Beyond: Undergraduate Research Journal

Volume 4 Article 6

September 2020

The Development and Evaluation of the Atlantic Tropical Cyclone Intensification Regression Model (ATCIRM)

Bruno Platero Huarcaya
Embry-Riddle Aeronautical University, platerob@my.erau.edu

Lexi Cruz
Embry-Riddle Aeronautical University, comstocl@my.erau.edu

The Development and Evaluation of the Atlantic Tropical Cyclone Intensification Regression Model (ATCIRM)

Cover Page Footnote

The authors would like to express their appreciation to Dr. Daniel Halperin and Dr. Tim Smith for contributing to and guiding this research project.

UNDERGRADUATE RESEARCH JOURNAL
Beyond

The Development and Evaluation of the Atlantic Tropical Cyclone Intensification Regression Model (ATCIRM)

Bruno Platero Huarcaya & Lexi Cruz

Abstract

Operational track forecasts of Tropical Cyclones (TCs) have been improved substantially in recent years and nowadays are sufficiently accurate. However, intensity forecasts have not shown similar improvements, especially for rapidly intensifying storms. The improvement of intensity forecast accuracy can help authorities in risk management and decision making to prevent loss of life and property. The purpose of our project is to develop a statistical linear regression model that provides better predictions for TC intensification over the ocean. Here, different predictor variables are studied, and 2011-2017 Atlantic basin storms are investigated. The final set of predictor variables selected for the model are Reynolds sea surface temperature, 700-500 hPa relative humidity, 200-800 km disk average 850-200 hPa wind shear magnitude, and 200 hPa divergence. Model performance tests, based on the 2018 Atlantic TC season, reveal a mean absolute error of 10.43 knots in the 24-hour intensity forecast. We conclude that Reynolds sea surface temperature is the most deterministic predictor, having the largest coefficient and test statistic, what is consistent with known TC physical mechanisms.

Introduction

The Tropical Cyclones' (TCs) intensity forecast is one of the most important elements used to assess the risks and potential damage of approaching TCs because it helps to identify what conditions affected areas will be subjected to. The intensity of a TC is highly correlated to how high the storm surge is upon landfall, and Edward Rappaport (2000) stated that the main cause for loss of life during the landfall of a TC is storm surge. Elsberry et al. (1992) also noted that many "emergency managers make evacuation decisions based on the predicted maximum 1-min sustained surface wind speed". Determining how severely an area will be affected by strong winds and storm surge can prevent loss of life and property. Therefore, an increase in intensity forecast accuracy would help authorities in their risk management process and allow them to issue accurate evacuation orders and warnings.

Although operational track forecasts of TCs have improved substantially in recent years and are sufficiently accurate, intensity forecasts have not shown similar improvements, especially for rapidly intensifying storms. In a Science magazine article that addressed the shortcomings of TC intensification forecasts, Dr. Robert F. Rogers, a meteorologist at the National Oceanic and Atmospheric Administration's Hurricane Research Division (HRD), explained:

> Predicting a hurricane's track is relatively straightforward because storms are propelled in one direction or another by the large-scale air currents in the atmosphere (…) We've gotten a much better handle on predicting those large-scale currents over the past 20 years (qtd. in Schembri, 2018).

In that same article, Dr. Kerry A. Emanuel, meteorologist and professor at MIT, pointed that "when it comes to predicting changes to a storm's intensity, the underlying physics becomes much more complicated". That's because hurricanes are complex, massive rotating heat engines." The microprocesses which determine hurricane intensification are much harder to model and there is a lack of data and knowledge on the lowest layer of the atmosphere where sea and air interact and most of a TC heat flux takes place (Schembri, 2018).

Another group of tropical meteorology experts also acknowledged that operational intensity forecasts have shown little improvement when compared to operational tracks forecasts, and that that is likely due to the difficulty in resolving the eyewall regions to reflect the physics of the boundary layers and air-sea interactions (DeMaria 2014). This aligns with the studies of Elsberry et al. (1992) that concluded that the inaccuracies in sea surface temperature measurements and the models' low resolution, which could not correctly resolve the eyewall evolution, make it difficult to forecast intensity changes in TCs. Even though significant improvements have been made in model resolution since 1992, it is still not high enough for accurate intensification predictions.

