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

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### Abstract

In a closed-canopy forest, stand dynamics play an important role in shaping the forest, and it has been hypothesized that dense forests are not sufficiently limited by climate to warrant climate reconstruction. We collected *Quercus prinus* tree-ring data from a dense forest in the Appalachians, and after removal of stand dynamics and age trends we found strong influence of early summer precipitation on annual tree growth. We used the new *Quercus prinus* chronology in a nested principal component analysis (PCA) of southeastern US *Quercus prinus* chronologies and thus further strengthened the early summer precipitation signal in the tree-growth proxy with favorable assessment of reconstruction skill. Our reconstruction was modeled using Bayesian regression, which allowed uncertainty to be quantified. The May-June precipitation reconstruction covers the period 1750-1981 and extends the instrumental record by 150 years. It shows key drought years identified by other regional reconstructions, as well as an 11-year quasi-periodicity, possibly related to solar variability. This reconstruction establishes a baseline precipitation record that can be used to measure changes brought about by global climate change.

**Keywords:** reconstruction, precipitation, Virginia, tree rings, climate, principal components, forest, dendrochronology

### 1 Introduction

Global circulation models project an increase in average global surface temperatures of 1.0 - 3.5 ° C by the end of this century due to continued increases in greenhouse-gas emissions (IPCC 2013). 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). The 24 models used to make predictions about climate change in the Intergovernmental Panel on Climate Change Fourth Assessment Report were not in consensus with respect to drought frequency in this region (IPCC 2007, Seager et al. 2009). Uncertainty in climate projections makes it difficult to predict water 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 (Seager et al. 2009, Sobolowski et al. 2012). Recent droughts have had major socioeconomic impacts as a result of devastation to both agriculture and crop production (Wang et al. 2010). To deal with these issues, it is important that both urban and water planners in the southeast have access to information regarding climate change projections and mitigation. Through the use of tree-ring based climate reconstructions, we can better understand past precipitation regimes at both decadal- and centennial time-scales, improving projections of future precipitation patterns.

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, Büntgen et al. 2007) is the limiting tree growth factor. Tree-ring data have also successfully been used for climate reconstructions in temperate climate regions characterized by high humidity such as the eastern US (LeBlanc 1993, Stahle et al. 1993, Cook et al. 1999). Tree growth in these regions is typically less sensitive to drought variability than trees in semiarid regions (Phipps 1997). The amount of environmental variability recorded in tree-ring time series from a certain area thus generally depends on the degree to which environmental factors are limiting tree growth in that area (Fritts 1976). Furthermore, it is traditionally understood that trees in a closed-canopy forest are not limited by climate to the same extent as trees growing on the forest border. Within a dense forest, stand dynamics play an important role in shaping the forest structure through their influence on radial tree growth and tree survival. As these interactions between individuals increase in strength, the climatic influence on tree growth becomes less dominant.

Despite these challenges to capturing a strong climate signal in tree-ring time series from southeastern US forests, numerous studies have identified significant climate-growth relationships (Pan et al. 1997, Speer et al. 2009, Rubino & McCarthy 2000) and several tree-ring based precipitation reconstructions have been developed for the southeastern US. The most prominent of these reconstructions is likely a spring rainfall reconstruction for the past 1000 years based on Bald cypress (*Taxodium distichum*) tree-ring chronologies from North Carolina, South Carolina, and Georgia (Stahle & Cleaveland 1992). Bald cypress trees grow in excessively wet swamps, yet tree growth is strongly positively correlated with spring and early summer precipitation. At drier sites in Virginia, Pan et al. (1997) demonstrated for four deciduous species that both annual ring-width and basal area increments were positively correlated with precipitation from the prior summer and autumn, and current summer. They also report negative correlations with air temperature of the current growing season. Speer et al. (2009) found similar correlations between precipitation and temperature and annual tree growth for oak chronologies from closed canopy forests in the southern Appalachian Mountains.

In this study, we determine the presence of a significant relationship between chestnut oak (*Quercus prinus*; QUPR from here on) annual growth series in the southern Appalachian Mountains and early summer precipitation and develop a regional QUPR tree-ring chronology. We then use the QUPR chronology to reconstruct early summer precipitation using Bayesian methods. Finally, we evaluated the reliability of the reconstruction by comparing it to other regional climate reconstructions.

### 2 Materials and Methods

#### 2.1 Tree-ring data

We sampled 56 QUPR trees (two increment cores per tree) at an Upland Oak-Pine forest located on the north facing slope of Brush Mountain in southern West Virginia (37 ° 22.2’ N, 80 ° 14.8’ W), with a site elevation of 558 m (BM in Figure [1](#x1-120051)). 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 the nearby Blacksburg weather station is 1073 mm and the mean annual temperature is 10.9 ° *C*.

The study site supports dominant QUPR trees amongst a canopy of many species, including scarlet oak (*Quercus coccinea*), northern red oak (*Quercus rubra*), red maple (*Acer rubrum*), Virginia pine (*Pinus virginiana*), pitch pine (*Pinus pungens*), and eastern white pine (*Pinus strobus*). Site access was adjacent to 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, but the closed canopy and stand density suggested that stand dynamics may also play a significant role in shaping the forest structure (Fritts 1976).

Tree-ring samples were prepared for analysis according to standard dendrochronological procedures (Stokes & Smiley 1996). Crossdating was performed based on the list method, which makes use of marker years that signify relatively favorable or unfavorable growth years in a stand (Yamaguchi 1991). All samples were measured using a LINTAB measurement stage with 0.01mm precision, and visual crossdating was checked using COFECHA software (Holmes 1983). We used inter-series correlation, a measure of stand-level signal, and mean sensitivity, to select a total of 76 tree-ring series from 53 trees to be used for site chronology development.

Non-climatic age and stand dynamics related trends were removed from the individual tree-ring series using smoothing splines with a 50 % amplitude cutoff at 50 years using ARSTAN software (Cook & 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 (Cook & Peters 1981).We assume 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. The Brush Mountain site chronology was then calculated by averaging the individually detrended series using a biweight robust mean (Cook and Peters 1997), and will hereafter be referred to as BM.

We computed the expressed population signal (EPS) to measure the common variability in our chronology at an annual resolution. EPS depends on both signal coherence and annual sample-depth, and EPS values that fall below a predetermined cutoff (0.85) indicate that the chronology is not dominated by a coherent signal, and is therefore deemed less than ideal for climate reconstruction (Wigley et al. 1984).

#### 2.2 Principal component analysis

Water availability may not be the primary limiting factor to tree growth in southeastern US sites, but a large sample size may be sufficient to compensate for this effect and help to identify the common climate signals despite site and individual variability. In regions that are subject to site heterogeneity, where significant climatic variance cannot be identified for a standard sample size, principal component analysis (PCA) can be an effective means to extract the common signal in multiple sites and thus overcome the lack of strength of climate signal in individual sites (Peters et al. 1981, Anchukaitis et al. 2006, Jacoby et al. 1989). Through the application of PCA, tree-ring data collected from a network of regional sites can be combined to reduce site level noise through the identification of a common climate signal across sites.

