WEATHER EFFECTS ON THE SUCCESS OF LONGLEAF PINE CONE CROPS

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Abstract—We used National Oceanic and Atmospheric Administration weather data and historical records of cone crops from across the South to relate weather conditions to the yield of cones in 10 longleaf pine (*Pinus palustris* Mill.) stands. Seed development in this species occurs over a three-year time period and weather conditions during any part of this span could have varying effects on the final seed crop. Weather had a significant effect on cone crops, but the relationship across many years was complex and could not be attributed to any small subset of variables.

INTRODUCTION

Longleaf pine (*Pinus palustris* Mill.) has long been known to have irregular cone crops, though it is not known what factors control the bounty of the cone crop. There are three critical stages in cone development that take place across three years: reproductive primordia development in July and August of year one, pollination in March of year two, and ovule fertilization in May of year three.

Previous research has attempted to relate weather to cone production of longleaf pine. Shoulders (1967) looked at rainfall effects on flowering while Pederson and others (1999) looked at precipitation and temperature effects on cone production. However, both of these papers looked only at a single location, whereas we have included 10 locations and more years of data.

DATA

In 1958, a spring binocular count of green cones on longleaf pine trees was initiated at the Escambia Experimental Forest in Alabama by the Forest Service, U.S. Department of Agriculture. This one location has now expanded to include 10 locations across the South (table 1; Brockway and Boyer 2014). It is important to

Table 1—Locations in six southern states at which counts of green longleaf pine cones were made and the climate divisions which correspond to them

Cooperator	State and County	State and Climate Division Number
Kisatchie National Forest	Louisiana, Grant	16, 5
Cedar Creek Company	Alabama, Escambia	1, 7
Blackwater River State Forest	Florida, Santa Rosa	8, 1
Eglin Air Force Base	Florida, Okaloosa	8, 1
Apalachicola National Forest	Florida, Leon	8, 1
Jones Ecological Research Center	Georgia, Baker	9, 7
Tall Timbers Research Station	Florida, Leon	8, 1
Fort Benning Military Base	Georgia, Chattahoochee	9, 4
Sandhills State Forest	South Carolina, Chesterfield	38, 4
Bladen Lakes State Forest	North Carolina, Bladen	31, 6

Note: State and climate division numbers are listed by NOAA (2015a).

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note that this paper is based on the count of green cones performed during April and May of the seed year, even though there will be some cone loss during the subsequent summer before the seed is released in the fall. To our knowledge, these are the only longleaf pine cone counts for which a long period of historical data were available.

In addition to this Forest Service data collection, weather data for the same periods were obtained from the National Oceanic and Atmospheric Administration's National Climatic Data Center (NOAA 2014) as averages for each climate division (NOAA 2015b) where cone counts were done (table 1). Variables used included monthly summaries of (1) average air temperature; (2) maximum air temperature; (3) minimum air temperature; (4) Palmer Drought Severity Index (PDSI) (positive is wet, negative is dry); (5) precipitation; (6) heating degree days (the number of degrees that each day's average temperature is <65 °F (NOAA 2015c); higher is colder); and (7) cooling degree days (the number of degrees that each day's average temperature is >65 °F (NOAA 2015c); higher is warmer). The combination of conelet counts and weather data resulted in 390 observations for analysis.

METHODS

Relationships between cone crops and weather were evaluated in two ways: as raw cone counts and as classes of bumper, good, and poor cone crops. The classifications are based on those of Brockway and Boyer (2014), but the number of classes was reduced to highlight differences (table 2).

Table 2—Definitions of longleaf pine cone crop quality used in this paper

Crop Quality	Cones per Tree
Bumper crop	≥100
Fair to Good crop	25 to 99
Poor to Failed crop	<25

There are three time periods thought to be very important in longleaf pine cone development that guided our initial variable selection. Primordia development occurs during July and August two years before the seed crop (year one); pollination occurs in March one year before seed crop (year two); and fertilization occurs in May of the seed year (year three) (Croker 1971, Eggler 1961). To include factors not accounted for by these time periods, we also used monthly weather data values for all other time periods from January of year one through June of year three just after the cone count was assessed. The variables for the pollination and fertilization stages are equivalent to the monthly values, but the variables included to represent the primordia stage were sums (precipitation, cooling degree days, heating degree days) or averages (PDSI, average temperature, maximum temperature, minimum temperature) of the values for the months of July and August. Furthermore, in this dataset, the value for heating degree days in July and August were always zero and could not be used in any analysis. This creates six new variables, but excludes four for the correlation analysis, resulting in a total of 212. For the discriminant analysis, the values for the months of July and August had to be excluded because they were already included in the primordia stage variables, resulting in 200 variables.

