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A Tree-Ring Reconstruction of Precipitation for the Tennessee Valley

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ABSTRACT:*Reconstructed spring-summer (May-June-July) precipitation in the Tennessee Valley is presented. Datasets incorporated include U.S. climate division precipitation and regional tree-ring chronologies. The period of 1895-1980 was used for model calibration and a rescaling technique was applied to create the reconstructions. Eastern Tennessee and western North Carolina precipitation was reconstructed to 1686 (294 years) utilizing stepwise linear regression. Predictors (i.e., tree chronologies) were pre-screened utilizing correlation and stability techniques to ensure accurate reconstructions. Total variance explained (r^2), reduction of error (RE), and root mean square error (RMSE) were utilized to assess model stability and skill. Model calibrations explain approximately 50 percent of the variance in spring-summer precipitation records. The reduction of error parameter indicated there is valuable information in the reconstructions. Calibrated regions had RMSE values between 5 and 6 cm. The reconstructions were evaluated with regard to variability and distribution of droughts and extreme years over the past 3 centuries. Long-term hydroclimatic variability in the Tennessee Valley indicated several (14-15) drought periods in which the spring-summer rainfall was below normal for at least 3 consecutive years. Three-year spring-summer drought periods were found to be the most common dry phases in the region. The longest spring-summer droughts lasted at least 6 years. Spring-summer climate in the 1700s had the highest variability and contained the most number of droughts within the region in the last 300 years. Approximately 50 percent of extreme spring-summer precipitation occurred during the eighteenth century. May-June-July (MJJ) precipitation in the 19th century was found to have similar variability and number of extreme occurrences compared to 20th century precipitation. A noticeable signal was not found between sea surface temperature oscillations (i.e., AMO, ENSO, and PDO) and spring-summer precipitation in the region. The reconstructions provide valuable climatic information that can be used to assess current conditions and manage water resources in the region.*

KEYWORDS:*Precipitation, Streamflow, Tree-Rings, Tree-Ring Proxies, Reconstruction, Drought*

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INTRODUCTION

Dendrochronology, the science of placing exact years in which tree-rings were formed to analyze spatial and temporal patterns of processes, has a long history in the southwestern United States. However, dendrochronology in the southeastern U.S. has been discontinuous, largely because the forests of the region are more mesic and have been extensively cleared and impacted by humans [1]. In much of the western United States, tree ring widths can provide a proxy for gauge records because the same climatic factors, primarily precipitation and evapotranspiration, control the growth of moisture-limited trees [2]. Moisture sensitive trees species are ideal in dendroclimatic research and the arid and semi-arid conditions of the southwest present this opportunity. Many misconceptions still linger among scientists that tree-ring research simply is not possible in the southeastern U.S. because of high decomposition and decay rates and a lack of trees that are long-lived or have sensitive patterns of tree rings to facilitate crossdating [1].

Dendroclimatology is the science which extracts climatic information from the annual growth layers of woody plants, and assumes that these growth layers reflect the environmental conditions under which they were formed [3] and [4]. Fluctuations in climate (i.e., temperature, precipitation) cause annual variations in tree-ring widths. Tree-rings have been widely used to reconstruct climatic conditions and indices in past decades.

Successful drought [5], [6], and [7], climate indices [8], [9], and [10], precipitation [11], [12], and [13], streamflow [14], [15], and [16], and temperature [17], [18], and [19] reconstructions provide valuable information. Greater understanding of past climate increases knowledge of current conditions. Increased knowledge of existing atmospheric conditions provides easier and more efficient decision making.

Reconstructed Tennessee Valley precipitation is the primary contribution of the presented research. [13] provides the foundation to this work. The spatial region is increased and the reconstruction is improved statistically and graphically. Analysis of long-term hydrologic variability in the Tennessee Valley based on the reconstructed precipitation is also examined. Although responses to climate are not as robust in southeastern U.S. tree species compared to species in the southwestern U.S., the opportunity still exists to develop a valuable reconstruction based on tree growth.

1.1 Site Description

The eastern region of the Tennessee Valley is within the scope of this research. The Tennessee Valley Authority (TVA) operates and maintains water resources in the region. TVA works to support economic development in the Valley and serves as an environmental steward of the nation's fifth largest river system. TVA dams store the water needed to generate clean, efficient electric power and help prevent hundreds of millions of dollars in flood damage in an average year. The eastern region of Tennessee (TN) and the western region of North Carolina (NC) are within the Southern Appalachian region and form the area of interest for the presented work. Annual precipitation in the region ranges from 90 to 180 cm (35-72 inches). The region is dominated by valleys and mountain ranges. Trees in the region contain (but are not limited to) the follow species: chestnut, beech, tulip poplar, spruce, pine, oak, spruce, bald cypress, and hemlock. Figure 1 provides a location map of the region of study.

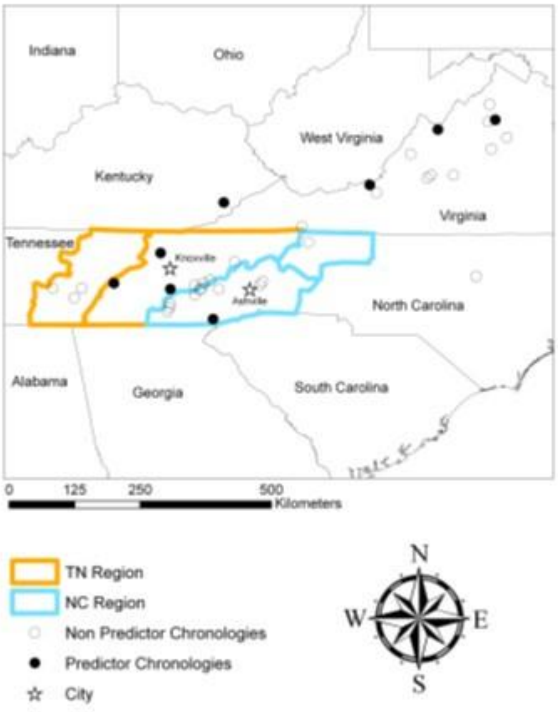

Figure 1: Location map identifying climate division boundaries and tree chronologies investigated. Dark circles indicate chronologies that entered into the stepwise regression models. Light circles were not entered into regression models due to stability or chronology length problems.

