

## Original Research Article

# **A Statistical Analysis and Exploration on Atlantic Hurricanes database (HURDAT2); Do We Expect The Worst?**

### **Abstract**

Hurricane occurrence exploration is a heavy task that requires sophisticated methods to accurately determine the occurrence and the impact of damage on the tropical environs. To control massive damage, several techniques have been developed to measure the accuracy of track forecasting. The accurate analysis and exploration of the occurrence of hurricanes are very crucial for the affected environs evaluation within a short time to minimize the loss of human life and property. Nevertheless, the exact analysis and exploration of these hurricanes is challenging and time-consuming. Therefore, this study proposed a statistical model whereby the analysis of variance (ANOVA) a linear regression scientific data statistical analysis model is applied on the dataset of Atlantic hurricane database (HURDAT2) for the exploration of hurricane occurrence and damage in the tropical environs. The best tracks of a 6 hour interval, location (latitude, and longitude), wind speed, central pressure of all identified hurricanes and subtropical typhoons from the year 2008 to 2017 (10 year period) are used to determine the  $R^2$  coefficient that measure the goodness and fitness of the model to reveal the variability of the real data. Statistical significance and reliability of the data are tested on significance  $p - value < 0.05$  where four different parameters are considered for the analysis in order to determine the destructive of these hurricanes in the tropical environs; latitude ( $X_1$ ), longitude ( $X_2$ ), the wind speed ( $X_3$ ), and central pressure. The results of our model proved significant with 99.3% accuracy, and a mean standard error of 1.4952 for all the hurricanes that were analyzed, and the year 2012 was established as a year that had much damage.

**Keywords:** Statistical analysis, exploration, occurrence, hurricane, damage, tropical cyclone.

### **1. INTRODUCTION**

Drastic climatic change experienced across the globe have led to many coastline environs to experience the occurrence of hurricanes or the tropical cyclones which has resulted in massive damages both to human life and properties. Hurricanes or tropical cyclones are surge storms that are characterized by a low-pressure center and copious thunderstorms which produce robust winds and flooding rains. They habitually form in the tropical environs between latitude of 23.5° North and South. A hurricane can also be referred as a tropical cyclone. There are a number of hurricane basins where these hurricanes occur on a regular basis, including the Northwest Pacific basin, the Atlantic basin, the Northeast Pacific basin, the North Indian basin, and the Australian or Southwest Pacific basin [1]. Due to the destructive potential of hurricanes, there has been a lot of research on hurricanes across the world trying to analyze and explore their occurrence.

Hurricanes are a part of the terrific, destructive, and harmful natural catastrophes, customarily producing high winds, storm surges, and intense rainfall and flooding along the coastal areas [2], [3]. The tropical cyclones and hurricanes destructive characteristics are

immense perils to coastline people and the environs [4], resulting in the death of more human lives than other natural catastrophes [3]. Since 1968 to 2010, approximately eighty-eight humid hurricanes developed yearly over the earth [5], [6], fourth eight (48) out of the 88 hurricanes attained the strength of a hurricane i.e., category 1 and 2 and twenty-one (21) acquired the strength of an extreme hurricanes that is, categories 3, 4, and 5 respectively [6]. For about two (2) generations globally close to 1.9 million people fell casualty of the hurricane catastrophes [5]. The hurricanes and tropical cyclones are liable for the massive and vast damages in the local economy, conservancy, and environs [5], [7], [8]. The strength, magnitude of the hurricanes grant an increase under certain climate change scenarios [9]–[11], and therefore, coastline persons and environs are more vulnerable to hurricanes.

For an efficient and precise provision of vital information in every step of hurricanes and tropical cyclones catastrophe management, tools such as remote sensing and spatial analysis are essential [12]–[14]. The remote sensing statistics unified with spatial analyses yield to appropriate information on development on environmental situations and the property infrastructure because of hurricane impacts and are crucial devices for lessening the impacts of prospective hurricanes. The aforementioned tools can also be applied predictively to explore the hurricane hazards over the threats, vulnerability, and measure capability planning, and to explore the possible forthcoming impacts of the likely climatology situations [15]–[18]. Additionally, the satellite remote sensing performs an important part in the tracking of hurricanes and tropical cyclones and thus, providing a precise exploration of the landfall [19], [20]. However, the study of the occurrence and damage of tropical hurricanes remain an open challenge. Therefore, in this work, a statistical model whereby the Analysis of variance (ANOVA) a linear regression scientific data statistical analysis model is applied on the dataset of Atlantic hurricane database i.e., the hurricane data version two (HURDAT2) that was extracted from [21] for the exploration of hurricane occurrence and damage in the tropical environs, and Origin85 is applied for graphical representation of results. The variance of the hurricanes is estimated using the sample variance, which is calculated using the shown relationship,

$$\sigma^2 = \frac{\sum_{i=1}^n (y_i - \bar{y})^2}{n - 1} \quad (1)$$

Conversely, the center focus of this study will be on, 1) statistical analysis and exploration of hurricane occurrence and damage in the tropical or coastline environs, in order to determine and explore from the analyzed dataset of hurricanes for the years 2008-2017, 2) which of the hurricanes had a massive damage and impact on the globe basin, and 3) investigate the statistical models that have been applied in the exploration and analysis of hurricanes or tropical cyclones occurrences.

The remaining part of this study is organized as; a review of the earlier methods and techniques used to analyze and explore the occurrence and damage of hurricanes in Section 2. Section 3 the proposed model to explore the occurrence and damage of hurricanes in the

coastlines while in Section 4, centers on the experiments of this model, the results and discussions achieved. Concluding remarks are presented in Section. 5.

## 2. RELATED WORK

### A. SURVEY ON HURRICANES

The historical hurricane data was reported and documented on a 6-hourly time period as per the World Meteorology Organization (WHO) guidelines and standards. For about 167-year period 1851 through 2017 numerous hurricanes have taken place reaching at least tropical storm strength (plus the subtropical storms) have been recorded over the North Atlantic zone. The establishment of these rainstorms and possible escalation into mature hurricanes happens above the warm tropical and subtropical waters as depicted in Figure 1.

