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IMPROVEMENT IN TRACK AND INTENSITY PREDICTION OF HURRICANE FLORENCE 2018 USING WRF AND HWRF MODELS WITH REGRESSION ANALYSIS

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Abstract. Hurricane Florence (2018) was one of the most destructive storms of the 2018 hurricane season. This storm produced a substantial amount of precipitation, which caused immense flooding along the coast. As a result, billions of dollars of damage were done to the coast. This study explored approaches to improve the prediction of the track and intensity of Hurricane Florence (2018) by utilizing the deterministic Numerical Weather Prediction (NWP) models and a statistical modeling-based ensemble technique. The Global Forecast System (GFS) data is employed to initialize the Weather Research and Forecasting (WRF) and Hurricane WRF (HWRF) models to produce numerous simulations with various scheme options and starting times. The simulation data from five different NWP (Numerical Weather Prediction) models including the HWRF, WRF, ECMWF (European Centre for Medium-Range Weather Forecasts), and GFS models, were then interpolated to prepare for the statistical models. With the interpolated data, a hybrid method with multiple linear regression (MLR), random forest, and simple ensemble (SE) was developed. This hybrid method used multiple linear regression and random forest to identify the significant factors for hurricane prediction in the training set, and an averaging ensemble was then applied to the significant factors' data. As verified in the testing data sets, the errors from the hybrid method were reduced, indicating the improvement of the predictability. It is found that our numerical simulations using the HWRF model with a statistical modeling-based ensemble technique improved the accuracy of the track and intensity prediction of Hurricane Florence (2018). Overall, these tools and methods can greatly improve the accuracy of the track and intensity prediction of future hurricanes like Florence and can help ensure better civilian preparedness for a hazardous storm.

1. Introduction.

Hurricane Florence (2018) was a powerful and long-lived hurricane that caused extensive damage in the Carolinas in September 2018, primarily as a result of both freshwater and saltwater flooding. Florence originated from a strong

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tropical wave that emerged off the west coast of Africa on August 30th. The wave steadily organized and strengthened into a tropical depression on the next day, then acquired tropical storm strength on September 1st. As it moved north-westward, Florence intensified rapidly on September 4–5, reaching Category 4. Then, it weakened rapidly to tropical storm on September 7. Florence re-intensified to hurricane strength on September 9 and major hurricane status by the following day. It reached its peak intensity on September 11, when the east coast received warnings from the NHC (National Hurricane Center). Then, it weakened to Category 1 on September 13, turned southward, and made the landfall the next day near Wilmington, North Carolina. Two days later it resumed northward then north-eastward direction, dissipated, and quickly went back to sea on September 18.

As shown in Fig.1, over the sea, Florence's track looks mostly straight northwestward, with a slight northward deflection on September 6—10. Starting on September 13, Florence stalled for two and a half days while turning southward and making landfall in North Carolina as a weakened Category 1 hurricane. However, this Category 1 storm created storm damage equivalent to a Category 5 hurricane. At its peak just before landfall, the 500-mile-wide storm had an area of tropical storm force winds that was 300 miles wide [1]. The combination of strong winds, size and slow speed prompted wide-spread record high storm surge (9 to 13 feet) across eastern North Carolina [11]. Many places received record-breaking rainfall, with more than 30 inches (760 mm) measured in some places (Fig.2). As the ninth most-destructive hurricane to hit United States, the storm caused a total of 54 deaths, and property damage and economic losses of $24.23 billion, with $24 billion in damages in the Carolinas alone [12].

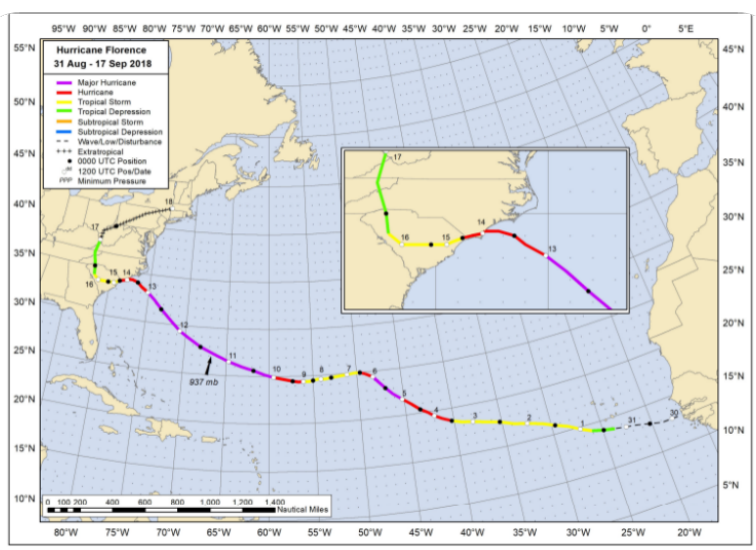

FIGURE 1. Hurricane Florence 2018 track from NHC

Strong storms such as tropical cyclones often cause flooding hazards in coastal areas due to a combination of storm surge, gusty winds, and precipitation. Accurate predictions are critical for effective disaster mitigation. While advanced storm surge/flood modeling systems have been developed, they are heavily dependent on