DATA

2.1 Tree-Ring Chronologies

Tree-ring chronology data is available from The International Tree-Ring Data Bank. Data is maintained by the NOAA Paleoclimatology Program and World Data Center for Paleoclimatology. Available data includes raw ring width measurements, wood density measurements, and site chronologies. Tree chronologies within and around the eastern Tennessee Valley (i.e., Tennessee, North Carolina, and Virginia) were investigated. All ring width series were uniformly processed using the ARSTAN program [20] as follows. Measured series were standardized using conservative detrending methods (negative exponential/straight line fit or a cubic spline two thirds the length of the series) before using a robust weighted mean to combine all series into a single site chronology [21]. Low-order autocorrelation in the chronologies that may, in part, be attributed to biological factors [22] was removed, and the resulting residual chronologies were used. The reconstruction length was unknown at the time of data collection, therefore all data was collected, resulting in 41 chronologies. Within the datasets collected, residual chronologies included years ranging from 1534 to 2000. Chronology distributions by U.S. state were: Tennessee (14), North Carolina (11), Virginia (15), and one Kentucky chronology. The locations of all chronologies investigated are shown in Figure 1.

2.2 Precipitation

Climate division precipitation data from the National Oceanic and Atmospheric Administration (NOAA) was incorporated. NOAA provides monthly climatic (i.e., temperature, precipitation, and Palmer Drought Severity Index) datasets for each U.S. climate division. Four climate divisions are contained within the scope of this research; two located in Tennessee (Eastern and Cumberland Plateau) and two within North Carolina (Southern Mountains and Northern Mountains). Climate division datasets are regional representations based on multiple weather stations located across the region. Datasets do not reflect localized phenomena which may be characteristic of the climatic record at a single station. See Figure 1 for a spatial representation of climate division boundaries included within this work.

PRE-SCREENING METHODS

3.1 Correlation

Correlation determines the strength of variance between two datasets over time. Arguably, the concept of correlation can be viewed as the foundation of both basic statistics (e.g., t-test) and advanced statistics (e.g., multivariate analysis of variance), because these other tests either explicitly or implicitly describe relationships or associations among variables of interests [23]. Two valuable pieces of information result from correlation analysis. The first is the sign of the correlation coefficient (r-value). A positive r-value indicates that as one variable increases (i.e., precipitation), the second variable also increases (i.e., tree-ring width). A negative relationship presents the opposite relationship between variables (i.e., precipitation increases and tree-ring width decreases). The second is the significance (p-value) of the correlation coefficient. Sample size is directly related to significance. As sample size increases, the r-value required for significance decreases, and vice versa. Significant, positive r-values are retained in this study.

3.2 Identifying Similar Precipitation Regions

Correlation analysis was performed between each of the four climate division precipitation datasets from 1895 to 1980. A t-test was also used to determine if the means of monthly precipitation between each climate division were significantly different from one another. The t-test is a hypothesis test for two population means to determine whether they are significantly different. A significance level of 95% ($p \leq 0.05$) was used. While correlation may determine that climate division precipitation data are highly related, the t-test focuses more on the magnitude (i.e., means) of the datasets. This determined the most applicable regional precipitation reconstruction to create. As an alternative to reconstructing the precipitation for each climate division, the t-test determined if regional precipitation could be reconstructed, and thus provide more value. [13] concluded that it is generally true that division data, or possibly other regionally averaged data, are superior to single-station data for dendroclimatic studies and recommended that exploratory studies in such regions involve calibrations with regionally averaged data. The results from the t-test provided the basis for the tree-ring reconstruction of the regional precipitation.

3.3 Seasonal Reconstructions

Correlation analysis was performed between seasonal precipitation and annual tree-ring widths. Due to varying climatological and biological influences in the region, a 95% (positive) significance level ($p \leq 0.05$) was chosen. This determined an initial estimate of the number of tree chronologies available to use as predictors for the reconstruction and the most significant season to reconstruct. [13] discovered tree-rings in the region contain the highest signal in May-June precipitation. In the presented work, ten different precipitation seasons were investigated to determine the most appropriate and valuable season to reconstruct. Three-month seasonal precipitation periods investigated were: January-February-March (JFM), April-May-June (AMJ), May-June-July (MJJ), and October-November-December (OND). Six-month seasonal precipitation periods included were January-June (JFMAMJ), April-September (AMJJAS), and July-December (JASOND). Furthermore, a two-month period, May-June (MJ), and annual precipitation were also considered.

3.4 Stability

A 20-year moving correlation time window was performed, as in [24] between seasonal precipitation and tree-ring widths. This ensured that reliable and consistent tree chronologies were used. Chronology stability throughout the record given the uncertainties (i.e., biologic factors, disturbances, and wildfires) is important for accurate model calibration and prevents a model from being over fitted. Correlation values were visually inspected and chronologies containing negative 20-year correlation values were removed from analysis.