To increase the strength of the precipitation signal in our chronology, we combined the BM chronology with four eastern US *Quercus* chronologies (3 QUPRand 1 *Quercus alba*) in a nested singular value decomposition PCA (Wold et al. 1987, Cook et al. 2007; Table 1, Figs. 1 and 2). These four chronologies extended back to at least 1845 (the length of the BM chronology) and were significantly correlated with regional precipitation anomalies (see below). Tree-ring data for the four *Quercus* sites were downloaded from the International Tree-Ring Database (ITRDB; http://www.ncdc.noaa.gov/paleo/treering.html) and individual ring-width time series were detrended using a smoothing spline with 50 % amplitude cutoff at 50 years (Cook & Peters 1981), and subsequently used to develop site chronologies. Chronology reliability for each of the four chronologies was assessed based on the mean sensitivity, inter-series correlation, EPS, and the first-order autocorrelation.

We applied a nested PCA approach to make use of the chronologies that extended prior to 1845 (Cook et al. 1999). The first PCA run (PCA1845) covered the period from 1845-1981, and included the BM chronology and all four *Quercus* chronologies. A second PCA run (PCA1750) covered the 1750-1981 period and only included the 3 chronologies that extended back to 1750 (LH, WD, and OC). Here, the goal of the PCA is to identify the common climate signal among the chronologies, and as such the axis explaining the largest amount of variance, the first principal component in both PCA1845 and PCA1750, was assumed to be the strongest common climate signal. More typically a PCA is used to determine the smallest dimension needed to adequately describe the variability in the larger dataset. In this case, the number of predictors is often determined based on criteria such as the Kaiser-Guttman rule, which states that the number of predictors is equal to the number of eigenvalues greater than 1. In PCA1845, only the eigenvalue associated with the first principal component axis (PCA1) was greater than 1, which provides additional support to the decision to use only a single axis as a predictor of climate. As such, only the PCA1 axes from both PCA runs were retained for further analysis and included in a climate correlation analysis. The PCA1 axes from PCA1845 and PCA1750 resulted in two chronologies, leading to two potential reconstructions, each with its own set of skill and accuracy statistics, as described in section [2.5](#x1-80002.5). To form the final SWV chronology (for southwest Virginia), we merged the two reconstructions at the year 1845 (1845-1981 from PCA1845 and 1750-1844 from PCA1750). We highlight that the BM chronology is determined for a single point, but that the SWV chronology is representative of the climate in the surrounding region as a result of being constructed from a PCA on growth series from sites spatially distributed around this point.

#### 2.3 Climate data

We applied a two-tier approach to select the optimal climate target for reconstruction. In a first step, we used monthly climate values from the Blacksburg climate station (37 ° 12’ N, 80 ° 24’ W; elevation 634 m; 1901-2006) in a correlation function analysis with the BM chronology. For this purpose, monthly precipitation sums, average temperatures, and Palmer Drought Severity Index (PDSI) values were computed from daily measurements. Pearson’s correlation coefficients were calculated for all months starting in April of the year previous to the growing season through current December, as well as for various seasons (Apr-June, July-Sep, Oct-Dec, Jan-Mar) and annual means. This analysis showed that the BM chronology was most strongly correlated with average May and June precipitation (r = 0.53, p < 0.01).

This result was then used in a second step as guidance for a spatial correlation analysis between the SWV chronology and a gridded (0.5 ° × 0.5 °) monthly climate data set for the period 1901-2006 [CRUTS3.10; Harris et al. 2014]. Spatial correlations were calculated using the KNMI Climate Explorer [[http://climexp.knmi.nl](http://climexp.knmi.nl/); Trouet & van Oldenborgh 2013]. The grid point showing the strongest correlation between the SWV chronology and May-June precipitation was then selected as a target for further climate-growth analysis and for reconstruction.

#### 2.4 Reconstruction methods

Precipitation was modeled using a Bayesian linear regression model, with the first PCA chronology (1750-1981) as a predictor. The precipitation model is written as

|  |  |  |
| --- | --- | --- |
| *yt* | ~ *Normal*(*μt*, *σ*2) | (1) |
| *μt* | = *β*0 + *β*1*xt*, | (2) |

where *yt* represents precipitation values for the identified grid cell and *xt* is the first PCA value at year *t*. Uninformative priors were placed on all three parameters as follows: *βi* ~ Normal(, 1000), and *σ*2 ~ Uniform(0, 100). Posterior distributions for all three parameters (*β*0, *β*1, and *σ*2) were sampled using an adaptive Markov Chain Monte Carlo (MCMC) algorithm with a Metropolis step method, in which proposal distributions were adjusted accordingly when acceptance rates fell outside the ideal range of 0.2-0.5. The algorithm was run for 100,000 iterations with a burn-in of 50,000. Parameter estimates were thinned so that only every tenth estimate was saved. The 0.025, 0.5 and 0.975 quantiles of these estimates were determined to define an upper and lower bound for a 95% credible interval, as well as the median. At each iteration, parameter estimates were used to compute estimated precipitation. A 95% predictive interval was computed from these precipitation estimates using the 0.025, 0.5 and 0.975 quantiles. Note that frequentist methods could have been used with similar results, but we preferred the simple interpretation of the Bayesian credible interval.

#### 2.5 Model calibration and verification

To assess the accuracy of the modeled precipitation anomalies and the temporal stability of the calibration model, we used a split-period (1901-1940 and 1941-1981) calibration/verification scheme. Both the 1901-1940 and 1941-1981 periods of climate data were used in turn as the calibration period (denoted by *yt* in [1](#x1-7001r1)), to determine if the accuracy of the reconstruction was sufficient to warrant further analysis. Data from the period not used for calibration served as verification data, and for both calibration/verification pairs we computed the mean squared error (MSE), reduction of error (RE) (Fritts 1976), coefficient of efficiency (CE) (Cook et al. 1994), and the variance explained (*r*2). Both the RE and the CE measure the predictive ability of the model specified using the calibration period relative to the means of the calibration (RE) or verification (CE) periods. Values greater than 0 indicate that the predictive ability of the model is better than predictions based on the mean alone. Also, data from the verification period are not used to fit the model, therefore 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.

#### 2.6 Reconstruction analysis

To define dry and wet regimes in the precipitation reconstruction, we first determined wet or dry years by assessing whether reconstructed precipitation values fell above or below a best fit line. Dry (wet) spells were defined when there were at least three consecutive dry (wet) years, on the condition that these dry spells were preceded or followed by two consecutive years of the opposite nature. Dry and wet regimes were also identified in all regional reconstructions that were significantly correlated with our precipitation reconstruction with the goal of identifying regional patterns. When these dry (or wet) periods overlapped with the periods identified in our precipitation reconstruction by two or more years, they were flagged as being common between reconstructions.

We performed a correlation analysis between our precipitation reconstruction and eight published regional drought, precipitation, and streamflow reconstructions, all primarily based on tree-ring data (Table 2). The two drought reconstructions described summer PDSI. The first reconstruction represents gridpoint 247 (80.0°W, 37.5°N) of the North American Drought Atlas (NADA), a gridded PDSI reconstruction field for the contiguous US for June through August over the last 2,000 years (Cook et al. 1999). The gridpoint used was selected based on proximity to our climate reconstruction target. The second drought reconstruction is a July PDSI reconstruction (JT) for Virginia and North Carolinian coastal regions (Stahle et al. 1998). In addition to these drought reconstructions, five precipitation reconstructions were considered. Three of these come from a set of reconstructions published by Stahle & Cleaveland (1992), 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. The fourth precipitation reconstruction describes May precipitation for the Mid-Atlantic region of the US (Maxwell et al. 2011) and the fifth reflects early summer precipitation anomalies for the Montpelier region (MP) and was based on tree rings and a meteorological diary (Druckenbrod et al. 2003). The final reconstruction used in this comparison was a Potomac River (PR) mean May-September streamflow reconstruction (Maxwell et al. 2012).

