A tree-ring based reconstruction of early summer precipitation in southwestern Virginia (1750-1981)

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ABSTRACT

### 1 Introduction

The Southern Appalachian region has supported continuous forest communities longer than any other area in North America, hosts many rare endemic species, harbors many disjunct species populations, and is therefore one of the most important centers of forest diversity on the continent [[1](#XNCNHP2012)]. The southern Appalachians also provide ecosystem services such as carbon storage, watershed and water quality protection, and serve as a timber source [[2](#Xzipper2011restoring)]. In order to protect these valuable resources, it is crucial that we thoroughly understand the past climate of this area and how it has influenced the many ecosystems within the region. A sound understanding of the past relationship between climate and southern Appalachian ecosystems will enable scientists and landowners to better manage natural resources in the future.

Global circulation models project an increase in average global surface temperatures of 1.0-3.5C by the end of this century due to continued increases in greenhouse-gas emissions [[3](#Xkattenberg1996climate)]. However, the influence of increased radiative forcing on precipitation regimes is not well understood, and this is particularly the case for the southeastern United States (US). Approximately one-third of the 24 models used in the Intergovernmental Panel on Climate Change Fourth Assessment Report project a decrease or no change in drought frequency in this region [[4](#Xpachauri2007climate), [5](#Xseager2009drought)]. Uncertainty in climate projections makes it difficult to predict water and power usage. The ability to do so is crucial because the southeastern US has experienced substantial increases in population and energy consumption over the last decade [[5](#Xseager2009drought), [6](#Xsobolowski2012evaluation)]. It is important that the public and planners in the Southeast have access to information regarding climate change projections and mitigation. Through the use of tree-ring based climate reconstructions, scientists may better understand past precipitation regimes at decadal- to centennial time-scales in order to better project future precipitation patterns in a changing climate.

In order to reduce uncertainty in climate model projections and to extend meteorological records further back in time, tree-ring data are commonly used as regional proxies, particularly in regions where drought (e.g., the American Southwest, Cook et al. 2004) or summer temperature (e.g., the European Alps, Buentgen et al. 2007) is the limiting tree growth factor. However, tree-ring data have also successfully been used for climate reconstruction in the eastern US [[7](#Xleblanc1993temporal)–[9](#Xcook1999drought)]. Traditionally it has been understood that trees in a closed-canopy forest are not limited by climate to the same extent as trees growing on the forest border (Fritts 1976). Within a dense forest, stand dynamics play an important role in shaping the forest structure through their influence on radial tree growth. As these interactions between individuals increase in strength, the climatic influence on tree growth time series becomes less dominant. Fritts (1976) presented a classic schematic diagram showing the generally understood relationship between correlation, sensitivity, and moisture limiting days [[10](#Xfritts1976tree)]. As can be seen in this simplified rendition of the classic plot (Figure [1](#x1-90061)), dense or closed-canopy forests typically have low correlation among trees and with climate and low mean sensitivity. However, Speer et al., found significant correlations between temperature, precipitation, and oak chronologies from closed canopy forest in the Southern Appalachian Mountains [[11](#Xspeer2009climate)].

In this study, we developed and analyzed the climate response in a chestnut oak (Quercus …) tree-ring chronology from interior forest trees from southwestern,Virginia, US. The objectives of this study were to:

1. Determine the presence of a significant relationship between the tree growth series and climate;
2. Assess the viability of a climatic reconstruction based on the Chestnut Oak growth series as proxy data;
3. Evaluate the reliability of the reconstruction by comparing it to other verified regional reconstructions.

### 2 Materials and Methods

#### 2.1 Tree ring data

The study site was an Upland Oak-Pine forest located on the North facing slope of Brush Mountain in South-West Virginia (37∘ 22.2’ N, 80∘ 14.8’ W), with a site elevation of 1830 ft ( figure [2](#x1-90072)). This region is classified as either humid continental or mountain temperate, and characterized by warm, humid summers and winters that are predominantly cool with intermittent warm spells. The mean annual precipitation (1901-2010) at Blacksburg weather station was 1073 mm and the mean annual temperature was 10.9∘C.

The study site supported older Chestnut Oak trees amongst a canopy of many species, including Scarlet Oak, Northern Red Oak, Red Maple, Virginia Pine, Pitch Pine, and Eastern White Pine. Site access was off of the Appalachian trail, but the site was selected to minimize human interference. The steepness of this slope suggested that climate may be a limiting growth factor, although the closed canopy and stand density suggested that stand dynamics may also play a significant role in shaping the forest structure.

We sampled a total of 36 chestnut oak trees and two cores were taken from each individual using a 5.15 mm increment borer. Samples were prepared according to standard dendrochronological guidelines (Stokes and Smiley [[12](#Xstokes1996introduction)]). Cross- dating was performed using reflected light microscopy and a LINTAB measurement stage to the 0.01mm, and then checked using COFECHA [[13](#Xholmes1983computer)]. Based on inter-series correlation coefficients, a total of 76 tree-ring series contained enough of a common growth signal to be used for further analysis.

Non-climatic age- and stand dynamics-related trends were removed from the tree-ring series using smoothing splines with a 50 % cutoff at 50 years (ARSTAN software, Cook and Peters 1997). This method allowed us the flexibility to remove the episodic-like interaction effects from the time series, while retaining the high-frequency climatic variability. Note that as with any filtering technique, inevitably some portion of the climatic signal will be lost through the removal of these non-climatic trends (REF). We here assumed that the loss of climatic signal was negligible, and comparison of the detrended time series with climatic data ultimately determined if the strength of the remaining signal was sufficient to perform further analyses. Furthermore, serial correlation is common in tree-ring time series, typically due to the change in availability of stored water or photosynthates. This autocorrelation effectively reduces the number of independent observations, and therefore must be taken into account through either reduction of the effective sample size to ensure that observation independence, or through autoregressive and/or moving average (ARMA) modeling (REF). All series were checked for autocorrelation to determine if prewhitening via ARMA modeling was necessary, and applied when deemed necessary.

