**Application of Statistical Methods to Improving Model Predictions of Rapid Intensification in Tropical Cyclones**

**IVY MACDANIEL**
Affilitation/Fall 2019: Austin Peay State University
imacdaniel@my.apsu.edu

*Significant Opportunities in Atmospheric Research and Science*

Science Mentor: Christopher Rozoff and Jonathan Vigh
Writing/Communication Mentor: Chris Davis
Coach: Kristen Aponte
Peer Mentor: Nathalie G. Rivera-Torres

August 5, 2019

**ABSTRACT**

The goal of this research is to improve predictions of rapid intensification (RI) in tropical cyclones (TCs) using a statistical algorithm. Forecasting RI in TCs is notoriously difficult because even in generally favorable conditions (e.g., high column water vapor, low vertical wind shear and high sea surface temperature), the occurrence and timing of RI is uncertain. In this paper, we discuss the use of logistic regression as a post-processing tool for numerical weather prediction (NWP) TC models. The baseline NWP model used in this study is the Hurricane Weather Research and Forecasting (HWRF) model based on the 2018 operational configuration. We have extensive reforecasts from 2015-2017 and real-time data from 2018 for both the Atlantic and Eastern Pacific basins. From the HWRF forecasts, we derive predictors describing aspects of a TCs environment and inner-core, which are tested for inclusion in the HWRF LOGistic regression (HLOG) model. Top HLOG predictors were determined for each basin using objective feature selection and leave-one-year-out cross-validation. Independent testing over the years 2015-2017 gives Brier Skill Scores (BSSs) of 0.30 and 0.36 for Atlantic and East Pacific, respectively. Testing the model on 2018 real-time HWRF forecasts, the BSS values were 0.24 and 0.13 for the Atlantic and East Pacific models. This talk will also compare these results with other probabilistic RI methods. Examining individual cases in the 2018 season, HLOG generally produced higher probabilities for storms that experienced RI compared to storms that did not experience RI. Overall, the HLOG appears to be a promising, simple, and computationally cheap NWP model post-processing technique.
This work was performed under the auspices of the Significant Opportunities in Atmospheric Research and Science Program. SOARS is managed by the University Corporation for Atmospheric Research and is funded by the National Science Foundation, the National Center for Atmospheric Research, the National Oceanic and Atmospheric Administration, and the University of Colorado at Boulder.
1 Introduction

Forecasting rapid intensification of tropical cyclones (TCs) still poses challenges even with extensive research done in that topic, yet it is also vital to hurricane research. It is still a mystery why some TCs experience Rapid Intensification (RI) while others do not, even in seemingly similar conditions. There were several theories, including those involving deep convection and internal processes within TCs (Bhalachandran et al., 2019). While deep convection may have affected how a TC experience RI, RI still remained a complex forecast scenario for models in general. In a broad sense, RI was generally defined as an increase of at least 30 knots in 24 hours, although it has also been defined over 48 and 72 hours depending on studies (Kaplan and Demaria, 2003). However, regardless of defined time frames, models still have difficulties forecasting RI even in a favorable condition. One well-known example of forecasting difficulty was Hurricane Patricia of East Pacific in 2015 (Fox and Judt, 2018). Models severely underestimated Patricia’s record-breaking rapid intensification of 105 knots in 24 hours. A similar study showed that the models generally predicted that Patricia would have peaked at Category 1 or 2 just prior to the landfall (Fig 1), not even close to observed Category 5 (Rogers et al., 2017). Patricia’s observed maximum wind was actually over 90 m/s, far above Category 5 threshold while the models severely underperformed with 40 to 50 m/s differences from the observed maximum wind despite being technologically advanced. Yet, Fox and Judt (2018) indicated that Patricia’s smaller size may have impacted the accuracy of forecast models, as the high-resolution models showed improvement with smaller storms than lower resolution models did. Otherwise, the study showed a very warm sea-surface temperature (SST) of at least 30 degrees Celsius along Patricia’s track, indicating that the high SST also played a role in record-breaking rapid intensification. Still to this day, the models still require improvement to predict whether a tropical cyclone in question will undergo RI. In hope to improve RI forecast, the concept of using logistic regression for forecast emerged (Rozoff and Kossin, 2011). Similar to this project, the previous study involved training statistical models with predictors that had shown best correlation with RI and using them in logistical regression. Therefore, the Brier Skill Scores were promising then, but the study had its own limitations. That is where the present study seeks to improve on previous work.