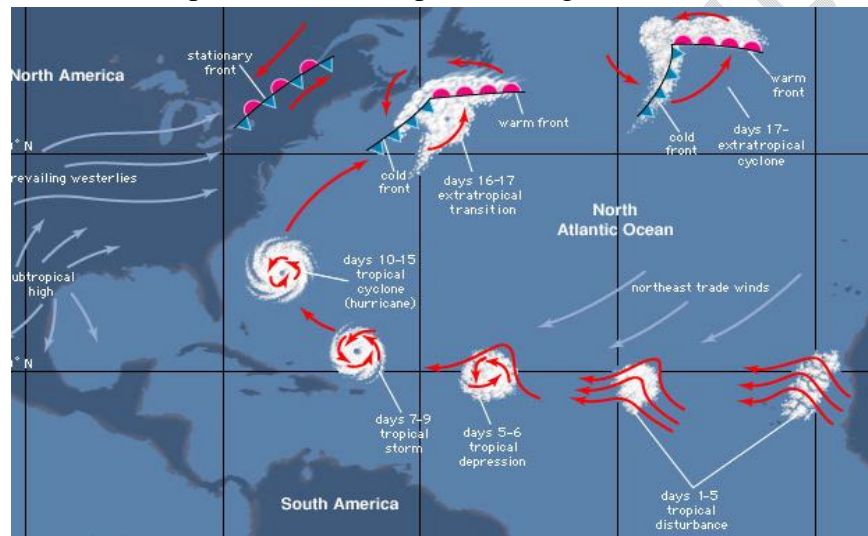


Figure 1: Life cycle of a North Atlantic Hurricane [22].

Ultimate dissipation or modification, on average of 7-8 days, usually takes place over the colder waters of the North Atlantic, or when the rainstorms travel over land and away from the sustaining oceanic environs [23]. Mostly the geographical zones influenced by hurricanes are frequently known as the tropical cyclone basins.

The wind standards segmenting the different phases of hurricanes are rather inflexibly determined, nevertheless, the capacity to quantify the winds with the exactness by the descriptions that rarely happen. The intense wind speed must regularly be contained in post-analysis by indirect information e.g., storm surge, loss, pressure, interwinds, and the review of satellite imagery [24], [25]. Fundamentally the highest uninterrupted wind is allotted at 6-hourly period by the trained analyst after taking into account the feasible and accessible information. Table 1 indicate the categories of hurricane types with their descriptions [26].

Table 1: The types and descriptions of hurricanes from U.S Department of Commerce, National Weather Service North Atlantic Hurricane Tracking Chart, 2017.

Category (Type)	Description
MH	Major Hurricane
HU	Hurricane
TS	Tropical Storm
TD	Tropical Depression
SS	Subtropical Storm
SD	Subtropical Depression
WL	Wave Low
ES	Extratropical Storm
ATCF	Automated Tropical Cyclone Forecast

The life process of the hurricanes spheres from a day to preferably several weeks. In the initial laps, the primary circulation is frail and moderate to intensify and regularity which usually takes five (5) days for a hurricane depression to strengthen into a tropical cyclone. Nevertheless, interruptions occur regularly during the strengthening because of flow over land, the locomotion over icy water, and destructive meteorological surroundings situations, for instance, the wind shearing [27].

## B. STATISTICAL METRICS

A remarkable work has already been carried out in various stages of hurricane hazard management through the application of satellite remote sensing and spatial analysis [2], [3], [13], [28], [29]. Different sorts of processing methods such as graphical elucidation, the ground bisects, data extraction and change detection, and dataset have been unified by researchers as unified moderate spatial resolution satellite imagery methods for evaluating hurricanes effects and reclamation. A variety of risk equations such as single criterion, the multi-criteria have been applied to evaluate the hurricane risks. Risk modeling tools have been used by many researchers to evaluate and assess the future effects of hurricanes under the climate change situations [3], [13], [30].

Bell et al. [31] carried out a research on statistical assessment of the OWZ tropical cyclone tracking scheme in ERA-Interim, the Okubo–Weiss–Zeta (OWZ) tropical cyclone (TC) detection scheme, to identify the hurricanes which was further evaluated on its capability to generate accurate hurricane track climatology in the ERA-Interim artifact over the 25 year duration from 1989-2013 [31]. The investigation focused on the hurricanes that attained a storm strength of (17ms) contained winds from which an objective criterion was determined to describe hurricane tracks once they attained the storm strength for both the observed and identified hurricanes. Some of the hurricane tracks are removed from the analysis due to lack of consistency between storm tracks on earlier strengths of the track segments [31]. To perform the termination transitioning of hurricanes the analytical subtropical jet (STJ) is applied and has been found to be desirable to a fixed latitude limit meridian. The method established the track coordinate deviation that was within the anticipated scope, however, the predominant dropped behind of the Okubo–Weiss–Zeta (OWZ-D).

Hallowell et al. [32] conducted a research on hurricane risk management of offshore with turbines via a stochastic process that involved the intricacy of hazard strength measures, engineering demand parameters (EDPs), and the loss measures to explore the likelihood of destructions/ disasters. The stochastic process was thus adjusted and utilized to a hypothetical situation. Nevertheless, the research work only quantifies the risk of a miss of the offshore wind turbines to hurricane produced storms and surfs.

To assess the impact and recovery of hurricanes, image data mining is a very crucial approach. Thus, it contributes to the detection and classification of the hurricane-impacted features, for example, the buildings, vegetation, highways, and railways for destruction valuation. Image data mining methodology remains very beneficial in the detection impassable entry paths and salvage supporting zones for tornado catastrophe retort arrangement, which is implemented by the use of new lattice frame [33]. The high-resolution imagery query features required are mined and retrieved from imagery through the use of image analysis in order to improve a content-based whereby the  $\sigma$ -tree carries out inquiries within the stored images for an element interplanetary depiction for equating important attributes [34]. On the other hand, the IKONOS imagery [33] was used to examine the hurricane catastrophe evaluation and the results proved the ability to identify destruction and exploration of zones that needed an urgent response.

The composite risk evaluation was conducted on the hurricane on the coastal regions of China [18] using spatial analysis and remote statistics incorporating several significant criteria. The outcomes showed that the investigation of extra related criterion through the use of the analytic hierarchy process offered an extra dependable and realistic risk evaluation information although not fully realized. A modern historical wind statistics founded on statistical archetypes for modeling catastrophe and hazard related by hurricanes known as humid or tropical cyclone risk model (TCRM) [35], was implemented by Arthur et al. [36] to examine the recovery times of tornado catastrophes in the zones of Australia, and established the significant of it in the deriving of the needed statistics. Program writing abilities plus massive barometric facts are needed for the archetypal. Additionally, it's uncertain if it can be used elsewhere in the globe.

The research by Li et al. [3], implemented the Gumbel and Pearson-III technique aimed at modeling the hurricane tornado gush hazard for a hundred (100 year) recovery period founded on thirty (30 years) tornado gush statistics in the global information system environ. The results indicate the precise modelling of hazards, however, the produced information had fewer details because of the application at the regional scale [3].