The Brush Mountain site chronology was developed based on individually detrended tree-ring series and will hereafter be referred to as BM.

Additional published Quercus prinus chronologies from nearby sites in the region were considered for inclusion in this analysis with the goal of achieving a stronger climatic signal. Only regional chronologies that started after 1845 and significantly correlated with the climate variable of interest using Pearson correlation with p < 0.05 were retained for further analysis.

#### 2.3 Climate data

Monthly precipitation sums and temperature and Palmer Drought Severity Index (PDSI, Palmer 1965) averages were computed from daily measurements at the Blacksburg climate station (37∘ 12’ N, 80∘ 24’ W; elevation 634m, ft?, length of time series?1901-2010?) were used in a correlation function analysis with thePCA time series. Pearson’s coefficientsalculatedfor all monthsstarting in year to the , as well as for seasons (Apr-June, July-Sep, Oct-Dec, Jan-Mar) and annualmeans.

The Blacksburg station monthly/seasonal climate variable with the strongest correlation with the BM chronology was then used as guidance for a spatial correlation analysis using a gridded (0.5∘× 0.5∘) monthly climate data set for the period 1901-2006 (Mitchell and Jones 2005). The gridpoint with the strongest correlation coefficient was then used as a target for reconstruction (section 2.4)

This information was used to guide the comparison between the BM chronology and gridded (0.5∘× 0.5∘) monthly CRU climate data, which allowed us to compare grid points of locations with higher elevations. Regions of significant correlation were examined using higher resolution CRU data (2.5∘× 2.5∘).

#### 2.3 Principle Component Analysis

Closed-canopy forests, in particular those in the Eastern US, are subject to site heterogeneity [[14](#Xpeters1981principal)]. Site heterogeneity describes the condition in which it is not possible to identify significant climatic variance for a standard sample size, and in severe cases perhaps even with an increased sample size. This condition is present when sites experience both spatial and temporal variation between trees as a result of stand dynamics. Principal component analysis (PCA) can be a useful tool to identify common patterns in climate-modulated tree growth between sites. Here, we combined the BM chronology with a set of X nearby *Quercus* tree-ring chronologies (Table 1, Fig. 1) in a nested singular value decomposition PCA analysis (REF). The first PCA (5 contributing chronologies) was performed on the 1845 - 1981 time interval, and the second PCA (Y chronologies) on the 1750 - 1981 interval. The PCA components with eigenvalues larger than one were retained for further analysis and the components explaining the largest amount of common variance in the tree-ring chronologies were included in a climate correlation analysis.

#### 2.4 Reconstruction methods

To perform the reconstruction of computed climate variable anomalies, we use Bayesian linear regression with the selected principal components as proxies. Linear regression is an attractive technique because of its straightforward application, and is commonly used in proxy reconstruction. However, this method is based on assumptions of linearity and stationarity. The assumption of linearity implies that the relationship between the dependent variable and the predictors is linear, while the assumption of stationarity requires that the relationship between the dependent variable being predicted and the predictors do not change throughout the time period being considered for reconstruction. These assumptions are checked by statistically evaluating the reliability of the reconstruction, as discussed below. We assume that the climate anomalies (CA) satisfy CAt ~ Normal(μt, σ2), where μt = β0 + βipc where pc is the first principle component. The parameters are assigned uninformative priors, where βi ~ MVN(⃗0, 1000 ⋅I) and σ ~ Uniform(0, 100). Model parameter distributions were determined using a Markov Chain Monte Carlo algorithm with a Metropolis step method. The number of iterations run was 100,000, with a burn-on of 50,000. For the sense of practicality, parameter estimates were thinned so that only every tenth estimate was saved to memory. Each iteration resulted in a set of parameters, and for each parameter set the predicted precipitation values were computed. From these computed precipitation values, we were able to compute quantiles which allowed credible intervals to be defined.

#### 2.5 Model Calibration and Verification

To assess the accuracy of the modeled precipitation anomalies, we split the data into two periods: 1901-1940, and 1941-1981. These periods served in turn as calibration and verification periods, which allowed us to assess the mean squared error (MSE), reduction of error (RE), coefficient of efficiency (CE), the squared correlation (r2), and the sign test (GLK) [[10](#Xfritts1976tree), [15](#Xnational2006surface)]. The MSE is a way to quantify the difference between to estimated anomalies and the true values, and is given by MSE(ŷ) = ![1-
N](data:image/png;base64,iVBORw0KGgoAAAANSUhEUgAAAAoAAAATBAMAAABbxYHdAAAAMFBMVEX///8AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAv3aB7AAAAD3RSTlMAECJ23VSZzasyZu9Eibv/8J7UAAAARklEQVQIHWNgYBBkAAJlVxDJkIqPZK2YAJaGE/9BAMZbzcBUw8AgnsBwgYHh5EsQaaDOtICB4QLzHaC2CwwVDAxcjxjUGQAAlBMAZHkQhQAAAABJRU5ErkJggg==)∑(yt -ŷt)2, where ŷ and y are the predicted and true precipitation values respectively. RE compares the predicted preipitation anomalies to values determined by the mean of the calibration period. To say the model is able to have a greater predictive ability than just the mean of the calibration period, the RE must be greater than zero. The CE is analogous to the RE, except that in this case the calibration mean in the RE is replaced by the mean of the verification period. The CE measures the predictive ability of the model based on the calibration period and compares the predicted value with the mean of the validation period. Since data from the validation period are not used to fit the model, the CE will always be less than the RE, but should still remain positive in order to assert that the model has sufficient predictive ability. The RE and CE are given by the following equations:

|  |  |
| --- | --- |
| RE = 1 - -MSE-(^y),    CE  = 1 - MSE--(^y),          MSE  (y¯c)               MSE (y¯v) | (1) |

where

|  |  |
| --- | --- |
| MSE (¯y*) = 1-∑  (yt - ¯y*)2,            N | (2) |

and yc, yv are the means over the calibration and verification periods. The r2 value is a commonly used statistic which evaluates the linear relationship between two variables. Lastly, we computed the Gleichläufigkeit (GLK) score, which measures the similarity of the relative annual change in value between two time series [[16](#Xspeer2010fundamentals)].