A demonstrative example of the shortcomings of TC intensity forecasting is Hurricane Michael in 2018. As this hurricane became a TC three days before landfall, the National Hurricane Center (NHC) had successfully predicted landfall to happen near Mexico Beach, Florida, Wednesday October 10, 2018 in the early afternoon. However, the intensity predicted at landfall was not above a Category 2 hurricane, when in fact it rapidly intensified to a Category 5 hurricane during the last 24 hours before landfall.

The purpose of this project is to develop a statistical linear regression model and determine if it can better predict TC intensification over the ocean. To do so, Atlantic basin storms from 2011-2017 are analyzed, limiting the data to observations where the storms were at least 100 km from a major landmass and above the Tropical Depression threshold, i.e., storms with maximum sustained surface winds of 34 knots or greater. The initial set of predictors selected for the model are Reynolds sea surface temperatures (RSST), 700-500 hPa relative humidity (RHMD), 200-800 km disk average 850-200 hPa wind shear magnitude (SHRD), 200-800 km disk average 850-500 hPa wind shear magnitude (SHRS), and 200 hPa divergence of the wind (D200). With these data the initial model is developed, optimized, and tested to determine its forecast accuracy. This project also intends to identify which of the variables are the most deterministic in predicting TC intensification.

Similar studies have been done before, such as DeMaria and Kaplan's A Statistical Hurricane Intensity Prediction Scheme (SHIPS) for the Atlantic Basin (1994). They analyzed named Atlantic TCs from 1989 to 1992 and developed a model using a multiple regression technique utilizing sea surface temperatures, vertical shear of the horizontal wind, persistence, and the flux convergence of angular momentum evaluated at 200 hPa data as their predictor variables (DeMaria et al., 1994 & 2005). This model was then improved in 2004 and has been used by the NHC, in conjunction with other models, to predict storm intensification.

In the present study, we introduce the Atlantic Tropical Cyclone Intensification Regression Model (ATCIRM). The ATCIRM was developed using a similar approach to DeMaria and Kaplan's SHIPS, but this study had different goals. It is not meant to be a replication of the SHIPS prediction tool; instead, ATCIRM analyzes similar variables on a smaller scale with a different data set.

Data and Methodology

Two separate data sets were used to develop the regression model. The predictors were obtained from the Automated Tropical Cyclone Forecasting System (ATCF) SHIPS archive (Sampson and Schrader, 2000). These data contain a set of over 50 atmospheric predictors, obtained from the National Centers for Environmental Prediction (NCEP) global model re-analyses or operational model forecasts, at a 6-hour forecast interval. Since our model predicts the 24-hour TC intensity change, the 24-hour forecasts of the relevant predictors were extracted from the SHIPS archive. The data were limited to Atlantic basin storms from 2011 – 2017 that reached the Tropical Depression threshold. In addition, the distance to the nearest major landmass (DTL) data column was examined at the 0-hr and 24-hour forecast so that the data points 100 km or closer to a major landmass at either of these times were not considered. The second data set contained the predictand: the change in maximum sustained windspeed in the 24-hour period. These data were obtained from the Hurricane Data 2nd generation (HurDat 2) Best Track data stored in the ATCF archives (Landsea et al. 2015). The data were based on a post-storm analysis performed by the NHC, who used all available observations. According to the HRD, these observations were mostly collected by ships, the Hurricane Hunter Navy, Air Force, and Environmental Science Services Administration (ESSA) aircraft reconnaissance planes, weather stations, dropsondes, and satellite imagery (Hurricane Research Division, 2019).