Rana et al. [13], used the global information system and remote sensing stationed basic and inclusive hurricane surge model assimilating the historical storm data and DEM. A return of 100 year period was considered for hurricane risk and proved the model to be effective in providing crucial information for the future hurricane risk management, the model was effectively applied by [13], [37] in torrent and flood risk modeling in Bangladesh but not to the whole world. Moreover, a study carried out by Hoque et al. [38], presented the direction in picking the best and useful datasets as well as the processing techniques for hurricane catastrophe management.

Recently, various approaches, for example, satellite remote sensing, and spatial analysis have been invented to collect data to assist in coping with normal catastrophes by means of spatial analysis and satellite remote sensing. With many kinds of techniques and heterogeneous potential data, to pick the best and useful processing technique and data for hurricane catastrophe management is a big challenge. The risk evaluation equation below has been suggested as the most essential,

$$r = v \times e \times m \quad (2)$$

Where  $r$  denotes the risk,  $v$  is the vulnerability,  $e$  is the exposure, and  $m$  represents the mitigation capacity for providing required information for the deterrence of hurricane catastrophe management. For the effective application of equation (2) and making definite decisions several approaches have been proposed e.g., the strategy analytic hierarchy process (AHP) in hazard evaluation process [38]. However, it remains hard to come up with the exact number of criteria that should be administered to attain the needed information as it relies upon the analysis context.

### **C. PAST HURRICANE DAMAGES**

The impact of damages by tropical cyclones are extremely variable and relies on severe hurricanes, which has been predicted as a cause of massive damages. Nevertheless, there are several other factors that must be considered, including wind blasts, the tornado size, the speed of translational movement which affects the rainfall and fresh-water flooding, the tornado tides that are affected by offshore water deepness and coastal alignment, the astral flow, the terrain topographies, the local structure codes, and the distance from the coastlines [23].

In 2017 as a result of tropical storms in Sierra Leone West African country, there were mudslides that claimed over 500 lives with a displacement of more than 20,000 people including 5,000 children [39]. In August 2017 hurricane Harvey hit Texas with high winds of up to 130mph (215km/h) and rainfall that affected power cuts and more than 200,000 customers were left without electricity [40]. Hurricane Harvey one of the deadliest hurricane in the last 12 years slammed the Gulf coast in Texas, near the Texas-Louisiana border, in the early hours of 26<sup>th</sup> August causing a huge destruction approximated to be 150 billion dollars through the severe rains [41] with prevalent flooding over the affected regions in Texas and Louisiana. As a result, it has attracted extensive research lately. For example, Gulati et al. [42], conducted an investigation on the usage of semi-parametric techniques to estimate the maximum damages valuation for the Florida community tropical cyclone damages. The analyzed results demonstrated that the yearly losses and destructions from the Florida community tropical cyclone damages did not incline to heavy-tailed, and so, neither the popular Hill's technique nor the moment's predictor works perfectly. But, Pickard's predictor yielded an 84% threshold which provided the best fitting for the maximum quantiles for the damages [42]. These hurricane damages and their related estimate of maximum figures were predicted through the usage of advanced computer simulation models that are known as catastrophe (Bcat) models. Historical data was used in these models to analyze thousands of years of hurricane activity and applied the

analyzed data alongside with the present coverage data and susceptibility models in order to predict insured damages [42]. The valuation of maximum damages was calculated through the matching empirical quantile. This is presented as,  $x_1, x_2$  and  $x_N$  which denote a random section of the damages of significance from the damage spreading. In addition, the assessment of  $x_{*p}$  is basically the order statistic  $x_{(k)}$ , matching the 100% experiential outcome. The expression  $k = n \times p$  can be an integer or not, thus, can be found by intercalating among two neighboring order statistics. Assuming the statistics for the binomial distribution confidence intervals for the estimate maximum damages can easily be calculated [42].

In reference to the prior discussed works, the increase in natural catastrophes in the world today is positively correlated with economic damages that come with the disasters [43], [44], and the growing trend in the catastrophes is frightening. Therefore, it is worthy of study to establish efficient and robust methods to measure the damages caused by tropical cyclones.

### 3. PROPOSED METHODOLOGY

Several techniques have been applied in analyzing the formation and impact of hurricanes in the prone areas, such as statistical models, which are based on the analysis of storm behaviour using the climatology and correlate a storm's position and the date to produce a forecast [45]. In addition, the traditional statistical model [46], the dynamical model [45], which forecasts the numerical weather prediction, and the weather research and forecast model [47].

Recent studies conducted by [48]–[52] endeavored at finding out the nature of different hurricanes along the Atlantic coast. Related studies for the Gulf coast have been relatively rare and even those which have largely focused on the impact of hurricanes like [53]–[55]. Motivated by the previous works, in this study we analyzed four parameters i.e., the latitude ( $N^\circ$ ), the longitude ( $W^\circ$ ), the wind speed, and the central pressure of the hurricane dataset for the year 2008 to 2017 that was obtained from [21] to understand the hurricane occurrence and damage by looking at the  $R^2$  and the significant F of each hurricane. The research focused on the regression of the four parameters as the hurricane strike the ground and advanced within.

Furthermore, we focused on the statistical analysis and exploration of hurricane occurrence and damage in the tropical/coastlines environs. Figure 1 illustrates the proposed framework of our work.

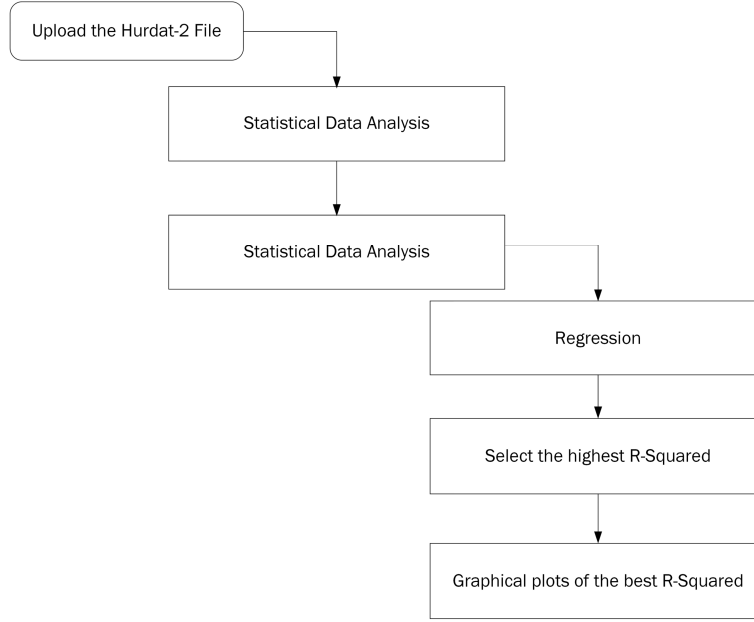


Figure 2: Proposed Statistical Analysis Model for HURDAT2 Dataset

Finding the coefficients of the hurricane formation from the HURDAT2 there are two metrics of determination i.e., the simple linear regression model that only considers a simple linear regression mean function of a single variable as formulated,

$$E(Y|X_1 = x_i) = \beta_0 + \beta_1 x_i \quad (3)$$

Now suppose we have a second and third variables  $x_2$ ,  $x_3$  with which to predict the response. By adding  $x_2$ , and  $x_3$  to the problem, we will get a mean function that depends on both the value of  $x_1$  and the value of  $x_2$ , and  $x_3$ ,

$$E(Y|X_1 = x_i, X_2 = x_2, X_3 = x_3) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 \quad (4)$$