### 3 Results

BEFORE YOU TALK ABOUT CLIMATE CORRELATION, YOU SHOULD TALK ABOUT THE BM CHRONOLOGY (HOW WAS INTERSERIES CORRELATION, WHAT YEARS WERE COVERED BY THE CHRON, ETC.), THEN HOW IT FIT TO OTHER CHRONOLOGIES (PCA), THEN COMES CLIMATE. SO, FIRST INTRODUCE FIGS. 3 AND 4.

The BM chronology correlated significantly with monthly temperature, precipitation, and PDSI values from May of the previous year to December of the current year for the period 1901 – 1981 (Fig. 4). Out of the 63 correlations computed between the BM chronology and the climate covariates, 13 (7) were significantly correlated at the 95 % (99 %) significance level.

Correlations with temperature were predominantly negative throughout the year, with a slightly positive trend during the growing season, the negligible values did not suggest a strong covarying relationship. We found significantly positive correlations between BM and precipitation of previous year June and current year May and June. The strongest correlation was found with total precipitation of the months May and June (r=…, p<0.01), Correlations with PDSI were consistently positive, with the strongest correlations occurring during the May through August growing season adn correlation was particularly strong for average June and July PDSI. Both the May-June precipitation sum (mjPR) and average June-July PDSI (jjPDSI ) were considered as candidate climatic targets fro reconstruction. The BM chronology was strongly correlated with both mjPR and jjPDSI, but an assessment of the reconstruction verification statistics (results not shown) suggested that the skill of a reconstruction based on this proxy data may not be sufficient.

To increase the signal to noise ratio in our tree-ring record and better identify regional precipitation effects, we therefore included oak chronologies from nearby locations in our analysis. A total of 8 *Quercus prinus* chronologies (Table 1) from the northeastern US from the ITRDB were considered for inclusion in a PCA analysis. Chronology reliability was assessed based on the mean sensitivity, interseries correlation, the expressed population signal, and the first-order autocorrelation. Four chronologies met the requirements for inclusion in the proceeding analysis: they were significantly correlated with the considered climate variables and covered the at least the same time period as the BM chronology (1845-1981). as shown in table [1](#x1-90011)). The locations and time series of the suitable chronologies, hereafter referred to as LH, WD, CC, and OC, are shown in figures [2](#x1-90072) and [3](#x1-90083). A nested PCA was performed using these identified chronologies in addition to BM,.

The first PCA was performed on all five chronologies for the overlapping time period 1845-1981, resulting in a first principal component which explained 47.5% of the common variance, and a second component which explained 22.3%. The scores plot (Fig. 3) illustrates the relationship between the five chronologies with respect to the first two principal components: all chronologies have a positive score along PCA1 and a negative score along PCA2, except for WD The second PCA was performed on the subset of four chronologies which extended back to the year 1750 (LH, BM, WD, CC). WHAT ARE THE RESULTS OF THE SECOND PCA? Overlapping portions of the first principal components that resulted from both decompositions were compared via correlation to confirm that both of these were in fact accounting for the same independent axis (pearson r= 0.91; p < 0.01). Principal components were merged at the year 1845 (PcA2:1750-1844, PCA1: 1845-1981) to form a single proxy record extending from 1750 to 1981. When comparing the merged PCA time-series with monthly climate variable,s, we generally find stronger correlations than for BM (Fig. 4). This is particularly true for tempeartures of theprevious year June (r=…, p<…), precipitation sums for the months May and June (r=, p<), and PDSI for the months… (r=…, p<) (Fig. 5).

In a next step, we tested mjPR and jjPDSI as potential reconstruction targets in a split calibration/verification scheme (REF; Table 4). Both the 1901-1940 and 1941-1981 periods of data were used in turn as the calibration period, to determine if the accuracy of the reconstruction was sufficient to warrant further analysis.

Overall(0.57 - 0.75, p<0.05) and GLK values (…, p<…) strongHowever, when the earlier period (1901-1941) was used as the calibration period, the RE and CE statistics for mjPR were low but greater than 0 and these statistics were higher for jjPDSI for the same period. RE and CE were also higher for mjPR using the later calibration period, whereas values for jjPDSI were negative, indicating a poor fit of the reconstruction model. RE and CE are key statistics to determine the skill of a reconstruction, and our decision to reconstruct early summer (May-June) precipitation rather than summer PDSI was based on these values. Our final MJPr reconstruction was calibrated against the entire 1901-1981 interval.

Posterior parameter distributions were determined from the adaptive Markov chain Monte Carlo (MCMC) algorithm and parameters means and credible intervals are shown in table [4](#x1-90004). The adaptive portion of the MCMC consistently maintained an acceptance rate between 0.2 and 0.5 by updating proposal distributions accordingly when acceptance rates fell outside ideal range, which ensured that there was good mixing. Predicted precipitation values were computed using each set of sampled parameters, and from these values we computed the appropriate quantiles to generate a 95% credible interval and an overall predicted precipitation mean. The resulting precipitation reconstruction extends from 1750 through 1981, which allows us to extend the instrumental mjPR record back 150 years. Figure [12](#x1-901712) shows a plot of the reconstruction and the associated uncertainty as described by the 95 % quantiles for the 1750-1981 period as well as the available averaged May-June precipitation data. The periodogram shows peaks with significant power at approximately, 4 and 11 years [13](#x1-901813).

The precipitation reconstruction was compared to other regional precipitation and drought reconstructions as external validation. For the southeastern US we identified a total of six published reconstructions that were used for comparison. Out of these six, two were drought reconstructions. The first was obtained from the North American Drought Atlas [[9](#Xcook1999drought)] which is a gridded reconstruction of annual PDSI values based on the months of June through August, and the second is a July PDSI reconstruction for Virginia and North Carolinian coastal regions developed by Stahle and Cleaveland [[17](#Xstahle1998lost)]. The remaining four reconstructions identified for comparison were precipitation reconstructions. The first set were developed by Stahle and Cleaveland for the North Carolina (NC), South Carolina (SC), and Georgia (GA) regions for the months of April though June for NC and March through June for SC and GA [[18](#Xstahle1992reconstruction)]. The last precipitation reconstruction for early summer anomalies was developed by Druckenbrod [[19](#Xdruckenbrod2003late)].