The predictor variables were chosen to best outline the factors that contribute to the intensification of TC. The relations between TC and heat engines, and the accuracy of system analysis methodologies for TC intensification prediction were subjects of extensive discussion. Given that this is a smaller-scale study than those previously completed by DeMaria et al. (1994), the variables were carefully chosen to reflect each part of the TC system. The selected variables were: 700-500 hPa relative humidity (RHMD), 200-800km disk average wind shear magnitude at the 850-200 hPa (SHRD) and the 850-500 hPa level (SHRS), Reynolds sea surface temperatures (RSST), and 200 hPa divergence (D200).

The RHMD was chosen as a predictor variable because it is important to determine whether a TC has entered an area of dry air or an area of moist air, as this has a significant effect on the strength of the storm. This happens because the "ultimate energy source for the tropical cyclone is evaporation from the ocean" (Elsberry et al., 1992). Relative humidity can represent the potential energy sources for the TC. The study also used the SHRD and SHRS to consider factors that may inhibit intensification. Elsberry et al. (1992) revealed that "vertical shear is cited by the forecasters as the primary impediment of achievement of the potential intensity for a given sea surface temperature". A TC that enters an area of high shear is often torn apart and weakened. RSST was selected because it is widely acknowledged that the sea surface temperature is one of the main contributing factors to TC development and intensification. Some experts even claim that "the cyclone intensity may be affected by an SST (sea surface temperature) decrease of only 1°C" (Elsberry et al., 1992). The warm water, or lack thereof, correlates to the amount of moisture and heat available to TCs, which can enable it to strengthen or weaken. Lastly, D200 was selected to consider the strength of the outflow of the hurricane, which can be related to the power and intensity of the storm. This relates back to a key analogy that compares each part of the hurricane to a heat engine:

> If the [TC] is interpreted as a heat engine, as Emanuel (1988) suggests, it involves a fuel tank (ocean), cylinders (eyewall convection), and exhaust pipes (upper-tropospheric outflow) (Elsberry et al.1992).

Once the data were properly formatted, the initial linear regression model was created. A hypothesis test was performed to determine the validity of this initial model and determine whether it was statistically significant. In addition to the hypothesis testing, the predictors' test statistics (t-stats) were examined, and the most deterministic predictors were identified. The t-stats were also evaluated to determine if they were all above the threshold of 1.961, and those that were not were removed.

Once the initial linear regression model had been created and tested, a correlation analysis was performed on all the variables to determine if there was multicollinearity between them. A variance inflation factor (VIF) test was performed on those predictors that had multicollinearity, indicated by high correlation values between them. Those predictors with high VIF values were removed from the model. Once the inadequate predictors had been removed, a second linear regression model was created with the remaining variables and a new hypothesis test was performed.

Finally, the strength, validity, and accuracy of the model were tested. Smaller-scale models were created for subsets of data, each containing a single year, creating a total of seven new models. With this, the coefficients of the new models were compared to the coefficients of the original model. The final model was also tested on storms from the 2018 season (i.e., an independent dataset), and its accuracy at predicting 24-hr TC intensification was measured. Additional statistical experiments were performed to try to optimize the model such as transforming the predictors with an exponential function and testing the predictors individually as a single variable regression model.

Results

The first regression model was created with a sample size of 1674 in the developmental dataset:

$$Y = 1.075609 * RSST + 0.196394 * RHMD - 0.21322 * SHRD - 0.06667 * SHRS + 0.04365 * D200 - 34.2199 \qquad [1]$$

Since in meteorology many atmospheric processes and parameters are influenced by each other, the correlation between predictors was a concern because multicollinearity could be detrimental to the model. Once the correlation analysis was performed, a high multicollinearity value of 0.79 was detected between SHRS and SHRD, shown in the first correlation chart (Table 1).

To determine which value was more redundant and statistically insignificant, a VIF test was performed on the SHRD and SHRS variables. The VIF values were 2.87 and 3.10 for SHRD and SHRS, respectively. It is important to note that that SHRD was more correlated to the predictand than SHRS. Therefore, SHRS is not highly deterministic in the result of the model.