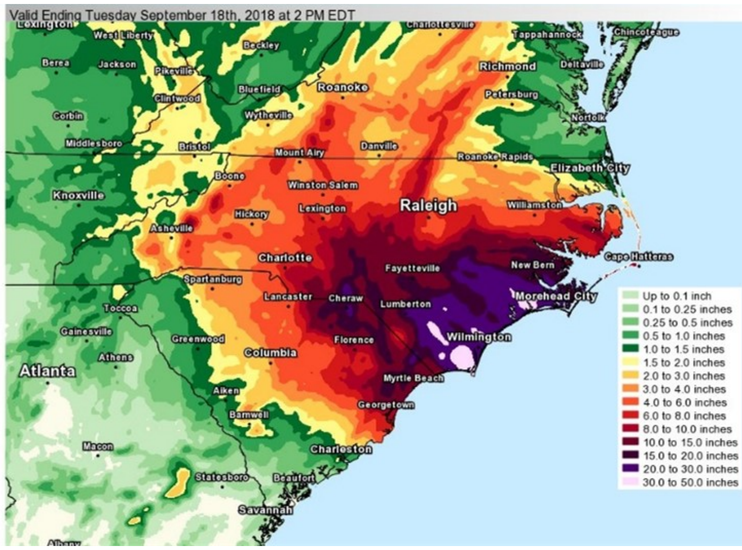

FIGURE 2. Observed precipitation of Hurricane Florence 2018

the accuracy of the tropical cyclone (TC) prediction [7]. Especially challenging is predicting instances when abrupt variations occur in TC track and intensity.

This study focuses on the accurate prediction of track and intensity near landfall. For the forecasting errors, we refer to the data in NHC for the annual average error in Fig.3 for the track and Fig.4 for the intensity. In 2018, the track error is about 33 nautical miles for 24 hours, and the intensity error is about 7 knots for 24 hours. We are using these as references to evaluate our ensemble model's performance. For Florence 2018, the ensemble techniques have been applied to investigate the flooding [3], and Johnson [5] employed the regression-based ensemble technique on the track. Some good statistical model based super ensemble techniques were developed in analyzing climate variables [6]. Our goal is to improve the predictions by combining deterministic NWP (Numerical Weather Prediction) and statistical models on track and intensity.

2. **NWP experiments.**

2.1. **WRF simulations.** The WRF-ARW (Weather Research and Forecast, Advanced Research WRF, denoted as WRF) is a state-of-the-art atmospheric modeling system designed for both meteorological research and weather prediction. It offers a host of options for atmospheric processes and can run on a variety of computing platforms [10]. WRF excels in a broad range of applications across scales ranging from tens of meters to thousands of kilometers, including meteorological studies, real-time NWP, idealized simulations, data assimilation, earth system model coupling, and model training and educational support. In studying this hurricane, we utilized WRF v4.4 and conducted numerous simulations [8]. The varied configuration options include the domain size, resolution, microphysics scheme, boundary layer model, cumulus parameterization, sea surface temperature updating, and pressure top. The starting time varied from September 10 to 11. The model initialization and boundary data are ERA-Interim and