RECONSTRUCTION METHODS

The period of 1895-1980 (n = 86) was used for model calibration and verification in both regions. Significant and stable tree chronologies were considered as initial predictors in model calibrations. Regression approaches are the most common statistical method in climate reconstructions. In the simplest case, a linear regression equation is used to reconstruct past values of a single climatic variable from ring-width indices of a single tree-ring chronology, or from a mean of two or more chronologies which have been merged to form a single chronology [13]. Following the procedure of [25], the F level for a predictor was allowed to have a maximum p value of 0.05 for entry and 0.10 for retention in the stepwise regression model.

Outliers are unusually large or small observations that can have a disproportionate influence on statistical results, which can result in misleading interpretations. Diagnostic measures, such as studentized deleted residuals and Cook's distance can be used to determine whether an outlier is an influential observation. Studentizing residuals is useful because raw residuals can be poor indicators of outliers due to their nonconstant variance. In the presented work, observations having large (i.e. absolute value greater than 2) studentized deleted residuals were considered outliers and removed from analysis.

The ability of the variables to predict precipitation was then tested using a split sample calibration-verification scheme [26] and [27] as follows. The same variables to predict precipitation were used in a regression equation to predict precipitation in the first half of the period 1895-1937 (n = 43), and the resulting regression equation was tested on the second half of the period 1938-1980 (n = 43). The variables were then calibrated with the second half of the period and tested on the first half. This presents an alternative method used to calibrate and verify models and would confirm or deny the results from stepwise regression.

[28] discovered that the final climatic reconstruction has less variability than the original climate data used in the regression analysis. In this study, predicted values were rescaled to the original variance. First, the mean of the predicted series is subtracted from each predicted value. Each centered observation was then multiplied by a scaling factor, k, defined as:

$k = s_x / s_p$………………………………(1)

where s_x and s_p are the standard deviations of the original and predicted values, respectively. Finally, the mean was added back to each predicted value. Although this rescaling method does not affect overall model skill, it does result in a more realistic climate reconstruction.

Statistics calculated to assess model skill and proficiency include overall variance explained (r^2) and reduction of error (RE). While r^2 only measures the patterns of similarity between two time series, it does not account for the magnitudes of the differences between observed values and their estimates. A statistic which accounts for differences in magnitudes between observed and predicted values is RE. The RE tests the ability of the regression model to estimate precipitation compared to estimates based on the calibration period mean. The value of RE may theoretically range from minus infinity to + 1.0. As [29] noted, RE is a very rigorous statistic and a positive value indicates the model has predictive skill [30] and [22]. Root mean square error (RMSE) was also calculated and provided an additional measure of model skill.

RESULTS

5.1 Identifying Similar Precipitation Regions

Correlation analysis indicated that all four climate division precipitation datasets are significant at $p < 0.01$. Results from the t-test indicated the there was not a significant difference in the means between spring-summer precipitation in the two TN climate divisions. There was also not a significant difference in the means between the two NC climate divisions. However, there is a significant difference between means of TN MJJ precipitation and NC MJJ precipitation. Therefore, the two TN climate divisions were merged (averaged) together and a similar technique was performed on the two NC climate divisions, similar to[27]. Furthermore, the two NC climate division precipitation datasets were more similar to each other than the TN datasets. A box plot of climate division precipitation is shown in Figure 2.

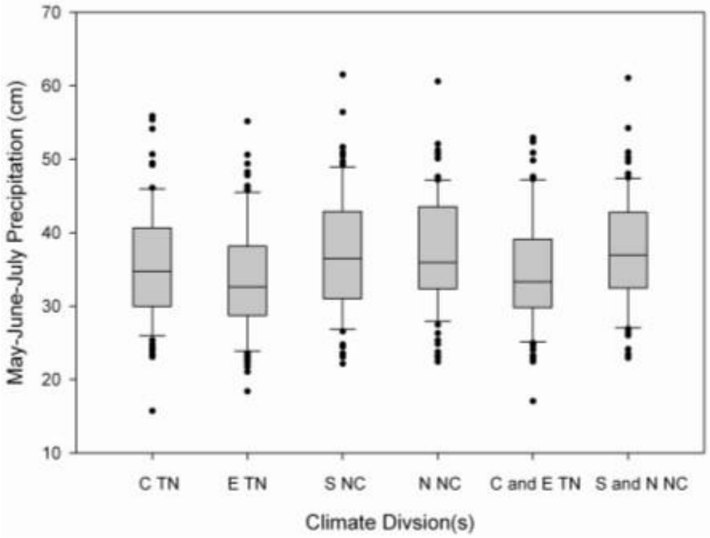

Figure 2: Box plot comparing MJJ precipitation values between four regional climate divisions. The climate divisions could not be combined because the means were found to be statistically different by the t-test. Circles represent outliers.

5.2 Seasonal Reconstruction

Similarly to [13], correlation analysis between seasonal precipitation data and this set of tree-ring chronologies indicate sensitivity primarily to climate conditions from spring-summer moisture. Large quantities of tree chronologies were found to be significant with MJ, AMJ, and MJJ precipitation. Furthermore, the three-month precipitation seasons of JFM, JAS, OND and six-month season of JASOND were insignificant (i.e., very few chronologies responding to precipitation). The six-month seasons of January-June and April-September contained average quantities of significant tree chronologies with precipitation. This was attributed to having the period of April through June contained within their time-series. After comparing the correlation (r) values, MJJ contained a stronger moisture signal compared to AMJ. Contrary to reconstructing MJ precipitation [13], it was determined that MJJ would be reconstructed. Although the climate signal is not as strong in MJJ as compared to MJ, reconstructing a three-month season provides more value and temporal information. Residual ring-width plotted against seasonal precipitation is shown in Figure 3. The Tennessee region contained 17 significant chronologies with MJJ precipitation and the North Carolina region contained 26 significant chronologies with MJJ precipitation.