A hypothesis test was also performed. The null hypothesis was assumed truthful: the model does not fit the data and the predictors do not influence the predictand. The t-stat and critical t-stats for all the coefficients were calculated and all predictors but one passed the hypothesis test: SHRS had a t-stat of -0.59, smaller in magnitude than the critical t-stat of +/- 1.961. Because of that, the SHRS predictor was eliminated from the model using a backward linear regression optimization method, which coincides with the results of the VIF tests. The model is now statistically significant, and it can be inferred that the predictors affect the predictand. Without SHRS, the new optimized regression model is:

$$Y = 1.091699 * RSST + 0.197384 * RHMD - 0.234427 * SHRD + 0.041933 * D200 - 34.7660 \qquad [2]$$

The final four predictors are Reynolds sea surface temperature, 700-500 hPa relative humidity, 200-800 km disk average wind shear magnitude at the 850-200 hPa level, and 200 hPa divergence. The new model has a mean absolute error of 9.64 knots when evaluated using all the 1674 data points. The minimum absolute error is 0.012 knots, and the maximum absolute error is 65.72 knots. The predictors were also tested individually as single variable regression models and as expected, these models have a higher mean absolute error (Table 2).

The model's regression statistics, analysis of variance (*ANOVA*) results, and correlation values are shown in Tables 3, 4, and 5, respectively. The correlation coefficient shows that the linear relationship of the regression model is not strong. Both R^2 and the adjusted R^2 are small and therefore the model's fit is not optimal. Only 18% of the variation in the change in intensity is explained by the predictors. The standard error of 13.5 shows that the data points do not fall sufficiently close to the model's regression line. However, R^2 and adjusted R^2 are very similar, suggesting that the model is generalizable. The significance F is smaller than 0.05, and the F statistic is much greater than the critical F statistic, validating the model because it shows that it is statistically significant. All the predictors had p values of much less than 0.05, strengthening the confidence in the linear regression model. The predictor's standard errors are low, and the absolute value of their t-stats are much greater than 1.961.

The new correlation data (Table 6) show that the highest correlation is -0.51 between Reynolds sea surface temperature and wind shear. This is an acceptable value and should not be detrimental to the model because wind shear is not physically dependent on sea surface temperature, except for areas with a strong sea surface temperature gradient.

When using the model to predict Atlantic TC intensification of the 2018 season's storms and then testing the error by comparing the predictions to the observations 24 hours later, the mean absolute error of the whole season is 10.43 knots. The minimum error is 0.02 knots, and the maximum error is 54.88 knots. Figure 1 shows the 2018 Official NHC forecast mean intensity error, and at 24 hours it is approximately 8 knots (Cangialosi, 2019). This confirms that the error level of the linear regression model is satisfactory. Table 7 shows the mean absolute error (*MAE*), minimum absolute error (*MIN AE*), and maximum absolute error (*MAX AE*) of the model, tested against the individual storms of the 2018 season. It is important to mention that the model tends to underpredict the magnitude of the 24-hour intensity change in both weakening and intensifying storms, and that when no changes are observed in this period the model tends to wrongly predict a weakening.

To determine if the model could be improved, residual plots were created for all the predictors (Figures 2-5). The residual plots for RHMD and D200 look randomly dispersed, so this linear model is probably most appropriate for them. However, the residual plots for RSST and SHRD show some heteroscedasticity, indicating that a transformation is necessary or that a variable is missing in the model.

In order to avoid heteroscedasticity, four new models were created and tested. In each model, one of the predictors was transformed with an exponential function. The mean absolute errors produced by these new models with the exponential transformation are shown in Table 8. These results show that the model did not improve, and that is consistent with the new residual plots obtained. The heteroscedasticity grew and shifted to the other side (Figure 6) indicating that these transformations are not adequate. Different transformations and additional testing with other predictors are required to further improve the model.