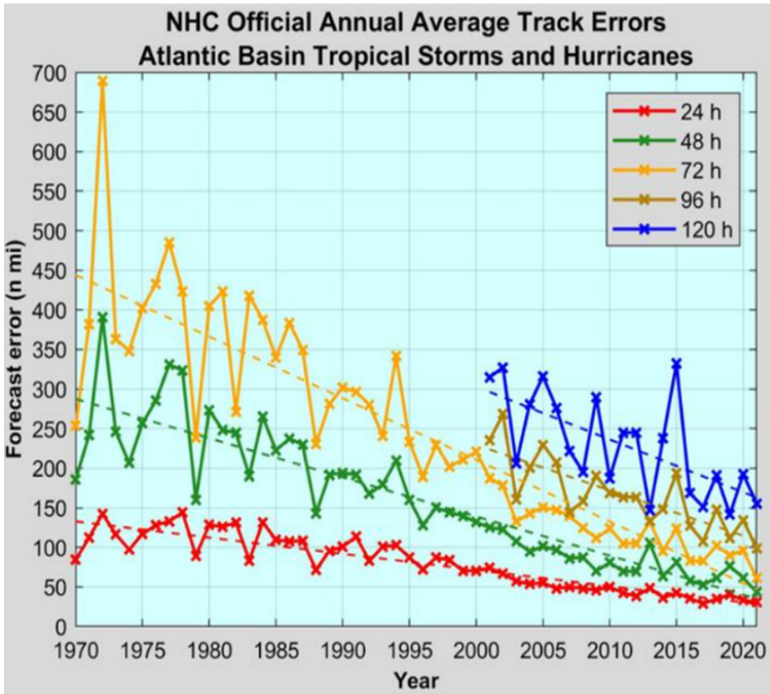

FIGURE 3. Track error from NHC

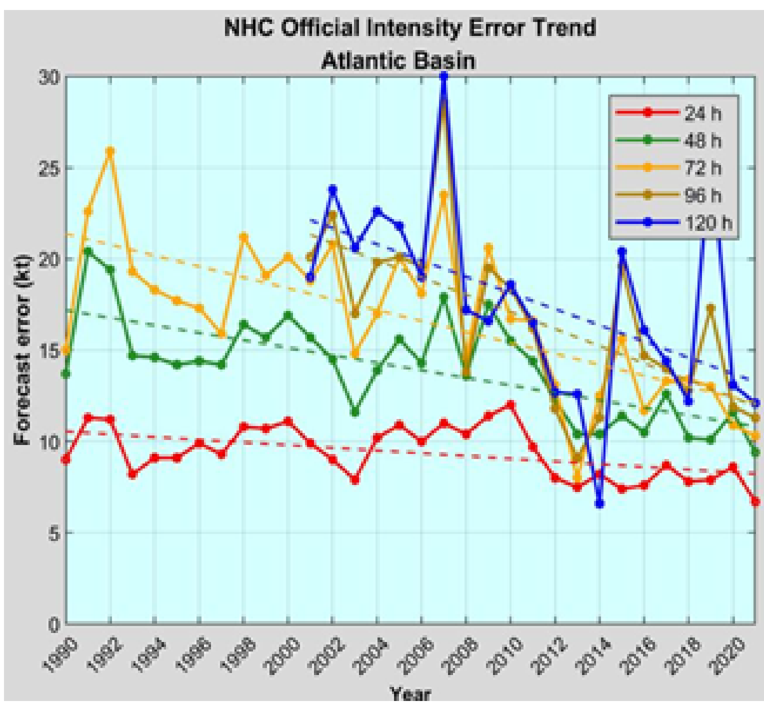

FIGURE 4. Intensity error from NHC

ERA5 (https://www.ecmwf.int/en/forecasts/dataset/ecmwf-reanalysis-interim, or https://rda.ucar.edu/datasets/ds627.0). Both are from the European Centre for Medium-Range Weather Forecasts (ECMWF) reanalysis.

The WRF simulated results are compared with the observation data (best track data) from HURDAT2 (https://www.aoml.noaa.gov/hrd/ hurdat/hurdat2.html) for the track and intensity. Our study [8] reveals that the WRF tracks are sensitive to the simulation domain with slight improvement from the frequent SST (Sea Surface Temperature) updating and deep high pressure-top. Overall, the WRF results match reasonably well with the observation data after two days' simulation, although some error persists. Figure 5 shows the track results of some simulation cases. In Fig.5, we can see two sets of tracks: one with a huge southward turning over the sea and made landfall in South Carolina; the other matches better with the observation, but still with big errors at the southward turning near landfall.