Our reconstruction correlated significantly positively with three of the six reconstructions (Fig. X). The strongest correlation was found between our averaged mjPR reconstruction and the Cook NADA PDSI (r=0.643, p<…), followed by the Druckenbrod early summer precipitation anomalies reconstruction (0.382), and the Stahle and Cleaveland NC averaged AMJ precipitation reconstruction(0.241) (see table [4](#x1-90004)). It is important to mention the length of these reconstructions. Are they all longer than our reconstruction, i.e., are all comparisons over the full length of our reconstruction?

### 4 Discussion

general structure of discussion:

1. climate signal in our BM chronology. How does this correspond with th literature? What have other researchers found for E US oaks? Include closed canopy discussion here.
2. Increasing strength of BM climate signal by applying PCA including nearby chrons. What is the spatial pattern of the precipitation relationship? Can this spatial pattern be explained? (Fig. 5)
3. WHAT ARE THE CHARACTERISTICS OF OUR RECONSTRUCTION? WHAT WERE THE DRIER/WETTER PERIODS IN THIS REGION? HOW WELL DOES THE RECONSTRUCTION REFLECT INDIVIDUAL EXTREME YEARS IN THE INSTRUMENTAL PERIOD? CAN YOU FIND ANY REFERENCES IN THE LITERATURE THAT CONFIRM WET/DRY PERIODS IN OUR RECONSTRUCTION?
4. COMPARISON WITH OTHERRECONS (TABLE 4): SIMILARITIES (!) AND DIFFERENCES. APPARENTLY, RECONS (NOT JUST OURS) DIFFER QUITE A LOT AMONGST EACH OTHER, THIS IS WORTH DISCUSSING
5. RESULTS OF THE SPECTRAL ANALYSIS: what is the potential meaning of the 4 and 11 year cycles? 11 years: sunspots. Sunspots have a well known influence on precipitation. Try and find some references there. 4 years: maybe ENSO? Do we know anything about influence of ENSO on precip in our region? Any other options?

In this study, we investigated the relationship between climate and annual radial growth of *Quercus prinus* growing at a closed canopy site in the southeastern US. After removing the portion of the signal that can be attributed to stand dynamics and intrinsic age trends, we found that the BM chronology was most strongly positively influenced by early summer (May through July) moisture from the year of ring formation.. Although the correlation between these early summer moisture measurements and the BM chronology were significant, we found that this relationship was not stationary, as indicated by an analysis of reconstruction statisitics such as the RE and CE. To isolate and strengthen the moisture-growth relationship component of the BM chronology we performed a nested principal component analysis on regional Qercus chronologies that also showed significant correlations with early summer moisture. The first principal component explained much of the variation, and was more highly correlated with moisture (both with mjPR and jjPDSI).

Similar climate-growth relationships have been identified in previous oak studies in the northdastern US [[11](#Xspeer2009climate), [20](#Xli2011dendroclimatic)] and can be explained by the ecophysiological mechanisms. Radial growth of oak species typically starts in April or May after leaf-out, and even in wetter years is 90% complete by the end of July [[21](#Xrobertson1992factors)]. In earlier months of the growing season, carbon is allocated predominantly to radial thickening, while later in the season the focus of this allocation is shifted to carbohydrate storage [[22](#Xzweifel2006intra)]. Under severe moisture stress, carbon allocation is shifted from shoot to root, thereby decreasing the root/shoot ratio (REF. Quercus prinus is considered to be more tolerant to drought stress than other oak species and exhibits several morphological adaptations in order to better cope with these moisture stress events [[23](#Xdickson1996oak)], but we found that its radial growth was strongly influenced by moisture availability. This suggests that in years with inadequate moisture, radial growth is not a priority, and carbon allocation is likely focused on maintenance or root development.

Reconstruction accuracy statistics showed that although both the early and late calibration periods had RE and CE values greater than 0, the later calibration period (1941-1981) had overall better ability to predict throughout the entire time period for which their was instrumental data available. These positive statistics suggest that the relationship is linear and stationary, at least throughout the 1901-1981 period. To increase the length of the calibration period as well as to use a calibration period closer in time to the time frame for which we wished to reconstruct, we used the entire 1901-1981 portion of first principle component time series as proxy data for mjPR in our Bayesian linear model. Despite our encouraging reconstruction statistics and high correlation between the proxy and climate variable, our model fit generated wide credible intervals which showed the uncertainty associated with the reconstruction.

Our reconstruction shows similar variability as other reconstructions of moisture variability in the southeastern US (Table 4). The strongest similarity was found with the NADA PDSI Cook reconstruction. A comparison of the relationship between these two moisture reconstructions identified two time periods in whic reconstructed values were not consistent, as shown in figure [14](#x1-901914) where the reconstructions are standardized prior to plotting to highlight both the similarities and the discrepancies. The first anomaly occurred in 1774, which our reconstruction identified as an early summer drought. Although this year showed low moisture relative to other years in several other regional reconstructions, the suggestion of drought was not as defined. A closer examination of the chronologies on which the principal component analysis was performed revealed that this drastic departure from the mean MJ precipitation signal was propogated through the PCA by the Craig Creek chronology. Since this year was not identified as a local minimum growth year in other chronologies we assume that this drastic reduction in growth at the Craig Creek site is site-specific, and is attributed to local disturbance with a localized effect on growth. The second anomaly manifested itself during the 1853 through 1866 period, where the correlation between both the NADA reconstruction and the mjPR reconstruction becomes no longer significant as shown by a 31 year windowed correlation (see figure [15](#x1-902015)). With the goal of better understanding this anomaly, we return to the five chronologies. A plot of a 31 year windowed correlation between each of the regional oak chronologies and the NADA pdsi reconstruction shows that all five chronologies show this same pattern of reduced correlation with the NADA pdsi reconstruction during these years, as shown in figure [16](#x1-902116). These years correspond with the persistent drought near 1860, which also coincides with a La Nina event which occured from 1855 - 1863. Although La Nina effects are typically seen on the West Coast, these events have effects on weather patterns throughout North America, and have even been shown to affect the Atlantic hurricane season (REF). As opposed to being driven by moisture availability, tree growth during these years was likely driven by the combination of high temperatures and low moisture availability brought on by the large-scale ocean-atmosphere phemomenon.

