing variables for each investigated station, and constructed and employed a machine learning based procedure to determine which contributing factors have the highest impact on water quality as well as the magnitude of the response. This technique yields a better understanding of the relationship between hurricanes and their impact on water quality and also provides a predictive capability where the impact of future hurricanes can be modeled and estimated.

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LIST OF SYMBOLS AND ABBREVIATIONS

DEM – Digital Elevation Model

HUC – Hydrologic Unit Code

JAXA – Japan Aerospace Exploration Agency

NLCD – National Land Cover Database

NOAA – National Oceanic and Atmospheric Administration

NWQP – National Water Quality Program

USGS – United States Geological Survey

SSURGO – Soil Survey Geographic database

CHAPTER I

INTRODUCTION

Water Quality and Hurricanes

The impacts of hurricanes on water quality is a topic that has been moderately studied by the scientific community. These studies are limited in geography as well as number. All of the studies reviewed have focused on areas in the eastern United States, possibly due to the limited geographical locations affected by occurrences of tropical storms and hurricanes. The limited number of studies quantifying the relationship between hurricanes and water quality parameters are primarily small-scale studies. The impacts of hurricanes on water quality typically revolve around measuring water quality parameters in single areas after a single event. The two areas most often studied are estuaries (Hagy et al., 2006; Peierls et al., 2003; Wetz & Yoskowitz, 2013) and urban areas (Adams et al., 2007; Pardue et al., 2005), with lakes (Steward et al., 2006), swamps (Rybczyk et al., 1995), and rivers (Mallin et al., 1999; Mallin et al., 2002) sometimes being studied. The findings of these studies are relatively consistent. Runoff from rainfall creates nutrient rich situations in estuary or lacustrine settings. Turbidity typically increases in estuary, riverine, and lacustrine settings (Mallin et al., 1999; Steward et al., 2006). Dissolved oxygen (DO) is consistently found to be lower than normal and sometimes completely anoxic for days after a storm (Hagy et al., 2006; Mallin et al., 1999; Pardue et al., 2005). A non-consistent finding is that salinity in bodies of water can both increase and decrease after a hurricane (Hagy et al., 2006; Mallin et al., 1999), where storm surges cause high salinity and rainfall causes low salinity, outcome depending on which of these phenomena is more impactful in the area of study.

Conditions typically return to normal within four days to a week after an event in urban and riverine settings (Adams et al., 2007; Mallin et al., 1999; Pardue et al., 2005), however some effects (e.g. DO, Turbidity) can last up to two months in estuaries (Peierls et al., 2003). Gaps in scientific knowledge exist in the form of large-scale studies. All of these studies focused at one event at a time or at one location over several events.

Objectives

The goal of this project is to evaluate and quantify the relationship between hurricane events and water quality parameters in a generalizable way. The main hypothesis of this study is the following:

"*Hurricane impacts to water quality indicators can be quantified and modeled using machine learning tools.*"

To evaluate this hypothesis and to accomplish the main study's goal, the following tasks constitute integral parts of this thesis:

a) Gather, quality control, and parameterize a host of hurricane spatiotemporal attributes, water quality parameters, and impacted basins characteristics.
b) Develop and evaluate methods to identify and record temporal signatures in water quality parameters before, during, and after individual events.
c) Quantification of potential direct relationship between individual controlling factors, individual response variable, and controlling factors and response variables.

d) Development and evaluation of machine learning-based predictive models for estimation of water quality impacts using hurricane attributes and basic characteristics.

e) Description of study findings, the importance of key controlling factors, uncertainties in this study, and opportunities for future enhancement of models' performance.

CHAPTER II

METHODS

Study Site

The study area is based in the eastern seaboard of the United States and the Gulf of Mexico. This large geographic area offers an opportunity capture a broad range of spatiotemporal conditions, as this study is an attempt to be as broad and generalizable as possible. The spatial extent of this study is defined as all U.S. Geological Survey (USGS) water quality stations within the wind swathes of every hurricane examined as determined by National Oceanic and Atmospheric Administration (NOAA) (Figure 1).

The storms examined in this study are all hurricanes (category 1-5) through the years of 2008 to 2018 (Table 1). These temporal limits are due to the widespread availability of USGS and NOAA data after 2008. Tropical storms and tropical depressions are not included in this study.

In order to investigate the impact of storms on key water quality indicators, data on hurricane attributes, watershed physical and climatic characteristics, and water quality indicators are collected, quality controlled, parametrized, and used to develop stochastic models describing their relationship. It is therefore important to obtain two categories of data: controlling factors and response variables. Controlling factors here are defined as those factors that might have an influence on water quality in the context of a hurricane. Soil type, for example, is a factor which falls into this category, as some soils may be more easily erodible than others and contribute to the resultant turbidity. Response variables here were defined as the parameters of water quality to monitor. Turbidity, for example, is a variable that falls into this category, being a measurement of water quality.

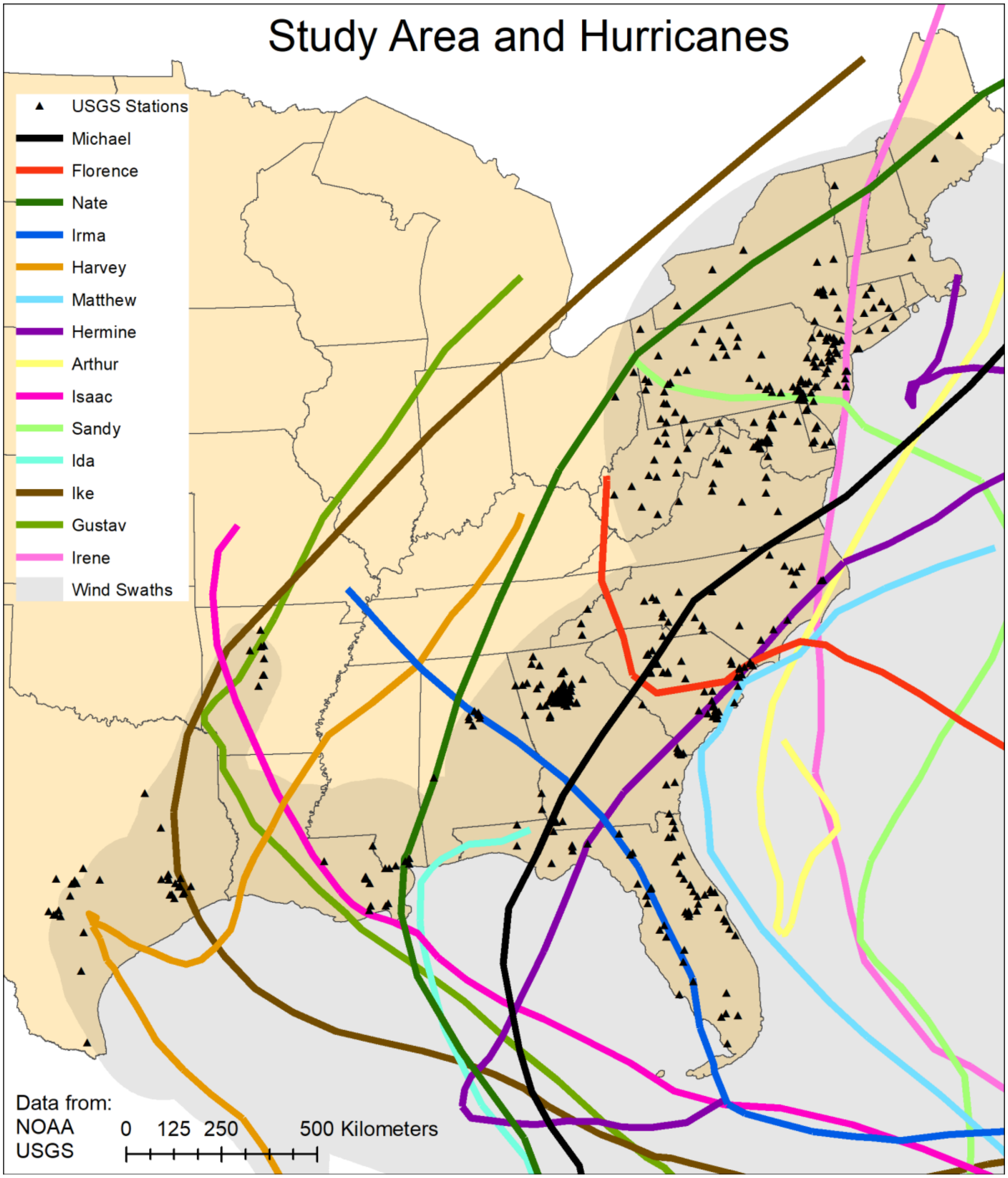

Figure 1. Map of the study area (defined by the extent of the wind swaths) showing the locations of USGS stations as well as hurricane tracks and their combined wind swaths.

Table 1. Storms used to investigate the relationship between water quality parameters and hurricanes.

Hurricane	Category	Landfall Date	Location
Gustav	4	9/1/2008	Louisiana
Ike	4	9/13/2008	Texas
Ida	2	11/10/2009	Alabama
Irene	3	8/27/2011	North Carolina
Isaac	1	8/28/2012	Texas
Sandy	3	10/29/2012	New Jersey
Arthur	2	7/4/2014	North Carolina
Hermine	1	9/2/2016	Florida
Matthew	5	10/8/2016	South Carolina
Harvey	4	8/25/2017	Texas
Irma	5	9/10/2017	Irma
Nate	1	10/8/2017	Louisiana
Michael	5	10/10/2018	Florida
Florence	4	9/14/2018	North Carolina

Controlling Factors

Controlling factors consist of factors related either to the physical station site or the storm itself. Storm strength, wind speed, the distance to the storm track, the distance to the point of storm landfall, the total storm precipitation, total precipitation over each

USGS station, and the total precipitation over each contributing area are all controlling factors belonging to each storm. The distance to the coast, contributing area size, climate zone, water body type, land use, mean slope of contributing area, and soil are all controlling factors unique to each USGS station.

Storm Strength

Storm strength is obtained by using the respective hurricanes' Saffir–Simpson Hurricane Wind Scale values (from 1 to 5). The value used is the storm's maximum category, applied to all stations covered by the storm regardless of the actual strength at the time the storm reached an individual station. Therefore, this controlling factor acts as a measure of the storm's maximum size and maximum strength, not local strength (which is represented by the next factor, wind speed). Data is obtained from NOAA (National Oceanic and Atmospheric Administration)'s NHC (National Hurricane Center) published hurricane data.

Wind Speed

Wind speed is obtained in knots, with the given values for each station being the estimated maximum ground wind speeds at the location of each USGS station. Estimated wind speed values range between 0 and 64 knots, with discrete values of 0, 32, 50, and 64 knots for each individual storm (Figure 2). This controlling factor allowed for local wind conditions to have an effect on the model. The wind data was obtained from NOAA NHC published hurricane data.

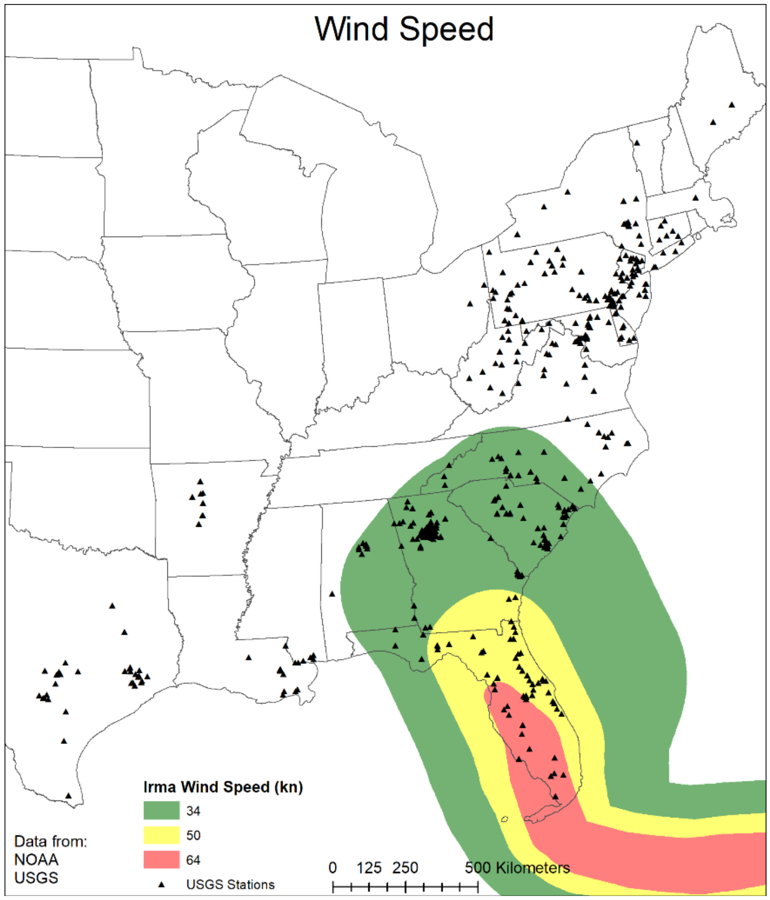

Figure 2. Map of wind speed data for hurricane Irma.

Distance to Storm Track

The distance to storm track is calculated as the linear distance in kilometers from each USGS station to the closest point along the central path of the storm. This data allows for the model to take the proximity of the storm into account. The storm path data is obtained from NOAA NHC published hurricane data.

Distance to Storm Landfall

The distance to storm track is calculated as the linear distance in meters from each USGS station to the point where the storm track intersected the contiguous US's coastline. In general, hurricanes typically weaken upon making landfall. Thus, this controlling factor allows for the model to take into account the proximity of each station to this phenomenon. In the case where a hurricane track intersects with the shoreline multiple times, the first such intersection is used. The storm path data is obtained from NOAA NHC published hurricane data while the coastline data is obtained from NOAA from their Medium Resolution Shoreline project.

Distance to Coast

The distance to coast is calculated as the linear distance in meters from each USGS station to the nearest line segment of NOAA's Medium Resolution Shoreline (Figure 3). This data allows the model to take into account the continental vs littoral nature of the station in spatial terms. Data is obtained from NOAA from their Medium Resolution Shoreline project.