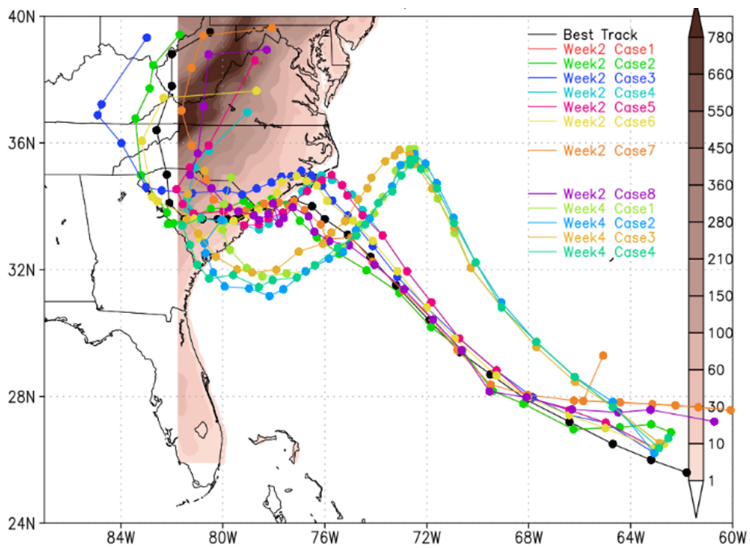

FIGURE 5. WRF-ARW simulations

2.2. **HWRF simulations.** The HWRF (Hurricane WRF) model is a specialized version of the WRF and is the operational backbone for hurricane track and intensity forecasts by the NHC. The HWRF system includes the WRF model software infrastructure, the NMM-E (Non-Hydrostatic Mesoscale Model on the E Grid) dynamic core, the MPIPOM-TC (Message Passing Interface Princeton Ocean Model-Tropical Cyclone), and the NCEP (National Centers for Environmental Prediction) coupler [13]. Studies show accurate predictions from HWRF for the track and intensity of hurricanes. The HWRF package v4.0 is well wrapped in Python scripts and the components are tightly streamlined with optimal schemes [2]. The initialization and boundary data are the GFS (Global Forecast System) forecasting data (https://rda.ucar.edu/datasets/ds084.1/).

The HWRF simulations were set on a parent domain covering $80^o \times 80^o$ with two moving nest domains ($24^o \times 24^o$ and $7^o \times 7^o$) on a rotated latitude/longitude E-staggered grid. The center of the stationary parent domain was at the location of the initial storm, and the nest domains moved along with the storm using a two-way interactive nesting. The resolutions were set at 0.099^o (about 11km), 0.033^o (about 3.67km), and 0.011^o (about 1.22km). We used 10 hPa for model top and 75 for vertical levels. The other schemes included SASAS (Scale-Aware Simplified Arakawa-Schubert) for cumulus parameterization, Ferrier-Aligo package for microphysics, GFS eddy-diffusivity mass flux scheme for planetary boundary layer, Monin-Obukhov scheme for surface flux, and RRTMG (Rapid Radiative Transfer Model for General Circulation Models) for radiation effects.

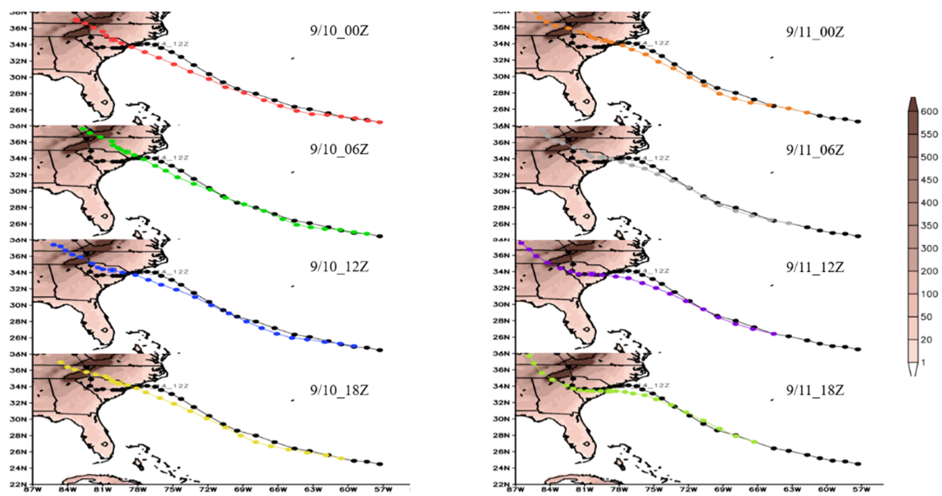

FIGURE 6. HWRF simulations

In HWRF simulations, we mainly varied the starting times [9]. The individual tracks in comparison with the observation data were plotted in Fig.6 for starting times on 09/10 and 09/11, and in Fig.7 for starting times on 09/12 and 09/13. It can be seen from these two figures that, in general, the closer the starting time is to the landfall time the better the simulation result is. The tracks from the cases with starting times on 09/10 are all straight in the northwest direction, while one day later (09/11) the tracks start to deflect toward the north before landfall, which can be seen clearly in case 9/11_18Z in Fig.6. The cases starting on 09/12 showed clear southward then northward turning after landfall. In Fig.7, the cases starting late 09/12 start to curve/turn north before landfall, while the cases starting on 09/13 show clear curving and turning northward before landfall and southward after landfall, matching very well with the observation track.

