A Deep Learning Driven Improved Ensemble Approach for Hurricane Forecasting

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INTRODUCTION and MOTIVATION

- Tracking the path and forecasting the intensity of hurricanes are challenging. Dynamical models produce a significant model-measurement error. Accurate forecasting is very difficult to achieve after landfall.
- For track forecasting (where the storm is going to go), dynamical models are generally the best. For intensity forecasting, statistical models generally perform better. We can combine the advantages of both models using an machine learning ensemble approach.
- Machine learning models are computationally efficient and are currently used widely for forecasting and ensemble purposes. Deep Neural network (DNN) techniques comprise a popular and powerful class of machine learning methods.
- Here, we used a deep learning-based approach to ensemble eight global and regional dynamical models for forecasting hurricane track and intensity.

MATERIALS and METHODS

Deep Learning Algorithm

- A deep convolutional neural networks (CNN) was implemented for predicting hourly ozone concentration. Inspired by biological processes, CNN is a class of deep, feed-forward artificial neural networks.
- CNN uses relatively little pre-processing compared to other machine learning techniques. This means that the network learns the features that in traditional algorithms were hand-engineered.
- In CNN (Figure 1), the convolutional layer applies a convolution operation to the input, passing the result to the next layer. The fully connected layer connects every neuron in the last convolutional layer to every neuron in the output layer, similar to the traditional multi-layer perceptron neural network (MLP).

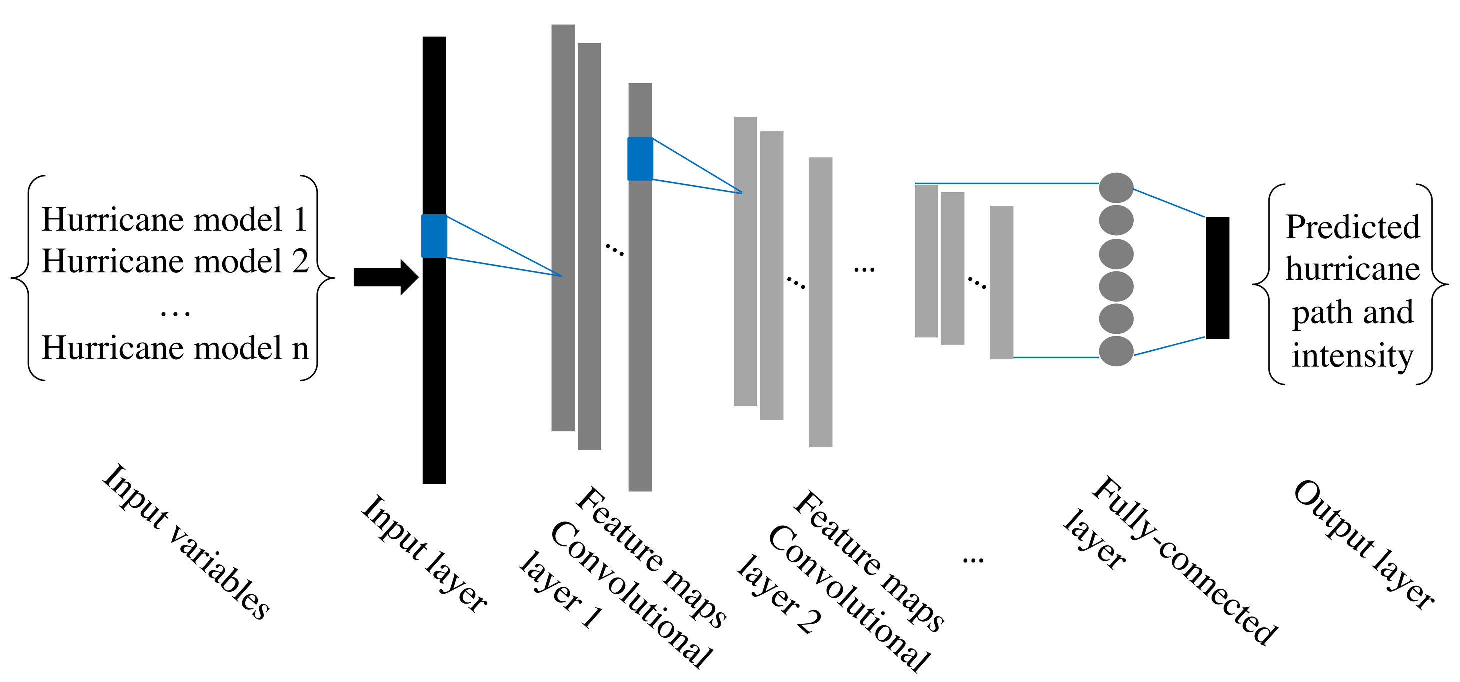

Figure 1: Schematic for the regressive 1D convolutional neural networks (ConvNet-1D).