A linear regression was also performed on smaller datasets, each containing one year's worth of data. Table 9 summarizes the model coefficients and their respective t-stats. The predictors' coefficients and t-stats vary a lot depending on the year with these smaller data sets and there is no clear trend, probably due to the smaller size of these data. However, when all the 2011-2017 observations are used, the sea surface temperature is the most deterministic predictor, and the divergence at 200 hPa is the least deterministic one. RSST being the most deterministic predictor is consistent with what would be expected meteorologically. It is known that warmer sea surface temperatures are favorable for TC intensification, and therefore RSST has a positive coefficient. The relative humidity and wind shear have a similar level of influence on TC intensification and it makes sense that RHMD has a positive coefficient because it favors intensification, and that SHRD has a negative coefficient because it opposes intensification.

Discussion

Even though the model passed the hypothesis tests, and it was concluded that it is statistically significant, some regression statistics such as the low R^2 and the high standard error suggest that there is room for model improvement. The low R^2 suggests that other variables might be necessary to make a more accurate prediction, since only a small percentage of the variability in the response variable is explained by the model. The high standard error suggests that there is a significant difference between the predicted values and the observed values. Even if R^2 is low, the predictors of the final model are all statistically significant, and therefore the mean change in the response is still represented by the predictors. It is also important to note that R^2 and the adjusted R^2 are nearly equal. This means that none of the predictors are redundant nor unnecessary, and that the model is generalizable.

In order to improve the model and fix its shortcomings, residual plots were created. The plots revealed that there is heteroscedasticity in the model, and that the variability of the predictand is unequal throughout the predictors' range. This suggests that a linear model might not be ideal for this data set and that a transformation on one or more variables is necessary, or that a new predictor variable should be added. To improve the model in the future, further research is necessary as the transformations tested did not yield better results. This would allow us to determine which transformations should be implemented on which variables, and/or what other predictor variables could be added to enhance the model.

When our model was tested on the 2018 Atlantic TC season, the mean absolute error was 10.43 knots. Even though this value might seem relatively high, the model's error shows comparable accuracy to that of the 2018 NHC official forecast, which had a mean 24-hour intensity error of 8 knots (Cangialosi, 2019). However, it is important to mention that the model had a maximum error of 54.88 knots for a given day, and this error level could potentially be inappropriate when it comes to emergency management and decision making.

Further research is necessary to determine why there were some instances that had such a high error, and what statistical methods could be implemented to minimize them. Since manually testing all possible transformations and regression techniques would be very cumbersome, implementing a machine learning regression technique is potentially a reliable approach. These new results could help either enhance the model to minimize these large errors or determine in which scenarios/atmospheric conditions should the model not be used.

Valuable conclusions can also be drawn from the regression model coefficients and t-stats. Reynolds sea surface temperature is the most deterministic predictor, having the largest coefficient and t-stat. This is consistent with what would be expected meteorologically. The fuel of the heat engine that constitutes a TC is water vapor, which depends on the surface temperature of the ocean. The next most deterministic predictors are the relative humidity and wind shear, which have a similar level of influence on TC intensification. Divergence at 200 hPa would have been expected to have a stronger impact on TC intensification. Physically, divergence aloft should intensify surface low pressure systems, but this is not clearly shown by the model since D200 is the least deterministic predictor. Therefore, further research would be necessary to understand why this is not the case.

Finally, our results help confirm the findings of previous studies: sea surface temperature most strongly affects TC intensification and therefore there is a need for a higher density of surface weather observing systems in the ocean and higher quality temperature measurements. Understanding and gathering data from the sea and the lowest layer of the atmosphere is fundamental to accurately predict TC intensification.

References

Cangialosi, J. P., (2019). National Hurricane Center forecast verification report. *National Hurricane Center (NHC)*, 79.

DeMaria, M. and J. Kaplan. (1994).A Statistical Hurricane Intensity Prediction Scheme (SHIPS) for the Atlantic Basin.*Wea. Forecasting*, 9, 209–220, https://doi.org/10.1175/1520- 0434(1994)009<0209:ASHIPS>2.0.CO;2

DeMaria, M., Mainelli, M., Shay, L. K., Knaff, J. A., & Kaplan, J. (2005). Further improvements to the statistical hurricane intensity prediction scheme (SHIPS). *Weather and Forecasting*, 20(4), 531-543.