Reconstructions that correlated significantly with our reconstruction were subsequently compared with each other using 31-year window running correlations, which facilitated the identification of periods of pattern similarity.

Furthermore, we used a spectral analysis to identify regional cyclical behavior (Torrence & Compo 1998). Spectral analysis was performed on our precipitation reconstruction and on the overlapping time periods of any additional significantly correlated reconstructions. Spectrum values were averaged with 2 frequencies per bin to simplify interpretation.

Finally, we performed a correlation analysis between our precipitation reconstruction and climate index reconstructions representing the El Niño Southern Oscillation (ENSO; Cook et al. 2008) and the North Atlantic Oscillation (NAO; Trouet et al. 2009).

### 3 Results

The BM chronology covered the period 1764-2010 CE, had an interseries correlation of 0.556, and a mean sensitivity of 0.208 (Table [1](#x1-120011)). The EPS was higher than 0.85 for 1845-1981 CE and we thus used the chronology over this period. A spatial correlation analysis between climate variables from the overlapping period 1901-1981 CE and BM identified the grid point 37.5 - 38 ° N, 80.5 - 81 ° W as the location that correlated most strongly with our chronology (Fig. 3). The BM chronology was significantly positively correlated with monthly PDSI values from April of the previous year to December of the current year (Fig. 4B), except for previous May and previous October. We found particularly strong correlations between BM and monthly PDSI over the May through August growing season, with the highest correlation being with average June and July PDSI (jjPDSI; *r* = 0.55, *p <* 0.01). Furthermore, we found significant, positive correlations with precipitation of the previous year June and current year May and June (Fig. 4A). When averaging monthly precipitation values over the months May and June (mjPR), correlation increased to *r* = 0.5 (*p <* 0.01). The BM chronology did not correlate with monthly temperature values (Fig. 4C).

Based on this climate-growth analysis, mjPR and jjPDSI were considered as candidate targets for reconstruction. An assessment of the calibration/verification statistics for a reconstruction based on the BM chronology alone (results not shown), however, suggested that the climate signal was not sufficient to warrant adequate reconstruction skill. We therefore combined the BM chronology with four existing oak chronologies from nearby sites (Fig. [1](#x1-120051), [2](#x1-120062)) in a nested PCA approach. All four chronologies were significantly positively correlated with the mjPR and jjPDSI values from the monthly data set obtained from the spatial correlation analysis (mjPR r: 0.38-0.55; jjPDSI r: 0.48-0.59; see Table 1).

The first PC axis (PC11845) of PCA1845 explained 57% of the common variance, with the second axis explaining 15.2%. All oak chronologies had a positive loading on PC11845, thus reflecting the correspondence between the time series and the common driver of tree growth amongst the chronologies. PC1 of the PCA1750 run (PC11750) explained 56% of the common variance and PC21750 explained 28.3%. PC11845 and PC11750 were strongly positively correlated over the period of overlap (*r* = 0.93, *p <* 0.001) and we merged the two PC1 time series at the year 1845 (PCA1750: 1750-1844, PCA1845: 1845-1981) to form a single chronology (SWV) extending from 1750 to 1981. When comparing SWV with monthly climate variables, we generally find stronger correlations than for the individually contributing tree-ring series (Fig. [3](#x1-120073)) and this is particularly true for mjPR (*r* = 0.61, *p <* 0.01) and jjPDSI (*r* = 0.63, *p <* 0.01). We thus tested mjPR and jjPDSI as potential reconstruction targets in a split calibration/verification scheme (Table 3). RE and CE values were negative for jjPDSI when using the later calibration period (1942-1981), 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 mjPR rather than jjPDSI was based on these values. Our final mjPR reconstruction, now referred to as rSWV, was scaled against the entire 1901-1981 interval. Estimates of rSWV and corresponding 95% predictive intervals (similar to a confidence interval) were computed for each year of the period of reconstruction using posterior parameter draws (Fig. [5](#x1-120095)).

Fifteen dry regimes were identified in rSWV (Table XXX). The lonest dry periods lasted 9 years, from 1894 – 1902 and from 1962 – 1970. The dry regime with the lowest average monthly precipitation was from 1772 – 1775, with 50.6 mm mean precipitation. All dry periods except for the 1759 – 1762 and 1799 – 1801 periods overlapped with dry periods in at least one or more regional reconstructions. The 1894 – 1902 dry regime was found to be overlapping (by a minimum of 2 years) with dry periods in all six regional reconstructions, while the 1821 – 1823, 1879 – 1881, and 1806 – 1813 dry regimes were common among five regional reconstructions. NADA and JT each had 9 out of 15 overlapping dry regimes, while WV and PR each had 8.

Thirteen wet regimes were similarly identified. The top ranked wet regime was from 1971 – 1976, with an average monthly precipitation of 143.2 mm. None of these regimes were identified as being present in all six reconstructions. However, four wet regimes were identified as present in four of the regional reconstructions: 1971 – 1976, 1949 - 1953

Six dry regimes were identified in rSWV. The longest dry period lasted 8 years, from 1894-1902. Other dry periods, in chronological order were: 1799-1801, 1836-1839, 1911-1914, 1930-1936, and 1954-1956.

I think it would be a good idea to also detect dry/wet periods in the other recons that you show in Fig. 7. Then, in the discussion, you can focus on these common periods. Which are the periods that most recons have in common? Etc.

We compared rSWV to other regional drought, precipitation, and streamflow reconstructions over the common period (1750-1981 CE; Table 4) and found positive correlations across the board. The strongest correspondence was found with the NADA summer drought reconstruction (*r* = 0.53, *p <* 0.01), but we note that the LH chronology was used in the construction of both rSWV and NADA and these records are thus not completely independent. Other significant correlations, in decreasing order of strength, were found for MP (*r* = 0.38, *p* < 0.01), the PR streamflow reconstruction (*r* = 0.33, *p* < 0.01), NC (*r* = 0.24, *p* < 0.01), WV (*r* = 0.23, *p* < 0.01), and JT (*r* = 0.21, *p* < 0.01).

A spectral analysis of the rSWV reconstruction showed significant peaks at 8, 11, 24, and 42 years (Fig. 6). This 11-year quasi-periodicity was also significant in PR and JT, but not present in any of the remaining reconstructions that were significantly correlated with rSWV. Additionally, we found that PR shared a 42 year quasi-periodicity with rSWV.

We found no significant correlations between rSWV and the ENSO or NAO reconstructions.

### 4 Discussion

Climate models generally project changing precipitation regimes and drought frequencies in the southeastern US, but projections are subject to large uncertainties and are not in consensus. One of the difficulties in constraining these projections arises from the lack of long-term meteorological data. In lieu of having such long-term records, we can make use of climate proxies such as tree rings to reconstruct past climate conditions and improve our understanding of long-term climate variability that helps constrain and inform climate models. The precipitation reconstruction developed here contributes to our understanding of the climate history of the southeastern US, a region that is lacking in long-term climate data, proxies, and reconstructions.