The main objective of adding the  $x_2$ , and  $x_3$  is to explain the part of  $Y$  that has not already been explained by  $x_1$ , and  $x_2$ .

Equation (3) can also be represented as,

$$\hat{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 \quad (5)$$

Whereby the beta coefficients are determined by

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x} \quad (6)$$

$\bar{y}$  is the mean of longitude and  $\bar{x}$  is the mean of latitude degrees respectively, gives the intercept value from the ANOVA table of the analyzed scientific data and  $\hat{\beta}_0$  is the intercept.

$$\hat{\beta}_1 = \frac{SXY}{SXX} = X \text{ Variable} \quad (7)$$

$X$  represents the latitude,  $Y$  represents the longitude, and  $s_{XY}$  is the summation of latitude and longitude degrees and  $s_{XX}$  is the summation of latitude.

Calculation of the Standard error ( $se$ ) of the provided data can be expressed mathematically as,

$$se(\beta_0) = \sqrt{\sigma^2 \left( \frac{1}{n} + \frac{\bar{x}^2}{SXX} \right)} \quad (8)$$

$se(\beta_1) = ANOVA \text{ value}$

$$se(\beta_1) = \sqrt{\sigma^2 \left( \frac{1}{SXX} \right)} \quad (9)$$

$se(\beta_1) = ANOVA \text{ value}$

Where  $se$  represents the standard error of the analyzed data,  $\sigma^2$  is the variance that is determined by the residual of sum squares ( $RSS$ ) divided by the number of observations minus 3 (the number of parameters in this case its 3 i.e., Lat, Lon, and CP),

$$\sigma^2 = \frac{RSS}{n - 2} \quad (10)$$

$R^2$  is the coefficient value that measures the goodness of fit of the model with the regression line that disclose the variability of the real data being analyzed. Hence,  $R^2$  is calculated as by the functional expression,

$$R^2 = \frac{SS_{Regression}}{SS_{Total}} \quad (11)$$

Where  $SS_{Regression}$  represents the sum of squares of regression error and  $SS_{Total}$  denotes the sum squared of total error.

The multiple linear regression was performed to test the significance of regression using the analysis of variance (ANOVA), which used the variance of the observed data to define if our model can be applied to the observed data. Table 2 features an example of the sampled hurricane to demonstrate the various coefficients extracted for our study.

Table 2: Model Summary.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.997	.993	.992	1.495	.993	1809.549	3	38	.000

a. Predictors: (Constant), The wind speed, West-degrees, North-degrees

b. Dependent Variable: The central pressure

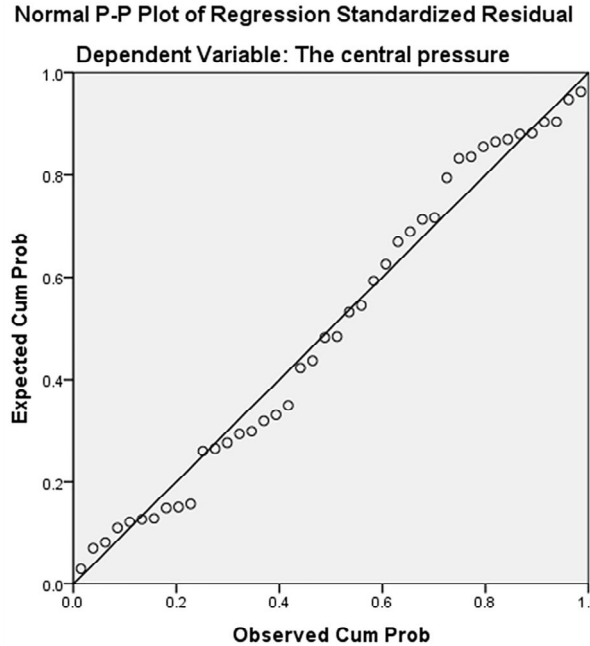


Figure 3: A plot of the sample MICHAEL hurricane data for the year 2012.

Figure 2 illustrates the fitted regression line passing on most of the observed points, thus revealing the variability of the observed data.

#### 4. EXPERIMENTS RESULTS & DISCUSSION

This section focus on experimental results with a significant  $p < 0.5$  on the ten years (i.e., 2008 - 2017) hurricane dataset, which is 6-hourly hurricanes. Four parameters, namely the latitude ( $N^\circ$ ), longitude ( $W^\circ$ ), the wind speed (m/s), and the central pressure (mb) were used to determine the  $R^2$  r-squared, p-value, and the significant F. The obtained results are listed in different tables illustrating the  $R^2$  with high values nearing 100%, the p-values with less than 0.05, the significant F, and the graphical representation of the r-squared of different years (i.e., 2008-2017).

##### a) Hurricanes statistical analysis of the year-2017

Table 3: Hurricane for the 2017, the highest r-squared results is indicated in bold.