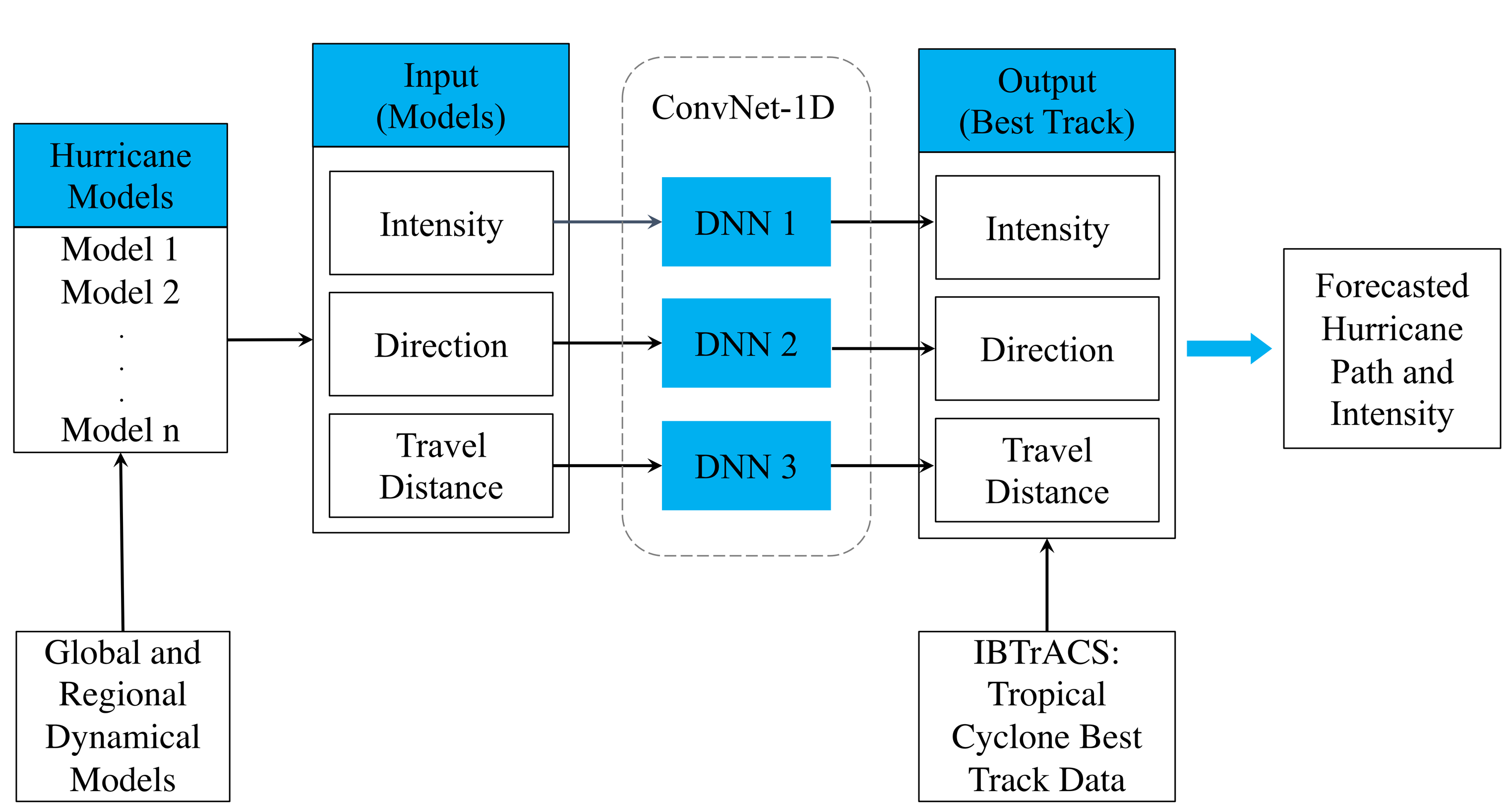

Figure 2: Schematic for the UH ML Ensemble Hurricane Forecasting System.

MATERIALS and METHODS (cont.)