We investigated the relationship between climate and annual radial QUPR growth at a closed canopy site in the southeastern US. After removing the portion of the signal attributed to stand dynamics and intrinsic age trends, we found that early summer (May through June) moisture was the strongest positive influence on radial growth. Similar climate-growth relationships have been identified by previous studies of oak in the southeastern US (Speer et al. 2009, Li 2011) and can be explained by ecophysiological mechanisms. Radial growth of oak species typically starts in April or May after leaf-out and is 90% complete by the end of July even in years with adequate moisture (Robertson 1992). QUPR is considered to be more tolerant to drought stress than other oak species and exhibits several morphological adaptations in order to better cope with moisture stress events (Dickson et al. 1996). However, we found that its radial growth was strongly influenced by moisture availability, suggesting that in years with inadequate moisture, radial growth is not a priority and carbon allocation is likely focused on maintenance or root development. The identifiable moisture response in the detrended BM chronology demonstrates that oaks in a closed-canopy forest can be used as paleoclimate proxies if the non-climatic portion of the low-frequency signal in the tree-ring time series is removed (Cook 1985, Cook et al. 1990).

To isolate and strengthen the moisture-growth relationship of the BM chronology, we performed a nested PCA including five regional summer moisture sensitive *Quercus* chronologies. The spatial pattern of the relationship between the resulting SWV chronology and early summer precipitation [indicates that spring moisture availability is the primary driver of tree growth in the Appalachian Region](#x1-120084) (Figure 3). We therefore used the PCA-based regional SWV chronology to reconstruct regional spring precipitation.

Our regional PCA-based precipitation climate proxy was linked to meterological data using a Bayesian hierarchical model, with the goal of being able to quantify prediction uncertainty. Reconstructing mean climate back through time is necessary to develop our understanding of the past, however, quantifying uncertainty around this mean climate estimate is of significant importance, i.e. in our understanding of the occurrence of extreme events. Assessing retrospective climate projections is challenging in the absence of long-term climate data; however, we can compare among reconstructions, often generated using different methods and proxies. An adequate quantification of the uncertainty around a climatic mean allows us to more formally assess differences between reconstructions. Bayesian hierarchical modeling provides a natural way to quantify uncertainty, through the estimation of posterior probabilistic distributions for model parameters, which can in turn be used to generate prediction uncertainties. Bayesian modeling has been used by others to reconstruct climate (see Tingley et al. and Toivonen). In the case of rSWV, we note that the uncertainty estimates are large. While it is preferable to be more certain, we argue the importance of acknowledging prediction uncertainty, and note that it allows us to ask whether other regional precipitation reconstructions fall within the bounds of our uncertainty estimates.

Our reconstruction shows similar interannual variability as other reconstructions of moisture variability in the southeastern US (Table 4). The strongest similarity was found with the NADA PDSI reconstruction (Figure 7), but we note the lack of full independence between these two records. Despite the overall strong agreement between both records, a 31-year windowed correlation between rSWV and NADA PDSI indicated that this pattern was not consistent for the period 1853-1866. In fact, the correlation analysis revealed that all five of the chronologies contributing to SWV showed a pattern of reduced correlation with the NADA PDSI reconstruction during this period, which coincides with a La Niña phase occurring from 1855-1863 (Cole et al. 2002). La Niña (negative ENSO) events typically have strong impacts on the West Coast , but have been shown to also affect temperatures in the eastern US (National Oceanic and Atmospheric Administration 2014) and the Atlantic hurricane season (Pielke et al. 1999). Temperature anomalies in the southeastern US during this La Nina phase, in combination with low moisture availability, likely led to a change in the otherwise stationary precipitation-growth relationship. It is worth noting that, despite this potential decadal-scale ENSO influence on SWV drought, we did not find a relationship between rSWV and reconstructed or instrumental interannual ENSO variability. This lack of ENSO influence on rSWV tree growth is likely due to the fact that (a) ENSO primarily influences southeastern US temperatures, whereas rSWV is sensitive to precipitation variability and (b) that the ENSO effect is strongest in the winter season whereas rSWV records early summer conditions.

The rSWV reconstruction shows anomalies that are consistent with the instrumental (1901-1981 CE) precipitation record (Figure [3](#x1-120073)). In particular, the reconstruction correctly identifies the severe US-wide dust bowl era drought in the 1930s as well as the epic drought of the 1950s (Fye et al. 2003). However, the rSWV reconstruction and instrumental record are less consistent prior to 1950 when compared at a decadal scale (Figure 5).This is indicative that the trees are either responding to a combination of other factors or are experiencing inconsistent lagged precipitation effects.

XXXX: Fix me!

In years prior to the instrumental record, the rSWV reconstruction records several dry periods including 1894-1902 CE. There is evidence of an overlapping dry period in the NADA, JT, and MP reconstructions. The other rSWV dry periods are less pronounced in the drought or precipitation reconstructions, or are not apparent.

The rSWV reconstruction shows an 11-year cyclicity (Figure [6](#x1-120106)), a pattern that has been observed in both instrumental and paleo-reconstructed temperature and moisture indices, such as the Northern Hemisphere annual average land air temperature record extending from 1851-1987 (REF?), the Northern Hemisphere annual temperature anomalies reconstructed from proxy data for 1579-1880 (REF?), as well as for many of the contiguous states using state-averaged instrumental temperature and precipitation records (Hancock & Yarger 1979, Lassen & Friis-Christensen 1995).

Did you run a spectral analysis on the other recons (Fig. 7)? Do any of them show a 11-yr cycle? If so, please include that here!

In particular, this cyclic pattern has been identified in June precipitation in the southeastern US (Hancock & Yarger 1979), but was not apparent in western US tree-ring based PDSI reconstructions (Cook et al. 1997). This observed 11-year quasi-periodicity is a characteristic of the solar cycle, which is reflected in terrestrial climate, and identified as one of the contributing factors that determine global temperature (Lassen & Friis-Christensen 1995, Reid 2002, National Research Council 1994). Solar periods of high and low activity can be measured by the number of sunspots or the solar cycle length (Friis-Christensen & Lassen 1991, Usoskin et al. 2003). A larger number of sunspots indicates greater solar activity and these changes in released solar energy may influence regional hydroclimate (Hancock & Yarger 1979, Nichols & Huang 2012). However, despite the presence of strong correlations between terrestrial climate records and solar cycles, physical mechanisms that explain the effects of external solar forcing on global circulation patterns have yet to be fully understood (Franks 2002).

We have shown that QUPR growth in the southern Appalachians is positively influenced by early summer precipitation and have successfully extended the instrumental record of May-June precipitation by 150 years. Extending the instrumental climate record improves our understanding of how climate affects tree growth and shapes ecosystems. This is particularly relevant in the Southern Appalachians, which is one of the most biologically diverse temperate forest systems. The Appalachian region has supported continuous forest communities longer than any other area on the North American continent, and hosts many rare, endemic species (NCNHP 2012). It further provides ecosystem services such as carbon storage, watershed and water quality protection, and serves as a timber source (Zipper et al. 2011). Understanding past climate-ecosystem relationships in this region will enable scientists and landowners to better manage natural resources in our current and projected changing climate. Our precipitation reconstruction will thus not only contribute to an improved understanding of decadal-to-centennial scale climate variability in the southern Appalachian region, but is also a valuable contribution to the climate information that is available to stakeholders.