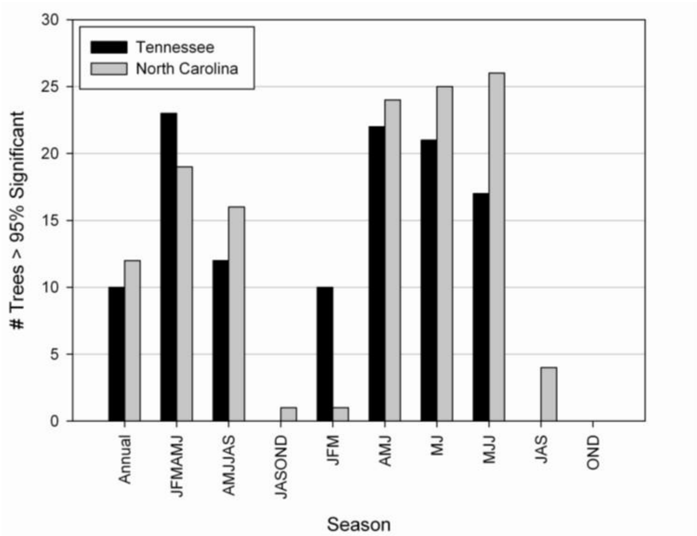

Figure 3: Seasonal correlation plot showing the number of trees that were at least 95% significant with different seasons of precipitation.

5.3 Stability

Stability analysis utilizing a 20-year correlation moving window was performed. Eleven of the 17 chronologies were considered stable in the TN region. The NC region retained 16 of the 26 chronologies after stability analysis. It was concluded that chronologies found to be unstable contained exogenous and/or endogenous disturbance factors that caused the chronology to have an inverse response to climate during the unstable period. While the overall correlation between a chronology and precipitation may be significant, incorporating an unstable chronology would decrease the model's overall predictive ability.

5.4 Calibration and Verification of the Reconstruction Model

Various spring-summer precipitation reconstructions were found to be feasible in both regions. Tennessee reconstruction possibilities were as follows: 1652 (2 chronologies entering the regression model), 1686 (4), 1752 (8), and 1800 (9). Possible North Carolina reconstructions included: 1598 (2), 1652 (5), 1686 (7), and 1752 (12). It was determined that reconstructing precipitation back to 1686 in both regions would provide the most value based on the balance between the length of the reconstructions and the predictability of the models.

The four chronologies entered as initial predictors into the TN calibration model were: Norris Dam, Piney Creek Pocket Wilderness, Lilly Cornett Tract, and Scotts Gap. After stepwise regression, the TN model retained two of the four chronologies, Piney Creek Pocket Wilderness and Scotts Gap. The Piney Creek chronology is an oak species (quercus alba) while Scotts Gap is a tulip poplar species (liriodendron tulipfera). Seven chronologies dating back to 1686 entering the NC model were: Norris Dam, Piney Creek Pocket Wilderness, Mountain Lake II, Watch Dog, Ramseys Draft Recollection, Kelsey Tract II, and Scotts Gap. The NC calibrated model also retained two chronologies after stepwise regression. They were Scotts Gap and Watch Dog, a chestnut oak (quercus prinus) species. Although Watch Dog is not located within the North Carolina region, the stepwise regression results indicate the chronology best reflects the regional climate conditions. Table I provides information for the chronologies entering into the regression models.

Table I: Tree chronologies that entered into the regression models. Listed chronologies were found to be stable and have an adequate period of record to create a reconstruction.

Chronology	State	Period	Species
Kelsey Tract II***	NC	1679-1983	TSCR CAROLINA HEMLOCK
Lilley Cornett Tract**	KY	1665-1982	QUAL WHITE OAK
Mountain Lake Virginia II***	VA	1554-1980	QUAL WHITE OAK
Norris Dam State Park*	TN	1633-1981	QUAL WHITE OAK
Piney Creek Pocket Wilderness*	TN	1651-1982	QUAL WHITE OAK
Ramseys Draft Recollection***	VA	1600-1981	TSCA EASTERN HEMLOCK
Scotts Gap*	TN	1686-1981	LITU TULIP POPLAR
Watch Dog, Massenhutten Mtn***	VA	1645-1981	QUPR CHESTNUT OAK

* Indicates a chronology that entered into both TN and NC models as an initial predictor
** Indicates a chronology that entered into the TN model as an initial predictor
*** Indicates a chronology that entered into the NC model as an initial predictor

Outlier years were found in both regions. Within the Tennessee region, the years 1896, 1967, and 1979 had unusually large studentized deleted residuals and were removed during model calibration. Additionally, the years 1896, 1903, 1905, and 1919 were considered outliers within the North Carolina region and were also removed. Removing outliers resulted in increased predictability in both regions compared to retaining outlier years.

The split sample verification method results confirmed the findings of stepwise regression. Overall variance explained was similar to that of stepwise with identical chronologies entering into each model. In both regions, the period 1895 to 1937 resulted in better model calibration. This suggests tree growth had an improved response to MJJ precipitation during 1895-1937 compared to 1938-1980 in both regions.

Model calibration and verification results exceeded those of [13]. Precipitation in the Tennessee region was calibrated resulting in the model explaining 48% of the total variance and is shown in Figure 4(a). The NC calibrated model explained 50% of the overall variance in MJJ precipitation records and is presented in Figure 4(b). Residuals from the regression equation displayed no autocorrelation or trends with the predictor variables, and were approximately normally distributed, criteria required to meet the assumptions of multiple linear regression.