This study demonstrates that oaks in a closed-canopy forest can indeed be used to generate paleoclimatic data, although care must be taken when attempting to remove the non-climatic portion of the signal. The development of a biologically motivated trend removal algorithm is needed to improve current practices in dendroclimatology. In addition, care must be taken in closed canopy forests when attempting to use growth series as proxy records as early tree growth can be dominanted by the effects of stand competition as opposed to climatic factors (REFS)

Cyclicity?

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Chron | Lat (N), Long (W) | SIC | MS | # Series | MSL | Period | Citation |
| BM | 37.37, 80.24 | 0.556 | 0.208 | 76 | 128.3 | 1764 - 2010 |  |
| LH | 35.62, 85.43 | 0.609 | 0.171 | 19 | 181.4 | 1750 - 1997 | Stahle, D.W. |
|  |  |  |  |  |  |  | & Therrell, M.D. 2005 |
| WD | 38.50, 78.35 | 0.523 | 0.163 | 26 | 250.8 | 1642 - 1981 | Cook, E.R. 1994 |
| CC | 37.35, 80.37 | 0.592 | 0.218 | 20 | 194.1 | 1722 - 2001 | Copenheaver, C.A. 2010 |
| OC | 39.88, 76.40 | 0.575 | 0.169 | 18 | 260.2 | 1631 - 1981 | Cook, E.R. 1994 |
|  |  |  |  |  |  |  |  |

Table 1: Site-specific details for the Brush Mountain (BM), Lynn Hollow, Watchdog Mountain (WD), Craig Creek (CC), and Otter Creek (CC) sites, including location, series intercorrelation (SIC), mean sensitivity (MS), number of series (# Series), mean series length (MSL), and the data citation.

|  |  |  |
| --- | --- | --- |
|  | Climate covariate | |
| Proxy | mjPR | jjPDSI |
| BM | 0.50 | 0.55 |
| LH | 0.55 | 0.43 |
| WD | 0.39 | 0.61 |
| CC | 0.39 | 0.50 |
| OC | 0.24\* | 0.25\* |
| PC1 | 0.64 | 0.67 |
|  |  |  |

Table 2: Correlations between the growth proxies (site chronologies and first principal component PC1) with both the averaged May-June precipitation (mjPR) and averaged June-July PDSI (jjPDSI). All correlation statistics were significant at the p < 0.01 level except those indicated by \*, which were significant at the p < 0.05 level.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | mjPR | | jjPDSI | |
|  |  | |  |  |
|  | | |  | |
|  | early cal. | late cal. | early cal. | late cal. |
| RE | 0.11 | 0.40 | 0.52 | -0.16 |
| CE | 0.11 | 0.39 | 0.48 | -0.33 |
| Calibration R2 | 0.69 | 0.57 | 0.61 | 0.75 |
| Verification R2 | 0.57 | 0.69 | 0.75 | 0.61 |
| GLK | 0.58 | 0.85 | 0.75 | 0.59 |
|  |  |  |  |  |

Table 3: Reconstruction accuracy statistics for mjPR and jjPDSI. Statistics include the reduction of error (RE), coefficient of efficiency (CE), calibration and verification period R2.

|  |  |  |  |
| --- | --- | --- | --- |
| Parameter | Mean | Median | 95% CI |
| β0 | 102.73 | 102.72 | (98.51, 107.21) |
| β1 | 67.73 | 68.02 | (51.65, 83.66) |
| σ | 23.19 | 23.07 | (20.28, 26.40) |
|  |  |  |  |

Table 4: Posterior parameter mean, median, and 95% credible intervals for β0, β1 and σ.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | Recon | PDSI | | Precip | | | |
|  |  |  |  |  |  |  |  |
|  | |  | |  |  |  |  |
|  | | | |  | | | |
|  | MJ Precip | J | NADA | NC AMJ | SC MAMJ | GA MAMJ | VAA |
| MJ Precip | 1 |  |  |  |  |  |  |
| J PDSI | 0.235 | 1 |  |  |  |  |  |
| NADA PDSI | 0.643\* | 0.502\* | 1 |  |  |  |  |
| NC AMJ | 0.241\* | 0.396\* | 0.424\* | 1 |  |  |  |
| SC MAMJ | 0.127 | 0.178\* | 0.352\* | 0.581\* | 1 |  |  |
| GA MAMJ | 0.091 | 0.196\* | 0.345\* | 0.474\* | 0.766\* | 1 |  |
| VA | 0.382\* | 0.288\* | 0.499\* | 0.132 | 0.090 | 0.109 | 1 |
|  |  |  |  |  |  |  |  |

Table 5: Correlation between the mjPR reconstruction and other reconstructions including the Cook (NADA PDSI) and Stahle and Cleaveland (J PDSI) PDSI reconstructions, the Stahle and Cleaveleand (NC AMJ, SC MAMJ, GA MAMJ) and Druckenbrod (VA) precipitation reconstructions.

A Reconstruction only available for period 1764 - 1966. \* Significant at the p < 0.01 level.

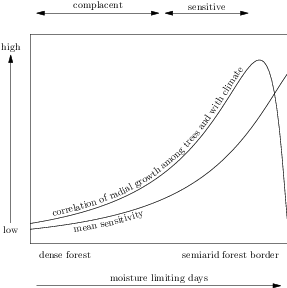


Figure 1: A simplified rendition of the diagram originally seen in [[10](#Xfritts1976tree)].