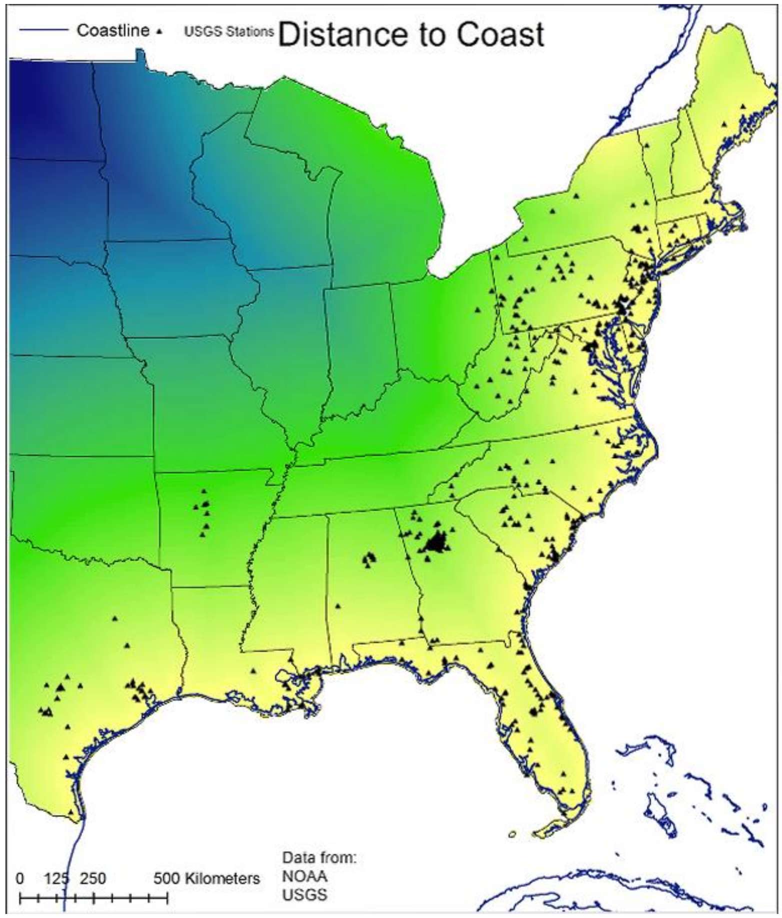

Figure 3. Map of the distance function used to generate distance data—in this case, distance to the coastline.

Total Storm Precipitation

Total Storm precipitation is calculated by summing the total daily rainfall over land of each hurricane from the day it achieved category 1 on the Saffir–Simpson Hurricane Wind Scale until the storm dissipated (defined as the exit of hurricane precipitation from the contributing area of the USGS stations affected by that storm). This total precipitation value takes into account the entire rainfall of the hurricane, and thus allows a measure of the hurricane's strength within the model which is not solely based on its wind speed. The data used for all precipitation factors is derived from the PRISM Climate Group's daily precipitation raster grids.

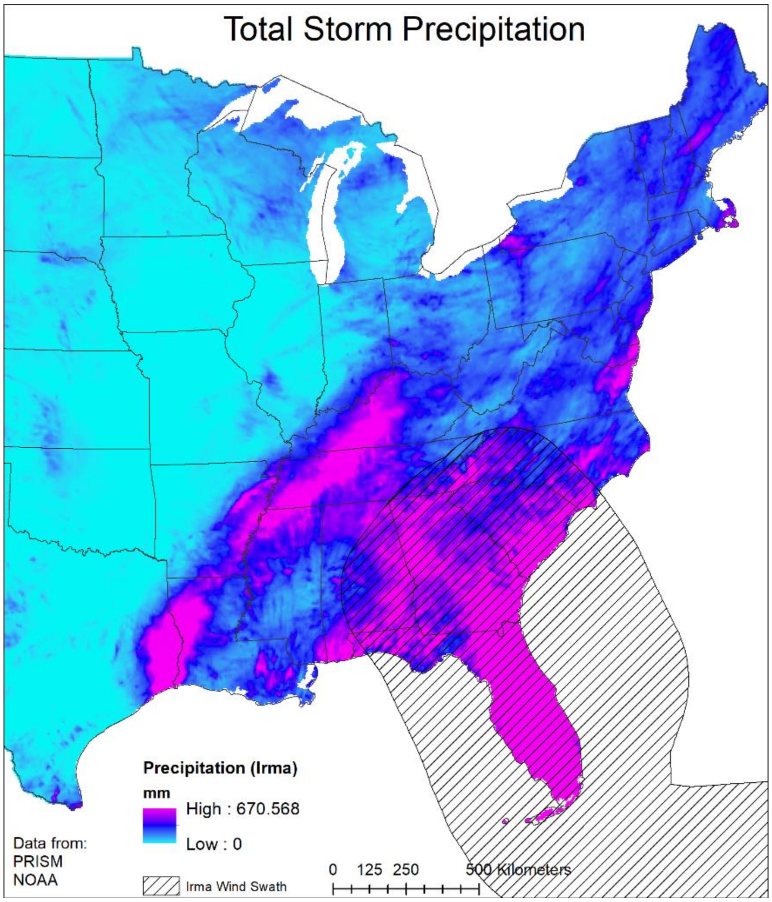

Figure 4. Map of the total calculated precipitation for Irma.

Total Precipitation Over USGS Station

Total precipitation over each USGS station is tallied by summing the total daily precipitation over each station using the methods and data described in Total Storm Precipitation. Here, however, the data summed is only that localized over each station.

This allows the model to take into account a spatially discrete level of precipitation individual to each USGS station. This acts as a local indication of local storm strength.

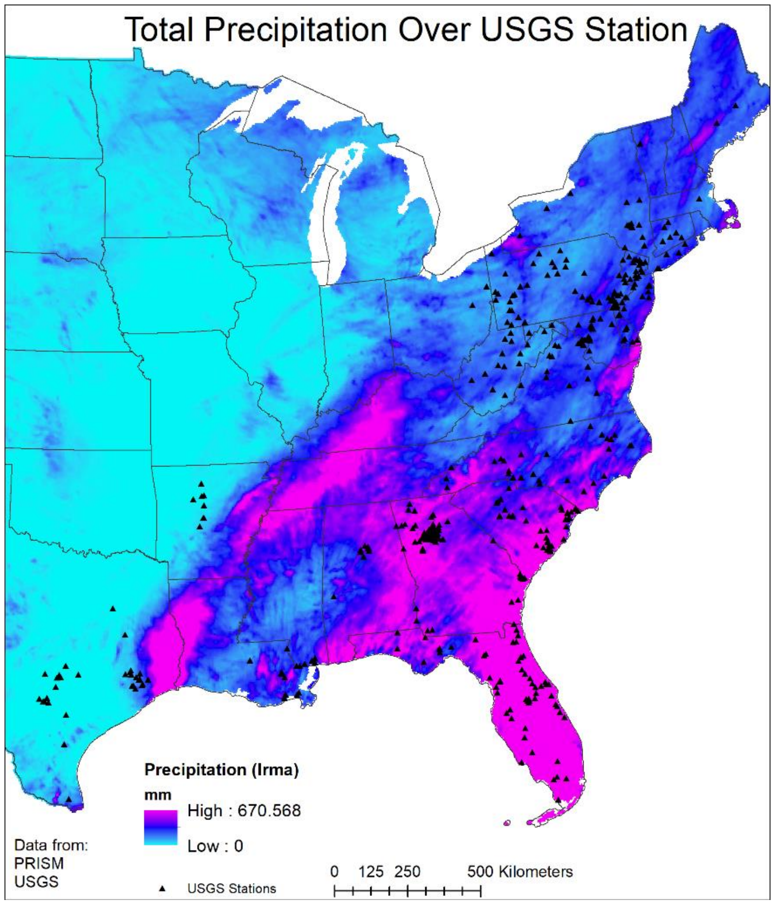

Figure 5. Map of the total calculated precipitation over each USGS station for Irma.

Total Precipitation Over Contributing Area

Total precipitation over the contributing area is obtained by summing the total daily precipitation within the associated contributing area of each station (see Contributing Area for a description of how contributing areas were calculated) using the methods and data described in Total Storm Precipitation. This controlling factor goes beyond a measure of local storm strength, as the precipitation deposited within each USGS station's contributing area supplies the flow of water through that station (Figure 6). Thus, while the other precipitation factors can be helpful for understanding the strength of the storm, this factor is one of the primary drivers of water quality levels.

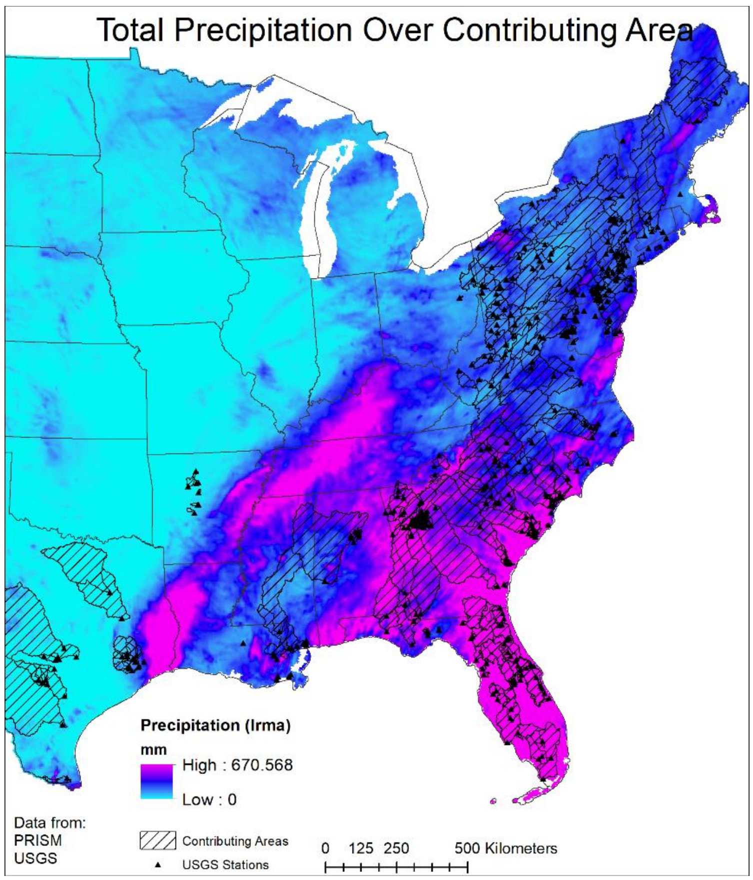

Figure 6. Map of the total calculated precipitation over each contributing area for Irma.

Contributing Area

Contributing areas for each USGS station are obtained by three separate methods, all resulting in the station's contributing area being reported in square meters. Out of 457 USGS stations, 278 have contributing areas published by the USGS as part of their USGS

Streamgage NHDPlus Version 1 Basins 2011 dataset. Where available, this data was used.

A further 80 contributing areas are delineated using the USGS's StreamStats tool. This tool is the method recommended to the author in correspondence with the USGS. StreamStats data is not available in all states, with Florida, Mississippi, Louisiana, and Texas unavailable.

A further 69 contributing areas are able to be calculated using HUC12s delineated by the USGS's Watershed Boundary Dataset (Data Model v2.3). Each HUC12 provided by the model is linked to those HUC12s upstream of it. These upstream HUC12s are all combined to the HUC12 where the USGS station was located, with the assumption that all water flowing through that HUC12 passes through the USGS station within the HUC12's watershed. While this introduces some error, results are checked against existing stream network data of the USGS's National Streamflow Network. It is found this method introduces minimal error (most USGS stations are located at the outlet of the various HUC12s. In the most egregious case, that of a station within the Delaware River basin, the contributing area size is erroneous by approximately +20%). With these three methods, 427 contributing areas are obtained (Figure 7).

The contributing areas of the remaining 30 stations are unable to be satisfactorily calculated using these methods. In some cases, the watersheds are too small and the resolution of available data precluded their use. Significantly, all stations along the Mississippi River are unused, as their contributing areas are roughly 40% that of the contiguous United States. This large watershed would have introduced unacceptable levels of noise in the form of up-river processes independent of hurricane conditions.

Without a satisfactory method for isolating the effects of hurricanes in the large contributing area of the Mississippi River, the stations are thus excluded from analysis.

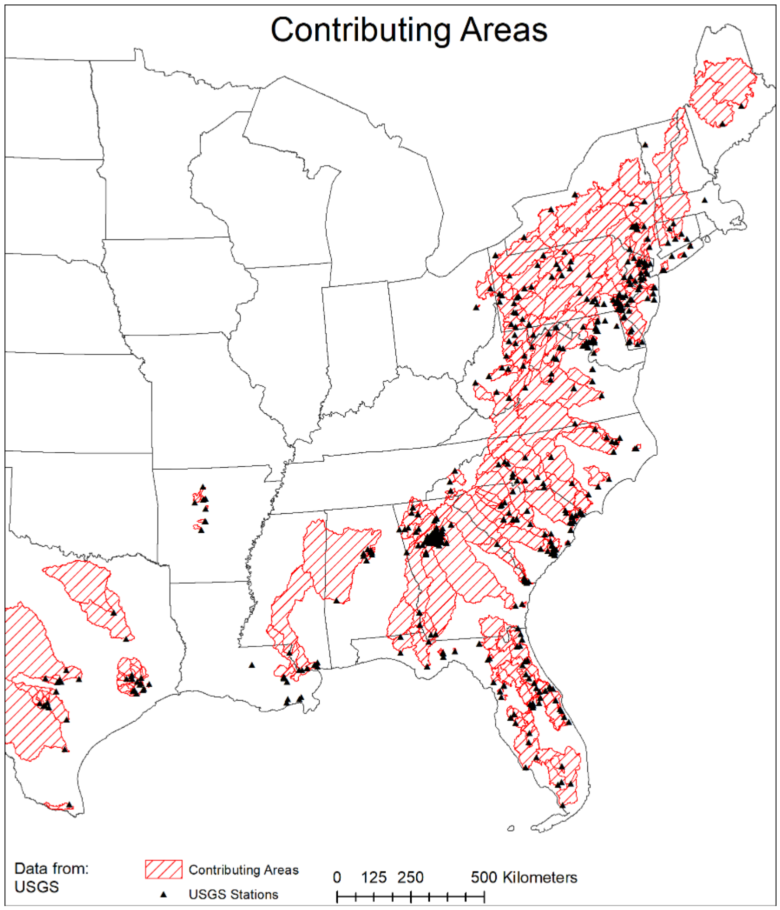

Figure 7. Map of contributing areas.

Climate Zone

Climate zones for each station is determined using existing Köppen climate classifications (Figure 8). Each USGS station is assigned the climate zone it resides in. This data allows for overall climate to be taken into account as a factor effecting water quality during storms. In order to analyze this data, it is divided into binary categories for each different Köppen climate classification, with a value of 1 being assigned to the climate type the station was located in, and 0 being assigned to all other values. This is necessary as the data is nominal data. This study used the Koppen Climate Classification for the Conterminous United States from the University of Idaho.