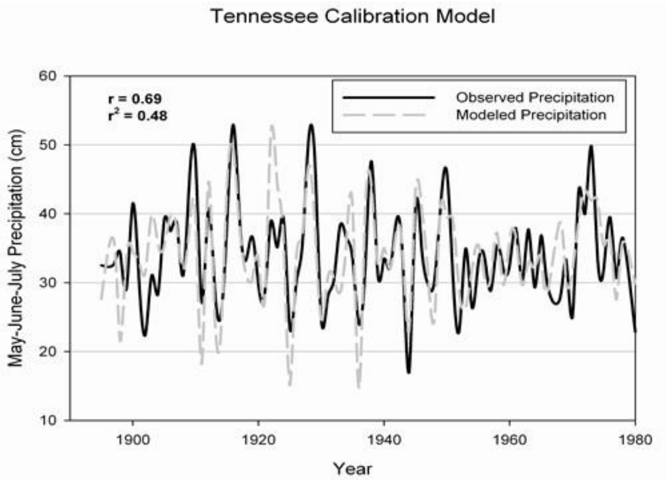

Figure 1(a): Calibrated reconstruction model for the Tennessee region. The model explains 48% of the variance in spring-summer precipitation.

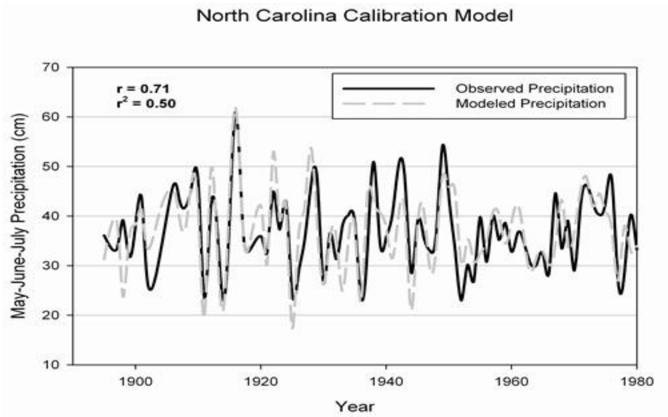

Figure 4(b): Calibrated reconstruction model for the North Carolina Region. The model explains 50 % of the variance in spring-summer precipitation.

Reduction of error values were positive in both regions indicating valuable reconstructions. The TN reconstruction RE is 0.37 while the NC reconstruction has an RE of 0.40. The RMSE was 5.4 cm (2.1 inches) and 5.7 cm (2.2 inches) for the Tennessee and North Carolina regions, respectively. Model statistics were calculated using the rescaled reconstructions for both regions and the parameters are shown in Table II.

Table II: Calibration and verification statistics for the reconstructed regions.

TN Reconstruction	
Calibration Period	1895-1980
r^2	0.48
RE	+ 0.37
RMSE cm (in)	5.4 (2.1)
NC Reconstruction	
Calibration Period	1895-1980
r^2	0.50
RE	+ 0.40
RMSE cm (in)	5.7 (2.2)

DISCUSSION OF RECONSTRUCTED TENNESSEE VALLEY PRECIPITATION AND LONG-TERM HYDROCLIMATIC VARIABILITY

The stepwise linear regression models were used to reconstruct MJJ Tennessee Valley precipitation for the years of the tree-ring record, back to 1686. The full reconstructions, rescaled and smoothed with a centered 5-year filter, are shown in Figures 5(a) and 5(b). The full reconstruction averages in the TN and NC regions were 34 and 36.7 (cm), respectively.

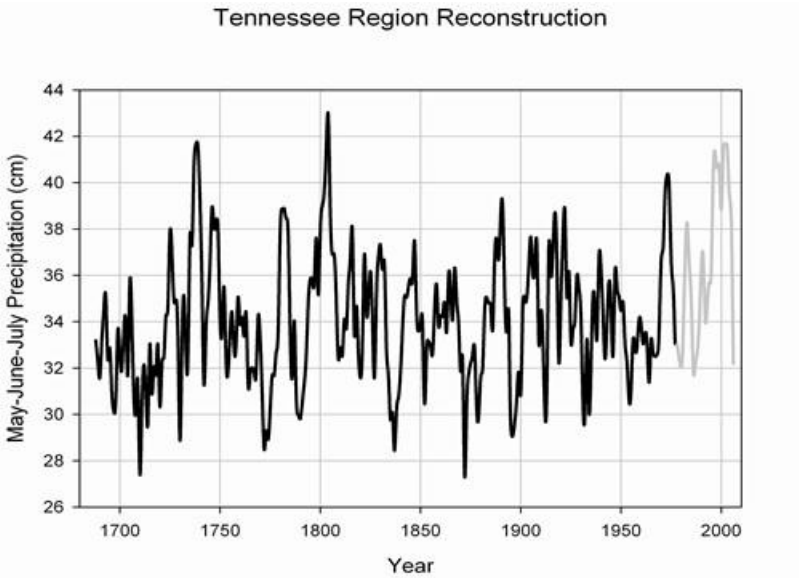

Figure 2(a): Full reconstruction of eastern Tennessee spring-summer precipitation, smoothed with a centered, 5-year filter. The dark line represents the reconstruction from 1686-1980. The gray line represents precipitation over the past 28 years (1981-2008).

