Project Summary:

Name of project: A deep-learning driven improved ensemble approach for hurricane forecasting

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Proposed start and end date: Start: July 1st, 2018. End: January 31st, 2019.

Budget Requested: $7,000.

Budget Summary: (a) Retrieval of model and in-situ data, $1500 (b) Developing weighting factors for model-measurement comparison, $1500 (c) Developing meteorology-dependent weighting factors, $1500 (d) Prediction and benchmarking, $500 (e) smartphone app development, $500

Project Outline:

Abstract

Numerical weather prediction (NWP) models are currently used to predict hurricane trajectory and intensity. One challenge of using such models is chaotic error growth due to uncertainties in initial conditions, deficiencies in physics and coarse grid resolution. Approaches using perturbed initial conditions such as the National Center for Environmental protection (NCEP)'s Global Ensemble Forecast System (GEFS) are used to reduce uncertainty and improve the forecast. However, these approaches have been modest at best. Hence, these issues entail a more comprehensive statistical approach to improve hurricane prediction. This study proposes a novel, artificial intelligence-driven ensemble approach to predict hurricanes, using multiple model output and historical events. First, we consider model-measurement error for a given hurricane parameter (e.g., path). Here, we map observational data to model output using a deep-learning method, an advanced form of artificial intelligence using neural networks. Next, we determine weighting factors for each model to optimally relate with observations. Further, we train another deep-learning algorithm to predict weighting factors as a function of observational meteorology. Consequently, during a hurricane event, we have multi-model output and weighting factors to obtain a more accurate real-time prediction. The resulting forecasts will be compared to HWRF, GEFS, and other model/ensemble forecasts to determine their advantages over the current capabilities of hurricane prediction.

Introduction

The Gulf Coast area is often prone to tropical storms and hurricanes – e.g., Katrina in Louisiana in 2005, Harvey in Texas and Irma in Florida in 2017, causing significant loss of life and property. Ensemble modeling for numerical weather prediction (NWP) models such as the NCEP's GEFS are currently used to predict hurricane trajectory but report a significant model-measurement error, potentially attributed to chaotic error growth by uncertain initial conditions, deficiencies in the representation of model physics and coarse grid resolution for the component models. Hence, a key challenge is to reduce uncertainty in forecasted hurricane path and intensity. Therefore, it is necessary to accurately develop appropriate weights for different model outputs in order to reduce error with respect to observations. Our current approach proposes to use a deep-learning approach, an advanced form of artificial intelligence, to weigh multiple model outputs to reduce error and hence improve forecast accuracy.

Objectives

To create an ensemble weighted average of multiple hurricane forecasts for accurate hurricane forecasting (b) introduce a dependency of weighting factors on meteorology to further improve accuracy.

Significance and impact

This project proposes to use artificial intelligence to significantly improve hurricane forecasting accuracy. The smartphone app developed as part of this study can help users/decision track a hurricane real time and make decisions quickly.

Key project steps

Sources of data

Observational data sources include the International Best Track Archive for Climate Stewardship (IBTrACS which provides hurricane tracks dating back to 1842) and the National Hurricane Data Center (https://www.nhc.noaa.gov/data/). Historical hurricane GIS tracks are also maintained by the National Oceanographic and Atmospheric Administration (NOAA). Further, NOAA's Atlantic Oceanographic and Meteorological Laboratory also archive hurricane data through its HURDAT program. There is a large set of numerical models for hurricane forecasting (NHC, 2017). These include the Navy Global Environmental Model (Metzger et al., 2013), Global Forecast System, UK Met Office Global Model (Met Office, 2018) and the Hurricane Weather Research and Forecast system (NOAA, 2018). No model covers each and every hurricane episode. However, since each model covers only a given set of episodes, we can expect a wide range of physical conditions to be represented. The physical quantities considered in this study include hurricane path, wind speed, and cyclone pressure.

Deep-learning architectures

Deep-learning is an advanced form of artificial neural networks, using a complex network of neurons and layers to analyze a system in detail. This study will use a Convolutional Neural Network (CNN) in conjunction with a Multilayer Perceptron (MLP) (Figure 1). For the first part, using the deep neural network, we combine a weighted ensemble of hurricane models. We map historical model outputs (e.g., track, intensity) to corresponding observations, then calculate the weighting factors for ensemble model. Since these weights are functions of meteorology, we use another deep network to calculate these using observed meteorological parameters (e.g., pressure, wind, etc.). Figure 2 shows a result from a deep CNN-MLP approach for ozone forecasting over one station in Seoul, Korea in 2017. The algorithm was trained with multiple parameters (NO_x, pressure, relative humidity, cloud cover, wind speed, temperature) dating back to 3 years. Model-measurement comparison indicated quite good metrics. For example, the median Index of Agreement, was above 0.8 (highest value 1) for most of the months, with 0.9 reported between July-November. Lowest values were 0.7 for January and December; it never went below this. A similar framework will be implemented for both tasks in this study.

Use of cloud server

We request use of cloud resources for this project, due to large memory requirement and computational cost of our deep-learning algorithm. In a standard server environment, we may have to request permission to use such memory storage or computational power. For instance, running a hurricane model may require tens of terabytes of storage or tens of nodes for a smooth, dependable computation process. Also, it is not uncommon for a standard server to crash due to in the burden of long, continuous computation process which uses multiple computational platforms (e.g., running HWRF and a Matlab code with two-way feedback). This is unlikely using cloud servers.

Additionally, using cloud servers, we can also have resources online within minutes, which is imperative for hurricane forecasting. Since most of the remote sensing data are available online, this will be beneficial for such application study; instead of downloading hundreds of gigabytes of data as initial or boundary condition of the models, or reloading model outputs for a proper evaluation, all required datasets are available by cloud servers. In the other hand, cloud not only handles data stored remotely but it also protects and recovers any data lost due to a server crash. Such a guarantee cannot be provided in a physical hardware platform as in a standard server.