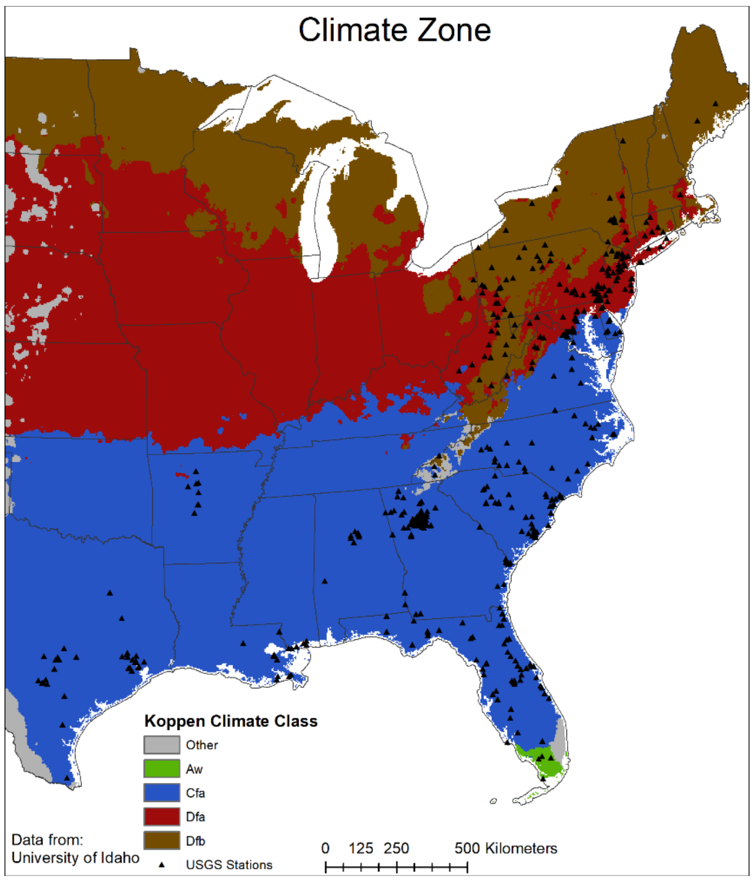

Figure 8. Map of climate zones.

Water Body Type

Each USGS station is assigned a water-body type based on the water body the station is installed in (Figure 9). Categorizing each station by water body type allows the model to take into account the differences in response between flowing bodies of water and more static ones. There is a total of four categories: stream, lake, estuary, ocean. Classification is accomplished by dividing each class into a separate entry and assigning a binary truth value to that entry. This is necessary to avoid assigning a ratio to this nominal data. Water body type data is from the USGS's Water Quality Data for the Nation program.

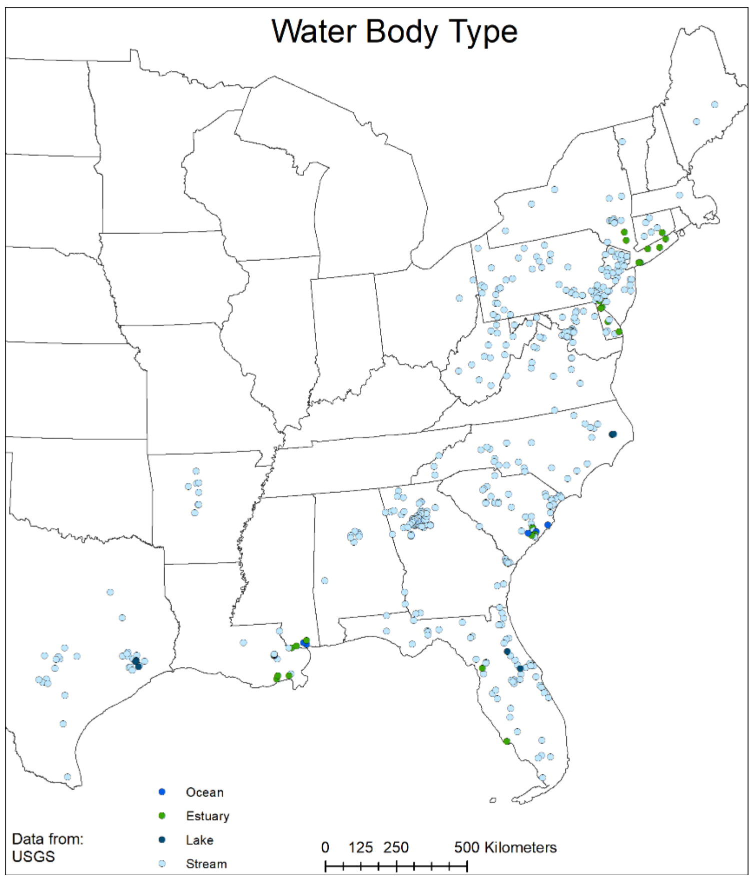

Figure 9. Map of each USGS station's water body type.

Land Use

Land use is determined by aggregating particular land use classes and producing four separate percentages of land use within each station's contributing area for input into the model. The four categories used are urban, agricultural, wetland, and forest. Land use data is collected from the USGS's NLCD (National Land Cover Database 2016). Each category is an amalgamation and reclassification of NLCD land use types: Urban land is defined as a combination of the developed open space, developed low intensity, developed medium intensity, and developed high intensity classes. Agricultural land was defined as a combination of the pasture/hay and cultivated crops classes. Wetland is defined as a combination of the woody wetlands and emergent herbaceous wetlands classes. Forest is defined as a combination of the deciduous forest, evergreen forest, and mixed forest land use classes (Figure 10).

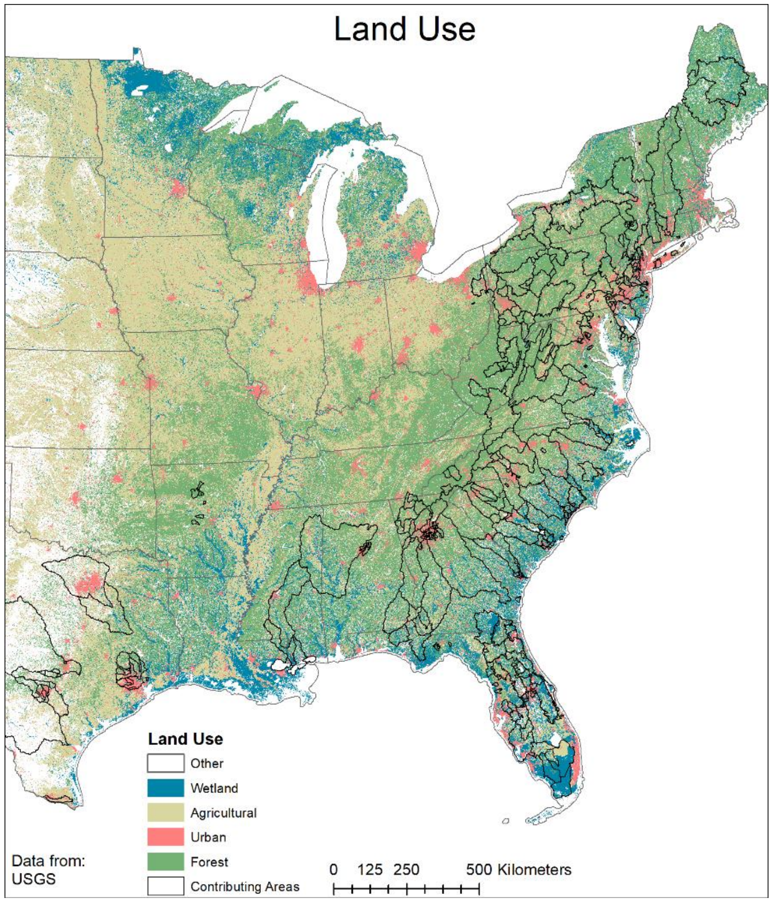

Figure 10. Map of each land use category.

Mean Slope of Contributing Area

The average slope of each contributing area is calculated by taking the mean slope within each USGS station's contributing area (Figure 11). This mean slope is a rough indicator of how flat or undulating each station's watershed is, and may be an important controlling factor for water quality parameters such as turbidity, which are influenced by erosion. The slope raster within each area consists of a 30m resolution raster obtained using the geodesic method of Esri's slope geoprocessing tool in concert with a 30m resolution DEM of the eastern United States. DEM data is obtained from ALOS Global

Digital Surface Model "ALOS World 3D - 30m, provided by the Japan Aerospace Exploration Agency.

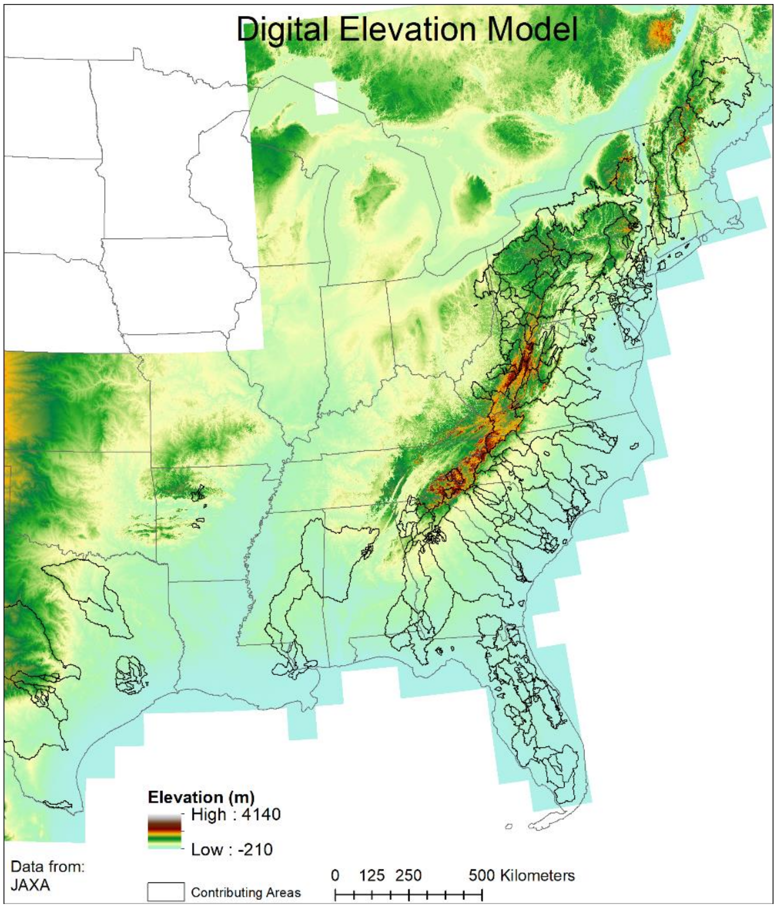

Figure 11. Digital elevation model used to calculate slope for each contributing area.

Soil Depth and Sand, Silt, and Clay Content in Contributing Area

Soil data is divided into four parameters: Soil depth, % sand, % silt, and % clay within the contributing area of each USGS station. All four parameters are calculated as the mean of that respective data within each contributing area. The inclusion of soil depth (Figure 12) and percentage information allows the model to account for soil's impact on erosivity and sediment supply. Soil data is obtained from the USDA's SSURGO (Soil Survey Geographic database)

Figure 12. Map of the average soil thickness, one of the soil factors applied to each contributing area.

Response Variables

Response variables are measures of water quality used as targets for model development. Seven types of response variables are considered: discharge, gauge height, dissolved oxygen, pH, nitrates/nitrites, and turbidity. This data is further divided into two categories per response variable: magnitude difference and duration. Magnitude difference is defined as the difference between the mean pre-hurricane value and hurricane value of the response variable. Duration is defined as the number of days during which the response variable's value remains outside of the first standard deviation of the pre-hurricane values.

USGS Data

A total of 1,037 individual USGS stations are within the study area. These stations possess a variety of instrumentation and some of these stations contain gaps of data for the corresponding period of hurricane activity. After an initial removing of superfluous stations without temporally useful data, 457 USGS stations remain to be used in the study. Of these 457, many stations were struck by multiple hurricanes and allowed for the collection of additional data. Each station affected by multiple hurricanes is therefore used several times, raising the number of instances with useful data to 815.

The time periods considered include 20 years of USGS daily data collected for each station from a starting date of 1990-01-01 to an ending date of 2019-05-19. After inspection, it is found that data availability was limited before 2008, but the earlier data is still retained for assistance in establishing seasonal trends.

Data Preprocessing

The USGS station data comes in the form of daily data on a per station basis. This daily data consists of three values per instrument: the mean value measured for that day, the maximum, and the minimum. These data are often incomplete with gaps present for various reasons. A station's instrument may have failed on a particular day and took months to repair. In other cases, the USGS stations were knocked offline by the very hurricanes themselves. Data is sometimes fragmentary in these cases, sometimes with minimum and maximum values being reported without mean values. Additionally, some data are in different units (imperial vs metric). Therefore, several preprocessing steps are required.

First, where imperial data and metric data overlaps, imperial data is converted to metric units. These data are then merged. Second, the mean, maximum, and minimum values are incorporated to provide an adjusted mean for analysis in the following way: where a mean value is available for a day, that value is used. Daily data in which a mean value does not exist, the average of the maximum and minimum values is used. In situations where the mean nor the maximum existed, the minimum value is used. In cases where the mean nor the minimum exists, the maximum value is used. Finally, in cases in which none existed, the entry is marked with the no data code (no_data).

Data Processing and Interpretation

It is necessary to detrend this new combined dataset to isolate hurricane impacts from seasonal variation. A yearly approach for detrending is used, with the data fit to a sinusoidal function and that function then subtracted from the data.

A custom algorithm is developed to de-trend, identify signatures, and create the final data products of magnitude difference and temporal duration of anomalous water quality. This is accomplished by first establishing a baseline with the detrended data. The algorithm is given the landfall date of each hurricane. Due to the size and velocity of hurricane storm systems, as well as the large spatial distribution of USGS stations, it is inadvisable to use the hurricane's landfall date as the division for pre and post hurricane windows. Therefore, the algorithm is programed to search for the onset of deviation from the water preexisting water quality parameters within a 6-day window around the inputted landfall date. This is accomplished by looking at the second derivative of the water quality data and setting a large spike in that second derivative (analogous with acceleration in positional data) as the established estimated date of storm effect. The algorithm then recorded the proceeding 5 days from that established estimated date of storm effect, the pre-hurricane window, recording a mean and standard deviation for the proceeding conditions. Upon the landfall date, the algorithm then measured the peak value of the response variable. This peak value is subtracted from the previously established mean to provide a magnitude difference. Where the peak value, or lack thereof, falls within the bounds of the pre-effect window standard deviation, a zero value result is recorded.

Obtaining the temporal duration of anomalous water quality is accomplished by defining normal conditions as being those conditions within the standard deviations of the pre-hurricane window. However, sometimes the water quality parameter does not return to the pre-effect window. Therefore, several conditions are defined. In a natural scenario where the water quality parameter returns to within the standard deviation of the pre-effect window, the number of days the water quality parameter is outside the standard deviation is taken as the temporal duration of the event. In these cases, the metadata is marked with a “natural” (Figure 13).