The intensity results (not shown here) are consistent with the track results. The maximum winds from the cases with early starting times on 09/10 and 09/11 show large discrepancies, while the later starting times on 09/12 and 09/13 show small errors with the simulation results varying around the observation values up and down. Overall, the case with starting time 09/13_00Z, which is 36 hours before the landfall time, provides the best results in track and intensity near landfall.

2.3. **Error analysis.** To better evaluate the performance of the simulation cases, we calculated the storm center errors (in distance) for the tracks (Fig.8) and the errors of the maximum winds (Fig.9) for intensity. Around landfall at 9/14_12Z, both cases with starting times at 9/13_00Z and 9/14_00Z have an error of 30 km. A

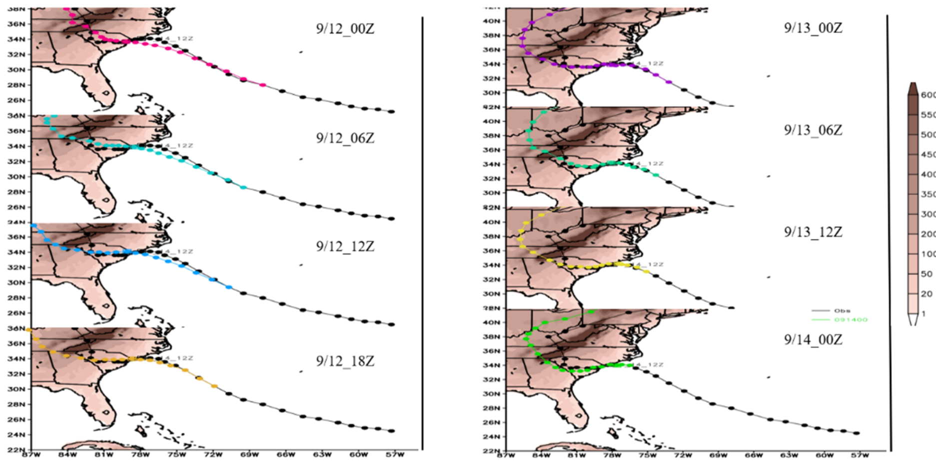

FIGURE 7. HWRF simulations

simple average of these two may result in a better case with a distance error 17 km at the landfall. In general, on average the location distance error within 24 hours is 44 km. The intensity error in Fig.9 also shows the best two cases of 9/13 and 9/14 with small errors of 2 and 3 knots. On average, the intensity error is 8 knots within 24 hours.

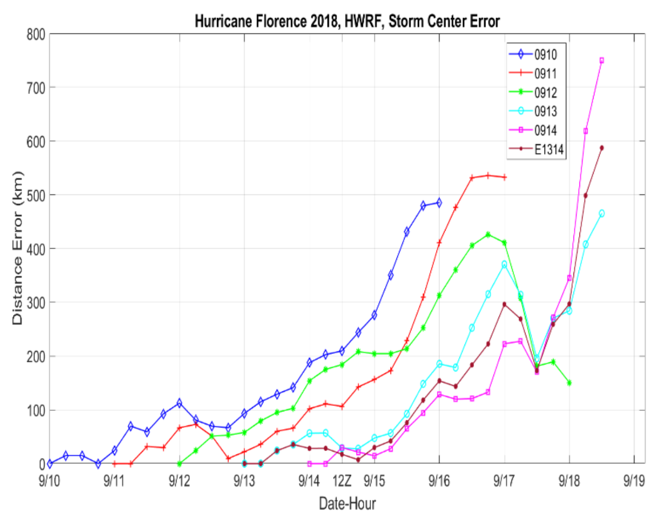

FIGURE 8. Track errors for HWRF simulations

3. **Methodology.**

3.1. **Data collection.** In this study, we retrieved and obtained data for Florence 2018 from various NWP models: WRF (one case), HWRF (one case), GFS (forecast data), and ECMWF (ERA-Interim, ERA5). The GFS forecast, ERA-Interim, and