We used SAS statistical software to analyze the data. Canonical discriminant analysis was done with the software's PROC CANDISC routine (SAS Institute 2004) using the 200 variables selected and the three cone-crop classes described in table 2. After this initial analysis, PROC STEPDISC (SAS Institute 2004) was used to try to reduce the number of variables included. Significant variables arising from PROC STEPDISC were then analyzed using PROC CANDISC to benefit from the dimension-reducing principal components analysis of this procedure, making it easier to visualize the results (fig. 1).

With PROC CORR (SAS Institute 2004), Pearson correlation coefficients were calculated for all the measured monthly weather variables from January of year one through June of year three, as well as for the six combined primordia variables. The monthly results were then plotted as bar graphs to enable visualization of the ups and downs of correlation through time (fig. 2).

RESULTS

With all 200 variables included for the discriminant analysis, all cone production classes were significantly different ($\alpha = 0.05$) based on Wilk's Lambda. When a stepwise discriminant analysis selected only 36 significant variables, all of the classes were still significantly different; however, this is not obvious from the graph (fig. 1). The variables selected as significant are listed in table 3. Of the significant variables, 17 were related to moisture and 19 were related to temperature. Since there are 58 possible moisture variables and 142 possible temperature variables, it is useful to note that 29 percent of the possible moisture variables and 13 percent of the possible temperature variables entered the model. Of the significant variables, 3 were from conditions in year three, 13 were from year two, and 20 were from year one. As percentages of the possible variables, this is 7 percent from year three, 16 percent from year two, and 26 percent from year one. A linear discriminant function using all of the variables failed to correctly classify the cone production class 8 percent of the time, while a linear discriminant function using the

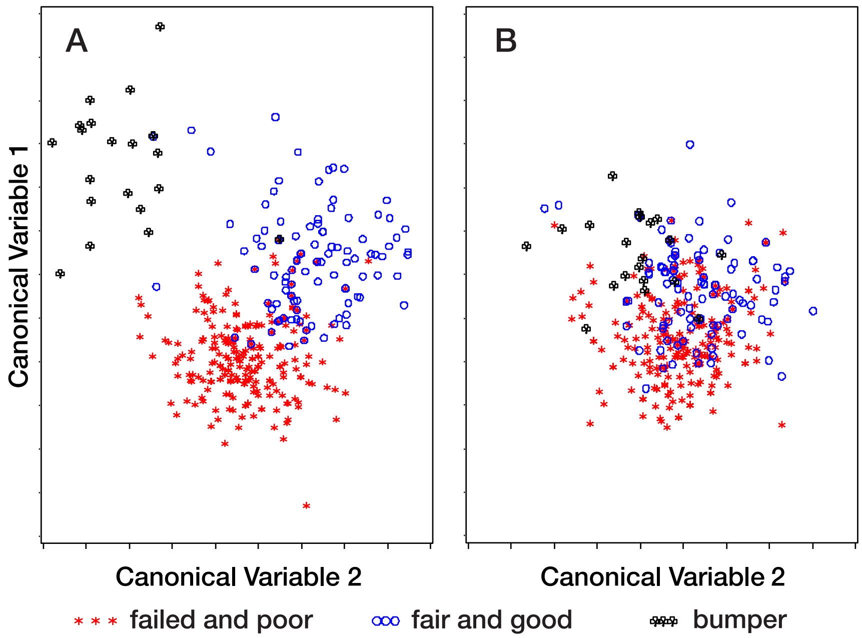

Figure 1—Results of canonical discriminant analysis showing that 200 variables visually delineate cone production classes (A), but that the 36 significant variables alone (B) do not. However, they are both statistically significant for discriminating between all classes. Note that there are no numbers on the axes because the canonical variables are combinations of the real variables, and thus the numbers have no obvious meaning.

36 significant variables failed to correctly classify cone production 24 percent of the time.

