4.8 DESIGNING AN ALGORITHM TO PREDICT THE INTENSITY OF THE SEVERE WEATHER SEASON

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1. INTRODUCTION

One of the greatest challenges in meteorology today is long-range forecasting. Weather-sensitive industries such as agriculture and energy use long-range climate forecasts to project future crop yields and the amount of natural gas or electricity required for a season. The Department of Defense (DoD) is also extremely in need of these forecasts. DoD is responsible for examining the influences of long-term weather phenomena on its operations by using future seasonal outlooks, especially for severe weather phenomena. Operational commanders routinely task the Air Force Combat Climatology Center (AFCCC) to produce outlooks for the upcoming severe weather season so they can tailor their operations to meet any threat. One possible use of such forecasts in the United States is the realignment of aircraft to optimize their training and operational effectiveness. However, at the present time, AFCCC does not have the capability to produce such outlooks. The goal of this research therefore, is to develop a predictive algorithm for the southeastern and south-central portion of the United States in support of AFCCC to use in forecasting the intensity of the spring and summer severe weather seasons.

This research focuses on global circulation oscillations and SSTs and their effects on the spring and summer severe weather seasons in the southeastern and south-central portions of the United States. Using standard statistical methods of regression and classification trees, this study creates a climatological algorithm for forecasting months ahead, the degree of severity of the spring and summer severe weather seasons for DoD installations within the area of interest.

2. BACKGROUND

2.1. *Global Atmospheric Circulations*

Circulations and currents within the atmosphere and the ocean transport energy from one part of the globe to another. Strong winds force the flow of the surface waters, which results in an upwelling of deep water in certain regions of ocean basins. The combination between this upward convergence cooling surface SSTs and solar heating warming SSTs results in gradients along the ocean surface (Trenberth, 1991). Consequently, the oscillation between the cooling and warming SSTs induces increasing/decreasing pressure gradients over the ocean surface. This change in pressure enhances global circulations and the strength of upper atmospheric winds illustrating the strong interaction between the oceans and the atmosphere (Trenberth, 1991).

Predicting the interaction between the oceans and the atmosphere has been a major challenge for all scientists, however, it has been discerned that global circulations and SSTs play a major role on weather and climate of the world (Gatenbein, 1995). To better understand global circulations, two approaches have been used to obtain temporal correlations: the teleconnection method and the rotated principle component analysis (RPCA). The teleconnection method uses meteorological parameters between one geographical location and correlates them with other point locations in its domain (Barnston, 1987). A teleconnection usually includes two to four centers of action, with the strength of the correlation used to determine whether or not the global circulation is peaking or is of significant strength.

The RPCA uses entire flow field values in a specific region of meteorological parameters to determine where the centers of action are, instead of pre-assigning centers of action like the teleconnection method. This process takes full advantage of large-scale global circulation patterns to produce robust solutions. There are several reasons why RPCA has not been fully used as the primary approach for analysis. Teleconnections are simpler to compute and less removed from the original data, and understanding all aspects of RPCA is difficult because of its interpretability (i.e., what they actually mean physically). However, both methods are analyzed to create indices across the globe.

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2.2. ***Sea Surface Temperatures (SSTs)***

The global circulations that moderate the atmospheric winds link the components of the atmosphere and ocean. Above-normal precipitation over the United States is often associated with excessive moisture transport from the ocean and its associated frequent storm activities passing over the United States. It has been suggested that the primary cause of drought is the change in the atmospheric circulation across North America by changes in SSTs (Trenberth, 1992). SSTs all over the globe are analyzed, and indices are created based on actual SSTs and their respective anomalies.