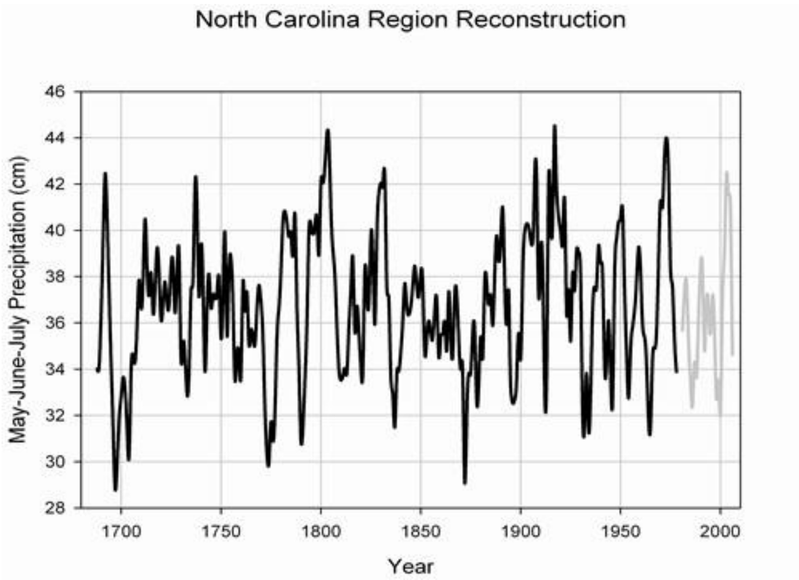

Figure 5(b): Full reconstruction of western North Carolina spring-summer precipitation, smoothed with a centered, 5-year filter. The dark line represents the reconstruction from 1686-1980. The gray line represents precipitation over the past 28 years (1981-2008).

Instrumental records can be evaluated in the context of a longer period of time based on climate reconstructions. This is useful in determining whether planning on the instrumental record incorporates the range of variability and extremes that is representative of long-term natural variability, and the range of natural variability that is likely to occur in the future [27]. In general, tree-ring reconstructions are conservative estimates of the observed values, and there is a tendency in moisture-sensitive trees for dry extremes to be better replicated than wet extremes, as trees are limited in growth by dry conditions, but not usually wet conditions [27].

Drought phases are defined here as three consecutive years in which the spring-summer precipitation was below the overall average. Following the procedure in [27], the severity of these dry phases was quantified by calculating the cumulative departures of the below average years and dividing this total by the number of consecutively below-average years for an annual average severity. In the TN region, two droughts occurred in the late 1600s. No droughts were present in the first half of the 18th century while five took place in the last half, including two back-to-back droughts (1751-1753 and 1755-1757) and one of the most severe droughts over the past three centuries (1772-1774). The 1800s contained three droughts and consisted of the longest dry event, in which there were seven consecutive years the MJJ precipitation was below the overall average (1833-1839). Furthermore, a drought occurred at the turn of the 20th century and four more droughts followed. Droughts in the TN region are show in Figure 6(a).

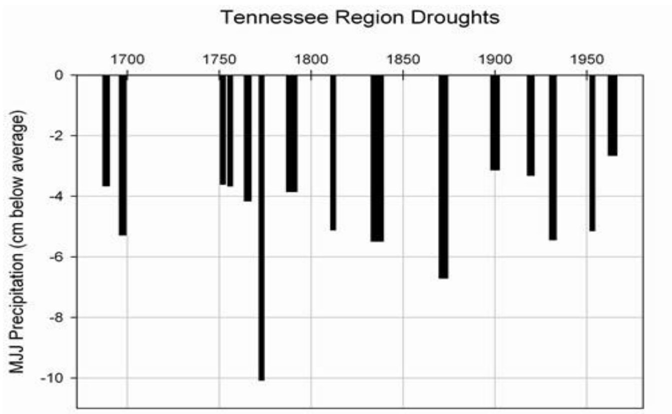

Figure 3(a): Western Tennessee droughts over the past 3 centuries. The length of the bar represents drought severity while the width of the bar represents longevity of the drought.

The drought regime of the NC region has noticeable similarities and differences when compared to the TN region. Two droughts also occurred in the late 1600s, but in contrast to the TN region, they were the most severe droughts over the period of reconstruction. The most severe drought took place during 1687-1689, but the second most severe drought lasted a year longer (1696-1699). Five droughts also occurred in the 18th century, but they were different temporally from the TN region. The 1800s contained 4 droughts including two in the 1830s. Three droughts occurred during the 20th century in the NC region including the longest spring-summer dry period in the past 300 years (1962-1967). Similarly to the TN region, the highest number of droughts occurred during the 1700s. Furthermore, the NC region was more likely to have two droughts occurring closer together in time compared to the TN region. The drought record for the NC region is shown in Figure 6(b).

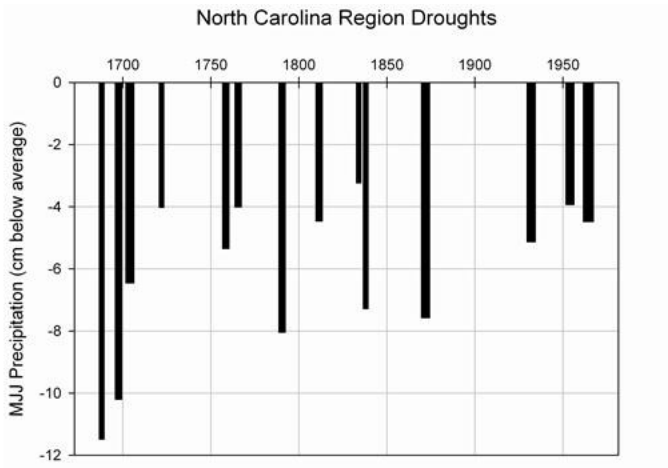

Figure 6(b): Eastern North Carolina droughts over the past 3 centuries. The length of the bar represents drought severity while the width of the bar represents longevity of the drought.

Individual extreme years were also determined to evaluate the long-term climate variability of the region. An extreme event was defined as a year in which the spring-summer precipitation was at least one standard deviation (σ) above or below the overall average. TN precipitation in the 1700s was found to have the most variability in the reconstruction. The wettest spring-summer year was 1739 and was preceded by two years that were also extremely wet. 1936 was the driest year, and it was preceded by an 'extreme' wet year. Furthermore, the latter part of the record (1950-1980) has the lowest variability in spring-summer precipitation in the last 300 years. Extreme spring-summer precipitation years in the TN region are shown in Figure 7(a).