2 Methods

The overall goal of the project was to train the model to produce forecast probability of RI of a selected storm. The developmental model used data from Hurricane Weather Research and Forecast (HWRF) model to create forecast probability using logistic regression. Hence the HLOG, or HWRF LOGistical regression model, was the whole scope of the project. The whole model was written in MATLAB, yet logistic regression (Eqn 1) is the foundation of the whole model.

\[
P = \frac{e^{a+b_n x_n}}{1 + e^{a+b_n x_n}}
\]  

In the equation, \(P\) is the probability of an event occurring, such as RI in this case. Although \(a\) is a constant, \(b_n x_n\) is primary variable with coefficient \(b\), and it could expand to \(n\) terms which allowed the model to apply as many predictors as selected in the equation. Thus, the equation is the sum of \(n\) predictors in this study. Early in developmental stage of this work, a basic logistic regression model was first created for a single predictor, namely a change in maximum wind velocity in a 24 hour period, to determine whether the code for the model worked. The Brier Skill Score was also introduced in the code for evaluation of model performance. The training data for the model were from 2015-2017 Pacific and Atlantic basins which were combined to create a larger sample of data. Early on, the first method was to remove a single storm from the data and run through loop of each storm. However, the first method was rather slow, so it was replaced...
by another one in which an entire season was removed from data. Otherwise, the second method used the same codes. Later, the remaining predictors were introduced in the codes to aid with refining the logistic regression. Each combination of few predictors selected using forward feature selection in MATLAB had to be reduced by removing highly correlated predictors to reduce overfitting. Afterwards, the predictors were evaluated with Brier Skill Scores.

For the independent testing, the 2018 data were used for testing and evaluating model performance in forecasting RI. Also, an individual storm from the basin that was being tested was selected for generating a forecast probability of RI over its lifetime. Then, the forecast probability was compared to observed maximum wind to evaluate whether HLOG accurately predicted RI or not.

3 Results

Early results showed that Brier Skill Scores for 2015-2017 data were 0.30158 and 0.3644 for Atlantic and Pacific basins respectively using on-year cross validation. For the 2018 data, the Skill Scores were 0.2427 and 0.1264 respectively. However, it should be pointed out that HLOG used different predictors for each basin for training and generating forecasts (Table 1). Also, five individual cases from 2018 independent testing illustrated how well HLOG forecast RI from both Atlantic and East Pacific basins. Hurricane Florence in the Atlantic (Fig 2) reached Category 4 twice in its lifetime, but HLOG gave 22% chance of RI at the time Florence experienced the first RI. It was interesting to point out that the first RI was not forecasted by several operational models previously, thus showing that HLOG could help improve RI forecasts, even if the probabilities were modest. Also, the HLOG gave 63% chance for the second RI, which was observed. Another Atlantic hurricane, Michael, had an observed RI in which the HLOG gave 69% chance (Fig 3). In Atlantic TCs that did not experience RI, the HLOG generally kept probabilities near zero or less than 20%, and Tropical Storm Debby (Fig 4) was one of these TCs. However, HLOG had some complications with East Pacific TCs due to possibly poor predictor combination or errors in HWRF data. For example, HLOG gave up to 69% chance that Hurricane Miriam would experience RI, but Miriam, which did intensify, did not experience RI (Fig 5). On the other hand, Hurricane Olivia, similar to Florence, did experience RI twice in its life (Fig 6). HLOG gave 73% chance for the first RI, but the model kept the probability below 5% during second observed RI. Upon analyzing results, it was theorized that HWRF may had some flawed data, especially for East Pacific, that caused HLOG to have some errors with East Pacific TCs, such as Olivia and Miriam. It was unclear how flawed the HWRF data were or which predictor(s) were flawed since the authors did not have enough time to investigate the flaws in HWRF by the time this report was published.

4 Discussion

Given the past difficulty forecasting RI, the early results were promising compared to several competitive models. However, more testing may be needed for the HLOG after the issues with East Pacific TCs are addressed; HWRF handled them poorly which affected HLOG predictor selection.

To conclude, preliminary results with HLOG showed promising results; hopefully, the same model could be expanded for future research in the subject. The model may be enabled for use in real-time forecasting, potentially as an operational model if the improved performance can be demonstrated over a large number of cases.
References


Figure 1: Plot of observed and predicted wind velocity (m/s) generated from various operational models for Hurricane Patricia (Rogers et al., 2017)

<table>
<thead>
<tr>
<th>HLOG Predictors for Basins</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Atlantic</strong></td>
<td><strong>East Pacific</strong></td>
</tr>
<tr>
<td>Change in maximum wind velocity in 24 hours</td>
<td></td>
</tr>
<tr>
<td>Storm heading</td>
<td>Storm speed</td>
</tr>
<tr>
<td>850-700 hPa relative humidity</td>
<td>Surface turbulent latent heat flux over 0-100 km from center</td>
</tr>
<tr>
<td>850-500 hPa inertial stability 100-250 km from center</td>
<td>Departure from maximum potential intensity based on thermodynamics</td>
</tr>
<tr>
<td>Radius of maximum wind speed</td>
<td>shear magnitude</td>
</tr>
<tr>
<td>Total consedate over 850-500 hPa and 0-50 km from storm center</td>
<td>Inertial symmetry over 0-50 km from storm center</td>
</tr>
</tbody>
</table>

Table 1: Predictors used by HLOG for both training and testing
Figure 2: Plot of observed wind velocity and probability of RI generated by HLOG for Hurricane Florence

Figure 3: Plot of observed wind velocity and probability of RI generated by HLOG for Hurricane Michael
Figure 4: Plot of observed wind velocity and probability of RI generated by HLOG for Tropical Storm Debby

Figure 5: Plot of observed wind velocity and probability of RI generated by HLOG for Hurricane Miriam
Figure 6: Plot of observed wind velocity and probability of RI generated by HLOG for Hurricane Olivia