In the correlation analysis, there were 57 significant variables ($\alpha = 0.05$). Of these, 32 described conditions in year one, 15 described conditions in year two, and 10 were conditions in year three. As percentages of the possible variables, 37 percent were from year one, 18 percent were from year two, and 24 percent were from year three. Fifteen of the significant variables were moisture related and 42 were temperature related, which is to say that 25 percent of the possible moisture variables and 28 percent of the possible temperature variables were significant.

It is important to know which variables were significantly correlated with cone crop, but it is also important to know if they exert a positive or negative influence on the crop. Table 4 lists the 30 months included in this study along with an indicator of what conditions are best for cone crops based on significant correlations. The results of previous studies by Pederson and others (1999) and Shoulders (1967) are also listed for comparison.

DISCUSSION

Shoulders (1967) found that low rainfall amounts in April, May, June, and July of year one reduced the flowering ability of trees, and high rainfall amounts increased it. We found that only rainfall in June and July of year one was significantly correlated with cone production.

Pederson and others (1999) found that warmer temperatures in May, June, and October of year one were positively correlated to cone yield. In year two, a cool April and warm July and August were positively correlated to cone yield. Our results generally agree, except that we found a warm winter was more important than a warm spring in year one. We also found some additional correlations, such as the positive influence of a cooler July, August, and September and a warmer October, November, and December in year one; a cooler June in year two; and a cooler winter and spring in year three.

Pederson and others (1999) also found that precipitation was positively correlated with cone crops during July of year one and during October and November of year two. This matches our results, except that we also found a positive correlation if conditions were wetter in June, September, and October of year one and wetter throughout the winter and spring of year three (fig. 2A-B). One reason why we may have found additional moisture correlations was that, in addition to rainfall, we also looked at PDSI, which smoothed out the trends of rainfall. While many of our correlations were not significant, the general trend expressed by PDSI is that it is beneficial to cone production for conditions to be dry before primordia formation and wet afterwards.

Figure 2 also shows other correlations between the weather data variables analyzed and cone yield. Average temperature correlations (fig. 2C) show