DNNs modeling time period:

- Training data: 2003 – 2016
- Next step prediction: 2017 (e.g. Hurricane Harvey)

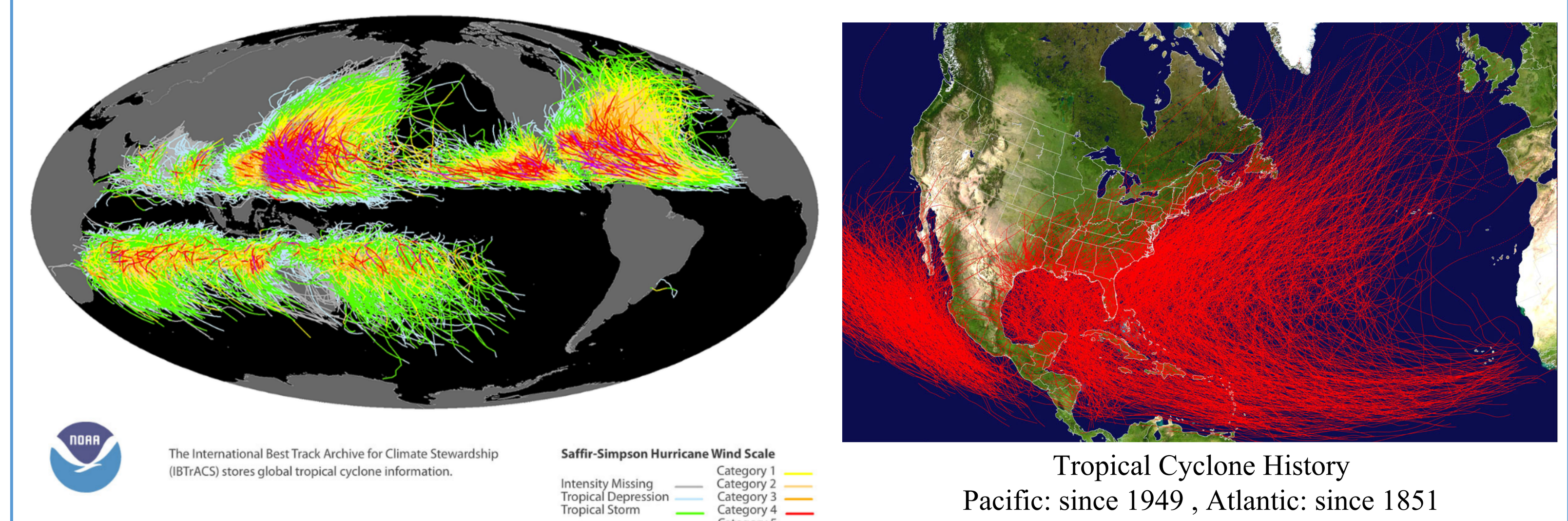

Figure 3: Historical tropical cyclone archive collected by International Best Track Archive for Climate Stewardship (IBTrACS) at https://www.ncdc.noaa.gov/ibtracs/.

Table 1: Summary of global and regional dynamical models for track and intensity used in this study.

ATCF[a] ID	Model Name	Horizontal Resolution	Cycle/Run Period	NHC Forecast Parameters
NVGM/NVGI	Navy Global Environmental Model	Spectral (~31 km)	6 hr (144 hr)	Track and intensity
AVNO/AVNI GFSO/GFSI	Global Forecast System	Spectral (~13 km)	6 hr (180 hr)	Track and intensity
EMX/EMXI/EMX2	European Centre for Medium-Range Weather Forecasts	Spectral (~9 km)	12 hr (240 hr)	Track and intensity
EGRR/EGRI/EGR2	U.K. Met Office Global Model	Grid point (~10 km)	12 hr (144 hr)	Track and intensity
CMC/CMCI	Canadian Determinitic Prediction System	Grid point (~25 km)	12 hr (240 hr)	Track and intensity
HWRF/HWFI	Hurricane Weather Research and Forecast system	Nested Grid point (18-6-2 km)	6 hr (126 hr)	Track and intensity
CTCX/CTCI	NRL COAMPS-TC w/ GFS initial and boundary conditions	Nested Grid point (45-15-5 km)	6 hr (126 hr)	Track and intensity
HMON/HMNI	Hurricane Multi-scale Ocean-coupled Non-hydrostatic model	Nested Grid point (18-6-2 km)	6 hr (126 hr)	Track and intensity

[a] The Automated Tropical Cyclone Forecasting System https://www.nhc.noaa.gov/modelsummary.shtml

RESULTS (Tropical Cyclones, 2017)

- All tropical cyclone of the North Atlantic in 2017 were selected as the case study for the UH ML Ensemble (UH MLE) Hurricane Forecasting System.
- Root mean square error (RMSE) were calculated for position and intensity for each cyclones individually (Figure 4).