2.3. ***Severe Weather Parameters***

Both global circulations and SSTs have a large but unknown effect on severe weather. The primary variable controlling the enhancement in thunderstorm activity is the position and strength of the jet streams. The increase in southeastern United States thunderstorm activity during the 1997-98 season is directly attributable to the stronger than normal upper-level polar jet stream across the region. Increased baroclinicity associated with the enhanced jet produced a 100-200 percent increase in lightning flashes and lightning days along the Gulf Coast (Goodman, 2000). This increase in the strength of the jet resulted from changing conditions in the Pacific SSTs. However, the underlying feature is that SSTs and global circulations are not directly responsible for the formation of individual thunderstorms, but rather, they are directly related to synoptic flow patterns (Rhome, 2000). Meteorologists are constantly searching for improved long-range severe weather forecasting techniques. Their hope is to reduce weather-induced loss of life and property by investigating the interactions between the earth's oceans and atmosphere.

3. DATA AND METHODOLOGY

3.1. ***Regions of Study***

Recently, Air Force Weather (AFW) reorganized into regional forecast Hubs across the United States known as operational weather squadrons (OWSs). This study encompasses two of the four continental Hubs; specifically, the 28th OSW at Shaw AFB and the 26th OWS at Barksdale AFB. Their coverage includes the southeastern and the south-central portion of the United States. Within each OWS area of responsibility (AOR), three bases were chosen for a comprehensive representation of the coverage area.

The southeastern stations chosen were:
- Shaw AFB, South Carolina
- Warner-Robins AFB, Georgia
- Pope AFB, North Carolina.

The south-central stations chosen were:
- Barksdale AFB, Louisiana
- Tinker AFB, Oklahoma
- Randolph AFB, Texas.

3.2. ***Predictors***

The predictor data in this study are broken up into two sets of variables. The first set is the teleconnection and RPCA indices. For all indices except the TNH index, three consecutive monthly values, December through February were averaged to create a single, winter value. In addition, just the February indices were examined since the averaging of the indices might factor out any trends near the end of the winter season that might prove crucial in finding correlations with the spring and summer severe weather seasons. As there were no February data for the TNH index, the TNH index will not be used in the February only comparisons, therefore, the averaging procedure was applied to the two months of December and January to create the TNH pattern's winter index. Winter values were chosen since these indices are highly significant during the winter season and the goal is to predict the spring and summer severe weather seasons based off of these highly significant winter indices. The indices that were examined are the:
- Southern Oscillation (SO)
- North Atlantic Oscillation (NAO)
- Pacific/North American Pattern (PNA)
- West Pacific Pattern (WP)
- East Pacific Pattern (EP)
- Tropical/Northern Hemisphere Pattern (TNH).

The second set of predictor data includes the SST indices that were also collected from the CPC. Specifically, the SST indices (Figure 8) that this study examined were the:
- North Atlantic (NATL): 5-20° North, 60-30° West
- Global Tropics (TROP): 10°South -10°North, 0-360°
- Nino 3.4 (NINO): 5° North-5° South, 170-120° West
- West Coast of United States(WESTUS)

The indices were examined from December through February and averaged over the period to create single, winter values as well as using the February data by themselves. These indices were not anomalies to SSTs, however, since they were the actual mean of the SSTs within their respective ocean basins. Anomalies were not chosen over the actual SST data since this research examined only the winter season of SSTs, therefore using anomalies to factor out the seasonal effects is not necessary. In addition, the winter values were examined each year of the 50-year POR, 1951-2000, and were also compared with the spring and summer severe weather season parameters.

3.3. ***Predictand***

The data sets predicted are the severe weather parameters. Each severe local storm season, defined as March though May for spring and June through August for summer, is described by specific

parameters. Any of the following parameters were used to illustrate severe weather events:
-Lightning data within 50 nautical miles
-Precipitation data greater or equal to 0.50 inches
-Tornado data within 50 nautical miles
-Thunderstorm observational data

4. RESULTS

4.1. *Multiple Linear Regression*

Multiple linear regression uses the method of least squares fit and is the method of choice to perform traditional statistics. Once significance of the model has been achieved, the coefficient of determination was checked to account for the total variation in the predictand (y-value) explained by all the predictors (x-values). Overall, R^2 values ranged from about 0.10-0.40, which are all rather weak correlations for uses in prediction, therefore no model was created to help with the final algorithm. However, knowing that correlations do exist proves valuable uses in statistics and show that the indices do show some sign of relationship with precipitation >0.50 and thunderstorm events.