### 5 Acknowledgements

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|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Chron | | Lat (N), | SIC | MS | N | MSL | mjPR | jjPDSI | Period | Citation |
|  | | Long (W) |  |  |  |  |  |  |  |  |
| BM | | 37.37, 80.24 | 0.556 | 0.208 | 76 | 128.3 | 0.50\* | 0.55\* | 1845 - 2010 | This study |
| LH | | 35.62, 85.43 | 0.609 | 0.171 | 19 | 181.4 | 0.55\* | 0.48\* | 1750 - 1997 | Stahle, D.W. |
|  | |  |  |  |  |  |  |  |  | & Therrell, M.D. 2005 |
| WD | | 38.50, 78.35 | 0.523 | 0.163 | 26 | 250.8 | 0.43\* | 0.59\* | 1735 - 1981 | Cook, E.R. 1994 |
| CC | | 37.35, 80.37 | 0.592 | 0.218 | 20 | 194.1 | 0.38\* | 0.50\* | 1800 - 2001 | Copenheaver, C.A. 2010 |
| OC | | 39.88, 76.40 | 0.575 | 0.169 | 18 | 260.2 | 0.24\*\* | 0.19 | 1745 - 1981 | Cook, E.R. 1994 |
|  |  | | | | | | | | | |

Table 1: Site-specific details for the Brush Mountain (BM), Lynn Hollow (LH), Watchdog Mountain (WD), Craig Creek (CC), and Otter Creek (CC) sites, including location, series intercorrelation (SIC), mean sensitivity (MS), number of series (N), mean segment length (MSL), correlations between the chronology with both the averaged May-June precipitation (mjPR) and averaged June-July PDSI (jjPDSI), the period for which the EPS is greater than 0.85, and the data citation. All correlation statistics between the chronologies and the weather data were significant (*p <* 0.01 indicated by \*, *p <* 0.05 indicated by \*\*), except for one (*p* = 0.19).

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Site | Location | Variable | Range (years) | Data type | Variance explained (R2) *A* |
| NADA [Cook et al. 1999] | 37° 30’ N, 80° 0’ W; VA | Jun-Aug PDSI | 1185-2006 | Tree rings | 0.55\* |
| JT [Stahle et al. 1998] | Coastal NC and VA | July PDSI | 1700-1984 | Tree rings | 0.44 |
| NC [Stahle & Cleaveland 1992] | Statewide NC | Apr-Jun precip | 933-1985 | Tree rings | 0.54 |
| SC [Stahle & Cleaveland 1992] | Statewide SC | Mar-Jun precip | 1005-1985 | Tree rings | 0.58 |
| GA [Stahle & Cleaveland 1992] | Statewide GA | Mar-Jun precip | 933-1985 | Tree rings | 0.68 |
| MP [Druckenbrod et al. 2003] | 38° 13’ N, 78° 10’ W; VA | Early summer precip | 1784-1966 | Tree rings & Meteorological diary | 0.39 |
| WV [Maxwell et al. 2012] | mid-Atlantic region | May precip | 1200-1997 | Tree rings | 0.28 |
| PR [Maxwell et al. 2011] | Potomac River | May-Sept streamflow | 950-2001 | Tree rings | 0.20-0.53 |
|  |  | | | | |

A *R*2 values as reported in cited references; may or may not be adjusted.

\* Median value of *R*2 for all gridpoints in the PDSI reconstruction grid (see [11]).

Table 2: Details for the eight southeastern US moisture reconstructions compared to the southwest Virginia reconstruction (rSWV).

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | Calibration proxy and period | | | | | |
|  | PCA1845 | | PCA1750 | | SWV | |
|  | 1901-1941 | 1942-1981 | 1901-1941 | 1942-1981 | 1901-1941 | 1942-1981 |
| RE | 0.10 (0.44) | 0.30 (-0.41) | 0.20 (0.26) | 0.42 (-0.66) | 0.10 (0.44) | 0.30 (-0.41) |
| CE | 0.10 (0.39) | 0.30 (-0.60) | 0.19 (0.20) | 0.41 (-0.88) | 0.10 (0.39) | 0.30 (-0.60) |
| Calibration r2 | 0.64 (0.58) | 0.56 (0.74) | 0.75 (0.62) | 0.55 (0.59) | 0.64 (0.58) | 0.56 (0.74) |
| Verification r2 | 0.56 (0.74) | 0.64 (0.58) | 0.55 (0.59) | 0.75 (0.62) | 0.56 (0.74) | 0.64 (0.58) |
|  |  | | | |  |  |

Table 3: PCA1845, PCA1750 and SWV reconstruction skill statistics for average May-June precipitation (mjPR), and average June-July PDSI (jjPDSI) in brackets. Statistics include the reduction of error (RE), coefficient of efficiency (CE), and the calibration and verification period *R*2.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | |  | | |  | |  |  |
|  | Recon |  | |  | | | |  |  |
|  | rSWV | JT | NADA | NC | SC | GA | WV | PR | MPA |
| rSWV | 1 |  |  |  |  |  |  |  |  |
| JT | 0.21\* | 1 |  |  |  |  |  |  |  |
| NADA | 0.53\* | 0.5\* | 1 |  |  |  |  |  |  |
| NC | 0.24\* | 0.40\* | 0.42\* | 1 |  |  |  |  |  |
| SC | 0.12 | 0.18\* | 0.35\* | 0.58\* | 1 |  |  |  |  |
| GA | 0.12 | 0.20\* | 0.35\* | 0.47\* | 0.77\* | 1 |  |  |  |
| WV | 0.23\* | 0.16 | 0.39\* | -0.05 | -0.02 | 0.02 | 1 |  |  |
| PR | 0.33\* | 0.21\* | 0.48\* | 0.14 | 0.04 | 0.06 | 0.24\* | 1 |  |
| MPA | 0.36\* | 0.29\* | 0.50\* | 0.13 | 0.09 | 0.11 | 0.19 | 0.15 | 1 |
|  |  | | | | | | |  |  |