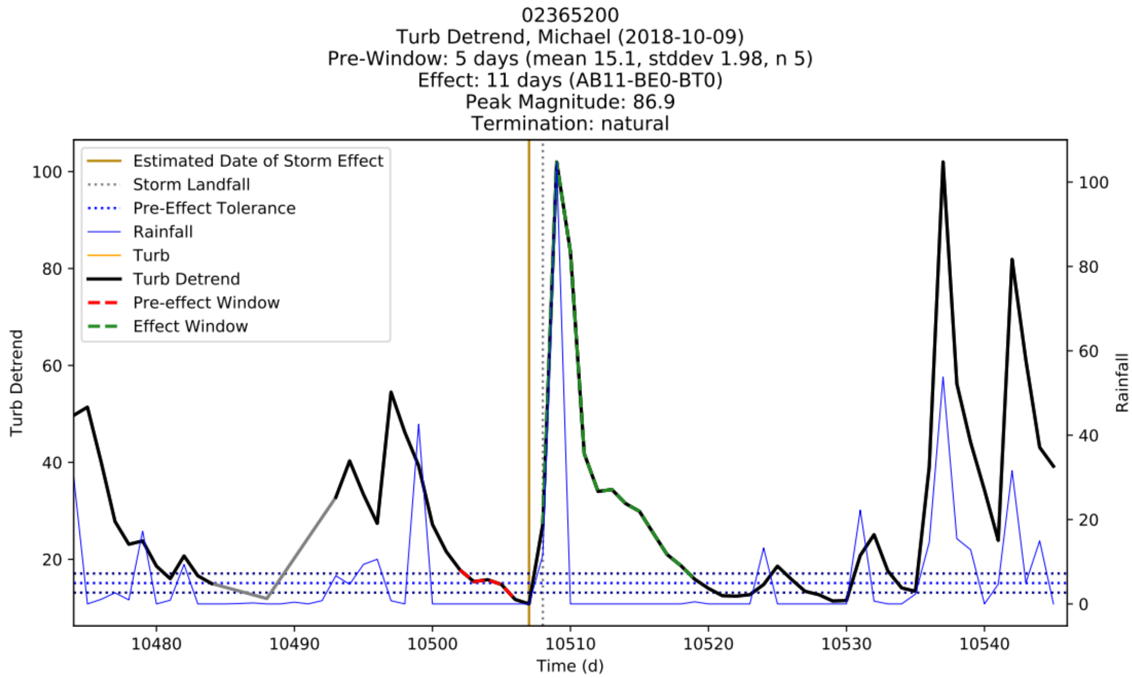

Figure 13. Data interpretation algorithm assigning a natural termination.

In some cases, data presents interpretive challenges. In the case that the instrument failed before the water quality parameter could return to the within the standard deviation of the pre-effect window, the number of days the water quality parameter is outside the standard deviation up until the cut-off is taken as the temporal duration of the event. In these cases, the metadata is marked with a “dropout” (Figure 14). In the case that the water quality parameter never left the standard deviation of the pre-effect window, the temporal duration is taken to be 0. In these cases, the metadata is marked with a “nan” (Figure 15). In a minority of cases, the water quality parameter does not return to the standard deviation due to the intervention of other storms. To distinguish these special cases, the algorithm always looks to see if the first derivative of the data in the post-effect window possesses a positive first derivative (indicating that the water quality parameter is halting its return towards mean conditions, possibly influenced by an external event). If the existence of a positive first derivative that occurs after the recorded peak value persists for longer than 3 days, the algorithm forces a termination. This is accomplished by extrapolating the slope of the data from the last day before the existence of a positive first derivative. The temporal duration is taken to be the number of days the data is outside of the standard deviation, including the extrapolated data. In these cases, the metadata is marked with a "forced" (Figure 16). The forced data is manually reviewed afterward and the method found to be a good fit for all affected stations.

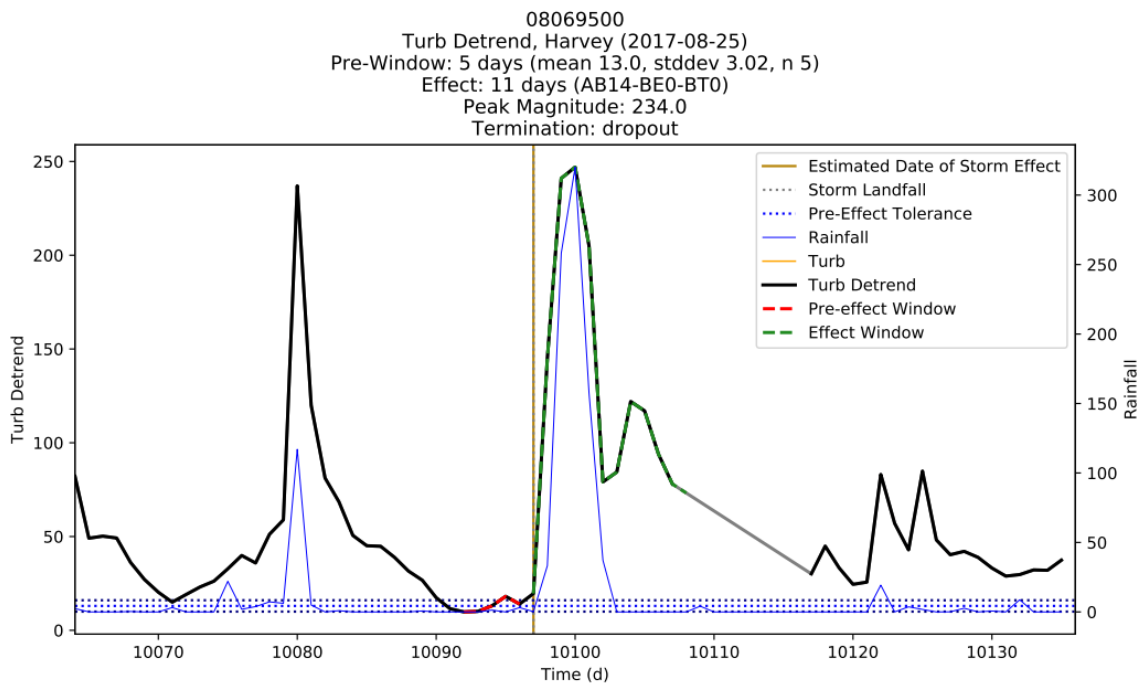

Figure 14. Data interpretation algorithm assigning a dropout termination.

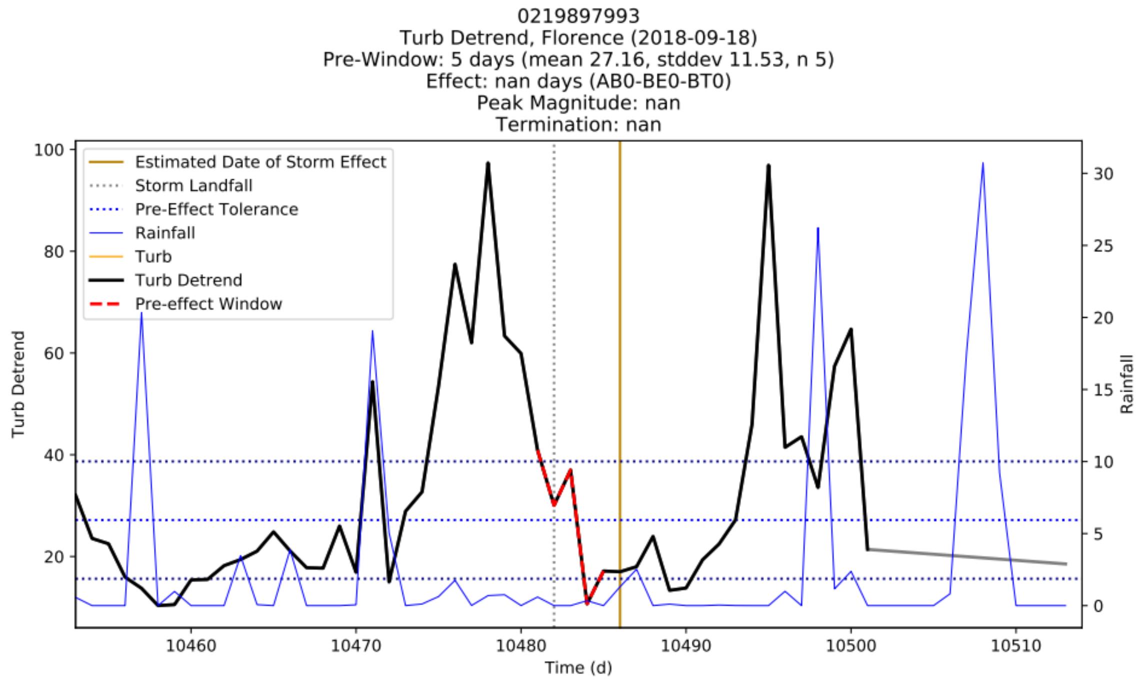

Figure 15. Data interpretation algorithm assigning a zero value.

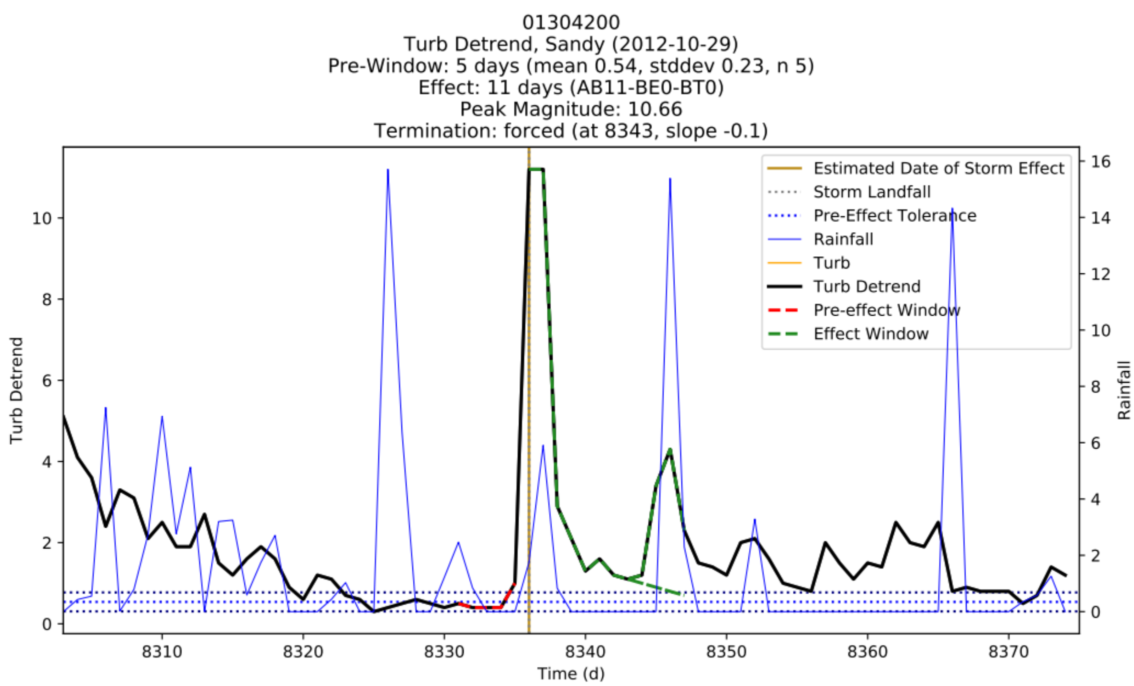

Figure 16. Data interpretation algorithm assigning a forced termination.

Data Analysis

With the proceeding work accomplished, we are left with a master dataset containing all contributing factors and all response variables associated with each USGS station. Not all USGS stations has instrumentation of all types. Out of the 815 stations there were 312 stations with discharge data, 188 stations with dissolved oxygen data, 226 stations with gauge height data, 15 stations with nitrates/nitrites data, 151 stations with pH data, and 121 stations with turbidity data. The mean of each parameter is taken, as well as a distribution of values to provide a description of water quality responses. After this, analysis proceeds to correlations and machine learning.

Data Correlation

Pearson's correlation coefficient is calculated between controlling factors and response factors. Most important of these are the correlations between controlling factors and response variables. Performing a correlation between each factor gives a better insight into which controlling factors are most important to each response variable. Additionally, each controlling factor and response variable's R values are squared and summed together. This sum of Pearson correlation coefficient values for each parameter offers a comparable measure of importance, with larger values corresponding to more correlation with the other parameters.

Machine Learning

A shallow neural network is employed to build a predictive model with controlling factors as inputs and response variables as outputs. MATLAB's shallow neural network fitting application is used to accomplish this. This function works by taking the inputs and targets, normalizing them, and sending the inputs through a network of neurons with varying weights. With the correct weights, the inputs should match the outputs when put through the network. This matching ability is measured by a performance parameter (goodness of fit).

Data is arranged in rows, with each row representing an instance with a USGS station during a particular storm event and its respective controlling factors and response variables. Models are developed considering all controlling factors and one response variable at the time. A total of 10 models are developed (5 response variables for magnitude plus 5 response variables for duration in days). Those datasets are divided into two groups chosen randomly, with a training dataset consisting of 85% of instances and a test dataset consisting of the remaining 15% of instances. Bayesian regularization is used to train the neural network due to its suitability for small and noisy datasets, at the expense of computational efficiency. Due to the use of Bayesian regularization, no validation dataset is required. This is because Bayesian regularization uses a form of backpropagation that is used in place of validation data, having its own form of validation (MATLAB, 2020).

An analysis to consider the number of neurons is performed before the neural networks were built. The discharge daily data (the response variable with the second lowest correlation to its controlling factors, 0.31 being the sum of its R squared value) and the turbidity daily data (the response variable with the second highest correlation to its controlling factors, 1.49 being the sum of its R squared value) are used to perform this analysis. A neural network with $n \times 5$ neurons is run using the parameters described above with the value of n ranging from 1 (5 neurons) up to 12 (60 neurons). It is found that the highest performance is offered at a neural network size of 50 neurons. Thus, 50 neurons are used for the neural networks in this study (Figure 17). A total of 10 neural networks are created, one for each response variable excluding nitrates and nitrites (due to poor sample size). Performance values are then reported for each neural network.

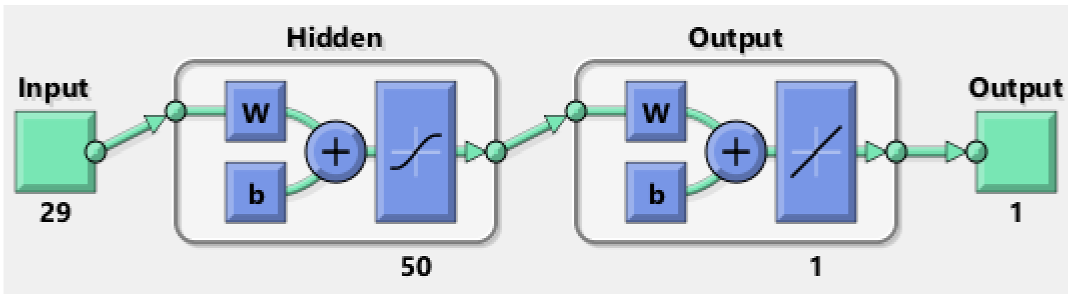

Figure 17. Neural Network (generated with MATLAB).