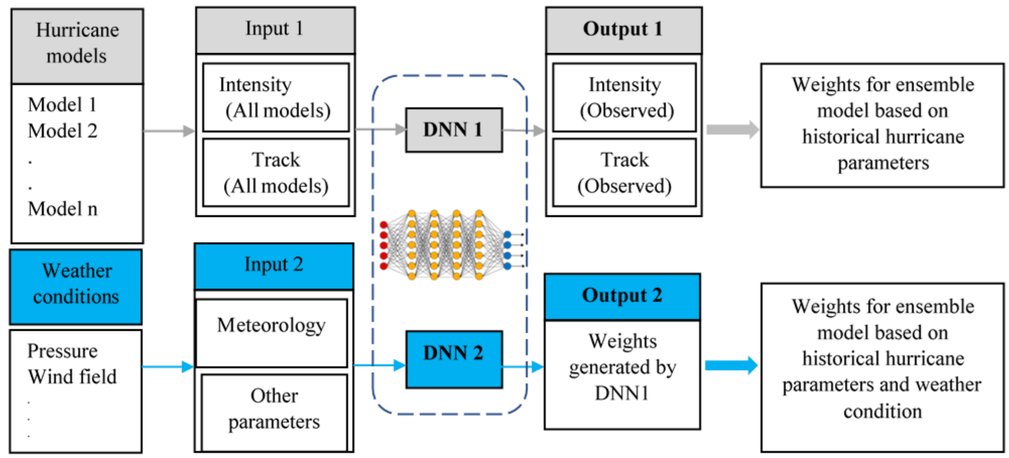

Figure 1: DNN algorithm representation

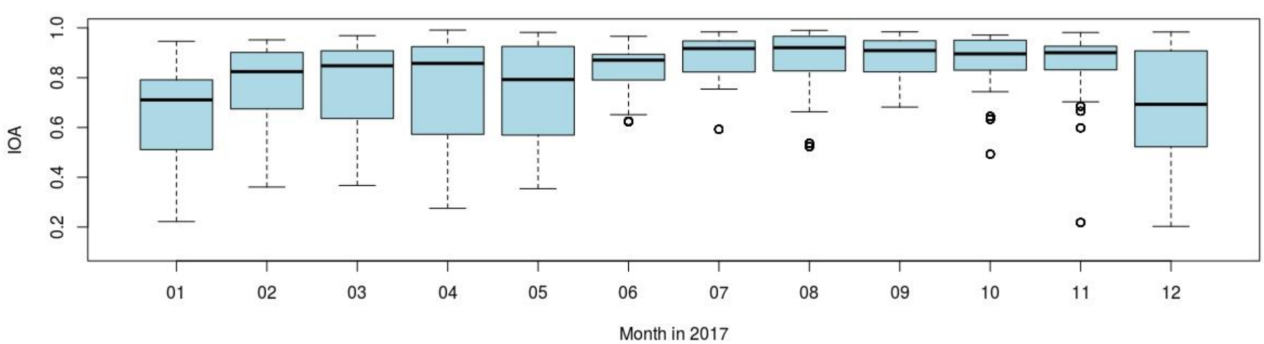

Figure 2: Sample result for deep CNN-MLP framework showing Index of Agreement for 2017.

Timeline

Task	Sub-task	Jul-Aug	Sep-Oct	Nov-Dec	Jan
1	Gathering model and in-situ data	■			
	Weights for model-measurement comparison	■			
2	Weights as a function of meteorology		■	■	
	Prediction and benchmarking		■	■	
3	Smartphone application			■	■

Outreach:

What groups/audiences will be engaged in the project?
We are involved currently with the Hurricane Resiliency Research Institute (HURRI), which is a group of six universities (Louisiana State University, Texas Tech University, University of Florida, University of Miami, University of Texas at Tyler, University of Houston) working on hurricane research. In the past, we have also worked with the Healthy Port Communities Coalition that is a group of non-profits working

in the Houston area and includes the Environmental Defense Fund, Houston Advanced Research Center and Public Citizen. We hope to utilize our working relationships with these organizations.

How will you judge that project has had an impact?
In the past, we ran a real-time air quality forecasting system and tracked the number of end-users (http://spock.geosc.uh.edu/enduser.html). We will do the same for this study, and check especially if state/federal agencies are using our work.

How will you share the knowledge generated by the project?
The results of this study will be published in a reputed journal of atmospheric sciences and machine learning technology communities. Additionally, we will transform our hurricane algorithm into a smartphone app so users can get a more accurate prediction of hurricane path as opposed to existing approaches. We have previously developed a web application for a numerical air quality modeling study from scratch (details here: http://spock.geosc.uh.edu/biomass.html) and can build on it to make a hurricane forecasting smartphone application. We will contact personnel from the National Weather Service (NWS) for potential collaboration after reaching a robust level of algorithm development.

Project Partners (as applicable):

Description of project partners (individuals and/or organizations) and their involvement:
Young-Joon Kim, Chief of Analysis and Nowcast Branch, Analysis and Mission Support Division, Analyze, Forecast and Support Office, National Weather Service (NWS) HQ: Dr. Kim is in charge of overseeing and prioritizing 0-18 hour forecasting tools used by NWS forecasters. Hurricane forecast falls into this temporal range, although goes beyond 18 hours, and he can promote a promising hurricane forecasting tools or algorithms for NWS' operational test if demonstrated to be useful.

References

Met Office, 2018. Met Office Numerical Weather Prediction models. https://www.metoffice.gov.uk/research/modelling-systems/unified-model/weather-forecasting

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