ATCF Cyclone number	YEAR - 2017								
					P-value of coefficients				Record (n)
	Name	$R^2$	MSE	RSS	$\beta_0$	$\beta_{1X1}$	$\beta_{2X2}$	$\beta_{3X3}$	
AL032017	CINDY	0.8824	1.5689	295.5674	1.12E-23	0.007211165	0.004923021	2.96986E-06	20
<b>AL112017</b>	<b>IRMA</b>	<b>0.9768</b>	<b>4.8291</b>	<b>60918.1176</b>	<b>4.98356E-81</b>	<b>4.93049E-05</b>	<b>8.05828E-13</b>	<b>2.59443E-22</b>	<b>66</b>
AL152017	MARIA	0.9383	6.6686	43297.6951	2.65079E-87	0.001391347	1.38436E-06	5.42184E-32	68
AL162017	NATE	0.9128	2.5795	1949.6652	1.18154E-42	0.000603269	0.000701845	2.63246E-12	32

From Table 3, it can be observed that IRMA hurricane significantly had a higher impact (98%) and much damage since, its p-value was found to be less than 0.05 ( $p < 0.05$ ) as

demonstrated. Although CINDY hurricane showed significance as confirmed from its p-value in Table 3, it registered the lowest impact, that is, 88%.

b) Hurricanes statistical analysis of the year-2016

ATCF Cyclone number	YEAR - 2016								
					P-value of coefficients				Record (n)
	Name	$R^2$	MSE	RSS	$\beta_0$	$\beta_{1X1}$	$\beta_{2X2}$	$\beta_{3X3}$	
AL012016	ALEX	0.5651	4.3232	922.8656	9.76296E-56	0.04405635	0.022166361	0.000224315	42
AL022016	BONNIE	0.8754	1.3594	675.4522	1.17665E-90	7.95354E-05	6.05151E-17	9.6356E-07	56
AL062016	FIONA	0.955	0.7949	362.2932	2.01741E-50	0.0001465	7.05933E-05	2.72197E-05	31
AL092016	HERMINE	0.8772	2.741	2308.5493	1.30465E-44	3.98585E-06	1.16868E-07	5.49043E-19	47
AL122016	KARL	0.9451	1.8046	2801.3248	1.1124E-110	1.59373E-09	0.00975366	5.30245E-11	54
AL132016	LISA	0.8802	1.5006	430.1506	7.26889E-43	4.67953E-06	0.001965867	5.28924E-10	30
<b>AL152016</b>	<b>NICOLE</b>	<b>0.9652</b>	<b>3.0746</b>	<b>15471.6995</b>	<b>1.16474E-64</b>	<b>0.01175076</b>	<b>1.76329E-06</b>	<b>5.27925E-35</b>	<b>63</b>

Table 4: Hurricanes for the 2016, the highest r-squared results is indicated in bold.

NICOLE hurricane significantly had a higher impact (97%) and much damage since, its p-value was found to be less than 0.05 ( $p < 0.05$ ) as demonstrated in Table 4. Though ALEX hurricane showed significance as confirmed from its p-value in Table 4, it registered the lowest impact, that is, 57%.

c) Hurricanes statistical analysis of the year-2015

Table 5: Hurricanes for the 2015, the highest r-squared results is indicated in bold.

ATCF Cyclone number	YEAR - 2015								
					P-value of coefficients				Record (n)
	Name	$R^2$	MSE	RSS	$\beta_0$	$\beta_{1X1}$	$\beta_{2X2}$	$\beta_{3X3}$	
<b>AL042015</b>	<b>DANNY</b>	<b>0.976</b>	<b>2.3375</b>	<b>6007.4463</b>	<b>2.81137E-51</b>	<b>0.030552798</b>	<b>0.019608334</b>	<b>7.75633E-21</b>	<b>31</b>
AL072015	GRACE	0.9729	0.4647	100.7226	1.77666E-23	0.00297909	6.93618E-05	4.3149E-11	17
AL092015	NINE	0.9194	0.5324	48.4856	1.21688E-25	5.78856E-05	0.000281711	4.56494E-05	19
AL102015	IDA	0.9695	0.4392	288.2660	6.8778E-120	2.55977E-05	2.52486E-10	5.36298E-18	31

In Table 5, DANNY hurricane significantly had a higher impact (98%) and much damage since, its p-value was found to be less than 0.05 ( $p < 0.05$ ) as demonstrated. Although NINE hurricane showed significance as confirmed from its p-value in Table 5, it registered the lowest impact, that is, 92%.

d) Hurricanes statistical analysis of the year-2014

Table 6: Hurricanes for the 2014, the highest r-squared results is indicated in bold.

ATCF Cyclone number	YEAR - 2014								
					P-value of coefficients				
	Name	$R^2$	MSE	RSS	$\beta_0$	$\beta_{1X1}$	$\beta_{2X2}$	$\beta_{3X3}$	Record (n)
AL012014	ARTHUR	0.9609	2.8961	8870.6616	2.9428E-31	1.22304E-05	2.90702E-09	6.72372E-31	47
AL032014	BERTHA	0.8075	2.1554	838.1143	2.46794E-88	9.46934E-09	3.96072E-05	8.06127E-09	47
<b>AL082014</b>	<b>GONZALO</b>	<b>0.9784</b>	<b>3.3368</b>	<b>17684.9794</b>	<b>9.36982E-45</b>	<b>9.9464E-11</b>	<b>6.23337E-06</b>	<b>8.41513E-14</b>	<b>39</b>
AL092014	HANNA	0.8932	1.0691	315.3064	5.46249E-55	4.11769E-05	0.001704968	1.42416E-15	37

From Table 6, we can see that GONZALO hurricane significantly had a higher impact (98%) and much damage since, its p-value was found to be less than 0.05 ( $p < 0.05$ ) as demonstrated. Although BERTHA hurricane showed significance as confirmed from its p-value in Table 6, it registered the lowest impact, that is, 81%.

e) Hurricanes statistical analysis of the year-2013

Table 7: Hurricanes for the 2013, the highest r-squared results is indicated in bold.

ATCF Cyclone number	YEAR - 2013								
					P-value of coefficients				
	Name	$R^2$	MSE	RSS	$\beta_0$	$\beta_{1X1}$	$\beta_{2X2}$	$\beta_{3X3}$	Record (n)
AL012013	ANDREA	0.6649	2.5968	133.7793	3.46736E-07	0.009131152	0.010556685	0.021563904	14
AL042013	DORIAN	0.8658	1.4595	645.8031	1.69536E-96	0.004993522	2.29358E-07	8.9109E-10	51
AL092013	HUMBERTO	0.9616	1.865	3661.1333	9.35654E-86	7.56483E-09	1.39551E-06	6.54185E-31	46
<b>AL102013</b>	<b>INGRID</b>	<b>0.9799</b>	<b>1.2151</b>	<b>1296.3761</b>	<b>6.75653E-21</b>	<b>0.002691928</b>	<b>0.005490583</b>	<b>6.56614E-16</b>	<b>22</b>
AL112013	JERRY	0.7622	0.8664	69.7488	5.39281E-39	0.002223675	0.002489598	7.77989E-09	33
AL142013	MELISSA	0.9768	1.3848	1774.3116	4.30527E-38	8.21259E-10	4.65987E-08	4.09607E-10	26

INGRID hurricane significantly had a higher impact (98%) and much damage since, its p-value was found to be less than 0.05 ( $p < 0.05$ ) as demonstrated in Table 7. Although ANDREA hurricane showed significance as confirmed from its p-value in Table 7, it registered the lowest impact, that is, 66%.

f) Hurricanes statistical analysis of the year-2012

Table 8: Hurricanes for the 2012, the highest r-squared results is indicated in bold.

