3C.7 A STATISTICAL MODEL FOR FORECASTING TROPICAL CYCLOGENESIS OVER THE ATLANTIC BASIN

Christopher C. Hennon*
UCAR Visiting Science Program, NOAA/TPC/NHC, Miami, FL

1. INTRODUCTION

Recent research has suggested that tropical cyclogenesis (TCG) arises from a complex interaction of mesoscale and microscale events within a favorable larger scale environment. Though operational dynamical models are becoming more robust at capturing smaller scale processes, difficulties persist in obtaining sufficient initiatial data as well as accurately parameterizing convective processes within cloud clusters. This paper describes a statistical model designed to forecast TCG up to two days in advance, using only large-scale data that would routinely be available to the forecaster.

2. DATA AND METHODOLOGY

Convection associated with every viable tropical cloud cluster that formed or propagated through the Atlantic Basin during the hurricane seasons of 1998-2001 was tracked via Infrared satellite imagery. If a cloud cluster formed into a tropical depression, it was classified as “DV”, or developing case. If a cloud cluster failed to form into a depression (or did so but outside of the 48-hour time horizon) it was classified as “ND”, or non-developing case. Table 1 lists some characteristics of the cloud cluster database for each season.

For each case, eight predictors of TCG were computed from the NCEP-NCAR Reanalysis (NNR) dataset (Kalnay et al. 1996). Note that the coarseness of the dataset (2.5°x2.5° horizontal resolution) limits the predictability of the model to large-scale features. The eight predictors were: latitude, daily genesis potential (DGP, McBride and Zehr 1981), maximum potential intensity (MPI, Holland 1997), low-level moisture convergence, precipitable water, 24-hour surface pressure tendency, and 6-hour 700 mb and surface relative vorticity tendency. These predictors were selected *a priori*, based on a literature review of TCG.

Corresponding author address: Christopher C. Hennon, UCAR VSP, Tropical Prediction Center,
11691 SW 17th St., Miami, FL 33186;
E-mail: christopher.hennon@noaa.gov

Predictor values were calculated for all cases by averaging all NNR grid points that were within a 2° radius of the cloud cluster center. To systematically identify differences between the DV and ND cases, two statistical techniques were evaluated: Linear discriminant analysis (LDA) and an artificial neural network (ANN). A more thorough treatment of the LDA results can be found in Hennon and Hobgood (2003).

TABLE 1

	1998	1999	2000	2001
No. of clusters	90	91	110	79*
Mean Duration (d)	2.5	2.3	2.3	2.7
No. of TDs	14	16	18	14**

* Artificially low due to data gaps in imagery
** Does not include 3 extra/subtropical systems

3. RESULTS

3.1 *Statistical Measures of Performance*

To assess the performance of the model, the probability of detection (POD), false alarm rate (FAR), and the Heidke Skill Score (HSS) were calculated. The POD is a ratio of the number of events (genesis) forecast correctly (hits) over the sum of the number of misses and hits. The FAR is the ratio of the number of false alarms (genesis incorrectly forecast) over the sum of the false alarms and correctly forecast misses. The HSS is a measure of how well forecasts perform compared to random forecasts. It is a scalar value computed from a standard 2x2 contingency matrix. The HSS accounts for the skill in detecting events as well as the false alarm forecasts.

Figure 1 shows the POD for each forecast hour. The light (dark) bars are for the LDA (ANN) classifier. The error bars on the ANN bars represent the standard error (90% confidence assuming normality). The POD ranges from near 0.5 at the 6 hour forecast period to 0.3 at longer forecast lead times. The FAR (not shown) is low for all forecast periods, ranging from 1-3%. Figure 2 shows the HSS for the LDA (light) and ANN (dark).

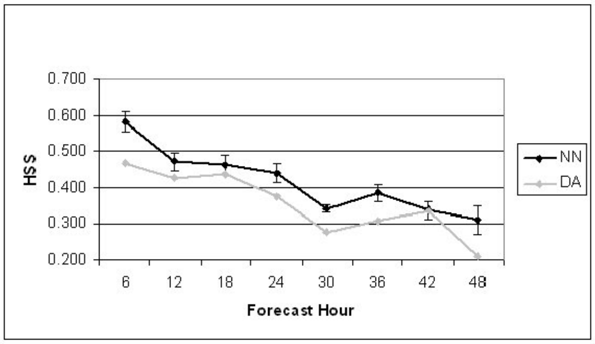

FIGURE 1. The Heidke Skill Score for each forecast hour for ANN (light) and LDA (dark).

Values range from near 0.6 at the 6-hour forecast time to 0.2-0.3 at 48 hours. For all times except 42 hours, the ANN has a higher HSS than the LDA, indicating that the non-linear classifier is more robust in the current model configuration.

3.2 *Case Study*

Hurricane Mitch (1998) was a historical storm, both in terms of intensity and loss of life. The cloud cluster which eventually spawned Mitch had a long pre-storm convective history as a late season easterly wave. For each observation (spaced 6 hours apart), a series of eight forecasts (6-48 hours) were issued. The output from the model is the probability of the observation belonging to the DV group. This probability was then scaled so that a positive (negative) value can be interpreted as “favorable (unfavorable) for development”. This scaling was done based on the optimal ‘decision boundary’, defined here as the probability boundary between the discrete DV and ND forecasts that give the best HSSs.

Figure 2 shows the forecast ‘spaghetti’ diagram for Mitch (LDA classifier only). The model did not

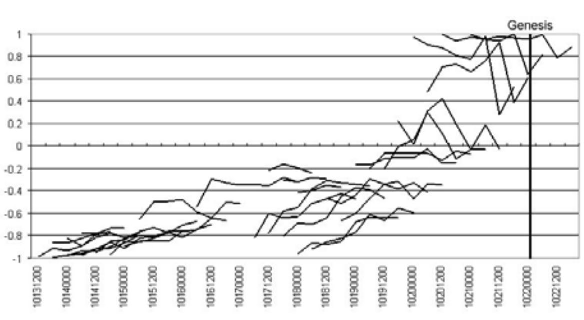

FIGURE 2. TCG forecasts issued for Mitch. Genesis time is shown as dark vertical line. Time progresses to the right.

predict development until Mitch encountered more favorable large-scale conditions in the Caribbean. Near genesis time, the TCG Index was very high, indicating that the model resolved the favorable change in conditions well.

4. CONCLUSIONS

A statistical model was developed that shows significant skill in predicting TCG, even though only large-scale predictors were considered. There are several areas of where improvement and/or modification are desirable. First, it is believed that the model lacks any useful knowledge of the moisture field structure. This could be a critical consideration for TCG. Second, it is thought that the integration of a higher spatial resolution dataset, such as the operational Global Forecast System (GFS), would demonstrate the potential operational use of this system. Early development in this area has shown promising results. Third, it is desirable to consider a wider range of predictors and then parse out the ineffective ones rather than the *a priori* method used here. Finally, this model was developed for the Atlantic basin activity. It is thought that the model structure would have to be “tuned” in order to apply it to different basins. This would be necessary since TCG in the Atlantic is somewhat unique, as a large number of tropical depressions originate from easterly waves.

Dynamical models are becoming increasingly robust at forecasting TCG, even several days in advance. As those models continue to improve, the statistical model described here may provide a useful baseline performance measure for them.

5. REFERENCES

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