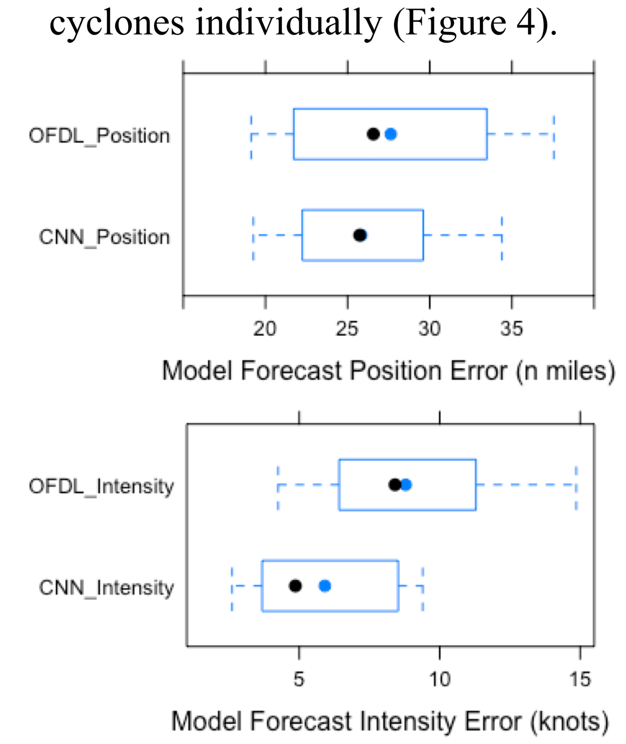

Figure 4: Box plots comparing UH Machine Learning Ensemble (UH MLE) Hurricane Modeling System and NHC official forecast (OFDL).

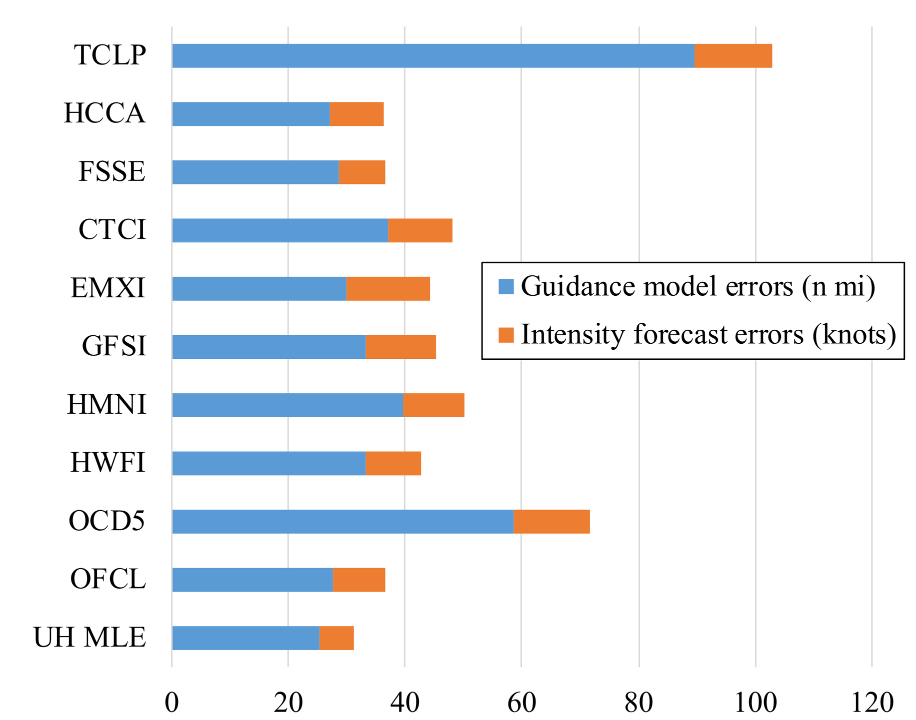

Figure 5: Homogenous comparison of official and selected model forecast errors for hurricane path (guidance) and intensity.