ATCF Cyclone number	YEAR - 2012								
					P-value of coefficients				
	Name	$R^2$	MSE	RSS	$\beta_0$	$\beta_1X_1$	$\beta_2X_2$	$\beta_3X_3$	Record (n)
AL022012	BERYL	0.8366	1.7553	457.3789	1.61455E-35	0.000200143	0.003773548	6.37755E-13	33
AL042012	DEBBY	0.9009	1.2844	209.8483	1.20238E-13	1.36544E-06	0.000526152	0.032650631	18
AL052012	ERNESTO	0.9372	2.6978	3800.0289	2.0906E-57	2.50378E-05	0.002100616	7.38266E-08	39
AL082012	GORDON	0.9908	1.4522	5017.9535	1.60429E-31	0.02103372	1.51286E-06	8.00572E-23	26
AL092012	ISAAC	0.939	3.3392	8066.2762	4.38785E-82	8.90507E-09	0.002358	8.78446E-23	51
<b>AL132012</b>	<b>MICHAEL</b>	<b>0.993</b>	<b>1.4952</b>	<b>12136.1198</b>	<b>1.72804E-62</b>	<b>4.43053E-09</b>	<b>0.001075176</b>	<b>9.41162E-42</b>	<b>42</b>
AL172012	RAFAEL	0.9815	1.8166	9094.5147	1.8695E-102	1.82313E-33	3.05788E-11	8.40555E-24	56
AL182012	SANDY	0.946	4.7587	16272.7438	3.01057E-25	1.32387E-11	4.38132E-09	1.59375E-14	45

Table 8 above, MICHAEL hurricane significantly had a higher impact (99%) and much damage since, its p-value was found to be less than 0.05 ( $p < 0.05$ ) as verified. Though BERYL hurricane showed significance as confirmed from its p-value in table 8, it registered the lowest impact, that is, 84%.

g) Hurricanes statistical analysis of the year-2011

Table 9: Hurricanes for the 2011, the highest r-squared results is indicated in bold.

ATCF Cyclone number	YEAR - 2011								
					P-value of coefficients				
	Name	$R^2$	MSE	RSS	$\beta_0$	$\beta_1X_1$	$\beta_2X_2$	$\beta_3X_3$	Record (n)
AL032011	CINDY	0.9833	0.7605	307.1025	1.08859E-11	0.018490984	0.048753969	4.94781E-08	13
<b>AL062011</b>	<b>FRANKLIN</b>	<b>0.9922</b>	<b>0.3878</b>	<b>210.0789</b>	<b>5.29719E-23</b>	<b>6.33998E-06</b>	<b>5.6228E-08</b>	<b>2.48838E-06</b>	<b>15</b>
AL092011	IRENE	0.9581	4.1013	15008.7989	5.64971E-51	3.64128E-05	7.47308E-14	9.55642E-06	43
AL142011	MARIA	0.9401	1.9391	2242.7284	1.20755E-70	8.50142E-09	1.84944E-09	5.38784E-07	42
AL152011	NATE	0.9631	0.9096	410.2796	9.27924E-15	0.00844571	0.000674963	5.03041E-05	23
AL172011	PHILIPPE	0.8909	3.1677	5000.1033	1.7113E-120	2.91113E-07	8.47715E-05	6.51051E-17	65
AL192011	SEAN	0.9041	2.5572	1478.9087	7.91478E-18	9.13814E-07	3.70117E-05	0.03753162	28

From Table 9, we can see that FRANKLIN hurricane significantly had a higher impact (99%) and much damage since, its p-value was found to be less than 0.05 ( $p < 0.05$ ) as demonstrated. Though PHILIPPE hurricane showed significance as confirmed from its p-value in Table 9, it recorded the lowest impact, that is, 89%.

h) Hurricanes statistical analysis of the year-2010

Table 10: Hurricanes for the 2010, the highest r-squared results is indicated in bold.

ATCF Cyclone number	YEAR - 2010								
					P-value of coefficients				
	Name	$R^2$	MSE	RSS	$\beta_0$	$\beta_{1X1}$	$\beta_{2X2}$	$\beta_{3X3}$	Record (n)
AL032010	BONNIE	0.8816	1.1961	149.0811	2.21341E-16	0.040282778	0.022612414	0.020847455	18
AL062010	DANIELLE	0.9559	3.825	14909.546	1.90112E-83	8.48921E-13	6.86784E-05	6.65284E-13	51
AL112010	IGOR	0.9665	4.9746	40723.6451	1.0352E-100	1.21234E-09	7.35777E-13	1.61662E-28	61
<b>AL142010</b>	<b>LISA</b>	<b>0.9669</b>	<b>1.5117</b>	<b>2267.6683</b>	<b>1.39824E-48</b>	<b>1.50543E-11</b>	<b>0.000444507</b>	<b>2.28542E-19</b>	<b>38</b>

LISA hurricane significantly had a higher impact (97%) and much damage since, its p-value was found to be less than 0.05 ( $p < 0.05$ ) as demonstrated in Table 10. Though BONNIE hurricane showed significance as confirmed from its p-value in Table 10, it registered the lowest impact, that is, 88%.

i) Hurricanes statistical analysis of the year-2009

Table 11: Hurricanes for the 2009, the highest r-squared results is indicated in bold.

ATCF Cyclone number	YEAR - 2009								
					P-value of coefficients				
	Name	$R^2$	MSE	RSS	$\beta_0$	$\beta_{1X1}$	$\beta_{2X2}$	$\beta_{3X3}$	Record (n)
AL012009	ONE	0.9358	0.4303	29.6963	1.26152E-19	1.78081E-05	0.001301862	0.00740087	15
AL032009	BILL	0.9773	2.8118	14312.9196	2.5172E-83	4.38424E-13	0.000211778	9.73978E-29	46
AL052009	DANNY	0.8684	0.5289	14.7625009	8.62002E-12	0.002889166	0.028150763	0.000791701	12
<b>AL082009</b>	<b>EIGHT</b>	<b>0.9907</b>	<b>0.1071</b>	<b>3.6799</b>	<b>4.56492E-09</b>	<b>0.027585414</b>	<b>0.041014167</b>	<b>0.001662216</b>	<b>7</b>

From Table 11, EIGHT hurricane significantly had a higher impact (99%) and much damage since, its p-value was found to be less than 0.05 ( $p < 0.05$ ) as validated. Though DANNY hurricane showed significance as confirmed from its p-value which is demonstrated in Table 11, it registered the lowest impact, that is, 87%.

j) Hurricanes statistical analysis of the year-2008

Table 12: Hurricanes for the 2008, the highest r-squared results is indicated in bold.