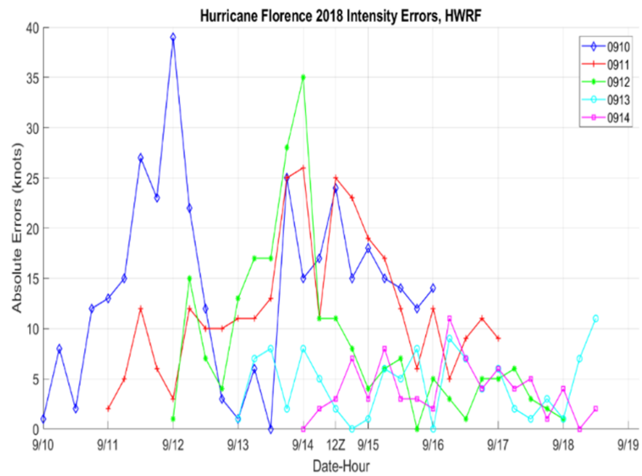

FIGURE 9. Intensity errors for HWRF simulations

ERA5 are downloaded from the RDA website. The initial time for these data is 09/11_00Z. These data from different NWP models are used in our statistical model-based ensemble method to improve the accuracy of prediction, especially for track and intensity. A simple analysis of these data on track and intensity is shown in Fig.10.

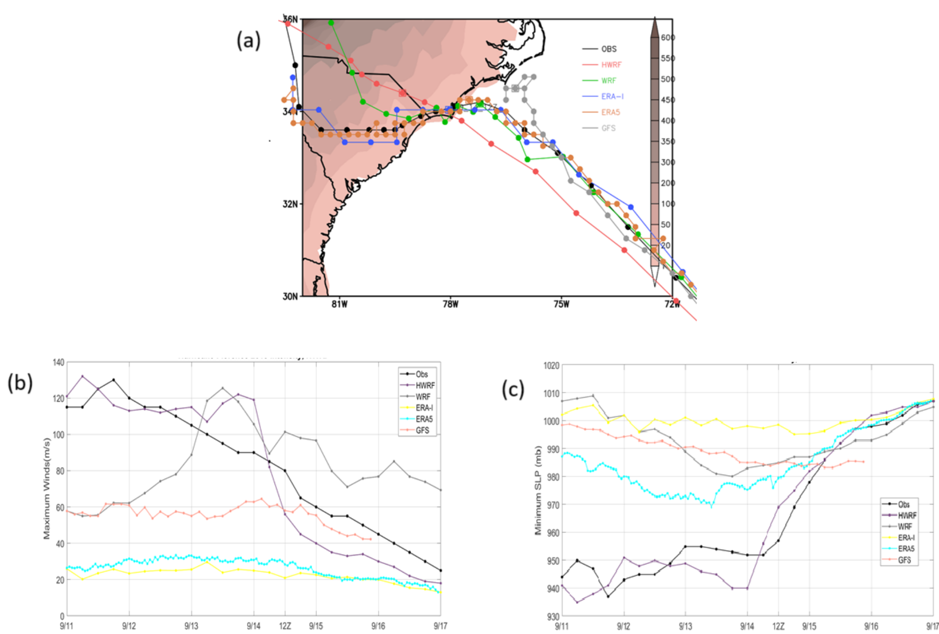

FIGURE 10. Track and intensity for the data collected

Overall, the track data from NWP models match well with the observation to some extent. Some discrepancies occur at the beginning in the WRF and ERA-Interim data. The big discrepancies occurred at the turnings before and after landfall. As shown in Fig.10a, the GFS forecast track stalled at the coast and never made landfall, the HWRF track went straight northwest and made landfall 12 hours early, the WRF track followed well with the observation until a half day after the landfall turning northward early. Relatively, the ERA-Interim and ERA5 tracks matched well with the observation in Fig.10a.

The intensity in Figs.10b & 10c, however, showed large discrepancies. In Fig.10b for the maximum winds, the worst case was the ERA-Interim, which remained at 20-30 m/s the whole time, the winds in ERA5 were about 10m/s higher than the ERA-Interim. Both the ECMWF data sets never picked up the hurricane strength. The GFS were about 60 m/s till 6 hours after landfall when the GFS wind started to match with the observation and decreased following the observation. The WRF simulation data started with 60m/s and picked up the hurricane strength in about two days, over predicted with higher values before the landfall, then decreased along with the observation but remained above after landfall. The HWRF simulation provided the best matching values for the hurricane intensity. With the largest error as 30 m/s at landfall, the HWRF data followed the observation in the entire simulation time. In Fig.10c for the minimum MSLP (Mean Sea Level Pressure), the worst case is again ERA-Interim with the highest values above the observation. The values from the GFS forecast and WRF were comparable to each other and did not match with the observation until almost one day after the landfall. Unlike the wind result, the ERA5 pressure values were lower/better than the GFS/WRF/ERA-Interim data. The best pressure data was from HWRF, starting with almost the same value of 945 mb, and remaining within 10 mb error in the whole simulation time.

