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Atlantic Tropical Cyclone Rapid Intensification Probabilistic Forecasts from an Ensemble of Machine Learning Methods

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Abstract

Atlantic tropical cyclone (TC) rapid intensification (RI) continues to be a major forecasting challenge, with forecast skill scores only about 15% better than climatology. To date, RI forecasts have been completed using linear discriminant analysis (LDA) on predictors optimized for RI forecasts, and no study has directly addressed machine learning's (hereafter AI) capability in forecasting RI. As such, the objective of this study is to quantify the RI predictability using proxy forecast model data and an ensemble of AI methods to generate probabilistic RI forecasts. Atlantic RI events from 1985 to 2011 were retained for all valid times (over water) for each TC, and these cases were used to train an AI ensemble optimized (through three steps) for RI prediction. First, backwards elimination feature selection was used on a blend of the proxy forecast data, predictors from the currently utilized LDA model, and observed TC track information (such as intensity and position) to optimize the predictor suite. Second, numerous configurations of three AI methods (support vector machines [SVMs], artificial neural networks [ANNs], and random forests [RFs]) were tested using bootstrap-based cross-validation to ascertain the best configurations of each AI method. Finally, the best AI configurations were used to generate probabilistic output for RI, weighted by each ensemble member's individual cross-validation performance. Resulting probabilistic forecasts were in line with the current LDA method, though the upper skill limit of the ensemble exceeded 30% improvement over climatology, which far exceeds the current LDA scheme.

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Keywords: Artificial neural networks; support vector machines; random forests; ensemble; probabilistic forecasts; tropical cyclone rapid intensification

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1. Introduction

Tropical cyclones (hereafter TCs) are important meteorological phenomena owing to their potential for major impacts along coastal areas. Despite their importance, the inherently complex thermodynamic and kinematic processes that drive TC intensification and weakening are poorly forecast by current dynamic weather models. To address this issue, statistical methods (such as the Statistical Hurricane Intensification Predictive Scheme – SHIPS[1]) have been implemented in operational TC intensification forecasts with modest success. Further confounding the forecasting problem is the nature of TCs which undergo rapid intensification (hereafter RI). RI is considerably more challenging to predict, as current operational predictive schemes[3] demonstrate skill scores relative to climatological RI forecasts of only 0.2[3]. This is a critical issue, as most hurricane-strength TCs undergo RI at some point in their life cycle, and all major (category 3 or stronger) storms undergo RI[4]. To allow for better preparation against these events, improved RI prediction is needed.

RI prediction within TCs is hampered by several key issues. First, an agreed upon definition of RI is lacking, as the National Hurricane Center defines RI as a 30-kt increase in sustained peak wind speed in 24 hours, while the National Weather Service defines RI as 42-mb or greater central pressure falls within a 24 hour period. The latent heat processes driving TC intensification are poorly represented in current dynamic weather models owing to their complexity and that thermodynamic processes are more commonly modeled using statistical methods than formal analytic equations. Further, many of the processes related to RI are inherently nonlinear, and current forecast implementations have only focused on linear statistical methods[3,5].

Despite these challenges, Atlantic Basin RI prediction has evolved from a more simplified probabilistic approach[2] which employed exceedance probabilities on five fundamental intensification predictors (many of which were included in the original SHIPS implementation) to more advanced linear discriminant analysis (hereafter LDA) methods[4], (the current operational SHIPS Rapid Intensification Index [SHIPS-RII]). Within this evolution, Kaplan and DeMaria specifically noted the need for implementation of machine learning methods to improve upon their exceedance probability work[1]. A subsequent study by Rozoff et al.[5] was the first effort to address this lack of machine learning effort, but their study utilized Bayesian inference and logistic regression.

There is a notable dearth of machine learning work with RI prediction. Grimes and Mercer[7] attempt to address this issue by revisiting the feature selection problem. Current operational models[3] use field-averaged characteristics of TCs, including relative dry air abundance, ocean heat content, previous 12-hour intensity changes, and satellite imagery. However, since the LDA methods require individual predictors as input, spatial information is averaged out to yield single values for the full TC domain. Grimes and Mercer[7] addressed this by using individual gridpoints within TC-centric spatial domains of Global Forecast System (hereafter GFS) reforecast fields[7], a suitable proxy for operational weather forecast data. Their study found that the predictors with the greatest discrimination power included equivalent potential temperature (which incorporates a measure of total heat within the TC) and several kinematic fields, including vertical wind shear and upper-level divergence. These fields were used in an initial predictive study of machine learning RI forecasting[8] which found modest predictability improvements using observational datasets. Mercer and Grimes[9] advanced the work further, assessing the importance of dynamic weather model resolution on RI and non-RI forecasts. They found that coarser resolution had better predictive skill in a support vector machine (hereafter SVM)[10] as considerable noise was introduced into the model at higher spatial resolutions. They also found that, for their subset of 10 RI events and 10 non-RI events, skill scores for 24-hour RI forecasts exceeded 0.2 consistently, which is a modest improvement over current forecast implementations. However, the limited dataset size likely influenced these results, thus the need for further analysis. Regardless, there is clear potential for further enhancement of RI prediction using machine learning methods.

To address remaining shortcomings, the objective of this current study was to assess RI predictability using a proxy forecast database on the full dataset of Atlantic Basin TC events from 1985-2009. In particular, the primary objective was to quantify improvements in current RI forecast methods by utilizing an ensemble of machine learning methods, which include SVMs, multi-layer perceptrons (MPs)[11], and random forests (RFs)[12]. These objectives were accomplished through two primary research phases. First, robust feature selection identifying those predictors within the forecast database that were most distinct between RI and non-RI environments was completed. Second, model tuning of each of the machine learning methods was done to obtain a 41-member machine learning ensemble from which an RI forecast probability RI could be obtained.