ATCF Cyclone number	YEAR - 2008								
					P-value of coefficients				
	Name	$R^2$	MSE	RSS	$\beta_0$	$\beta_{1X1}$	$\beta_{2X2}$	$\beta_{3X3}$	Record (n)
AL052008	EDOUARD	0.9399	1.4948	349.3686	1.05134E-15	0.033912838	0.017093727	0.001305343	14
AL082008	HANNA	0.8547	3.0309	2430.5919	1.57822E-69	7.09286E-05	0.000799606	8.36839E-11	49
AL102008	JOSEPHINE	0.9677	0.9646	807.5615	1.16599E-53	0.017685271	0.031838121	5.43484E-18	33
AL122008	LAURA	0.6626	3.2525	623.1169	4.20118E-43	3.12442E-06	1.75963E-06	7.24163E-05	34
<b>AL152008</b>	<b>OMAR</b>	<b>0.9801</b>	<b>2.242</b>	<b>6934.4738</b>	<b>3.07446E-23</b>	<b>0.000120815</b>	<b>3.02433E-05</b>	<b>8.5268E-22</b>	<b>32</b>

OMAR hurricane significantly had a higher impact, i.e., 98% with much damage. This can be seen from its p-value of  $<0.05$ , as demonstrated in Table 12. Although hurricane LAURA showed some significance as confirmed by its p-value in Table 12, it registered the lowest impact of 66%.

Figure 4 defines the combination of all hurricanes for the ten years, i.e., 2008-2017, which were analyzed and the ones that had a significant  $p$ -value  $<0.05$  and their corresponding  $R^2$  values.

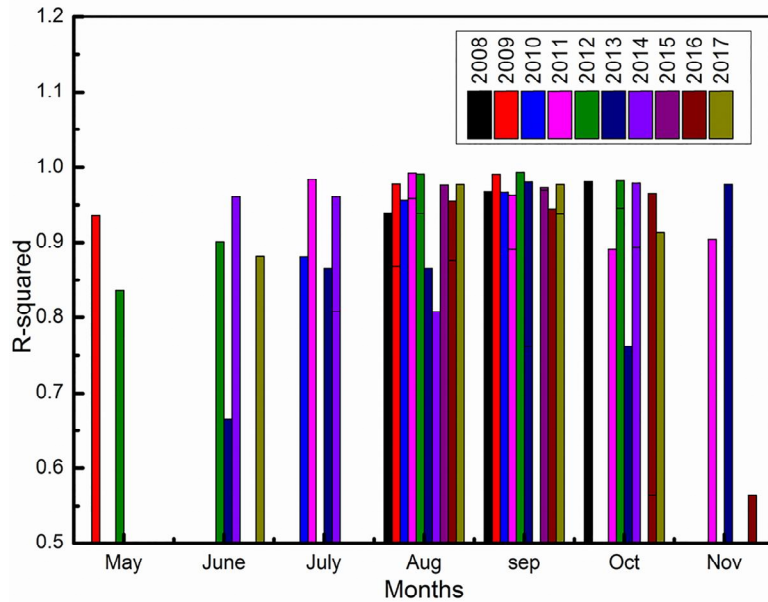


Figure 4: Combined Results for all Tables 3 through Table 12 for Hurricane occurrence in 2008-2017.

From Figure 4, we can see that only seven (7) months, i.e., May to November, experienced various hurricanes, whereby some years had the same fierce and violent tempest extending to the second month. For example, hurricane Maria of 2017 was experienced in September and October, respectively.

k) The best  $R^2$  for the 10 years (2008-2017) data that was analyzed on four (4) parameters

Table 13: The highest R-Squared for the years-2008-2017, the highest r-squared results is indicated in bold.

Year	Name	$R^2$	MSE
2008	OMAR	0.9801	2.242
2009	EIGHT	0.9907	0.1071
2010	LISA	0.9669	1.5117
2011	FRANKLIN	0.9922	0.3878
<b>2012</b>	<b>MICHAEL</b>	<b>0.9930</b>	<b>1.4952</b>
2013	INGRID	0.9799	1.2151
2014	GONZALO	0.9784	3.3368
2015	DANNY	0.9760	2.3375
2016	NICOLE	0.9652	3.0746
2017	IRMA	0.9768	4.8291

The determination and choosing of the highest  $R^2$  value was based on the simple graphical method and the behavior analysis of the extreme value in compassion with other hurricanes of

other years. From Table 13, we notice that hurricane Michael had the most and much damage in the year 2012 with a percentage of 99% and an MSE of 1.4952 of all the hurricanes that were analyzed from the year 2008 to 2017 (10 years), thus clearly discloses the massive damages of tropical storms that were precisely predicted in the year 2012, applying Equation (12) unto the Henri hurricane that took place in year 2012,

$$R^2 = \frac{SS_{Regression}}{SS_{Total}} \quad (12)$$

We replace the coefficients in the equation with the values from the analysis of variance table in order to determine the maximum value of the  $R^2$ ,

$$R^2 = \frac{12136.1198}{12221.0714} = 0.9930\% \quad (13)$$

The study also considered single variables to find out the effect of our model using equation (3). Figure 5 is a result of the different parameters that were tested to prove our model's efficiency and effectiveness when applied on a single parameter and multiple parameters separately.

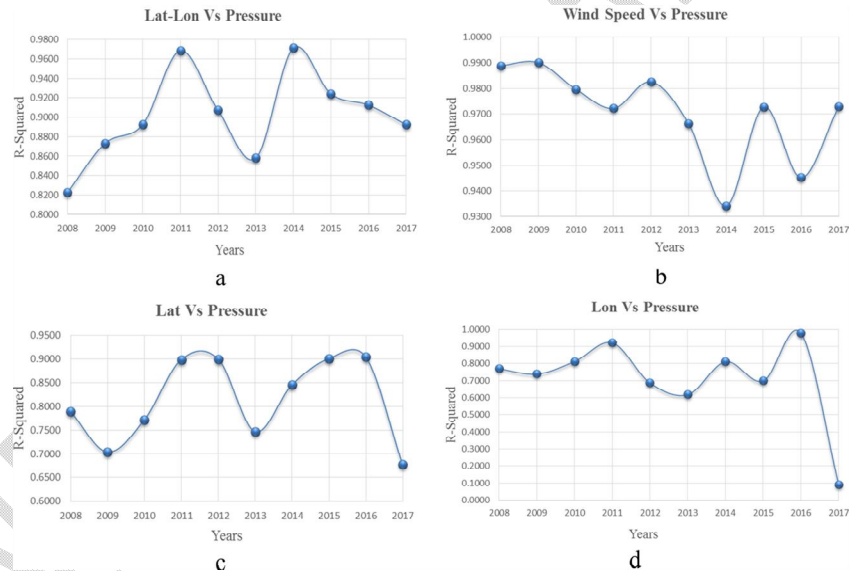


Figure 5: Chart a) two parameters that were tested that is Latitude & Longitude against pressure, b) the wind speed against pressure, c) Latitude against pressure, and d) Longitude against pressure.