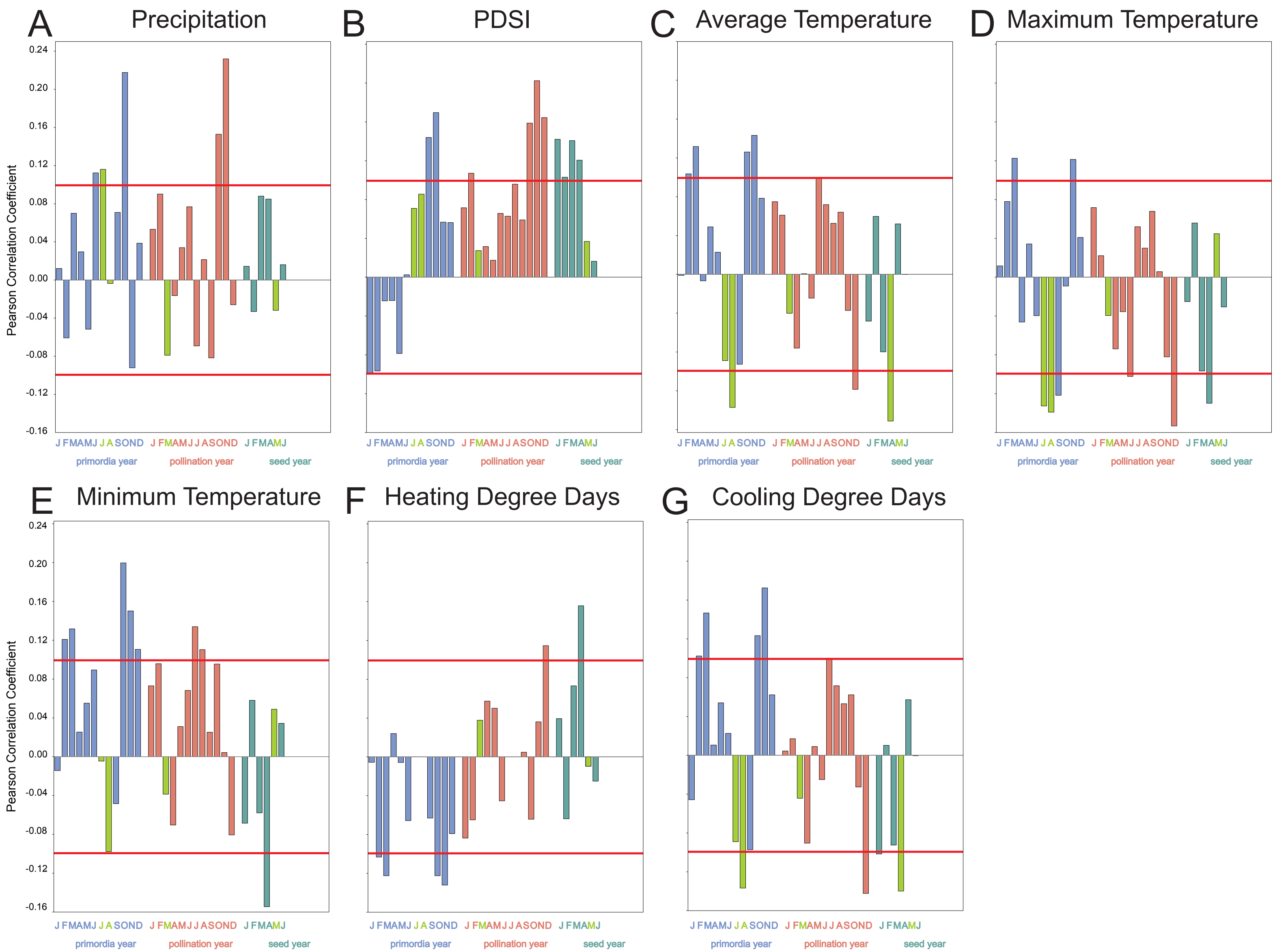

Figure 2—Pearson correlation coefficients are plotted for each of the weather variables analyzed. The red line in each graph marks the approximate limit for significance of the correlations. The bars colored light green indicate the important stages in seed development (primordia development, pollination, and ovule fertilization). This figure includes the following monthly variables: (A) precipitation, (B) Palmer Drought Severity Index (PDSI), (C) average temperature, (D) maximum temperature, (E) minimum temperature, (F) heating degree days, and (G) cooling degree days.

Table 3—Weather data variables included in the significant discriminant function by stepwise discriminant analysis

Variable Description	Correlation
August minimum temperature in year two	positive
July and August temperature in year one	negative
July cooling degree days in year two	positive
June cooling degree days in year three	negative
September precipitation in year two	negative
October precipitation in year one	positive
April heating degree days in year one	positive
May PDSI in year one	negative
November maximum temperature in year one	positive
April minimum temperature in year one	positive
July and August precipitation in year one	positive
April precipitation in year two	negative
April PDSI in year one	negative
March heating degree days in year three	positive
June temperature in year three	negative
August precipitation in year two	positive
October PDSI in year two	positive
April cooling degree days in year two	negative
September heating degree days in year one	negative
June minimum temperature in year two	positive
July precipitation in year two	negative
July maximum temperature in year two	positive
August cooling degree days in year two	positive
May minimum temperature in year two	positive
December PDSI in year one	positive
September PDSI in year one	positive
November heating degree days in year one	negative
October PDSI in year one	positive
October heating degree days in year one	negative
February precipitation in year one	negative
March heating degree days in year one	negative
November PDSI in year one	positive
November precipitation in year one	negative
February precipitation in year two	negative
March PDSI in year one	negative
September maximum temperature in year one	negative

Note: The order of the variables in the table is the order of entry into the model, indicating greater significance to variables at the top. Whether this variable has a positive or negative effect on the cone yield is obtained from the correlation analysis.

PDSI = Palmer Drought Severity Index.

that it is better to be warmer before and after primordia formation, but cooler during the actual event. It is also better to be cooler through the winter and spring of the year after pollination. Maximum temperature correlations with cone yield (fig. 2D) basically mirror those done with average temperature, but they tend to have stronger negative correlations. Minimum temperature correlations (fig. 2E) have stronger positive correlations. These results suggest that temperatures too hot and too cold are negatively associated with cone crop, and that there is likely some moderate temperature that is best. Heating degree days (fig. 2F) is another measure of deviations from an average, and the correlations suggest that it is better to be warm until pollination and mostly cooler afterwards. Correlations between cooling degree days and cone crop (fig. 2G) suggest that it is also good to have a warm summer after pollination; this is not shown as strongly by heating degree days, which go to zero in the summer months.

