A NEURAL NETWORK MODEL FOR PREDICTING ATLANTIC HURRICANE ACTIVITY

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Abstract—Modeling techniques such as linear regression have been used to predict hurricane activity many months in advance of the start of the hurricane season with some success. In this paper, we construct feedforward neural networks to model Atlantic basin hurricane activity and compare the predictions of our neural network models to the predictions produced by statistical models found in the weather forecasting literature. We find that our neural network models produce reasonably accurate predictions that, for the most part, compare favorably to the predictions of statistical models.

1. Introduction

Over the last 10 years or so, there has been a great deal of research devoted to building models that predict Atlantic seasonal tropical cyclone activity for the period that starts on June 1 and ends on November 30. Most notably, William Gray and his colleagues (Christopher Landsea, Paul Mielke, and Kenneth Berry) at Colorado State University have constructed linear regression models that predict activity in advance of the start of the hurricane season. When the season is two months old, they use up-to-date information to predict activity for the August to October time period which is the most active portion of the hurricane season. The predictions produced by the Gray, Landsea, Mielke, and Berry (GLMB) models are of great interest to government officials and decision makers in the insurance industry (see Stevens [7] for additional details).

Using the data sets that GLMB have published in the weather forecasting literature, we set out to construct neural network models to predict Atlantic hurricane activity and then compare the predictions produced by the neural network models to the predictions produced by the regression models. In Section 2, we review the published data sets and the GLMB regression procedure. In Section 3, we describe our neural network modeling effort and compare the predictions produced by our models to the predictions of the GLMB models. In Section 4, we present our conclusions.

2. Background

In this section, we review the types of models, data sets, and model-building methodology that GLMB have used to predict hurricane activity.

Types of Models and Data Sets

GLMB built models of the form

$$Y = f(\text{Wind, Rain, Other factors}) + \varepsilon$$

where Y is one of seven dependent variables such as the number of hurricanes, Wind, Rain, and Other Factors are composite functions of independent variables, and ε is the random error. The definitions of the seven dependent variables are given in Table 1 (See [2], [3], and [4] for the definitions of the independent variables). Gray and his colleagues constructed regression models for three different prediction periods. The model denoted by GLMB1 is a long-range model that generates predictions by December 1 – six months prior to the June 1 start of the hurricane season. The model denoted by GLMB2 uses data available by June 1 to predict activity for the entire season from June to November. This model is shown in Table 2. GLMB1 was published in the literature in 1992 (see [2]), followed by GLMB2 in 1993 (see [3]), and GLMB3 in 1994 (see [4]).

GLMB1 uses five independent variables and GLMB2 uses nine independent variables to generate predictions for seven dependent variables (H, HD, NS, NSD, IH, IHD, and HDP). In building GLMB1 and GLMB2, Gray and his colleagues used 41 years of data from 1950 to 1990.

Model-building Methodology

To build the three models, GLMB used least-absolute deviation (LAD) regression (a special case

Table 1. Definitions of Dependent Variables+

Variable	Name	Definition
H	Number of Hurricanes	A hurricane is a tropical cyclone with sustained low-level winds of 74 miles per hour or greater.
HD	Number of Hurricane Days	A hurricane day is four 6-hour periods during which a tropical cyclone is observed or estimated to have hurricane-intensity winds.
NS	Number of Named Storms	A named storm (e.g., Tropical Storm Alberto, Hurricane Andrew) can be a tropical storm (maximum sustained winds between 39 and 73 miles per hour) or a hurricane.
NSD	Number of Named Storm Days	A named storm day is four 6-hour periods during which a tropical cyclone is observed or estimated to have attained tropical-storm or hurricane-intensity winds.
IH	Number of Intense Hurricanes	an intense hurricane is a hurricane that reaches a sustained low-level wind of at least 111 miles per hour during its lifetime.
IHD	Number of Intense Hurricane Days	An intense hurricane day is four 6-hour periods during which a hurricane is at least a category 3 on the Saffir-Simpson scale (see [6]). A category 1 hurricane is the weakest, while a category 5 hurricane is the most intense.
HDP	Hurricane Destruction Potential	This is a measure that takes into account a hurricane's potential for wind and storm-surge destruction. HDP is the sum of the square of a hurricane's maximum wind speed for each 6-hour period of its existence.
NTC	Net Tropical Cyclone Activity	NTC=(%NS + %H + %IH + %NSD + %HD + %IHD)/6 where each season's percentage value from the long-term mean is used for the six measures of seasonal activity.