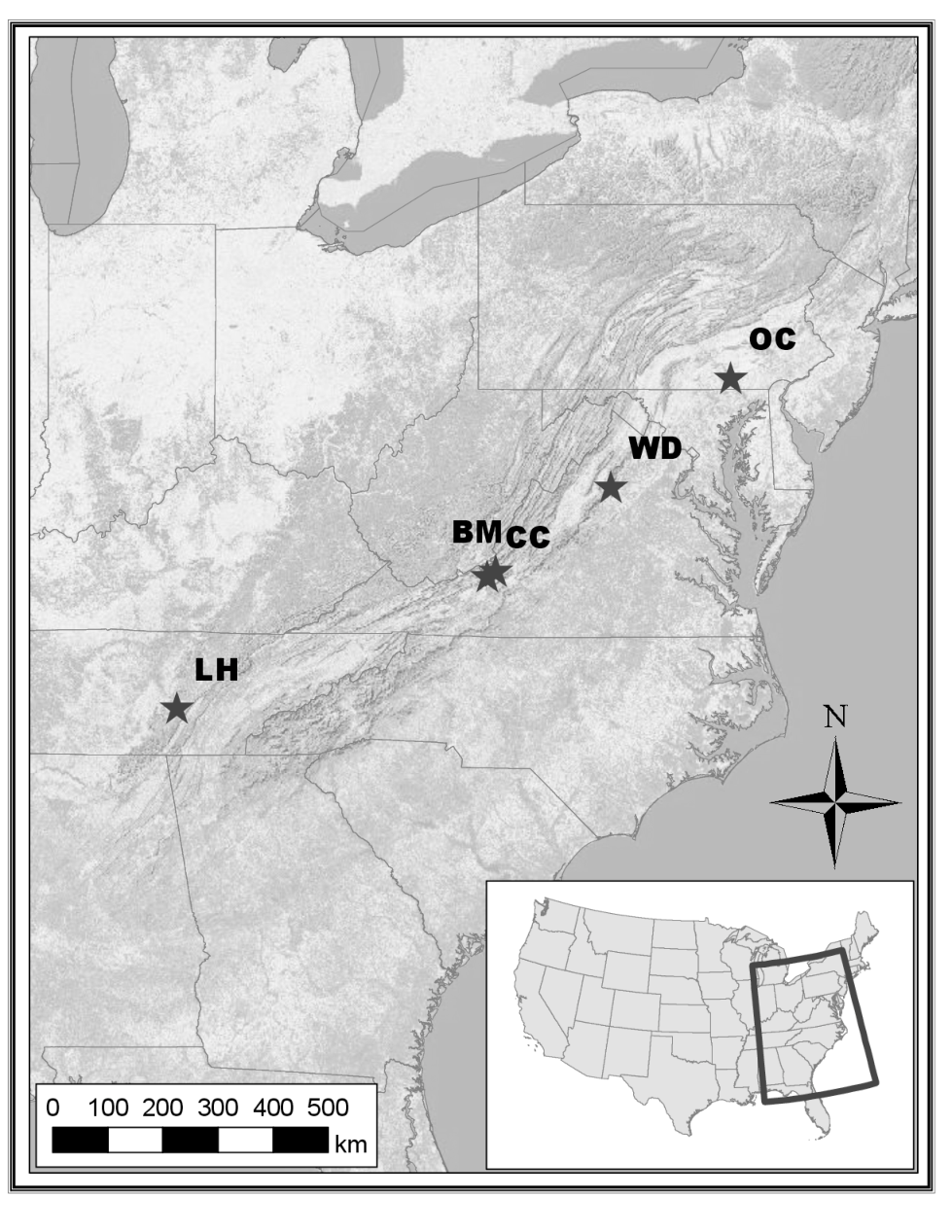
Table 4: Annual correlation (1750-1981) between the southwest Virginia reconstruction (rSWV) and other reconstructions including the NADA and JT drought reconstructions; the NC, SC, GA, WV, and MP precipitation reconstructions; and the PR streamflow reconstruction. All values indicated by \* indicate significant correlations at the *p <* 0.01 level.

A Reconstruction covers only the period 1764 - 1966.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Rank | Period | Mean precip (mm) | NADA | JT | NC | WV | PR | MP |
| 1 | 1772 -1775 | 50.6 | \* |  |  | \* |  | - |
| 2 | 1759 – 1762 | 57.8 |  |  |  |  |  | - |
| 3 | 1911 – 1914 | 58.1 |  | \* |  | \* |  |  |
| 4 | 1930 – 1936 | 64.5 |  | \* | \* | \* |  | \* |
| 5 | 1954 – 1956 | 71.6 |  |  | \* |  |  |  |
| 6 | 1962 – 1970 | 80.6 | \* |  |  | \* | \* | - |
| 7 | 1789 – 1792 | 80.9 | \* |  |  |  | \* |  |
| 8 | 1864 – 1871 | 82.0 |  | \* | \* |  | \* |  |
| 9 | 1821 – 1823 | 82.3 | \* | \* |  | \* | \* | \* |
| 10 | 1894 – 1902 | 85.4 | \* | \* | \* | \* | \* | \* |
| 11 | 1836 – 1839 | 85.7 | \* | \* |  |  | \* |  |
| 12 | 1879 - 1881 | 88.3 | \* | \* | \* | \* | \* |  |
| 13 | 1806 – 1813 | 88.5 | \* | \* | \* | \* | \* |  |
| 14 | 1799 -1801 | 87.5 |  |  |  |  |  |  |
| 15 | 1857 – 1859 | 90.2 | \* | \* |  |  |  |  |

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Rank | Period | Mean precip (mm) | NADA | JT | NC | WV | PR | MP |
| 1 | 1971 – 1976 | 143.2 | \* | \* | \* | \* |  | - |
| 2 | 1949 – 1953 | 141.2 | \* |  |  | \* | \* | \* |
| 3 | 1755 – 1758 | 139.4 |  |  |  |  |  | - |
| 4 | 1927 – 1929 | 137.7 | \* | \* |  |  |  | \* |
| 5 | 1793 – 1798 | 133.5 | \* |  |  | \* | \* |  |
| 6 | 1776 – 1783 | 133.2 | \* | \* |  |  |  | - |
| 7 | 1937 – 1943 | 131.3 | \* |  |  |  |  |  |
| 8 | 1907 – 1910 | 130.5 | \* | \* |  | \* | \* |  |
| 9 | 1891 – 1893 | 124.3 |  | \* |  |  |  |  |
| 10 | 1915 – 1917 | 121.0 | \* |  |  |  |  | \* |
| 11 | 1840 -1843 | 115.9 |  |  |  | \* |  |  |
| 12 | 1882 - 1884 | 115.5 | \* | \* | \* | \* |  |  |
| 13 | 1830 - 1835 | 114.5 | \* |  | \* | \* |  |  |

Table XXX: Dry (a) and wet (b) periods identified in rSWV ranked in order of severity as determined by mean precipitation over the period. Dry and wet periods were also identified for the regional reconstructions significantly correlated with rSWV, and in the case where there periods overlap by two or more years, they are identified by a \*.

Figure 1: Regional chronology sample locations.

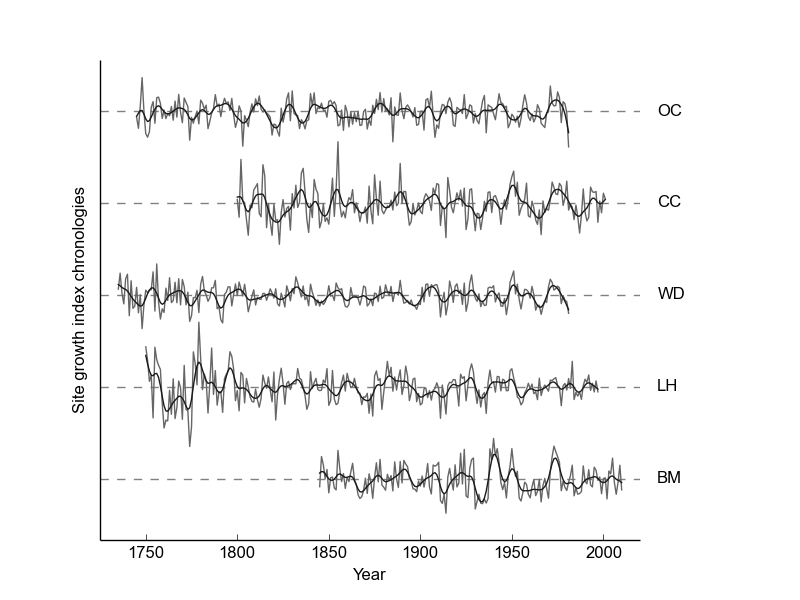


Figure 2: The five chronologies used in PCA1850. The chronology built from the sample data at Brush Mountain (BM) appears at the bottom, while the others are the regional chronologies from Lynn Hollow (LH), Watchdog Mountain (WD), Craig Creek (CC), and Otter Creek (OC).