Overall, even though R^2 values were weak (<0.50) for all model runs, statistical conclusions can be drawn from the analysis. First, there was no apparent advantage of looking at February indices over winter indices, however, this process was used again for data mining and regression trees since the data are already formatted and deeper relationships could have been overlooked. Second, the proximity of an index to the region will increase the significance and eventually the correlation of the model. Both the PNA and the NATL had greater influence on the southeastern region than other indices. Finally, multiple linear regression showed that SST indices appeared more often in the model runs than did global circulations. Even though R^2 remained low, the results above provided helpful information in the data mining and regression tree processes. Knowing what key indices to use for each model would aid in the tree building process and eventually into an algorithm usable by OWS forecasters.

4.2. *Classification and Regression Trees (CART)*

CART analysis deals with complex relationships involving several predictands and predictors, and was used in this research when traditional statistics had been exhausted. From the thunderstorm, precipitation, and tornado data sets, CART established classification trees that predicted a categorical predictand. These classification trees consist of binary decision rules that split nodes (decision points) either to the left or right based on a test against a significant predictive value and will continue to branch until a terminal node (final node) was reached (Burrows, 1992). CART provided a way to examine data and discover important grouping cases to formulate rules and to make predictions. An element of the CART analysis was validating the tree. There are several methods of validation, however, the 10-fold cross-validation method was used in this study since it is an improvement over the traditional holdout method, where a certain percent is removed from the data, when dealing with a smaller sample size.

Before any classification trees could be created, the thunderstorm, precipitation, and tornado data sets had to be categorized to best solve the problem to this research. Just like the tradition statistics portion of the research, lightning data wasn't used during the CART analysis due to the small size of the data set. The goal was to answer how intense the severe weather season would be, and a classification into below normal, normal, and above normal categories was achieved through ranking the data into equal thirds. However, since all data sets contained seasonal values, the data couldn't be split exactly into equal thirds, although for the thunderstorm and precipitation data sets, the data was split close enough to fit into the below normal, normal, and above normal categories. After ranking and splitting the data into below normal, normal, and above normal categories, the classification trees were created. The next step was to determine if the tree was the best tree for creating an algorithm for forecasters to use. In order to determine if the best tree was created, several factors had to be determined:
-the purity of the tree,
-the sample size of the terminal nodes,
-the cross-validation risk estimate.

All of these factors were used to reach the improvement over climatology, which only was shown in the results if it was better than 0%. First, the purity of the tree was determined. Only terminal nodes of 100% were used to obtain the highest improvement. Terminal nodes less than 100% were not chosen since the cross-validation risk estimate multiplied by any terminal node less than 100% would not result in any improvement above climatology. Next, any terminal node sample size less than three would not be used since two years of data did not represent at least 5% of the thunderstorm and precipitation data sets. This same process was used for continuity in the tornado data sets. Finally, obtaining the lowest cross-validation risk estimate was achieved by rerunning trees with different stopping rules explained in the CART methodology section of this research. Subtracting the cross-validation risk estimate from 100% would result in the tree accuracy. Once the tree accuracy was determined, the difference from climatology was determined by subtracting the tree accuracy from the climatology. Then, the improvement over climatology would be that difference divided by the climatology. Once all improvements were shown to be above 0%, the criteria were used as determined from the tree to provide a forecast algorithm to predict the intensity of each severe weather category.

Example forecast algorithm:

South-central summer thunderstorm forecast algorithm.