From the above analysis, the WRF and HWRF simulations with starting time 9/11 have large errors for the prediction of landfall location, but their intensity match with the observation data with little errors. The ERA-Interim and ERA5 match well on track with small error but have large errors on intensity. With large variation and discrepancies, we use this set of data to test the regression-based ensemble techniques.

3.2. **Statistical modeling.** The main steps of the regression-based ensemble technique are: first interpolate the data, then separate the data into training set and testing or forecasting set, use the training set to build the regression model, test or forecast using the testing set, and lastly revise the regression model(s) accordingly. In the regression models, the usual sampling size is about 1000 data points [4]. However, the 6-hourly observation data has only 4 data points for one day. The other data sets could be 3-hourly and hourly, which are still not enough. Interpolating the data into smaller time intervals (i.e., 3 mins) helps with the consistent time stamps for the data points and provides sufficient sampling size for regression model training. The goal is to predict landfall, specifically the location and the intensity. The earlier times data are used to train the regression model. Thus, we separate the data into a training set covering 9/11_00Z to 9/14_00Z and a testing set for the rest for 9/14_00Z to 9/15_00Z. We use the training set to train the model, then use the model to test. The observation data (interpolated) is used to supervise the data in the training stage and to verify (evaluate) in the test (forecasting) stage.

Lastly, we revise the model based on the verification and evaluation results. For a new model, the last two steps (training and testing) may be repeated.

Figure 11 shows an example of interpolating the observed track data in latitude and longitude. The left is the original data, and the right is the interpolated data. The thick short blue line shows the cut off place for the training set and testing/forecasting set. Similar interpolation is conducted on the intensity data with the same cut off place for the training set and testing/forecasting set. The figure is omitted here.

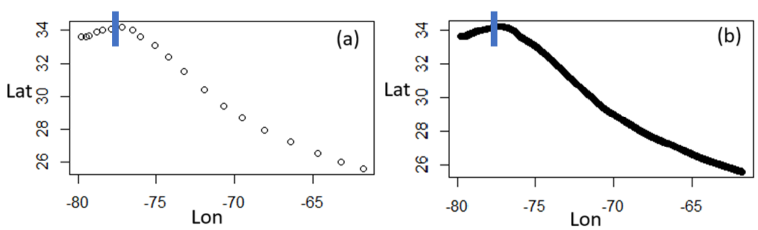

Figure 11. An example of interpolated data for the observation track. (a) The original track data; (b) The interpolated data.

The statistical models employed in this study are multiple linear regression and random forest regression. The traditional simple ensemble takes the average of all the ensemble members included in the model. The data from NWP models serve as predictors, and the observed data serves as the real value of the predictant. In this study, different statistical models are built/trained separately for different variable fields. The RMSE (root mean square error) is utilized in this study to measure the performance of the models. The definition of the RMSE is

$$RMSE = \sqrt{\frac{\Sigma_{i=1}^{n}(\hat{y_i} - y_i)^2}{n}}$$

4. **Results and discussions.**

4.1. **Latitude.** When considering all 5 NWP models data as predictors, the following summary was obtained:

	Coefficients Estimate	Std. Error	t-value	Pr $(>\lvert t \rvert)$
HWRF	-0.0154	0.009296	-1.659	0.09746 .
WRF	-0.0087	0.003232	-2.709	0.00685 **
GFS	0.1445	0.010434	13.852	$<$ 2e-16 ***
ERA-I	0.3184	0.018298	17.402	$<$ 2e-16 ***
ERA5	0.5614	0.014705	38.180	$<$ 2e-16 ***

The trained regression model is

$$\hat{Y} = -0.0154X_1 - 0.0087X_2 + 0.1445X_3 + 0.3184X_4 + 0.5614X_5$$

where X_1 is the latitude from HWRF, X_2 is from WRF, X_3 from GFS, X_4 from ERA-I, and X_5 from ERA5. Note that there is no intercept in the model. Since the predictors are the numerical simulation values for the same variable in the deterministic system but from different physical models, there is no shift in the values. With the physical background of the predictors, the intercept should be 0. The above model is called the full model. In the summary table, the 2 stars and

3 stars beside the P-value for WRF, GFS, ERA-I, and ERA5 indicate that these four are the statistically significant predictors. However, the P-value for WRF is relatively/significantly higher than those for the other three predictors.