CHAPTER III

RESULTS AND DISCUSSION

Evaluation of Response Variables

The analysis and quality control of response variables in this study have given insights on important characteristics and relations. On average, most parameters do not persist for longer than a week (Table 2), the exception to this being discharge with a mean duration of 15 days and elevated water levels with a mean duration of 24 days. Additionally, a surprising result is the lowering of nitrate/nitrite levels on average. While the reason for this negative reaction is not investigated in this study, a reason that could be put forward is a potential ‘flushing effect’, where so much fresh water in the form of precipitation is dumped on an area that the surface pollutants are diluted and washed downstream. All response variables show a skewed distribution of the duration (Figure 18). While most stations did see a return to normal conditions within a week, both pH and turbidity at specific stations persisted for up to two weeks. This may be explained by those stations being located in areas of reduced water movement such as lakes or estuaries. Mean magnitude differences were calculated ranges between maximum hurricane conditions and pre-hurricane conditions while mean duration is the number of days to return to pre-hurricane conditions (Table 2). Most results are within expected ranges, however, results for DO conflict with previous studies, which show lowered DO levels after hurricanes (Hagy et al., 2006; Mallin et al., 1999; Pardue et al., 2005); though it should be noted these studies were limited in geographic scale and temporal scope.

Additionally, it is important to note that these differences from the pre hurricane mean and duration vary significantly depending on the size of the contributing area, how much precipitation it received, and many other factors. A correlative analysis and/or machine learning-based predictive model can quantify the relationship between these contributing factors and the response variables. These mean values are a useful benchmark, establishing expected courses of action for each water quality parameter after a storm. However, without accounting for the different setting of each individual station, one should interpret isolated parameters cautiously.

Table 2. Response variables. Mean response is listed in units above/below pre-hurricane conditions. Mean duration is the number of days to return to pre-hurricane conditions.

Statistics	**Discharge (cfs)**	**DO (mg/L)**	**GH (ft)**	**N/N (mg/L)**	**pH**	**Turb (FNU)**
Mean difference	6600	0.74	4.1	-0.12	-0.36	100
Std dev of dif.	18356.9	0.9	6.6	0.2	0.5	130.3
Mean duration	15	3.4	24	3.5	7.2	5.5
Std dev of dur.	18.8	4.8	147.9	6.1	19.4	5.1
Sample Size	312	188	226	15	151	121

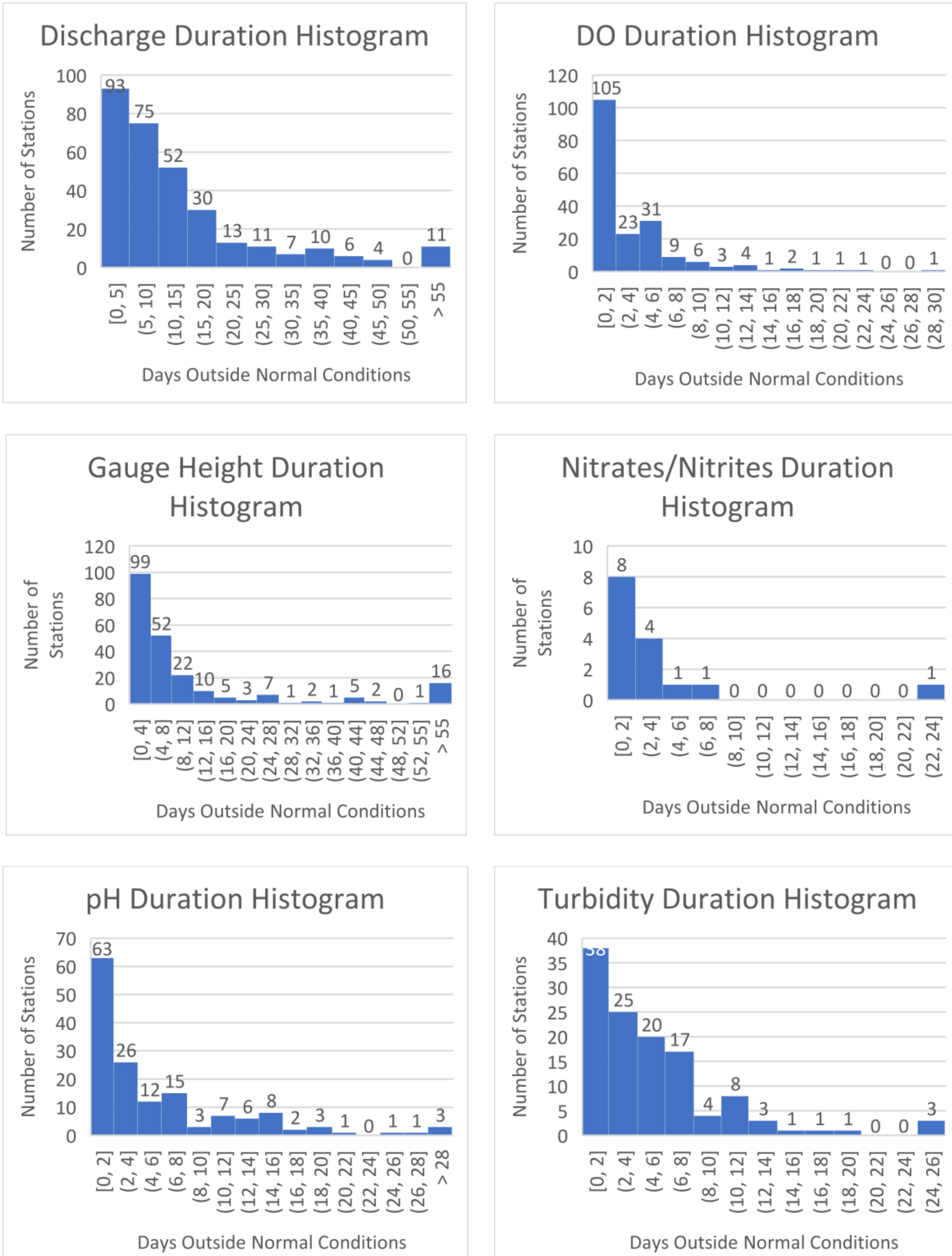

Figure 18. Histogram for the duration of elevated gauge height levels in days for every station.

Correlation of Controlling Factors and Response Variables

Person's correlation coefficient was calculated for all controlling factors and response variables are correlated with one another (Table 3). Lower correlation coefficient values can be attributed to there being a large number of contributing factors that influence each response variable. Therefore, the correlations should be interpreted liberally, keeping in mind that each controlling factor accounts for a percentage of influence upon each response variable.

In addition to the correlation coefficients themselves, each controlling factor's and each response variable's correlation coefficients are summed, giving combined controlling factors and combined response variables values respectively (Table 4). For contributing factors, each of these values represent the relative 'importance' of each factor in terms of how well correlated they are overall. For example, we can see that the local precipitation over the USGS station has the highest relative 'importance' among contributing factors. This implies it is the most influential factor in determining the overall result of a hurricane in terms of the response variables studied here. For response variables, they can be interpreted somewhat differently: they are a measure of how well these correlations work to predict each response variable. In the case of high values, such as T Dur (the duration of turbidity outside the pre-hurricane mean), it implies that the chosen controlling factors do a good job of describing the response variable.

It is important to remember that this is a two-dimensional analysis. It is helpful in that it highlights direct correlations between controlling factors and response variables. However, response dependent on a particular combination of several factors (such as turbidity levels where the slope and soil parameters combine with high precipitation values to creative a particularly erosive environment) may not be obvious in this analysis. This multidimensional analysis is best performed using machine learning. Additionally, while correlative analysis is performed using the nitrates and nitrites data, its geographically limited scope and sample size of 15 precludes any statistically significant conclusions from that data.

Table 3. Definition of terms used in tables 4 and 5.

Term	Definition	Term	Definition
Cs	waterbody class, stream	Lw	land use, wetland
Cl	waterbody class, lake	S	mean slope
Ce	waterbody class, estuary	Sd	soil depth
Co	waterbody class, ocean	Ssa	soil sand content
Dt	distance to hurricane track	Ssl	soil silt content
Dl	distance to hurricane landfall	Sc	soil clay content
Dc	distance to coastline	CRV	combined response variables
SC	storm category	D Dif	discharge magnitude difference
W	windspeed	D Dur	discharge duration
Pa	precipitation, total storm precipitation	DO Dif	dissolved oxygen magnitude difference
Pb	precipitation, total over USGS station	DO Dur	dissolved oxygen duration
Pc	precipitation, total over contributing area	G Dif	gauge height magnitude difference
KAw	Aw Köppen climate class	G Dur	gauge height duration
KCfa	Cfa Köppen climate class	N Dif	nitrates/nitrites magnitude difference
KDfa	Dfa Köppen climate class	N Dur	nitrates/nitrites duration
KDfb	Dfb Köppen climate class	pH Dif	pH magnitude difference
CA	contributing area	pH Dur	pH duration
Lu	land use, urban	T Dif	turbidity magnitude difference
La	land use, agriculture	T Dur	turbidity duration
Lf	land use, forest	CCF	combined controling factors

Table 4. This table shows the correlation coefficients of controlling factors and response variables. Values are color coded based on their relative intensity, with green for the mean R^2 values and blue and red for correlation coefficients. Controlling factors and response variables have been abbreviated.

	D Dif	D Dur	DO Dif	DO Dur	G Dif	G Dur	N Dif	N Dur	pH Dif	pH Dur	T Dif	T Dur	CCF
Cs	0.00	0.04	0.04	0.02	0.14	0.04	-0.18	0.16	0.26	-0.24	0.01	-0.37	1.51
Cl	N/A	N/A	-0.05	-0.07	-0.05	-0.01	N/A	N/A	-0.53	0.45	0.13	0.51	1.80
Ce	0.00	-0.04	-0.07	-0.10	-0.10	-0.03	0.18	-0.16	0.10	-0.05	-0.13	0.03	1.00
Co	N/A	N/A	0.08	0.19	-0.08	-0.02	N/A	N/A	N/A	N/A	N/A	N/A	0.37
Dt	-0.11	-0.21	-0.02	0.03	-0.08	0.01	-0.03	-0.35	0.01	0.02	0.12	-0.17	1.18
Dl	-0.16	-0.20	-0.13	0.01	-0.25	-0.10	0.01	0.10	0.04	-0.07	0.12	-0.33	1.53
Dc	-0.15	-0.15	-0.20	-0.05	-0.18	-0.10	-0.20	-0.03	0.03	-0.09	0.21	-0.33	1.72
SC	-0.07	-0.07	0.11	0.07	-0.07	-0.01	0.31	0.00	-0.09	-0.01	-0.01	-0.21	1.03
W	0.06	0.18	0.19	0.02	0.06	0.00	0.00	0.30	-0.18	0.01	-0.08	0.23	1.34
Pa	-0.12	-0.05	-0.03	-0.03	-0.14	-0.05	0.04	0.16	-0.02	-0.02	-0.03	0.01	0.72
Pb	0.37	0.25	0.23	0.06	0.70	0.10	0.22	0.20	-0.30	0.33	0.06	0.53	3.36
Pc	0.53	0.09	0.13	-0.02	0.38	-0.02	0.33	-0.27	-0.17	0.43	0.07	0.46	2.90
KAw	-0.04	0.14	N/A	N/A	-0.07	0.00	N/A	N/A	N/A	N/A	-0.12	-0.05	0.42
KCfa	0.05	-0.07	0.18	0.12	0.08	0.02	0.51	0.03	-0.19	0.06	0.04	-0.02	1.37
KDfa	0.01	-0.02	-0.12	-0.09	-0.05	-0.02	-0.51	-0.03	0.18	-0.09	-0.20	0.04	1.37
KDfb	-0.06	0.08	-0.19	-0.14	-0.01	-0.01	N/A	N/A	0.03	0.04	0.34	-0.04	0.93
CA	0.51	0.02	-0.11	-0.21	0.16	0.12	0.27	-0.23	0.09	0.04	-0.10	0.02	1.88
Lu	-0.20	-0.16	0.25	0.33	-0.06	-0.07	-0.39	0.34	0.03	-0.09	0.09	-0.07	2.08
La	0.12	0.17	-0.10	-0.23	0.22	0.09	0.05	0.11	-0.05	0.08	0.15	0.26	1.62
Lf	0.13	0.01	-0.29	-0.22	0.03	0.04	-0.12	-0.06	0.15	0.04	-0.07	-0.17	1.33
Lw	-0.01	0.09	0.24	0.12	-0.06	0.01	0.32	-0.31	-0.10	0.01	-0.21	0.04	1.51
S	-0.02	-0.07	-0.20	-0.07	-0.12	-0.04	-0.20	-0.17	0.06	-0.07	0.01	-0.23	1.26
Sd	0.06	0.12	0.14	0.01	0.09	0.07	0.39	0.25	-0.17	0.08	-0.01	0.25	1.64
Ssa	0.03	0.03	0.13	-0.05	0.10	0.01	0.27	0.23	-0.09	0.13	-0.09	0.05	1.20
Ssl	0.00	-0.05	-0.14	0.03	-0.03	0.04	-0.32	-0.15	0.25	-0.08	0.09	-0.01	1.21
Sc	-0.04	-0.17	-0.02	0.11	-0.07	-0.06	-0.37	-0.12	0.25	-0.14	0.04	-0.22	1.61
CRV	2.88	2.48	3.40	2.39	3.39	1.09	5.22	3.76	3.38	2.67	2.53	4.66	

The response variables themselves show strong correlations between some water quality parameters (Table 5). These correlations can be helpful to determine which water quality response variables might be proxies for others. For instance, elevated levels of nitrates and nitrites are correlated (0.69) with a long duration of elevated turbidity. This enables the duration of elevated turbidity to be inferred if a USGS station is equipped with a nitrate/nitrite instrumentation, even if that station lacks the ability to measure turbidity. It also allows future predictions to be made, for peak levels of nitrate and nitrites now correlate with a duration of turbidity in the future.

Table 5. This table shows the correlation coefficients between response variables. Values are color coded based on their position between -1 and 1. This table uses the same naming scheme for response variables as Table 4.

