Hurricane Forecasting

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Received: 10-Jan-2023, Manuscript No. JCWF- 23-21750; **Editor assigned:** 12-Jan-2023, PreQC No. JCWF- 23-21750 (PQ); **Reviewed**: 20-Jan-2023, QC No. JCWF- 23-21750 (Q); **Revised**: 28-Jan-2023, Manuscript No. JCWF- 23-21750 (R); **Published**: 30-Jan-2023, DOI: 10.35248/2332-2594.23.11(1).1-2

Abstract

Hurricanes, which are becoming more complicated and powerful as the planet warms, are one of the biggest natural disasters of the twenty-first century. More research including evolving storm traits is consequently required to help in the forecast of significant hurricanes. With this in mind, we provide a novel methodology based on automated decision tree analysis that can identify the most critical cloud structure factors from GOES data as predictors of hurricane intensity in the Atlantic and Pacific seas.

Keywords: Coupled atmospheric–hydrological models • Two-way coupling • Hydrometeorological Forecasting • Hydrology atmosphere coupling

Introduction

As global temperatures rise, it becomes increasingly difficult to predict complex ocean-atmosphere interactions, and hence the potential for a Tropical Cyclone (TC) to grow significantly stronger in the short term . Given the poor quality and temporal duration of the data, it has long been debated whether there is a positive trend in intensity-related research.However, it is becoming clear in the literature that a number of TC features have evolved during the last 40 years. Furthermore, there are differences in both shape and strength depending on the place where they originate .Hurricanes are powerful tropical cyclones that form in the Atlantic or Northeast Pacific seas and act differently from other types of storms. In the midst of such complexities, it is difficult to determine which hurricane-related characteristics or combinations of parameters and pre-existing elements are critical to the hurricane's growth. To improve early prediction and decision-making, advanced approaches should be developed to represent this complexity [6]. A greater understanding of the most powerful hurricane features and antecedents to hurricane development might surely help us be better prepared for future devastating storms..Several ways to predicting storm origin and intensity progression have been developed during the last two decades. For intensity prediction, the most widely used models are dynamical (or numerical), statistical, and blended statistical-dynamical. Dynamical models, for example, the Hurricane Weather Research and prediction (HWRF) system , which employ numerical models to account for the underlying physical processes driving the atmosphere, with all of the modifications and challenges it involves.Nonetheless, in this context, it would be beneficial to address the potential of complex nonlinearity. Finally, statistical-dynamical techniques that combine the capabilities of probabilistic forecasts with dynamical models, such as the Statistical Hurricane Intensity Prediction Scheme (SHIPS) and others, might give direction in the prediction of future occurrences. Even still, there are several drawbacks to these models, such as an insufficient knowledge of air-sea interaction mechanisms and a lack of high-quality observations of the inner core.

Incorporating Machine Learning (ML) has resulted in amazing breakthroughs, ranging from standard ML methods, such as neural networks to more sophisticated deep learning approaches with complex structures.

There are additional ensemble learning approaches for classification, regression, and other issues, such as Random Forests (RF) or random decision forests , which are less time-consuming than putting up a neural network. Nonetheless, as the number of trees in the forest rises, they may select the most relevant properties from the training dataset and learn complicated nonlinear patterns of change over time. Fundamentally, each conclusion leads to more nodes (decision outputs), which branch out into various possibilities in a "treelike form."

Finally, environmental activities definitely leave their imprints on the size, shape, and temperature characteristics of the TC cloud. Some studies, for example, have found a link between storm/TC size (and other anatomical structural factors) and intensity fluctuations. The same is true for other criteria, such as the temperature structure of the storm, which might be just as crucial, if not more, in terms of TC intensity increase. Indeed, there is a foundation for employing Brightness Temperature (BT) information (from GOES imagery), estimated in the outer bands and centre characteristics of TCs for each TC strength category (tropical storm, minor hurricane, and major hurricane) .

In light of this, we provide a unique ML framework for determining an ideal set of TC cloud features to assess the hurricane's progression to a major hurricane. ML can adapt and make (not always clear) nonlinear relationships between what it sees in TC satellite data and severity classifications (based on the maximumintensity that the TC attained during its lifetime). To establish this complex relationship, we use an RF classification model that has been trained to accurately predict classes and categorise the output into different groups based on changes in the temperature and anatomical characteristics of the TC cloud at different lead-times (defined as the time to maximum development from the start of the computation).

Model construction and evaluation metrics

A classification prediction model was created on the ensemble of RF for each lead-time using 5-fold randomised cross-validation, as mentioned in this study. Other non-parametric supervised algorithms, such as support vector machine and k-nearest neighbours, were also investigated.

Furthermore, in order to increase the computational efficiency of our RF models, we modified the key hyper-parameter (the number of iterations, aka trees) by setting a halting condition based on the mean k score. For each iteration, the overall aim is to update the RF with a new tree until there is little to no change. This is the point at which each model hits "performance saturation" (i.e., the model's predictive power does not improve considerably).In this case, we assume that the accuracy stabilises when the k metric is slightly above and relative to the mean value for five consecutive rounds. Although the k scores initially vary across the iterations, we find that the RF typically saturates no later than 100 trees. On this account, the number of iterations was chosen at random and increased in 5 tree increments until it reached 100 iterations.