DeMaria, M., Sampson, C. R., Knaff, J. A., & Musgrave, K. D. (2014). Is Tropical Cyclone Intensity Guidance Improving? *Bulletin of the American Meteorological Society*, *95*(3), 387–398. doi: 10.1175/bams-d-12-00240.1

Elsberry, R. L., Holland, G. J., Gerrish, H., Demaria, M., Guard, C. P., & Emanuel, K. (1992). Is There Any Hope for Tropical Cyclone Intensity Prediction?—A Panel Discussion. *Bulletin of the American Meteorological Society*, *73*(3), 264–277. doi: 10.1175/1520-0477-73.3.264

Emanuel, K., and Zhang, F. (2016). On the Predictability and Error Sources of Tropical Cyclone Intensity Forecasts. *Journal of the Atmospheric Sciences*, *73*(9), 3739–3747. doi: 10.1175/jas-d-16-0100.1

Hurricane Research Division. (2019). Link to the Reanalysis Data. Retrieved May 13, 2020, from https://www.aoml.noaa.gov/hrd/data_sub/re_anal.html

Landsea, C., Franklin, J., & Beven, J. (2015). The revised Atlantic hurricane database (HURDAT2). NOAA/NHC. [Available online at nhc.noaa.gov.]

National Hurricane Center. (n.d.). Automated Tropical Cyclone Forecast Archive. Retrieved February 2, 2020, from https://ftp.nhc.noaa.gov/atcf/archive/MESSAGES/2011/

Rappaport, E.N., 2000: Loss of Life in the United States Associated with Recent Atlantic Tropical Cyclones. *Bull. Amer. Meteor. Soc.*, 81, 2065–2074

Sampson, C. R., & Schrader, A. J. (2000). The automated tropical cyclone forecasting system (version 3.2). *Bulletin of the American Meteorological Society*, *81*(6), 1231-1240.

Schembri, F. (2018, October 15). Why scientists had trouble predicting Hurricane Michael's rapid intensification. Retrieved from https://www.sciencemag.org/news/2018/10/why- scientists-had-trouble-predicting-hurricane-michael-s-rapid-intensification