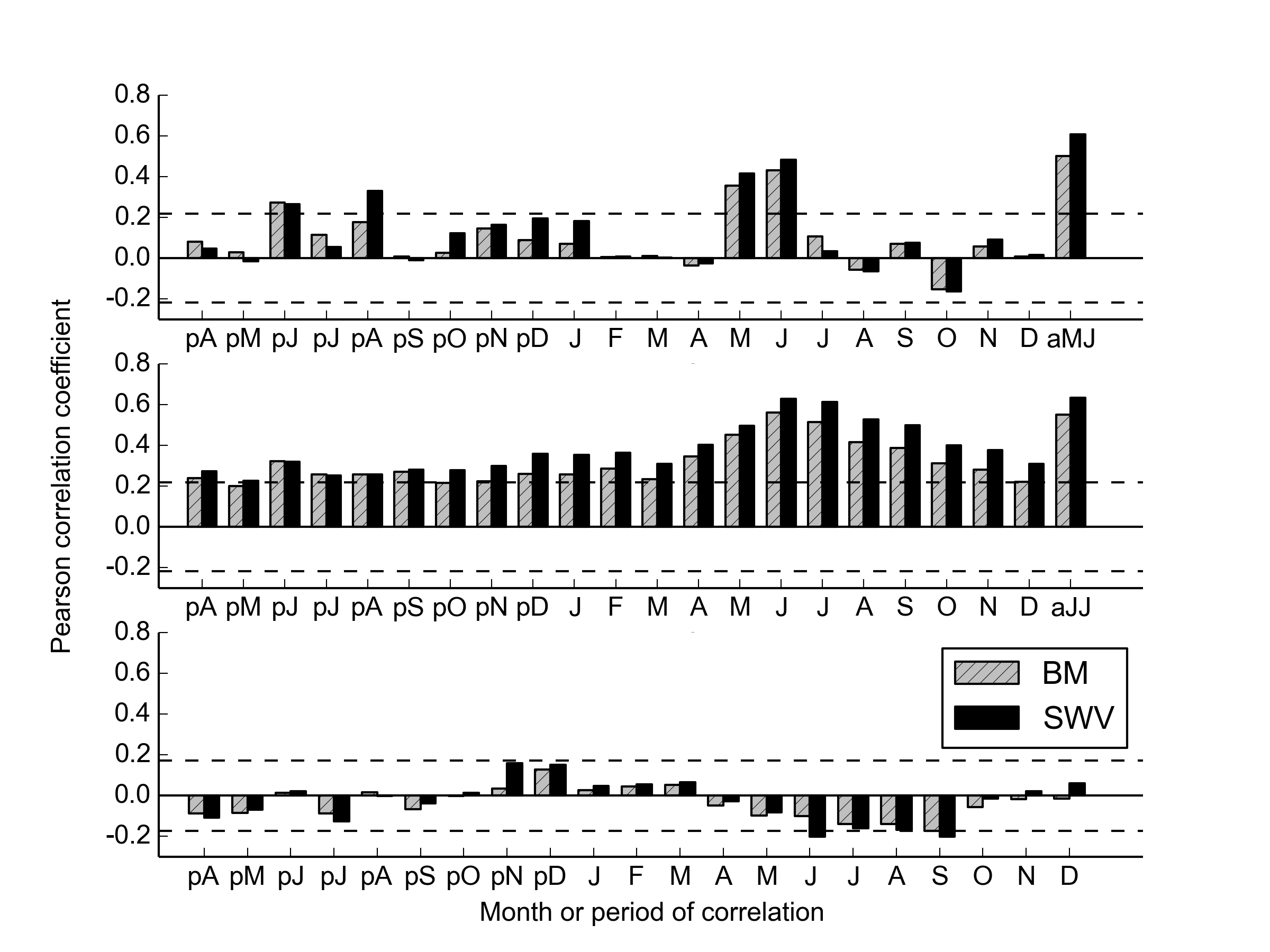


Figure 4: Correlation between the Brush Mountain (BM) and southwest Virginia (SWV) chronologies and the gridded (Top) monthly precipitation from previous April (pA) through December (D) as well as for average May and June (aMJ); (Center) average PDSI from previous April (pA) through December (D) as well as for average June and July (aJJ); and (bottom) average monthly temperature from previous April (pA) through December (D).

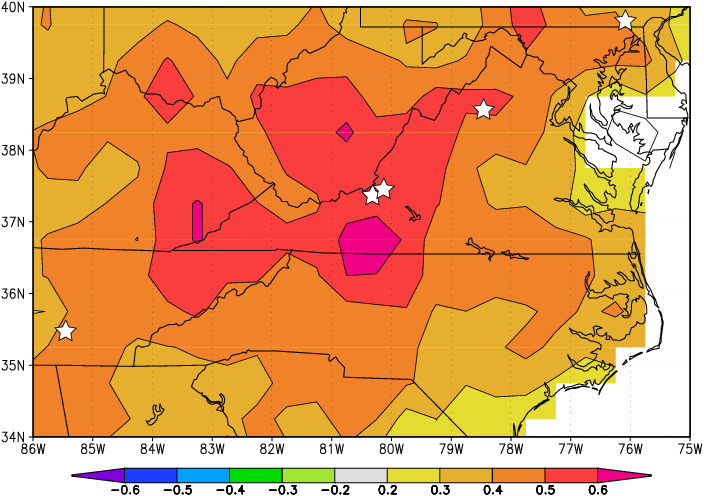


Figure 3: Correlation map (1901-1981) between the southwest Virginia chronology (SWV) and gridded average May-June precipitation (CRUTS3.10). Stars indicate the sample sites of the chronologies included in the nested principal component analysis resulting in the growth series extending from 1750-1981 (PCA1750).