	D Dif	D Dur	DO Dif	DO Dur	G Dif	G Dur	N Dif	N Dur	pH Dif	pH Dur	T Dif	T Dur
D Dif	1.00											
D Dur	0.22	1.00										
DO Dif	-0.02	0.16	1.00									
DO Dur	-0.12	0.05	0.75	1.00								
G Dif	0.85	0.21	0.08	-0.07	1.00							
G Dur	0.19	0.57	0.34	0.07	0.09	1.00						
N Dif	0.24	-0.56	N/A	N/A	-0.14	-0.30	1.00					
N Dur	-0.17	0.62	N/A	N/A	0.26	0.79	-0.43	1.00				
pH Dif	-0.19	-0.07	0.09	0.14	-0.19	-0.25	-0.41	0.25	1.00			
pH Dur	0.27	0.13	-0.05	-0.10	0.27	0.28	0.62	-0.39	-0.44	1.00		
T Dif	0.08	-0.01	-0.15	-0.03	0.12	0.06	0.38	-0.15	-0.23	0.14	1.00	
T Dur	0.21	0.28	0.28	0.07	0.15	0.14	0.69	-0.46	-0.29	0.44	0.12	1.00

Discussion of Correlation Results

Precipitation seems to play a major role in nearly all response variables based on its sum of R^2 values. That two types of precipitation dominate as a controlling factor is not surprising for a host of reason; large quantities of precipitation beget discharge, flooding, erosion, and more. What is surprising, however, is that while Pb (precipitation over the USGS station) and Pc (precipitation over the contributing area) show this, Pa (total precipitation of the storm) has nearly no correlation with other factors. Total storm precipitation is more a measure of storm strength than precipitation affecting the station:

It represents the total quantity of precipitation generated by the storm over its lifetime. Combined with the similar low sum of correlations related to SC (storm category), this this implies that the general strength of the hurricane plays a minor, if any, role in contrast to more local factors.

Both the duration and magnitude difference of pH show a moderate correlation with Cl (stations located in lakes), showing a correlation of -0.53 for magnitude difference and 0.45 for duration. This is in contrast with pH's correlation with Cs (stations located in streams) which has a correlation of 0.25 for magnitude difference and -0.24 for duration. This indicates that pH levels fall further and remain lowered in lakes, while in streams they have a limited drop and limited persistence. This is possibly due to the layered nature of some lakes, where water circulation to lower layers of the water body can be limited. These lower layers may be influenced by the increased flow of a storm event, with low pH water mixing with areas of limited circulation. After the storm has passed, these areas of limited circulation then may cause the lowered pH values to persist. In contrast, streams' rapid flow may cause pH levels to return to normal quicker, and for their impact to be lower.

Turbidity duration shows a similar correlation as pH when measured in lakes and streams. A similar affect may cause turbidity to become 'trapped' in lakes, while circulating rapidly through streams. Interestingly, the magnitude difference of turbidity does not share this effect; only turbidity's duration does. Turbid waters may be dispersed within lacustrine settings, or perhaps they settle out more easily in calm waters. That the duration of turbid waters is longer in lakes works to discredit this second proposition.

Machine Learning

A neural network is created for each response variable, both in terms of magnitude difference and duration of effects. A neural network for Nitrates and Nitrites, however, is not developed due to their small sample size of 15. All other parameters are run and then evaluated by performing a correlation analysis between their training and testing datasets (Figure 19).

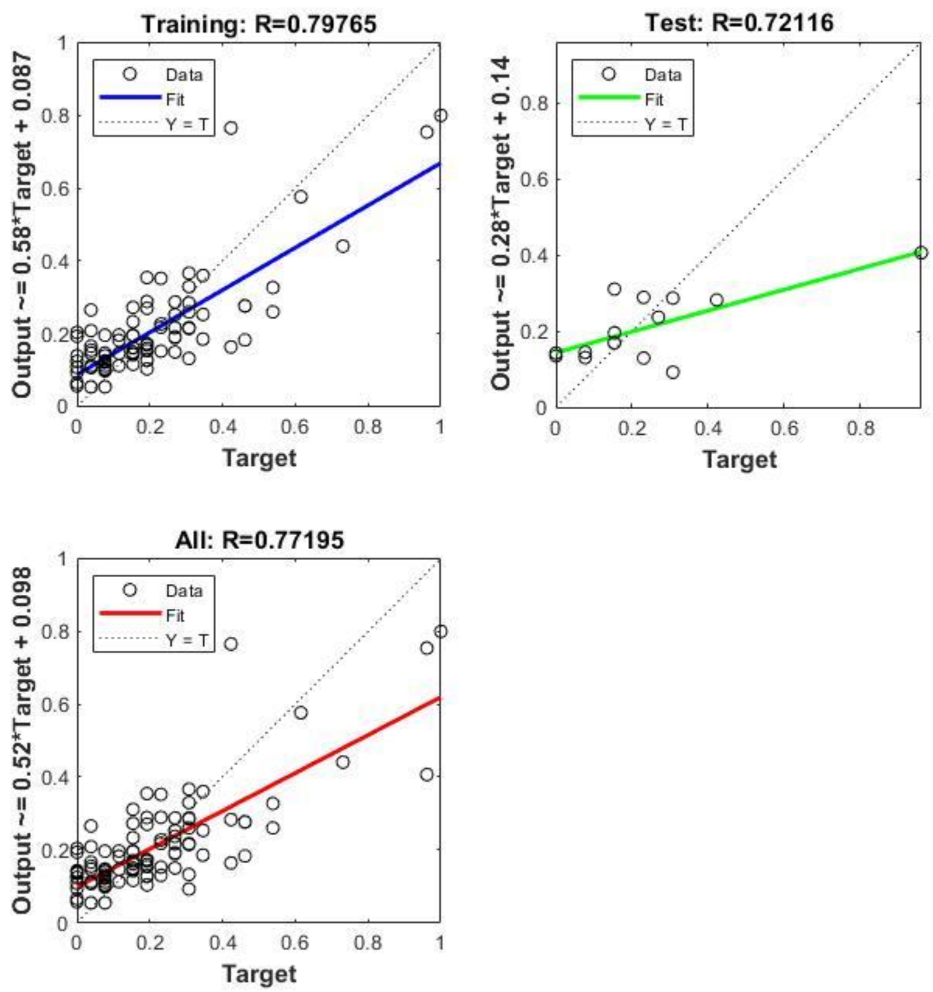

Figure 19. Neural network correlation results for turbidity duration. Training data is used by the network and compared with separate test data for a measurement of accuracy.

In general, the parameters with high combined response variable sums and high sample sizes did the best. Resulting R^2 values for each neural network were obtained (Table 6). Regression plots of each neural network are available in Appendix A.

Table 6. Neural network R^2 values.

Model	Training R2 Value	Testing R2 Value
Discharge Difference	0.99	0.78
Discharge Duration	0.59	0.50
DO Difference	0.27	0.27
DO Duration	0.21	0.26
Gauge Difference	0.77	0.71
Gauge Duration	0.11	0.10
pH Difference	0.47	0.43
pH Duration	0.49	0.09
Turbidity Difference	0.86	0.79
Turbidity Duration	0.58	0.61

Discussion of Machine Learning Results

The neural networks developed for discharge magnitude difference, gauge height magnitude difference, and turbidity in general perform the best. This is likely due to the high sample size of these response variables. The poor performance of the gauge height duration neural network does show that sample size is not the only factor for the successful deployment of a neural network though. Aside from gauge height duration and pH duration, the rest of the neural networks do show the ability to account for some factors. Theoretical shortcomings, detailed in Limitations, as well as noise in the data may account for these results, with the R^2 value of 0.79 seeming to be the currently attainable maximum for even the best performing neural networks.

The impact of future hurricanes on water quality can be predicted using this machine learning technique if we know the physical and climate characteristics of a region. This can be helpful in water quality management and hazard preparedness. A city using this model (or a similar model) can predict the effect of a hurricane on its water resources short and long term. Predictions can be made about how long an area's fresh water supply may be impacted, as well as to what degree. If there are limits or thresholds for water treatment plants and water supplies, this allows those stakeholders to come up with contingencies such as stockpiling of enough resources to last through a predicted duration of lowered water quality.

Limitations

Limitations for this study are mostly based on the data used. There is a proliferation of noise in the water quality data from sources such as broken instrumentation, incorrect readings, and gaps in the record. Some of these limitations with data availability, such as that of stations being knocked out by the hurricane as it passes, are unavoidable. Smaller gaps in the data can be accounted for using interpolation but doing so risks the introduction of further noise or the introduction of incorrect data. This is especially the case where this interpolation is made during or immediately after a storm's passage, possibly missing peak measurements.

Another limitation in this study was in the algorithm used to interpret the USGS station data to derive a magnitude difference and duration of response variables. The neural networks of the magnitude differences all outperformed their response variable's duration neural networks. This suggests that the algorithm has difficulties in evaluating long term trends. The algorithm used was accurate for short term trends and determining peak values of water quality parameters after a hurricane. However, the algorithm was less successful at defining long term effects, with the algorithm unable to differentiate between effects wrought by the storms studied and the effects of local rainfall, resulting in the forced termination of the post hurricane window in these situations. Additionally, the algorithm is only able to ascertain a peak value in one direction (positive or negative). The previous studies of dissolved oxygen after hurricanes (Hagy et al., 2006; Mallin et al., 1999; Pardue et al., 2005) concluded that DO levels are significantly lowered after a hurricane, in contradiction with the results of this study. This discrepancy could be explained as there being two peaks for DO values after a hurricane: a first positive peak occurring due to the aeration of the water surface when droplets of precipitation fall upon it, and then a second negative peak somewhere later, after waters have calmed and circulation within water is limited. The algorithm used in the study would only be able to detect the first positive peak in such a scenario. A similar situation may apply to nitrate/nitrite levels as well, as studies have shown those levels being elevated when in lacustrine and estuarian settings (Steward et al., 2006). An improvement could be made by enhancing the capacity to evaluate long term trends by either refinement of the algorithm used or another method entirely.

CHAPTER IV

CONCLUSIONS

This study produced three major contributions: the evaluation of each response variable, the correlations between controlling factors and response variables, and neural networks modeling the relationship between these data. The evaluation of each response variable is of significant value due to the sample size, geographical, and temporal destruction of measurements. They represent ten years' worth of hurricane influence on the eastern coast of the United States. These evaluations can be interpreted as the generalized effects of hurricanes upon water quality parameters. Thus, hurricanes, in general, result in an initial rise in DO levels, an initial lowering of nitrate/nitrite levels, a lowering of pH levels, and an elevation of turbidity levels.

The correlation of these response variables with each other and each controlling factor goes further than simply mapping the general response, and provides a measure of the influence of each faction upon the other. They highlight the roll of lacustrine environments contributing to prolonged bouts of lowered pH levels and persistent turbidity levels. They also show that local precipitation levels dominate over nearly all other controlling factors.

The neural network in this study can be used to predict future impacts on water quality. Hurricane characteristics can be input for a known location, and water quality impacts can be predicted for hurricanes of different intensity. While the accuracy of these neural networks acts as a limit on that predictive capability, the discharge neural networks, gauge different neural network, and turbidity neural networks are about to make predictions on a reasonable level ($R^2 > 0.50$). The accuracy of these models can be improved with future work. That future work should focus on refining USGS data and improving the method for data preprocessing and interpretation. Such avenues of research should be pursued. These predictions are useful for stakeholders such as disaster response agencies and water treatment facilities, allowing them to quantify and plan for future outages. In a changing climate, this capability may save lives, resources, and prove invaluable.

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APPENDICES

APPENDIX A

Neural Network Regression Plots

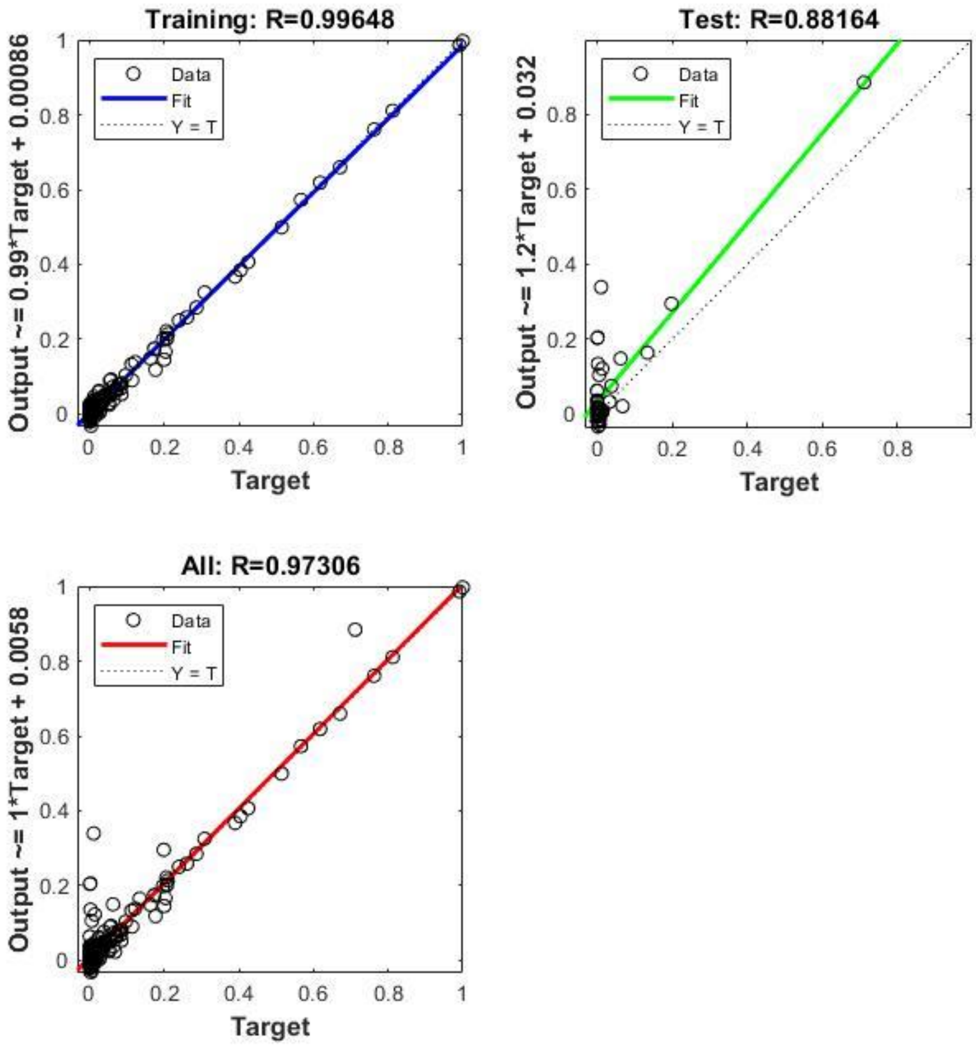

Figure A1. Discharge magnitude difference.