The results on three (3) parameters (i.e., latitude, longitude, wind speed),

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \quad (14)$$

Taking equation (5) into account, the four (4) parameters (i.e., latitude, longitude, wind speed, and pressure), and their results is a represented in Figure 5.

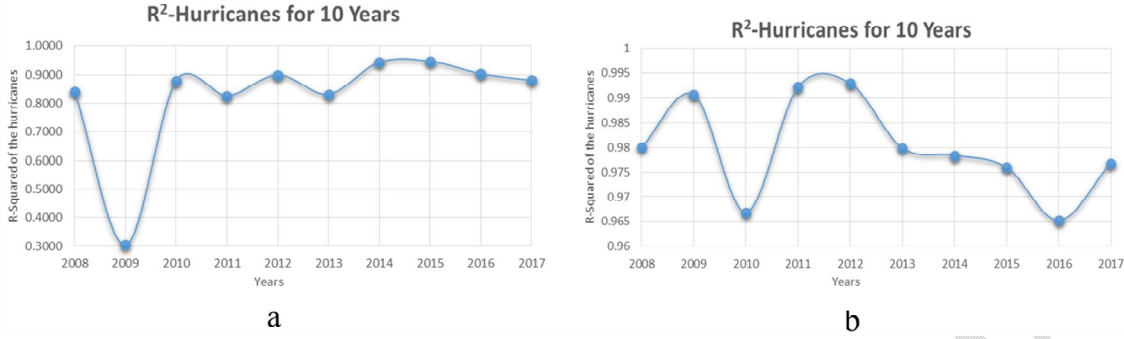


Figure 6: Chart a) Three parameters (Lat, Lon, wind speed) were tested, and b) the chart on four parameters (Lat, Lon, wind speed & pressure).

Table 14 presents the results obtained on different parameters that were tested to explore the response and impact of the variables on our proposed model.

Table.14: Results obtained on different parameters.

Parameters	$R^2$	MSE	Hurricane name	Year
Lat, Lon & Pressure	0.9715	1.6243	Fay	2014
Wind Speed & Pressure	0.9900	1.6051	Fred	2009
Lat & Pressure	0.9039	1.9735	Colin	2016
Lon & Pressure	0.9775	0.9542	Colin	2016
Lat, Lon & Wind Speed	0.9459	1.9837	Henri	2015
Lat, Lon, Wind speed & Pressure	0.9930	1.4952	Michael	2012

From Table 14, we can clearly ascertain that the more the number of parameters combined and used as predictors the higher the response achieved.

The four parameters considered in our model, i.e., the latitude (N<sup>o</sup>), longitude (W<sup>o</sup>), the wind speed (m/s), and the central pressure (mb) for the analysis and prediction of hurricane occurrence and damage on the tropical environs, it reveals strong relationships in the geographical location for most ocean basins around the globe. In our study, first, we calculated the strength of damage and prediction of hurricanes to obtain the  $R^2$  of each cyclone for a period of 10 year. Then, we chose the highest  $R^2$  with almost 100%.

The results of our model reveals that hurricane Michael (2012) periodically broke off the outside of the eye and propagated azimuthally (around the tropical cyclone) at 99.3% with the mean of latitude 31.1N<sup>o</sup>, longitude 42.7W<sup>o</sup>, the wind speed 59.5m/s and the central pressure 991.8mb that was used to measure the location. Thus, obtained by the statistical expression,

$$\begin{aligned} \bar{x} &= \frac{\sum x_i}{n} \\ &= \sum x_i = x_1 + x_2 + x_3 + \dots x_n \end{aligned} \quad (15)$$

Where  $n$  is the number of observations in this case it was 42 and  $x_1, x_2, x_3, \dots, x_n$  represents the number of each record of latitude (N<sup>o</sup>), longitude (W<sup>o</sup>), wind speed (m/s), and the central pressure (mb) that was captured and recorded in an interval of 6hours.

Considering Tables 13 and 14 it shows that hurricane Michael had the highest R-squared for the ten years that were tested on and Figure 7 shows the thread of the occurrence of the identified hurricane.

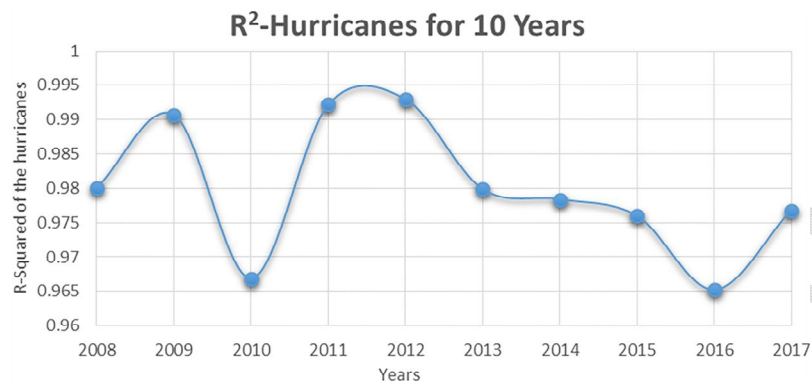


Figure 7: R-Squared analysis for the years-2008-2017.

From Figure 7, we can clearly see that an extreme tropical cyclone was expressed in the year 2012, but the question remains Do We Expect The Worst in the coming years?

## 5. CONCLUSION

The  $R^2$  of the analyzed hurricanes for the ten years (2008-2017) showed a good agreement between the analyzed and the best observed tracks from National Hurricane Center (NHC). Our model for a statistical analysis and exploration of Atlantic hurricanes occurrence and damage in the tropical environs proved to have the ability to predict the best results that shows the hurricane of massive damage, thus it can be effectively applied to establish the impact of hurricanes regardless of the region of hurricane occurrences. Our model achieved an accuracy  $R^2$  of 99.3% and mean standard error (MSE) of 1.4952 of the analyzed hurricanes. Future study is required to determine the best practices of minimizing the ambiguity of life-threatening coastal disaster predictions due to climate change, with the natural erraticism or variability of surf climate.

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