It should be noted that correlations were tallied by their significance, but that even the highest correlations are still quite low. Exceeding a significance value allows for counting, but it should not be considered definitive. There is always statistical error, and it is expected that some of the tallied significant correlations are not actually significant. The real value of the correlation analysis is in looking at trends and their strengths.

The discriminant analysis primarily showed that weather data alone can be used to predict cone crops. However, it is a complex function requiring many inputs that can be difficult to obtain. Many of the variables that were significant in the discriminant function are also significant in the analysis of correlation coefficients, but several were not. At this time, it is not possible to determine if the inclusion of these variables is the result of a complex interaction or a statistical artifact.

CONCLUSIONS

Cone crops are not simple, cyclical events that are independent of weather. Temperature and moisture during the three years leading up to a cone crop have significant effects on the crop size. One weakness in this study is that it is based on the spring cone count, and events that affect the final seed yield are not all accounted for. However, spring cone counts have been used for years as good estimates of the expected yield of mature cones. The main weakness of using only the spring cone count is that the lead-time for taking advantage of a good or poor seed year is short. Given that the weather two years before a cone crop is often significant, it may be possible to develop a model to predict cone crops two years in advance. This would be a useful tool for forest managers and could be a future research effort.

Table 4—A summary of the results from the correlation analysis of the current study, along with the conclusions of Pederson and others (1999) and Shoulders (1967), showing the weather conditions that were found to be best for cone crops in each study

Year	Month	Current Study	Pederson	Shoulders
bud year	January			
	February	warmer		
	March	warmer		
	April			wetter
	May		warmer	wetter
	June	wetter	warmer	wetter
	July	wetter, cooler	wetter	wetter
	August	cooler		
	September	wetter, cooler		
	October	wetter, warmer	warmer	
	November	warmer		
	December	warmer		
pollination year	January			
	February			
	March			
	April		cooler	
	May			
	June	cooler		
	July	warmer	warmer	
	August	warmer	warmer	
	September			
	October	wetter	wetter	
	November	wetter	wetter	
	December	wetter, cooler		
seed year	January	wetter, cooler		
	February	wetter		
	March	wetter, cooler		
	April	wetter, cooler		
	May			
	June			

Notes: Variables related to moisture are PDSI and precipitation. Variables related to temperature are average monthly temperature, monthly high temperature, monthly low temperature, monthly heating degree days, and monthly cooling degree days. Although these variables express different aspects of moisture and temperature respectively and have different levels of significance, there were no conflicts in the trend expressed.

Missing cells indicate that no significant relationship was found.

LITERATURE CITED

Brockway, D.; Boyer, B. 2014. Longleaf pine cone prospects for 2013 and 2014. http://www.srs.fs.usda.gov/longleaf/2014_Cone_REPORT.pdf . [Date accessed: May 8, 2015].

Croker, T.C. 1971. Female strobilus stages of longleaf pine. Journal of Forestry. 69(2): 98-99.

Eggler, W.A. 1961. Stem elongation and time of cone initiation in southern pines. Forest Science. 7(2): 149-158.

NOAA. 2014. Index of /pub/data/cirs/climdiv. http://www1.ncdc.noaa.gov/pub/data/cirs/climdiv/ [Date accessed: December 5, 2014].

NOAA. 2015a. U.S. climate divisions. http://www.ncdc.noaa.gov/monitoring-references/maps/us-climate-divisions.php. [Date accessed: December 11, 2015].

NOAA. 2015b. An overview of NCDC's new climate division dataset. http://www1.ncdc.noaa.gov/pub/data/cirs/climdiv/nCLIMDIV-briefing-cirs.pdf. [Date accessed: May 29, 2015].

NOAA. 2015c. Questions about heating, cooling degree days. http://www.erh.noaa.gov/cle/climate/info/degreedays.html. [Date accessed: May 29, 2015].

Pederson, N.; Kush, J.S.; Meldahl, R.S. 1999. Correlating climate and longleaf pine cone crops: is there a connection? In: Kush, J.S., comp. Report No. 4. Longleaf pine: a forward look, proceedings of the 2nd Longleaf Alliance conference. Charleston, SC: Longleaf Alliance: 140-143.

SAS Institute Inc. 2004. SAS/STAT 9.1 User's Guide. Cary, NC: SAS Institute Inc. 5121 p.

Shoulders, E. 1967. Fertilizer application, inherent fruitfulness, and rainfall affect flowering of longleaf pine. Forest Science. 13(4): 376-383.