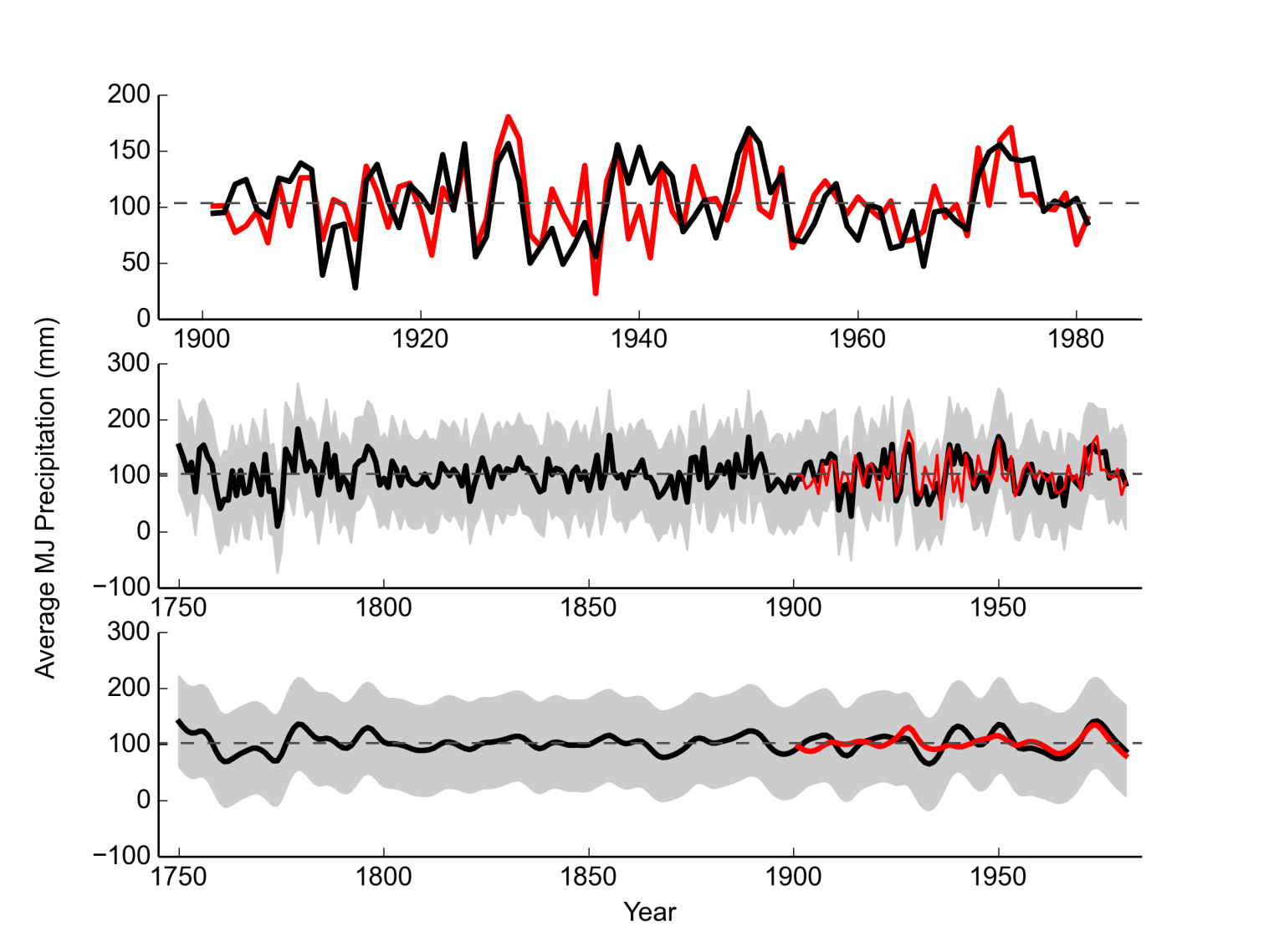


Figure 5: Top panel: southwest Virginia reconstruction (rSWV, black curve) and the average May-June precipitation (red curve; 1901-1981). Middle panel: rSWV reconstruction (black curve), 95% credibility interval (shaded grey area), and average May-June precipitation (red curve) for the 1750-1981 period of reconstruction. Bottom panel: Smoothed (10-year) rSWV reconstruction (black curve), 95% credible interval (shaded grey area), and average May-June precipitation (red curve). Smoothing performed using a 10-year smoothing spline to highlight decadal-scale variability.

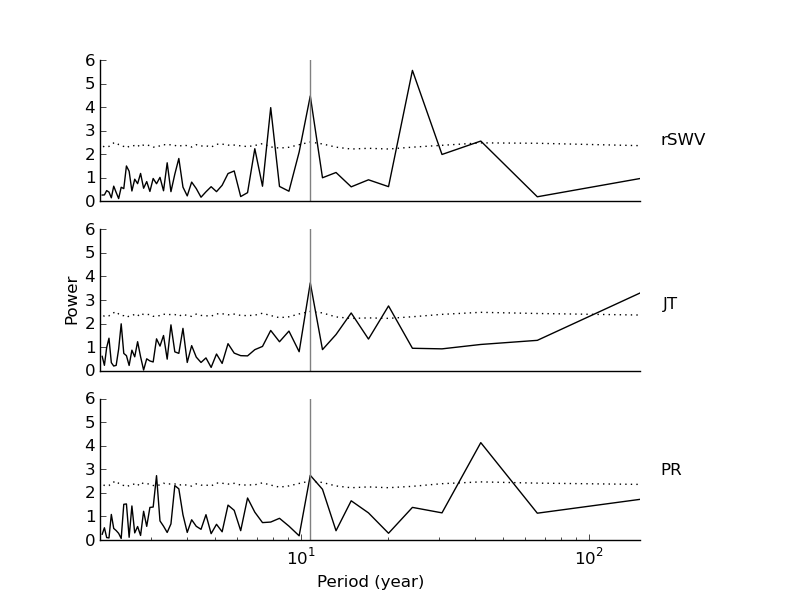


Figure 6: Periodograms of the southwest Virginia (rSWV), July Temperature (JT), and Potomac River streamflow (PR) reconstructions. All three show a common significant peak at 11 years, while rSWN shows additional significant peaks at 8, 11, 24, and 42.

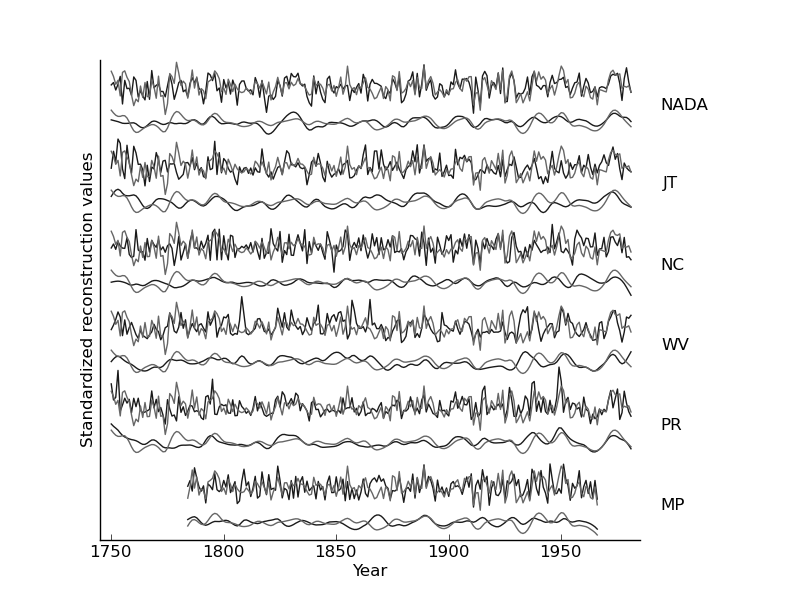


Figure 7: The standardized average May-June precipitation southwest Virginia reconstruction (rSWV, grey lines) is plotted on top of the other moisture reconstructions (NADA, JT, NC, WV, PR, and MP; black lines) which were significantly correlated to rSWV. Standardized reconstructions are shown at an annual scale and at a decadal-scale obtained by application of a 10-year smoothing spline. Particularly notable differences between rSWV and the other reconstructions are the year 1774 and the interval 1863-1872.

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