Appendix 1 Figures

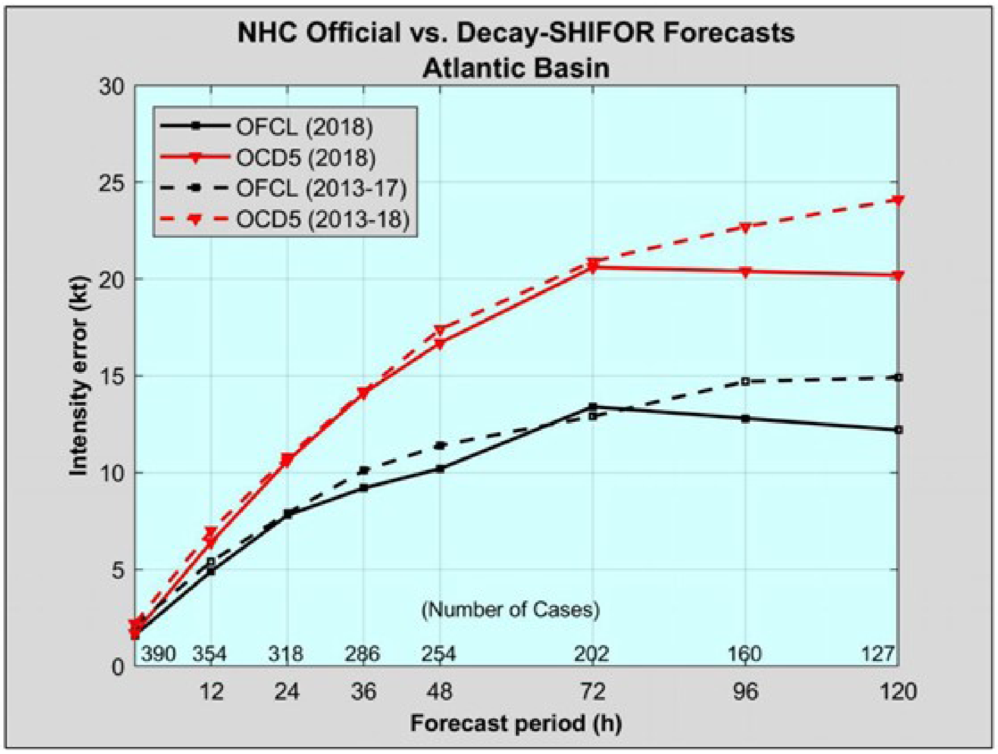

Figure 1. NHC official and Decay-SHIFOR5 (OCD5) Atlantic basin average intensity errors for 2018 (solid lines) and 2013-2017 (dashed lines). Retrieved from Cangialosi (2019), Fig. 8.

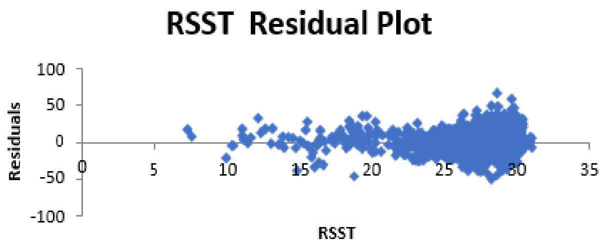

Figure 2. Residual plot for the RSST predictor.

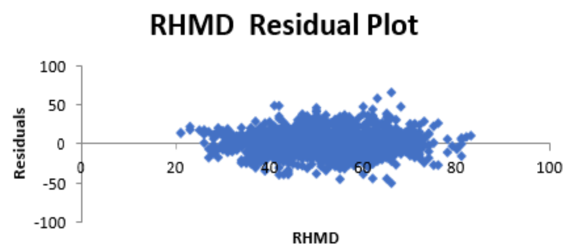

Figure 3. Residual plot for the RHMD predictor.

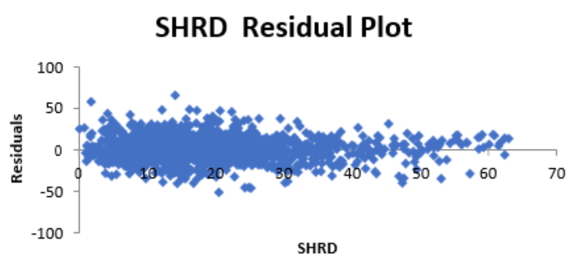

Figure 4. Residual plot for the SHRD predictor.

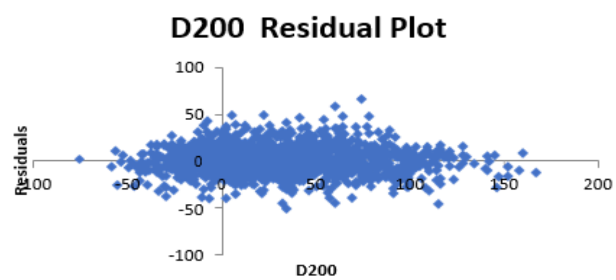

Figure 5. Residual plot for the D200 predictor.

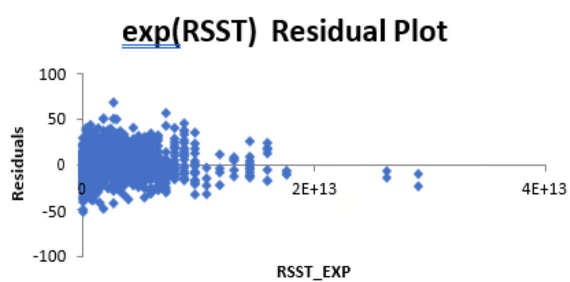

Figure 6. Residual plot for the exponentially transformed RSST predictor

Appendix 2 Tables

Correlation	RSST	RHMD	SHRD	SHRS	D200	VMAX
RSST	1					
RHMD	0.239313	1				
SHRD	-0.50447	-.024937	1			
SHRS	-0.50102	-0.14912	0.790265	1		
D200	0.009222	0.462894	0.117104	0.253493	1	
VMAX	0.352139	0.251268	-0.3108	-0.25359	0.148903	1

Table 1. Correlation table of the initial model.