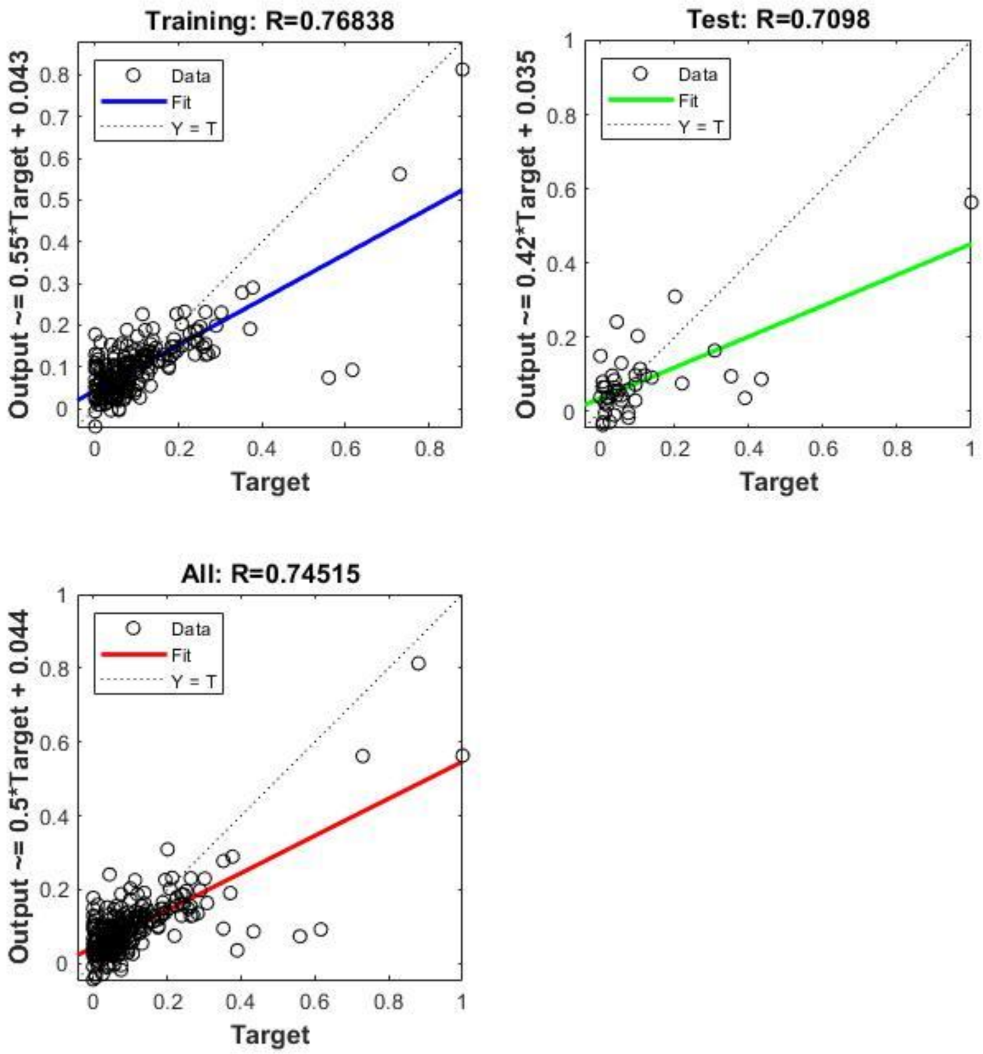

Figure A2. Discharge duration.

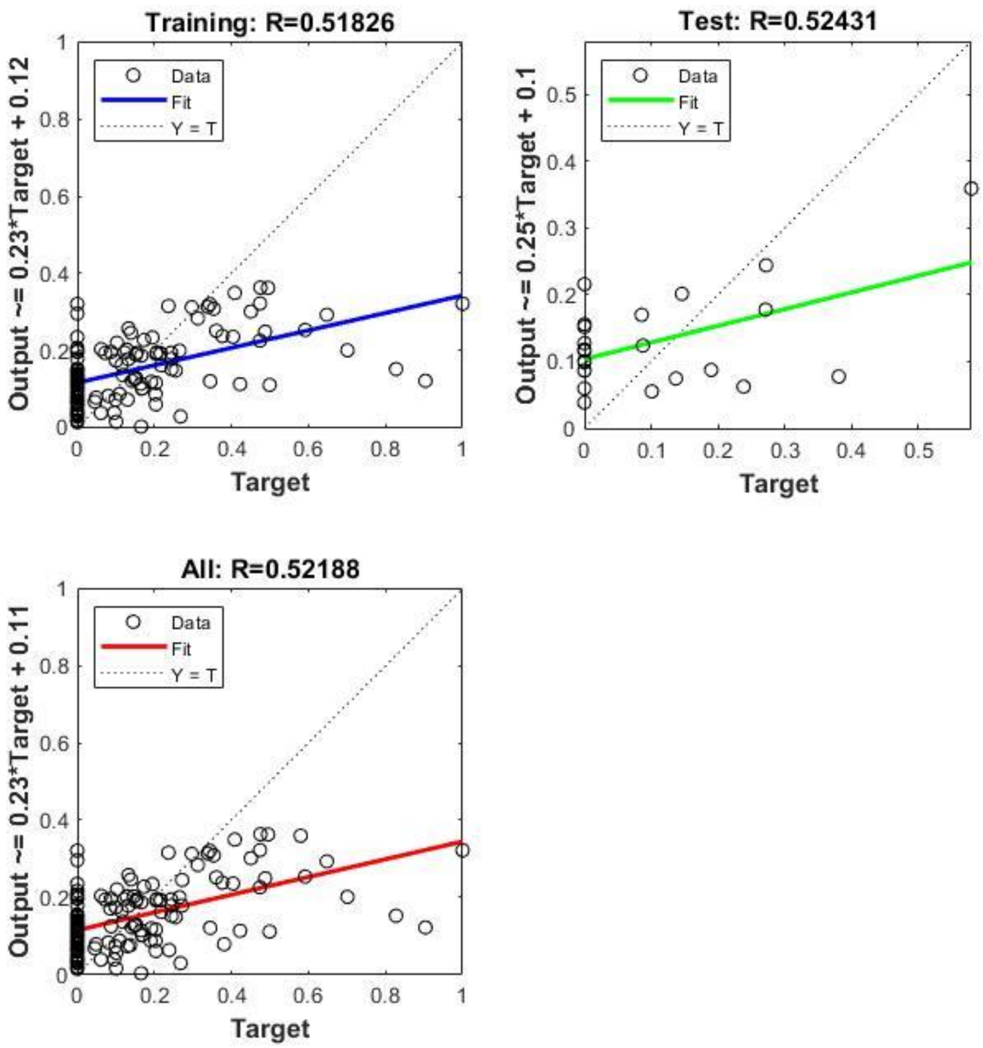

Figure A3. DO magnitude difference.

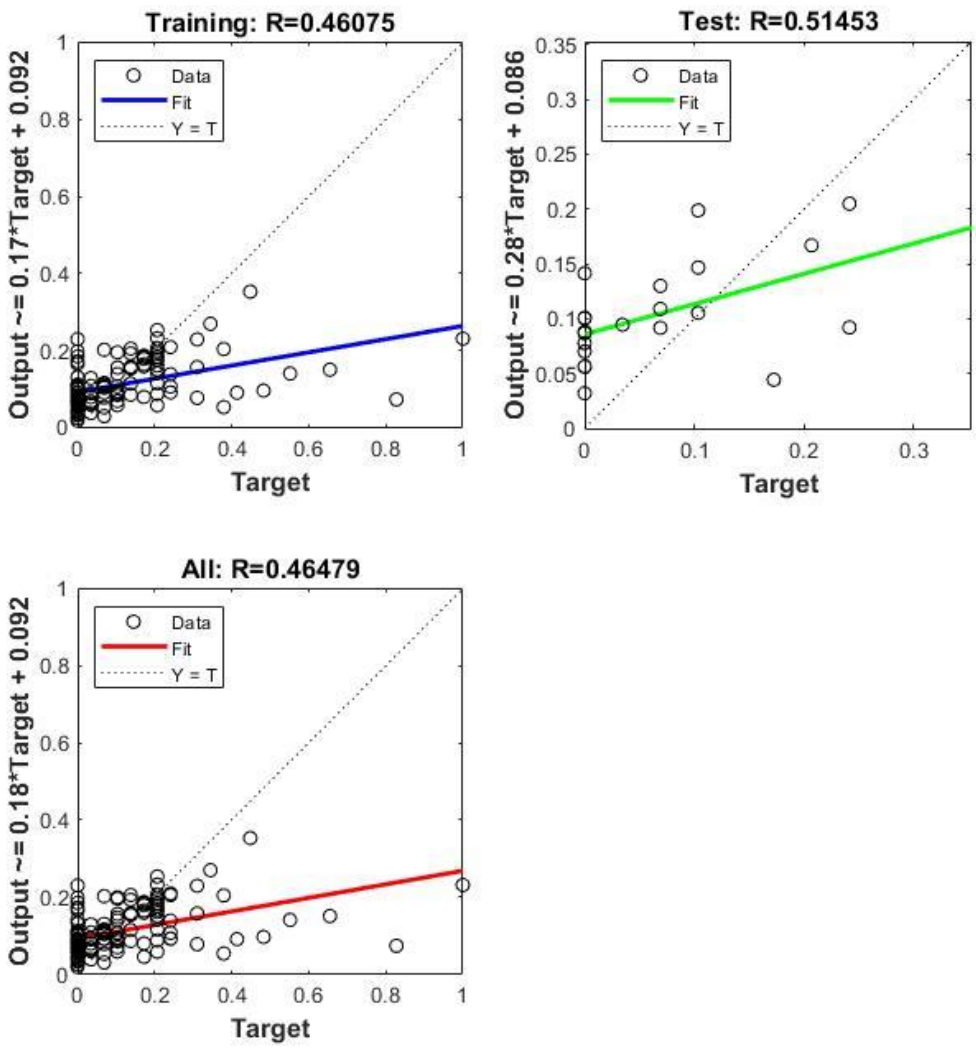

Figure A4. DO duration.

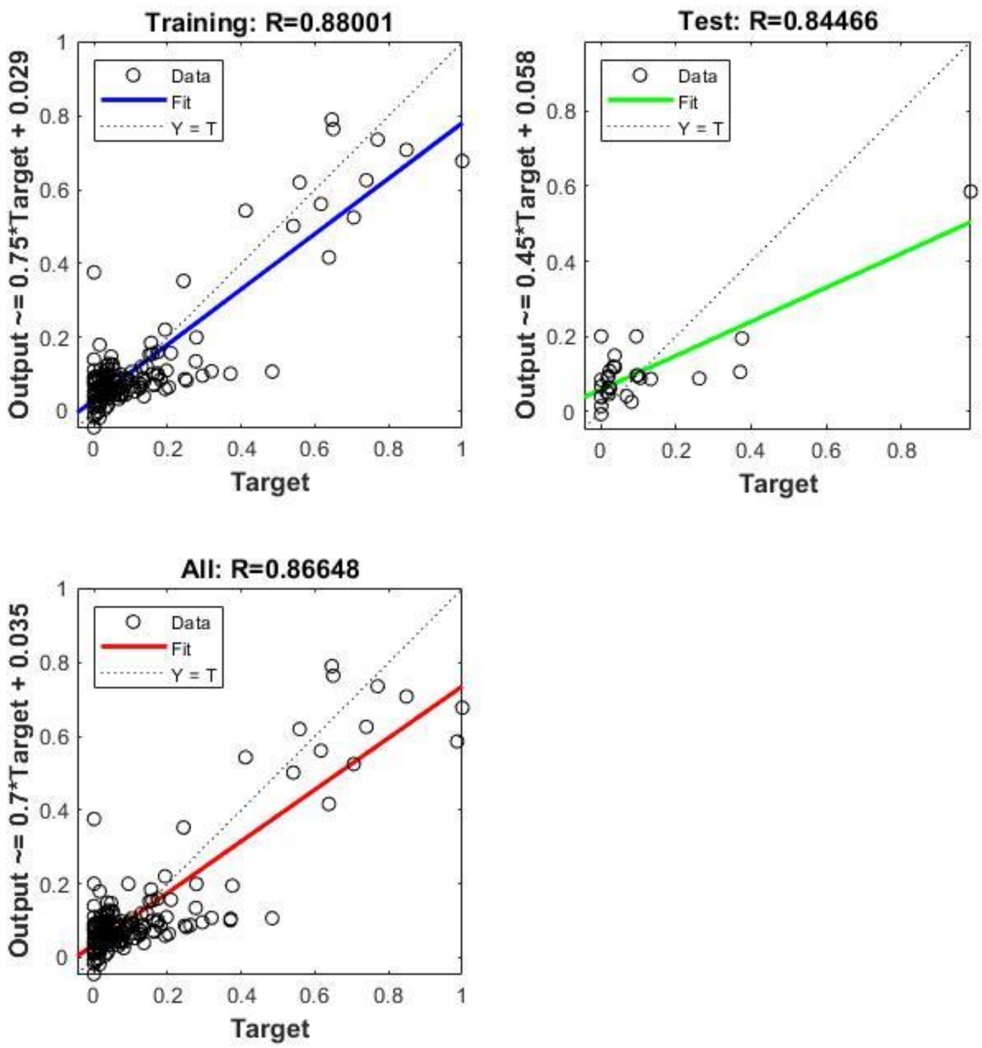

Figure A5. Gauge height magnitude difference.

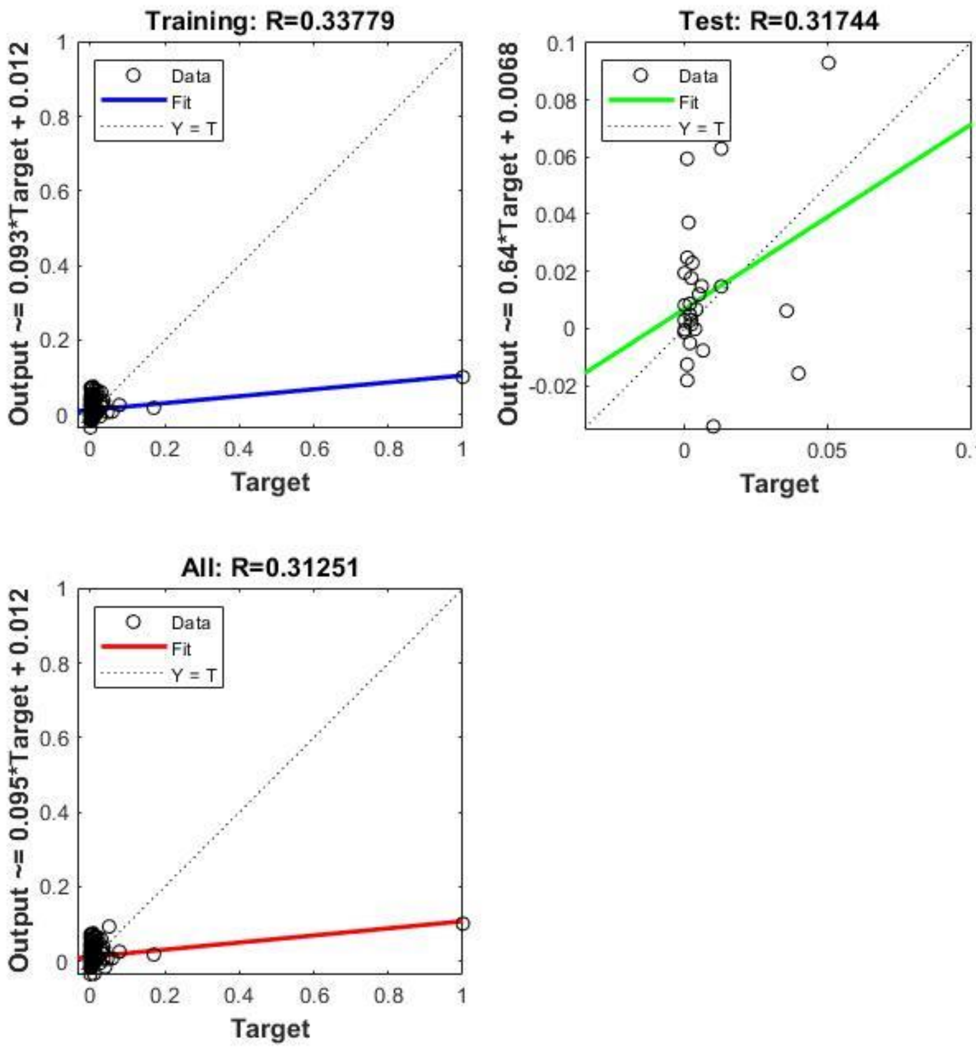

Figure A6. Gauge height duration.