After the null hypothesis test, we reached a reduced model with three predictors in the regression model. We obtained the following summary:

	Coefficients Estimate	Std. Error	t-value	Pr $(>\|t\|)$
GFS	0.1254	0.009229	13.59	$<$ 2e-16 ***
ERA-I	0.3369	0.017682	19.05	$<$ 2e-16 ***
ERA5	0.5380	0.012701	42.36	$<$ 2e-16 ***

In this reduced model, all the coefficients are positive, and they add up to 1. In a sense, these coefficients can be considered as the weights. It tells us that the ERA5 and ERA-I resemble the observation track very well.

We also did the simple ensemble by averaging all the ensemble members. To compare with different regression models, we employed the random forest regression model which picks up significant contributors automatically. The results are shown in Table 4.1. For latitude, the random forest model gives the best result, with error 15 nautical miles. The NHC error for the track is about 33 nautical miles. The simple ensemble on the reduced model members also provides a good result.

Table 4.1. Errors from Various Models for Latitude

Model	MLR Full Model	SE Full Model	MLR Reduced Model	SE Reduced Model	Random Forest Model	NHC
RMSE (deg)	0.4653696	0.4343811	0.4690583	0.3124698	0.2503998	
Distance (nautical miles)	27.94	26.08	28.16	18.76	15.05	33

4.2. **Longitude.** For some reason, the performance of the models on the longitude is quite different. Similar to the models for latitude, we obtained the full model with all 5 NWP models as predictors and the reduced model with GFS, ERA-I, and ERA5 predictors. The results of the root mean square errors are displayed in Table 4.2. Surprisingly, the results from random forest did not improve the MLR. The best model (the smallest error) is the simple ensemble on the full model, with an error of 22.8 n miles, comparable with the NHC error.

Table 4.2. Errors from Various Models for Longitude

Model	MLR Full Model	SE Full Model	MLR Reduced Model	SE Reduced Model	Random Forest Model	NHC
RMSE (deg)	0.6375	0.38	0.674112	0.49	1.4577	
Distance (nautical miles)	38.25	22.8	40.45	29.4	87.62	33

4.3. **Intensity.** Prediction of intensity is always much harder than that of track. Here is a quick report for some of the regression models on the maximum wind. Again, we have the full model and reduced model. Only the ERA-Interim is excluded in the reduced model. The summary of the full model for maximum wind of MLR is:

	Coefficients Estimate	Std. Error	t-value	$\Pr(>\|t\|)$
(Int.)	86.2848	7.034765	12.265	< 2e-16 ***
HWRF	0.26694	0.026322	10.141	< 2e-16 ***
WRF	-0.5412	0.007779	-69.567	< 2e-16 ***
GFS	2.57476	0.118608	21.708	< 2e-16 ***
ERA-I	0.02239	0.097575	0.229	0.819
ERA5	-0.48353	0.051040	-9.474	< 2e-16 ***

It is clearly indicated that ERA-I is not a significant contributor in representing the maximum winds. The summary of the reduced model is:

	Coefficients Estimate	Std. Error	t-value	$\Pr(>\|t\|)$
(Int.)	87.11558	6.029308	14.449	< 2e-16 ***
HWRF	0.26502	0.024951	10.622	< 2e-16 ***
WRF	-0.5405	0.007376	73.296	< 2e-16 ***
GFS	2.58118	0.115280	22.390	< 2e-16 ***
ERA5	-0.48596	0.049906	-9.738	< 2e-16 ***

Similar work has been conducted for the minimum SLP (sea level pressure). All the results for maximum wind and minimum SLP for intensity are shown in Table 4.3. For both, the averaging on the reduced model provides the best result, comparable with the NHC error. The random forest regression improved the MLR on the maximum wind, but not for the minimum SLP. The result from the MLR on the maximum wind is comparable with the best result and NHC error, so not too far off.

Table 4.3. Errors from Various Models for Intensity

Model	MLR Full Model	SE Full Model	MLR Reduced Model	SE Reduced Model	Random Forest Model	NHC
Max Wind RMSE (kt)	15.2449	19.52458	15.4436	14.4	34.40646	13
Min SLP RMSE (mb)	21.98858	10.6756	21.34215	9.19942	12.36754	

5. **Conclusion.** In conclusion, we applied simple ensemble (SE), multiple linear regression (MLR), and random forest regression (RFR) techniques. For latitude, the RFR provides the best result, improving the NHC's forecast significantly. For longitude, the SE on the full model provides the best result, improving the NHC's forecast. For intensity, the SE on the reduced model provides the best result, comparable with the NHC's forecast. Overall, the hybrid of SE with MLR and RFR is recommended.

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