RESULTS (Hurricane Harvey, 2017)

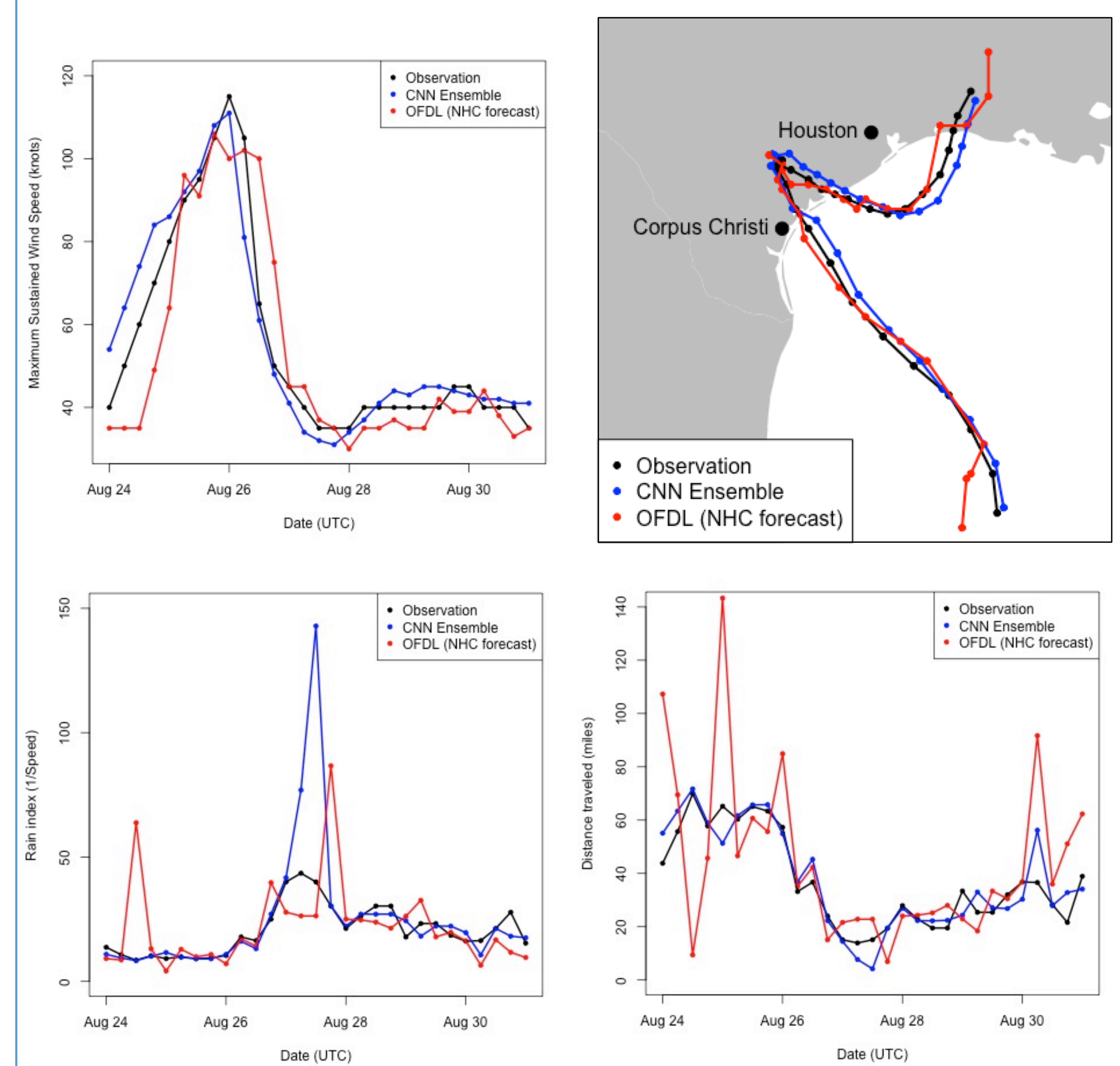

Figure 6: 24-hour forecasts of the UH ML Ensemble Hurricane Forecasting System in 6 hour cycle for hurricane Harvey (August 2017).

CONCLUSIONS

Summary

- We developed a three-step DNN-based ensemble hurricane forecasting model using the output of eight dynamical hurricane models being used in ATCF system.
- We used all tropical cyclones in Atlantic Ocean from 2003-2016 and tested the model for those in 2017.
- The preliminarily results of our model show statistical advantages over NHC official forecasts.

Challenges:

- Long-term forecasting could cause significant source of uncertainty. We plan to use wavelet transform to reduce this uncertainty.
- Prediction of flooding (during a tropical cyclone) is very challenging due to lack of reliable hourly measurements.
- There is limited data available for 2D and 3D models. Hurricane model data (input/ouput) is required for building a big data.

ACKNOWLEDGEMENTS

This study was partially supported by funding from the Department of Earth and Atmospheric Sciences (EAS Research Grant) of the University of Houston.

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