Optimal combination of key structural parameters linked to tropical storm intensification

To see if the TC severity categories have a positive relationship with the morphological and thermal behaviour of the cloud system, we examined its size, shape, and inner-outer core temperature development every 6 hours (beginning from the greatest intensity peak). The paragraph that follows provides analysis for a variety of lead-times.The difference in median temperature between the interior (eye) area and the exterior boundary was then computed. IBTrACS provided a 0.6°0.6°(0.7°0.7°) window in the middle of the TC cloud for its internal area. After analysing all photos, we determined the ideal window size between the internal-to-external temperature bands, and we discovered that similar or slightly larger windows may still catch the highest temperature variations between these opposing locations. Other temperature change metrics inside the TCs, such as the temperature gradient, were compared and produced comparable findings.Finally, the morphological elements of the system related to the exterior boundary were examined (using the MATLAB regionprops function), as storms are known to develop symmetry and a circular shape as they strengthen. We looked at circularity ("roundness") and eccentricity (deviation from a perfect circle) separately and jointly.

All of the TC cloud properties were then merged into our RF models, together with the TC intensity information, using (the MATLAB fitensemble function with) a new configuration (see Materials and Methods), which we automated to forecast the two classes, TSs and MHs. First, owing to some imbalance between the two classes, we resample the data to ensure that each class (and lead-time) has an equal amount of samples. We first undersampled the majority class (TS) by eliminating samples at random, increasing the presence of the minority class of samples (MH) in the training set .The train-test technique was then run on an 80/20 split (the best of all tested splits), with 80% of the dataset kept for training and 20% for testing and no overlapping cases. Given the modest size of the available dataset, it was judged unnecessary to divide the training phase into validation and training in order to re-test the model configuration. Nonetheless, our RF classifier is made up of many decision trees, and it employs bootstrap aggregation (or bagging) and feature randomness, a method of randomly selecting subsets from the original training set when building each tree in order to combine the predictions from all models, which reduces the variance of the performance while maintaining decision trees' low bias.A measure of variable relevance was calculated using the ensemble forecasts (using the MATLAB predictor Importance function). The temperature characteristics, area, and shape of the TC system were found as the most relevant predictive factors.We also discovered that combining both circularity and eccentricity, rather than each one separately, reflected the huge changes in cloud structure slightly better (not shown). All of the grouped variables in the models produced the best results since they assist "balance" every element of the TC.

Anticipating major hurricane events

For many forecasting lead-times, an in-depth review of our RF models' ability to anticipate MHs is provided below. Given that the average'maturity time' of a developing significant TC storm is just 2 days-3 days , experiments were performed to provide forecasts (running backwards) from the greatest sustained wind speed (referred to as 0 h) up to 54 h using a time step of 6 h. A lead-time of 18 hours, for example, suggests that MH is predicted based on TC traits 18 hours before the peak.The precision (pMH) for MH prediction was between 72% and 93% (67% and 82%) in the Atlantic (NE Pacific) Ocean, and between 69% and 77% with both basins combined across the whole forecasting window. The average k- values were 0.58 (and 0.46), indicating overall significant (moderate) agreement between each model prediction and the actual class values for both TSs and MHs.The total number of occurrences ranges from 114 (Atlantic) to 192 (Pacific) up to 42 hours, but after that, the numbers decrease (with 80 events as the worst-case scenario for 54 hours in the Atlantic area).

Individual cases that attained RI were also analysed for predictions made with our RF models. For the Atlantic, we offer seven cases: category 4 Iota (2020), category 4 Laura (2020), category 5 Emily (2005), and category 4 Ian (2022), and category 5 Willa (2018), category 4 Odile (2014), and category 5 Patricia (2015). Emily and Patricia piqued our interest since they were challenging to anticipate using numerical weather prediction algorithms . Notably, Patricia, a hurricane that strengthened at an unusually quick rate, was the strongest storm ever recorded in the NE Pacific and North Atlantic basins.At least 80% of our models predicted an MH (up to 48 hours ahead). Emily, the Atlantic basin's first-ever category 5 hurricane, passed through two RI phases and was anticipated by 100% of our models (up to 54 h ahead). All of our RF models projected that the MH status would persist during the maximal development period. Odile is another example of RI that was not expected by official predictions because to poor organisation of the cyclone's inner core and the cyclone's vast size, but was predicted by at least 80% of our models (66 h ahead).Another intriguing characteristic is that 60% to 100% of our models predicted MH status even when applied to new data after the training period (1995-2019), as in the instance of Iota and Laura in 2020 (up to 42 h) or Ian in 2022. (up to 60 h in advance). It is worth noting that these three events, which involved some of the most deadly storms in US history, all underwent RI within 24 hours.

The predictive power of our models was tested outside the range of usual lead-times in all of the examples covered here (6 h–54 h). As predicted, as the number of trained/tested data examples declines (i.e., for lead-times more than 54 h), the RF models become less trustworthy.

Summary

In summary, this work proposes some novel definitions of hurricane properties linked to the anatomy (size, shape) and temperature (difference between the outer borders and the inner-core) of the cloud system, as produced using a k-means clustering method applied to GOES data. Furthermore, these factors were optimally blended and nonlinearly connected to the maximum intensity of the TC system using a unique random forest method (trained in a 5-fold cross-validation) to anticipate big hurricane occurrences in advance.

Thus, our findings show that including significant cloud properties of a developing tropical cyclone, such as morphology and temperature, into a machine learning system is effective as a benchmark for predicting a likely transition into a major hurricane. The suggested evaluation technique also allows for the incorporation of other candidate characteristics or variables (to be examined gradually). So yet, there aren't enough examples in different seasons to train and test models. However, if additional data is available, analysis may be undertaken to investigate the impacts of environmental variables such as seasonality.

Cite this article: Deck, R. Hurricane Forecasting. J Climatol Weath Forecast. 2022, 11 (1), 001-002