Station	Category	Criteria*	Tree Accuracy / Climatology / Improvement
Barksdale	Below Average	wpo>-0.75 natl>25.80 nao≤0.55	42% / 33% / 27%
	Below Average	-0.75<wpo≤-0.50 natl≤25.80	42% / 33% / 27%
	Above Average	wpo≤-0.75 natl≤25.40	42% / 33% / 27%
Randolph	Below Average	trop≤28.10 nino>26.60 nao≤-0.05 -1.05<so≤0.25	48% / 33% / 45%
	Below Average	trop≤28.10 nino>26.60 nao>-0.05 wpo>-0.95 westus≤25.70	48% / 33% / 45%
	Average	trop≤27.60 nino≤26.60 ep>-0.95 nao≤-0.20 so≤1.30	48% / 33% / 45%
	Average	trop≤28.10 nino>26.60 nao≤-0.05 so≤-1.05	48% / 33% / 45%
	Above Average	trop≤27.60 25.2<nino≤26.2 ep>-0.95 nao>-0.20	48% / 33% / 45%
	Above Average	27.6<trop≤28.10 nino≤26.60 ep≤1.35	48% / 33% / 45%
	Above Average	trop>28.10	48% / 33% / 45%
Tinker	Below Average	PNA>1.02	44% / 33% / 33%
	Below Average	PNA≤1.02 WESTUS≤22.90 NAO>0.02	44% / 33% / 33%
	Below Average	PNA≤1.02 WESTUS≤22.90 NAO≤0.02 EP≤-0.15 TNH>-0.04	44% / 33% / 33%
	Below Average	PNA≤1.02 WESTUS>23.30 NINO>26.60 SO>-1.10 WPO≤0.65	44% / 33% / 33%
	Average	PNA≤1.02 22<WESTUS≤23 NINO>26.60 SO>-1.10	44% / 33% / 33%
	Above Average	PNA≤0.56 WESTUS>22.90 NINO>26.60 SO≤-1.10	44% / 33% / 33%

*winter indices are capitilized

If the criteria were not met at all, then climatology would still be the best prediction, however, there was a significant increase in the algorithm over climatology using all three severe weather parameters. Since the three weather parameters are dependent sets with each other, it would be difficult to combine the three data sets into one severe weather product, and a lot of information would be lost in the combination process. The advantage of keeping the data sets individualized was that specific long-range forecasts could still be made with each severe weather parameter. In addition, the three severe weather parameters only partially define the severe weather season since there are other parameters that could be used to define it at as well. Therefore, the algorithms in the tables above are to be used separately to characterize the severe weather season.

Overall the CART results were positive. They confirmed that algorithms with reasonable predictability could be produced for forecasting the intensity of the severe weather season. The predictive tables produced in this study are deemed ready to use by AFCCC and OWS forecasters to answer such questions each year.

5. CONCLUSIONS

The main goal of this research was to create a climatological algorithm if statistical relationships were found between spring and summer severe weather parameters and SST and global circulation indices. Forecast algorithms were created using CART analysis, specifically classification trees, which improved upon climatology on multiple cases. Thunderstorm data showed improvements up to 45%. Precipitation data showed improvements up to 73%. Finally, tornado data showed improvements up to 132%.

CART analysis and traditional statistics provided conclusions about each data set as well as regional trends. First, they showed that there was no advantage of using February indices over winter indices, therefore, both indices were used in the final classification tree process and climatological, forecast algorithm. Second, the regional trends identified in traditional statistics showed that the PNA and NATL indices correlated well with the three stations in the southeast. Finally, CART analysis showed that the EP showed the best relationship several times with the south-central spring and summer precipitation forecasts, and the NAO showed the best relationship several times with the southeast spring and summer tornado forecasts. Overall, CART results identified positive trends that existed between the severe weather parameters and the SST and global circulation indices. CART confirmed that climatological, predictive algorithms could be produced for forecasting the intensity of the severe weather season.

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