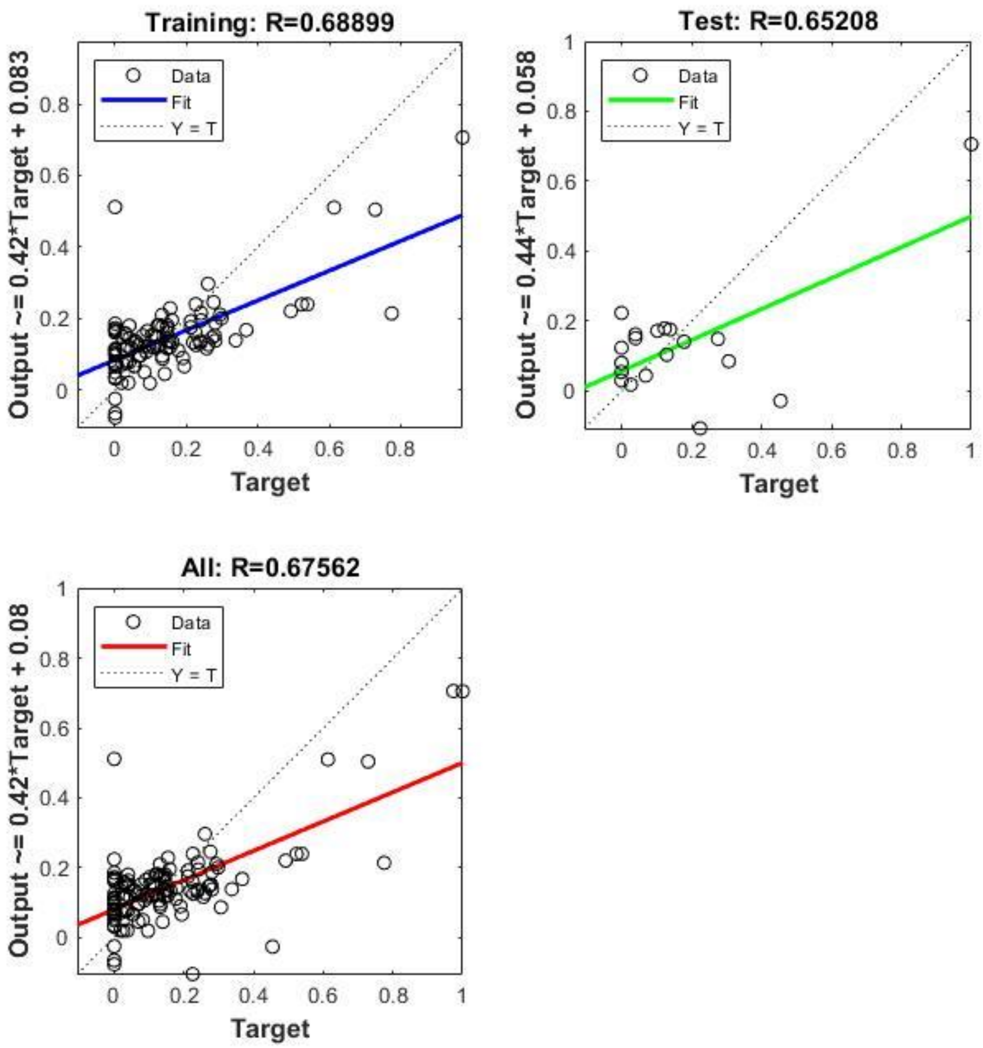

Figure A7. pH magnitude difference.

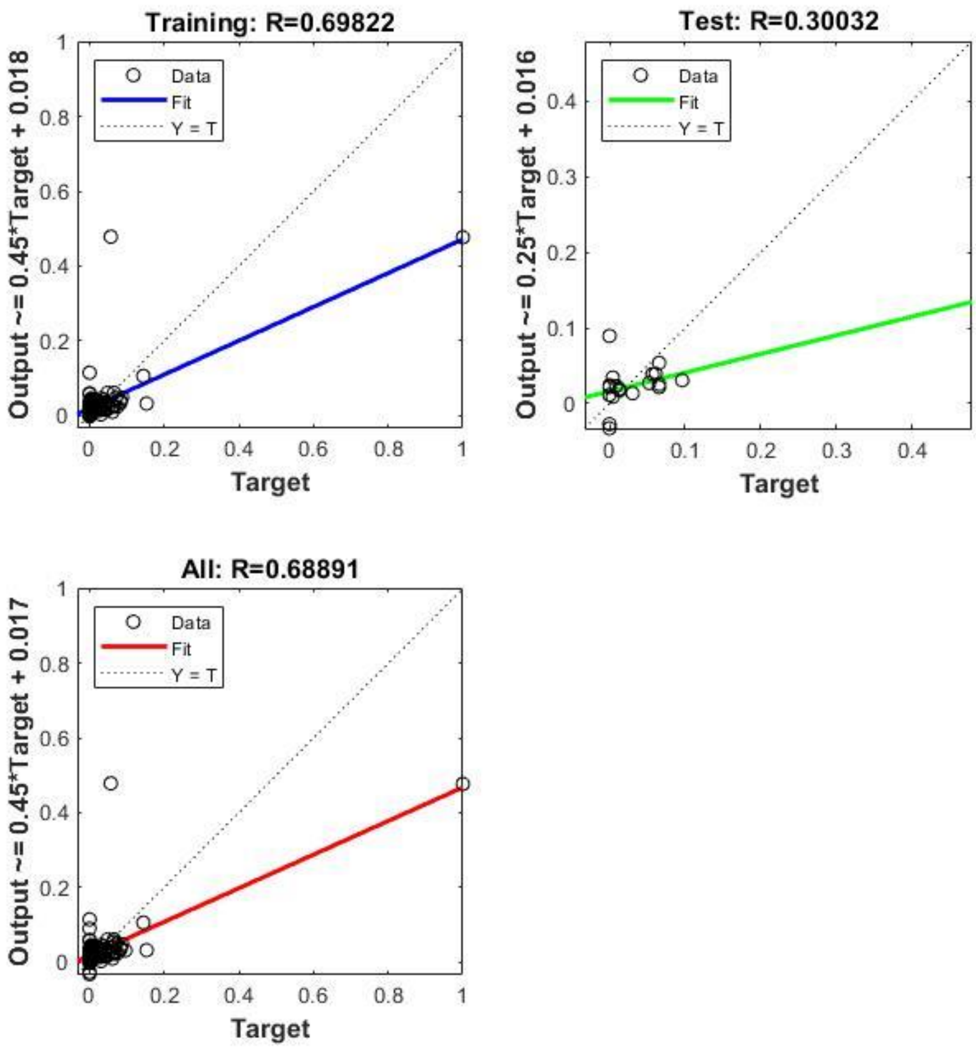

Figure A8. pH duration.

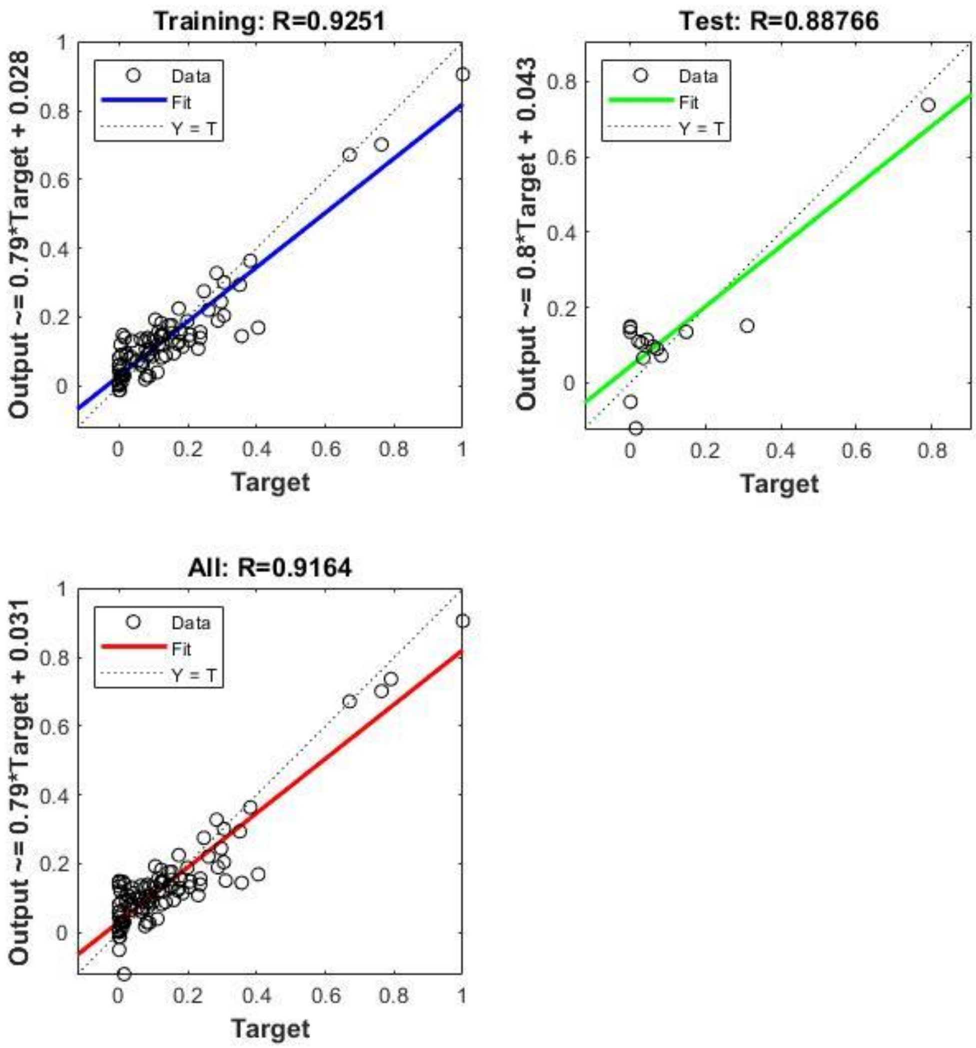

Figure A9. Turbidity magnitude difference.

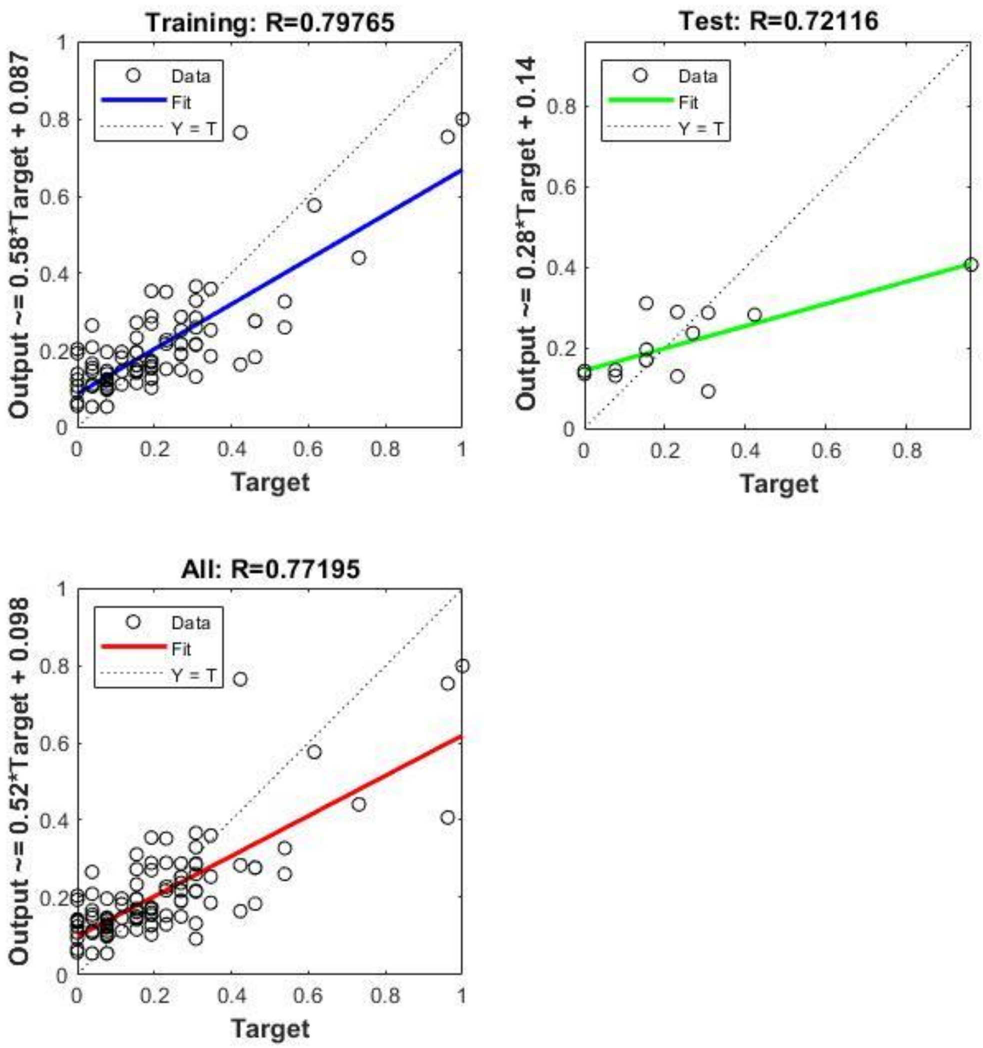

Figure A10. Turbidity duration.