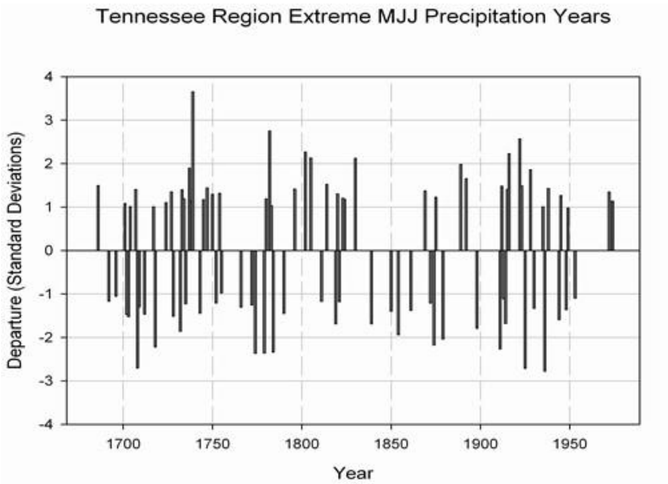

Figure 4(a): Extreme spring-summer precipitation years in Eastern Tennessee.

Similar to the TN Region, 1700s NC spring-summer precipitation was found to have the most variability. The driest year was found to be 1774, in which the MJJ precipitation was more than 3 standard deviations below the overall average. After 1800, the number of extreme years (wet and dry) decreased significantly. A noticeable similarity in both regions is a period (close to 40 consecutive years) of no extremely wet years, beginning in the early 1830s and ending in the late 1860s. The wettest year was 1916, and it occurred after another spring-summer wet year. In both regions, there were no visual signs of long term persistence that could be explained by sea surface temperature oscillations. Figure 7(b) illustrates extreme spring-summer precipitation years in the NC region.

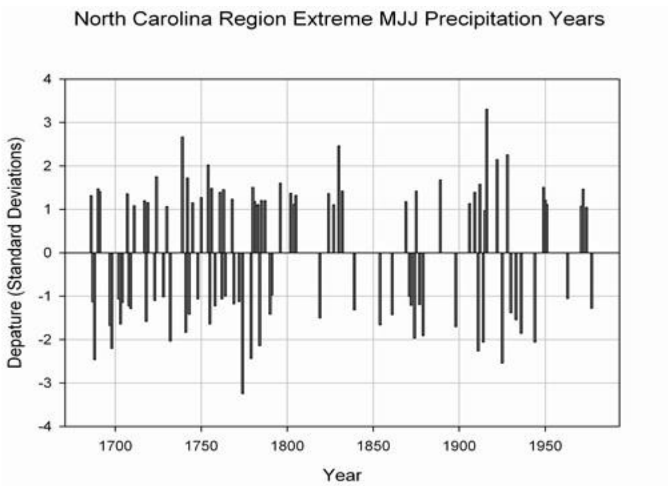

Figure 7(b): Extreme spring-summer precipitation years in western North Carolina.

CONCLUSIONS AND FUTURE WORK

Tennessee Valley spring-summer precipitation has been reconstructed from tree-ring chronologies in the region. The reconstructions date back to 1686 and explain approximately 50 percent of the variance in precipitation records. Twentieth century precipitation variability was representative of nineteenth century in the region; however precipitation in the eighteenth century had significantly more variability. Eighteenth century droughts were most common and consisted of more than 30% of all droughts in the region. Additionally, nearly half of all years in the 1700s were considered to have extreme spring-summer precipitation.

Although southeastern U.S. climate reconstructions are not as robust when compared to reconstructions in the southwest U.S., they still provide valuable information. Differences in climate between the two regions present vast opportunities in understanding both past and present regional climate patterns. A good record of past climate exists for the southwestern U.S., but little knowledge exists about the history of climate in the southeast part of the country; consequently, few studies exist for this region with which to compare the findings of this work. Due to the climatic and biological persistence within the region, it is difficult to create an accurate precipitation reconstruction because tree growth is driven by a number of environmental variables.

Future work may investigate tree-growth in the region with climate indices (i.e., ENSO, AMO, and PDO) and gridded sea surface temperatures. Climate response to oceanic variability is very unique in this region. Incorporating the slight Atlantic Multidecadal Oscillation (AMO) signal ubiquitous in the Tennessee Valley may result in a more accurate precipitation reconstruction. Reconstructing other regional climate parameters, including temperature, presents additional research opportunities. The results of this study suggest that tree growth in the southeast U.S. is affected by numerous limiting factors, which is important, but causes a problem at the same time because the accurate reconstruction of one climate variable is difficult.

Value would also be found in extending the chronologies found to contain a significant response to precipitation in the region. Many of the chronologies in the region available on the ITRDB were last cored in the 1980s. This makes it difficult to compare the recent change in climate with climate of past centuries. It is anticipated that reconstruction studies that follow will find value in this work, and this study can be used as a foundation when evaluating past climate in the region.