+ Variable names and definitions from GLMB [2], [3], and [4]

Table 2. Regression Model

Timeframe	Model
August 1	GLMB2

$$Y = \beta_0 + \beta_1 W + \beta_2 R + \beta_3 E + \varepsilon$$
$$W = a_1 U50 + a_2 U30 + a_3 |U_{50} - U_{30}|$$
$$R = a_4 R_S + a5 R_G$$
$$E = a_6 SLPQ + a_7 ZWA + a_8 SOI + a_9 SSTA$$

U_{50}, U_{30}, $|U_{50} - U_{30}|$ July data used to make an extrapolation to September

R_S Rainfall that occurs in June and July of the current year

R_G Rainfall that occurs from August through November of the prior year

SLPA, ZWA, SSTA, SOI Data taken in June and July

Table 3. Configurations and Parameter Settings for Neural Network Modes

Configuration	NNA	NNB
Network Type	Feedforward	Feedforward
Learning Algorithm	Backpropagation*	Backpropagation*
Input Layer	9 Variables	13 Variables
Hidden Layer	3 Nodes	3 Nodes
Output Layer	7 Variables	8 Variables

*We use a variant known as quick backpropagation.

Parameter	Setting for NNA and NNB
Learning Rate	0.20
Sigmoid Function Slope	0.40
Momentum Term	None
Training Length	100 Iterations

Table 4. MAE values for models predicting by August 1

Model	NS	NSD	H	HD	IH	IHD	HDP
GLMB2	1.5	8.4	1.1	6.7	0.6	2.0	21.2
NNA	1.0	7.2	0.9	5.0	0.5	1.6	14.9

Table 5. AC values for models predicting by August 1

Model	NS	NSD	H	HD	IH	IHD	HDP
GLMB2	0.4	0.6	0.4	0.5	0.6	0.6	0.5
NNA	0.6	0.6	0.5	0.6	0.6	0.7	0.7

Table 6. Predicted and Observed Values for the 1993 Atlantic Hurricane Season

Model	NS	NSD	H	HD	IH	IHD	HDP
GLMB2	9.8	52.1	6.5	23.9	1.7	1.1	50.4
NNA	10.1	40.9	5.1	16.2	1.1	4.3	53.0
OV	8	30	4	10	1	0.75	23

Table 7. Predicted and Observed Values for the 1994 Atlantic Hurricane Season

Model	NS	NSD	H	HD	IH	IHD	HDP
GLMB2	8.9	28	4.7	12.2	0.6	0.2	30.2
NNA	7.0	20.4	5.8	8.5	1.3	1.8	21.4
OV	7	28	3	7	0	0	15

of linear programming) and a jackknife solution procedure. We describe their methodology for the GLMB2 model (see Table 2). For each of the seven dependent variables, GLMB determined the values of a_1 through a_9 empirically using LAD regression and a jackknife procedure. The jackknife procedure is a cross-validation method in which a model is built to forecast a single year. With 41 years of data, GLMB withheld one year, built a model on the remaining 40 years of data, and predicted the value of the withheld year. The procedure was repeated 41 times and produced 41 predicted values for each of the seven dependent variables. The cross-validated predicted values and the observed values and the observed values for each of the 41 years are then compared via an agreement coefficient. Essentially, the agreement coefficient measures how close observed and predicted value pairs come to falling on a line of unit slope that passes through the origin.

To predict future results, GLMB generated estimated values for β_0, β_1, β_2, and β_3 for each of the seven dependent variables. They calculated the regression coefficients using the jackknife solution weights for a_1 to a_9, LAD regression, and a nonjackknife solution procedure (that is, all 41 years of data were used). To illustrate, the prediction equation for the seasonal number of intense hurricanes was

$IH = 3.45 + 0.04(1.0U_{50} + 0.61U_{30} - 0.46\,|U_{50} - U_{30}|) + 1.14(1.0R_S + 0.59R_G) - 0.67\,(1.0SLPA + 0.05ZWA + 0.47SOI + 0.63SSTA)$.

GLMB developed six other prediction equations corresponding to the remaining dependent variables (see [3] for complete details).