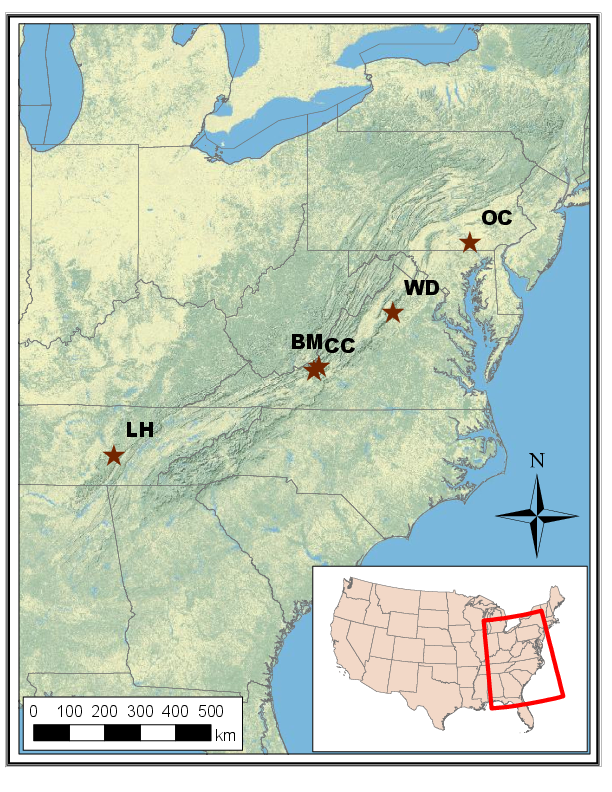


Figure 1: Regional chronology sample locations.

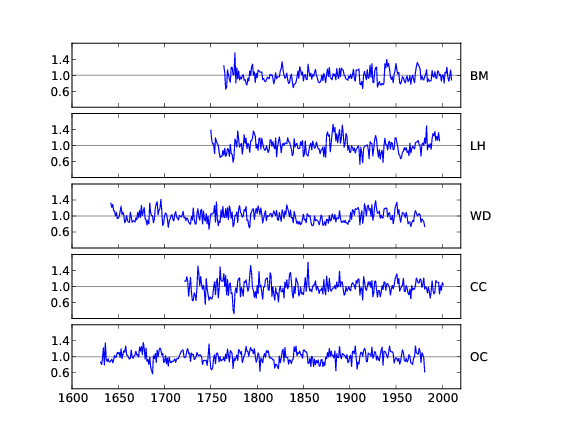


Figure 2: Plots of the five chronologies used in the principal component analysis. The top panel shows the chronology built from the sample data at Brush Mountain (BM), while the others are the regional chronologies from Lynn Hollow (LH), watchdog Mountain (WD), Craig Creek (CC), and Otter Creek (OC).

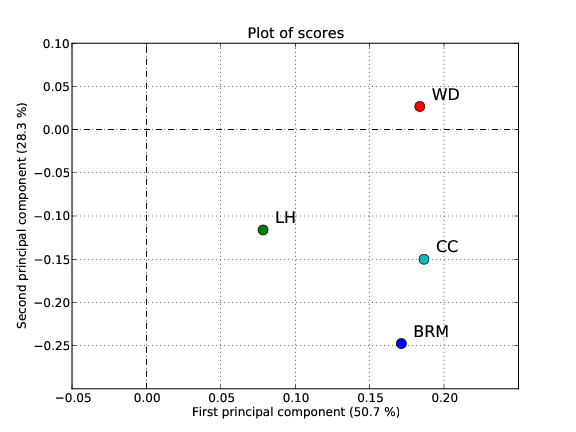


Figure 3: Plot showing the sample site scores when plotted on the First principal component versus second principal component axes.

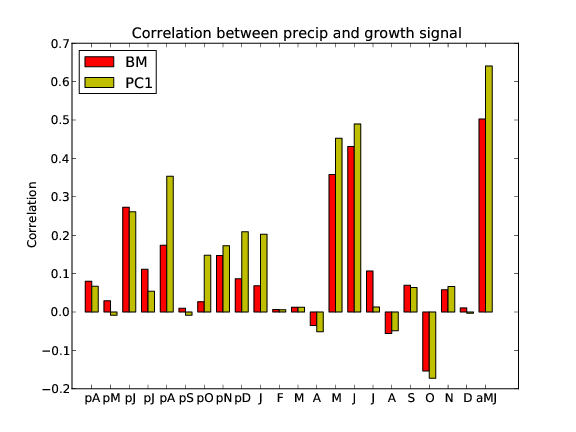


Figure 4a: Correlation between the site (BM) and regional (PC1) tree-ring chronologies and monthly precipitation from previous April (pA) through December (D) as well as for averaged May and June (aMJ).

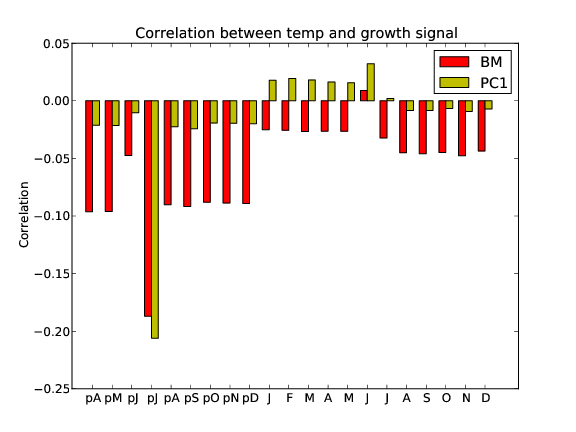


Figure 4b: Correlation between the growth proxies (BM or PC1) and average monthly temperature from previous April (pA) through December (D).