	RSST	RHMD	SHRD	D200
MAE	10.57972	10.70034	10.83447	10.96876

Table 2. Mean absolute error (MAE) of each single-variable regression model in knots.

Regression Statistics	
Multiple R	0.434381
R Square	0.188686853
Adjusted R Square	0.186743588
Standard Error	13.50821026
Observations	1675

Table 3. Regression Statistics.

ANOVA	*df*	*SS*	*MS*	*F*	Significance *F*
Regression	4	70870.45527	17717.61	97.09785	2.35822E-74
Residual	1670	3047273.8134	182.4717		
Total	1674	375598.2687			

Table 4. Analysis of Variance results.

	Coefficients	Standard Error	t-stat	P-value
Interecept	-34.76604278	4.015060201	-8.65891	1.1E-17
RSST	1.091699207	0.121252051	9.003553	5.8E-19
RHMD	0.197384214	0.039214347	5.033469	5.34E-07
SHRD	-0.234427057	0.036201942	-6.47554	1.24E-10
D200	0.041933712	0.010329946	4.059432	5.15E-05

Table 5. Model coefficients, Standard Errors, t-stats, and P-values.

Correlation	RSST	RHMD	SHRD	D200	VMAX
RSST	1				
RHMD	0.239313244	1			
SHRD	-0.504465183	-0.249368434	1		
D200	0.009221567	0.462893565	0.117104	1	
VMAX	0.352138758	0.281268242	-0.3108	0.148903	1

Table 6. Correlation table of the final model.

	MAE	*MIN AE*	*MAX AE*
Alberto	5.767	0.137	15.724
Beryl	8.427	0.191	26.243
Chris	12.407	0.747	29.789
Debby	4.412	1.164	10.805
Ernesto	6.629	3.037	9.668
Florence	16.223	0.025	54.876
Helene	9.504	0.097	20.141
Isaac	10.287	1.734	18.350
Joyce	5.654	1.361	14.343
Kirk	8.594	0.544	20.823
Leslie	8.573	0.018	28.174
Michael	24.020	18.118	28.083
Nadine	11.966	1.292	18.885
Oscar	13.841	0.723	26.371

Table 7. Mean absolute error (MAE), minimum absolute error (MIN AE), and maximum absolute error (MAX AE) for each 2018 storm in knots.

	exp(RSST)	exp(RHMD)	exp(SHRD)	exp(D200)
MAE	10.33346	10.2622	10.24401	10.25044

Table 8. Mean absolute error of each transformed regression model in knots.

		Intercept	RSST	RHMD	SHRD	D200
2011	Coefficients	-46.776	1.736	0.043	-0.024	-0.024
	t-stat	-3.824	6.381	0.316	-0.257	-0.961
2012	Coefficients	-33.654	1.119	0.138	-0.109	0.025
	t-stat	-4.281	4.415	1.949	-1.440	1.127
2013	Coefficients	-4.665	-0.096	0.226	-0.386	0.057
	t-stat	-0.546	-0.326	2.555	-4.431	2.214
2014	Coefficients	-62.705	1.707	0.498	-0.186	0.003
	t-stat	-4.128	3.613	2.539	-1.253	0.060
2015	Coefficients	-54.748	0.917	0.632	-0.140	-0.070
	t-stat	-3.551	1.943	4.900	-1.139	-1.713
2016	Coefficients	-29.030	0.889	0.134	-0.172	0.112
	t-stat	-3.250	3.402	1.394	-2.216	4.522
2017	Coefficients	-18.903	0.564	0.334	-0.710	0.070
	t-stat	-1.603	1.529	2.493	-6.527	2.581

Table 9. Coefficients and t-stats of the regression models created with a year of data for 2011-2017.