3. Neural Network Modeling Effort

In this section, we describe the neural network configurations and parameter settings, the computer program, the learning rule, and the training session that we use to build two neural network models that predict hurricane activity. We compare the results of our neural network models to the results of the GLMB models (that is, the GLMB2 model built on 41 years of data for August 1 predictions and the GLMB3 model built on 42 years of data for June 1 predictions).

Neural Network Configurations and Parameter Settings

The neural network model that we use is a three layer feedforward structure with an input layer, a hidden layer, and an output layer. We build two neural network models: (1) the model denoted by NNA uses data available by August 1 to predict activity for the most active portion of the hurricane season and (2) the model denoted by NNB uses data available by June 1 to predict activity for June to November. The configurations and parameter settings for NNA and NNB are given in Table 3.

We coded a computer program in the C language to build our neural network models. Our program runs on a Sun workstation and uses a backpropagation learning algorithm. Based upon previous experience, we end the training session when the number of iterations reaches 100 in order to avoid overtraining the network.

Training and Testing the Neural Network Models

In the applied neural network literature, the most common way of evaluating a model is to train a neural network on one set of data (known as the training set), use the resulting model to make predictions on a different set of data (known as the test set), and then evaluate the performance of the model by comparing the observed values to the predicted values for the test set data. However, the small sizes of the two hurricane data sets (41 and 42 observations) makes it difficult to split them into useful training and test sets. Instead, we use a jackknife procedure (as did GLMB) to train our neural network. We train our model on N - 1 years of data and test our model on the remaining one year of data. We repeat the training procedure N times. This yields N predicted values for each of the dependent variables. We evaluate each model's performance by calculating the mean absolute error (that is, MAE = Σ |Observed Value - Predicted

Value| /N) and the agreement coefficient (denoted by AC).

Results of Neural Network Models

We develop seven nonjackknifed neural network models (denoted by NNA) using all 41 years of data from 1950 to 1990 and compare the predictions of these models to the predictions of the GLMB2 models reported by Gray et al. [3]. Table 4 gives the MAE values and Table 5 gives the agreement coefficient (AC) values for the neural network models and the regression models.

In examining Tables 4 and 5, we see that for each dependent variable, NNA always produces better results than GLMB2, that is, NNA produces the lowest MAE value and the highest AC value for each dependent variable.

In 1994, GLMB published adjusted data for three dependent variables (IH, IHD, and HDP) and introduced a new variable NTC (see [4] for details). We develop eight nonjackknifed neural network models (denoted by NNA) using all 41 years of adjusted data from 1950 to 1990 and compare the predictions of these models to the predictions of the GLMB2 models reported by Gray et al. [4].

In examining the results, we see that for each dependent variable, NNA always produces better results than GLMB2, that is, NNA produces the lowest MAE value and the highest AC value for each dependent variable.

We also develop eight nonjackknifed neural network models (denoted by NNB) using all 42 years of data from 1950 to 1991 and compare the predictions of these models to the predictions of the GLMB3 models reported by Gray et al. [4].

In examining the outcomes, we see that for each dependent variable, NNB always produces better results than GLMB3, that is, NNB produces the lowest MAE value and the highest AC value for each dependent variable.

Predictions for the 1993 and 1994 Atlantic Hurricane Seasons

We develop predictions for the 1993 Atlantic hurricane season using our NNA model and compare the neural network predictions to the predictions produced by the GLMB2 model. The predicted values generated by each model are given in Table 6. In examining this table, we see that NNA and GLMB2 always produced predicted values that were larger than the observed values. In four cases (NSD, H, HD, and IH), the neural network predictions were closer to the observed values than were the regression model predictions.

We develop predictions for the 1994 Atlantic hurricane season using our NNB model and compare the neural network predictions to the predictions produced by the GLMB3 model. The predicted values generated by each model are given in Table 7. In examining this table, we see that GLMB3 produced predicted values that were larger than the observed values in eight cases, while the predictions of NNB were larger in seven cases. Both GLMB3 and NNB overestimate hurricane activity in 1994. Gray and his colleagues attribute the lack of 1994 hurricane activity in part to the continued warm equatorial Pacific El Niño conditions (see Stevens [7]).

4. Conclusion

In this application, our neural network models were easy to construct, fit the data reasonably good predictions for the 1993 and 1994 hurricane seasons, and are easy to replicated. In addition, our neural network models showed a slight edge in accuracy over the regression models. It appears to us that neural network models are good alternatives to traditional statistical models. Neural networks should be given serious consideration when trying to build models that predict Atlantic hurricane activity.

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