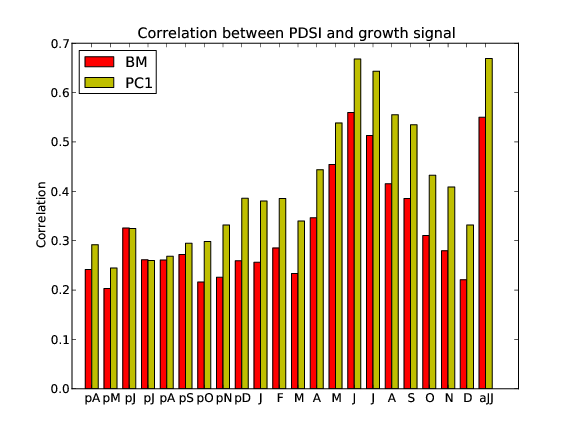


Figure 4C: Correlation between the growth proxies (BM or PC1) and average PDSI from previous April (pA) through December (D) as well as for averaged June and July (aJJ).

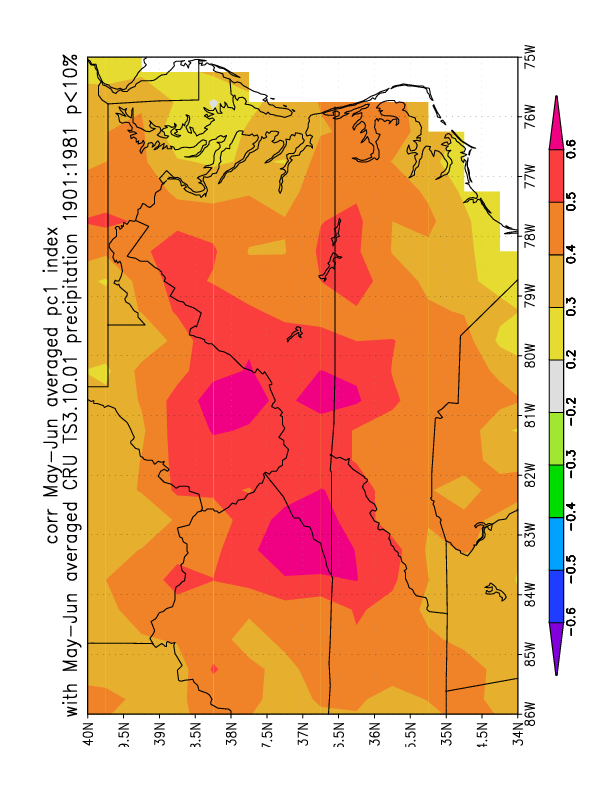


Figure 5: Correlation map showing the correlation between the first principal component and gridded May-June precipitation sums

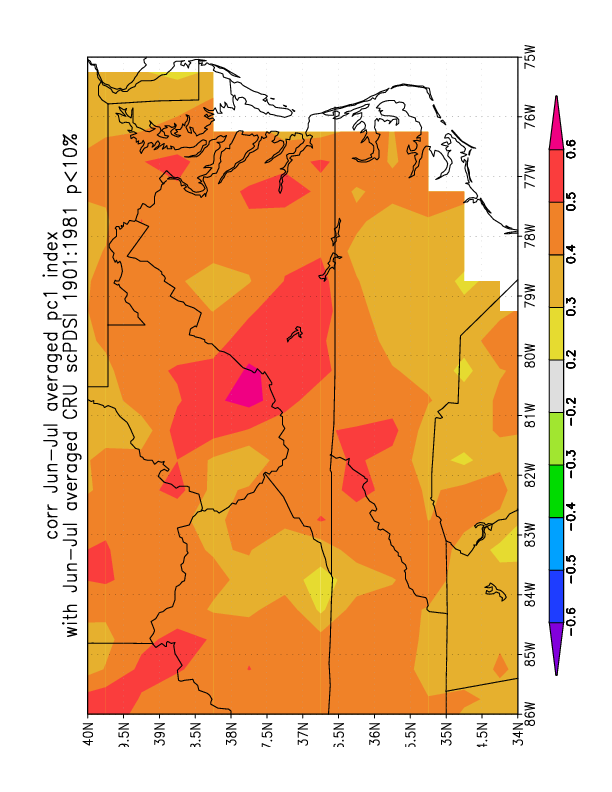


Figure 9: Correlation map.

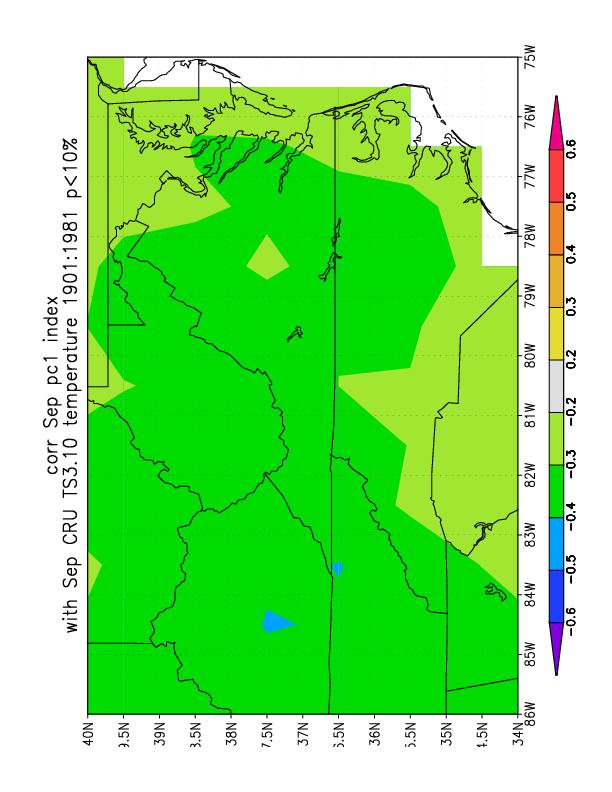


Figure 10: Correlation map showing the correlation between the first principal component and September temperature.