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REFERENCES

[1]. Grissino-Mayer, H.D. 2009. An introduction to dendroarchaeology in the southeastern United States. Tree-Ring Research 65(1): 5-10.
[2]. Meko, D. M., C.W. Stockton, and W.R. Boggess. 1995. The tree-ring record of severe sustained drought. Water Resources Bulletin 31: 789-801.
[3]. Fritts, H. C. 1971. Dendroclimatology and dendroecology. Quaternary Research 1: 419-449.
[4]. Hughes, M. K., P.M. Kelly, J.R. Pilcher, and V.C. LaMarche, Jr. 1982. Climate from tree rings. Cambridge: Cambridge University Press.
[5]. D'Arrigo, R., P. Baker, J. Palmer, K. Anchukaitis, and G. Cook. 2008. Experimental reconstruction of monsoon drought variability for Australia using tree rings and corals. Geophysical Research Letters 35(12): L12709.
[6]. Cook, E.R., R. Seager, M.A. Cane, and D.W. Stahle. 2007. North American drought: reconstructions, causes, and consequences. Earth-Sciences Reviews 81(1-2): 93-134.
[7]. Girardin, M. P., J.C. Tardiff, M.D. Flannigan, and Y. Bergeron. 2006. Synoptic-scale atmospheric circulation and Boreal Canada summer drought variability of the past three centuries. Journal of Climate 19(10): 1922-1947.
[8]. Braganza, K., J.L. Gergis, S.B. Power, J.S. Risbey, and A.M. Fowler. 2009. A multiproxy index of the El Nino-Southern Oscillation, AD 1525-1982. Journal of Geophysical Research-Atmospheres 114: DO5106.
[9]. Gray, S. T., L.J. Graumlich, J.L. Betancourt, and G.T. Pederson. 2004. A tree-ring based reconstruction of the Atlantic Multidecadal Oscillation since 1567 AD. Geophysical Research Letters 31(12): L12205.
[10]. Cook, E.R., R.D. D'Arrigo, and M.E. Mann. 2002. A well-verified, multiproxy reconstruction of the winter North Atlantic Oscillation index since AD 1400. Journal of Climate 15(13): 1754-1764.
[11]. Dettinger, M. D., D.R. Cayan, H.F. Diaz, and D.M. Meko. 1998. North-south precipitation patterns in western North America on interannual-to-decadal timescales. Journal of Climate 11(12): 3095-3111.
[12]. Stahle, D. W., and M.K. Cleaveland. 1994. Tree-ring reconstructed rainfall over the southeastern USA during the medieval warm period and little ice-age. Climatic Change 26(2-3): 199-212.
[13]. Blasing, T.J., D.N. Duvick, and D.C. West. 1981. Dendroclimatic calibration and verification using regionally averaged and single station precipitation data. Tree-Ring Bulletin 41: 37-43.
[14]. Woodhouse, C. A. 2001. A tree-ring reconstruction of streamflow for the Colorado front range. Journal of the American Water Resources Association 37(3): 561-569.
[15]. Meko, D. M., C.A. Woodhouse, C.A. Baisan, T. Knight, J.J. Lukas, M.K. Hughes, and M.W. Salzer. 2007. Medieval drought in the Upper Colorado River Basin, Geophysical Research Letters 34(10): L10705.
[16]. Cleaveland, M. K. 2000. A 963-year reconstruction of summer (JJA) streamflow in the White River, Arkansas, USA, from tree-rings. Holocene 10(1): 33-41.
[17]. Wiles, G. C., R.D. D'Arrigo, and G.C. Jacoby. 1998. Gulf of Alaska atmosphere-ocean variability over recent centuries inferred from coastal tree-ring records. Climatic Change 38(3): 289-306.
[18]. Yadav, R. R., W.K. Park, and A. Bhattacharyya. 1999. Spring-temperature variations in western Himalaya, India, as reconstructed from tree-rings: AD 1390-1987. Holocene 9(1): 85-90.

[19]. Cook, E. R., B.M. Buckley, R.D. D'Arrigo, and M.J. Peterson. 2000. Warm-season temperatures since 1600 BC reconstructed from Tasmanian tree rings and their relationship to large-scale sea surface temperature anomalies. Climate Dynamics 16(2-3): 79-91.
[20]. Cook, E.R. 1985. A time series approach to tree-ring standardization, Ph.D. dissertation, University of Arizona., Tucson.
[21]. Cook, E.R., K. Briffa, S. Shiyatov, and V. Mazepa. 1990. Tree-ring standardization and growth-trend estimation, in Methods of Dendrochronology: Applications in the Environmental Sciences, edited by E. R. Cook and L. A. Kairukstis. Springer, New York pp. 104-123.
[22]. Fritts, H. C. 1976. Tree Rings and Climate. Elsevier, New York.
[23]. Chen, P.Y. and P.M. Popovich. 2002. Correlation: Parametric and Nonparametric Measures. Sage Publications, Inc. Thousand Oaks, California. pp. 1.
[24]. Biondi, F., and K. Waikul. 2004. DENDROCLIM2002: A C++ program for statistical calibration of climate signals in tree-ring chronologies. Computers and Geosciences 30(3): 303-311.
[25]. Woodhouse, C.A., S.T. Gray, and D.M. Meko. 2006. Updated streamflow reconstructions for the Upper Colorado River Basin. Water Resources Research 42(5): WO5415.
[26]. Meko, D. M., and D.A. Graybill. 1995. Tree-ring reconstructions of upper Gila River discharge. Water Resources Bulletin 31: 605-615.
[27]. Woodhouse, C. A. 2003. A 431-yr reconstruction of western Colorado snowpack from tree rings. Journal of Climate 16: 1551-1561.
[28]. Graumlich, L. J. 1987. Precipitation variation in the Pacific Northwest (1675-1975) as reconstructed from tree rings. Annals, Association of American Geographers 77(1): 19-29.
[29]. Fritts, H. C., G.R. Lofgren, and G.A. Gordon. 1979. Variations in climate since 1602 as reconstructed from tree rings. Quaternary Research 12: 18-46.
[30]. Lorenz, E. N. 1956. Empirical orthogonal functions and statistical weather prediction. Statistical Forecasting Rep. 1, Department of Meteorology, Massachusetts Institute of Technology, Cambridge, MA. pp. 57.

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