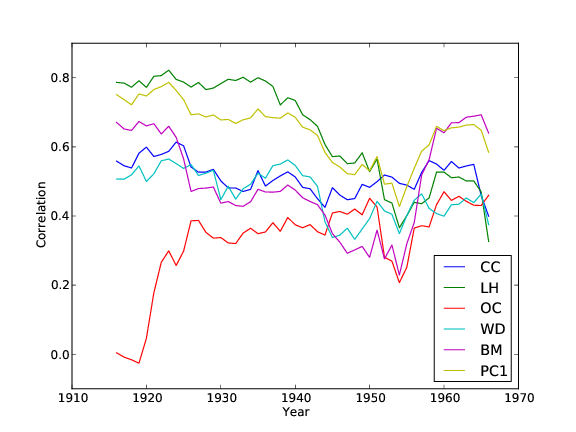


Figure 6: A 31-year windowed correlation plot showing the correlations between each growth proxy (chronologies and first principal component) and mjPR. Correlation points are plotted above the window centers.

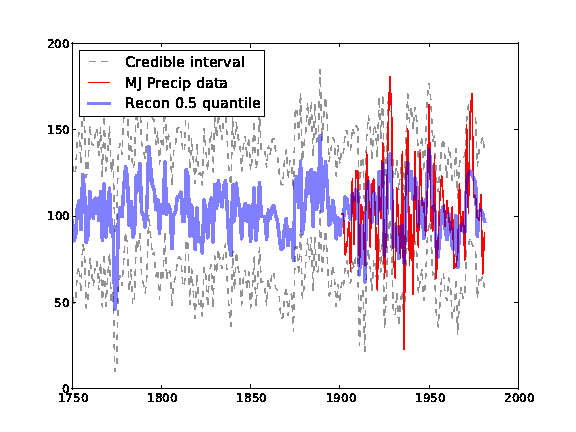


Figure 7: Average May-June precipitation (mjPR) reconstruction (blue line) and 95% credible interval (grey lines). Precipitation data is plotted in red for years available (1901-1981).

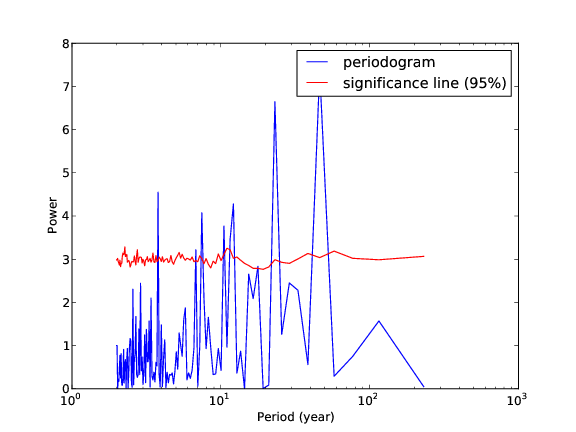


Figure 13: Periodogram showing periodicity of high amplitude at 46.2 and 23.1 years, as well as periodicity that is less pronounced with periods of 3.7, 7.5, 10.5, 11.6, and 12.2 years.

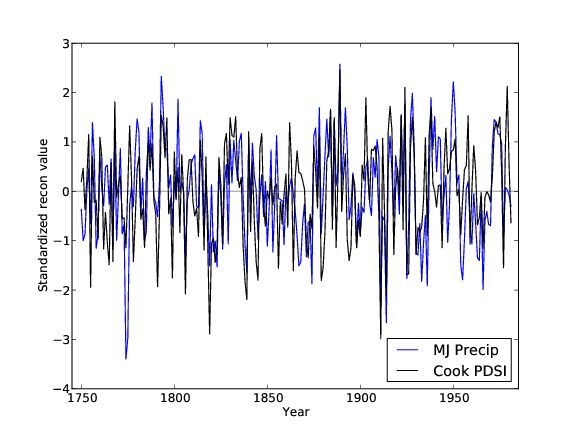


Figure 14: Both the mjPR reconstruction and the Cook PDSI reconstruction are standardized and plotted against time to highlight both the similarities and the differences. Particularly notable differences include the year 1774, and the interval 1855-1863.

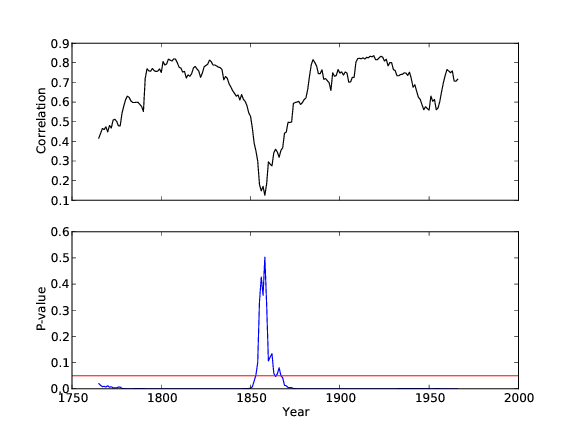


Figure 15: A 31 year windowed correlation plot between the mjPR and Cook PDSI reconstructions shows the discrepancy during the 1855-1863 interval. In the top panel correlation values are plotted about window centers, while the bottom panel shows the corresponding p-value (black) as well as the line of significance (red).

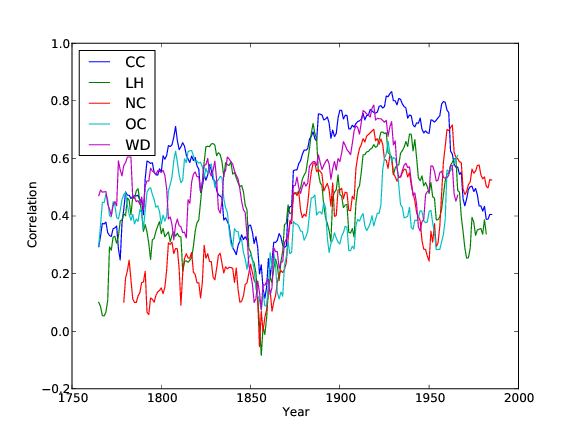


Figure 16: A 31 year windowed correlation plot between each of the chronologies and the Cook PDSI reconstruction. Note the interval of abrupt lack of! correlation during the years 1855-1863.

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