Report as of FY2010 for 2009TN61B: "Drought Variability in Reconstructed Streamflow"

Publications

• Dissertations:

• Articles in Refereed Scientific Journals:
Executive Summary and Research Results

On behalf of the graduate research assistants (Cody Moser, Tate Geren and Ross Ogle), Co-PI (Henri Grissino-Mayer) and the PI (Glenn Tootle), we hereby submit our final report *Reconstructions of Tennessee Valley Precipitation and Streamflow*.

The scientific objectives of the two-year research project were to:

1. Evaluate available tree-ring chronology data and identify streamflow gages of interest. (Year 1)
2. Evaluate methodologies used to reconstruct streamflow. (Year 1)
3. Examine linkages between reconstructed streamflow and large scale oceanic / atmospheric phenomena that act at interannual and interdecadal time scales. (Year 2)
4. Develop probabilistic forecasts of droughts, and frequency / duration analysis of droughts. (Year 2)

The research provided outstanding training and support for the above mentioned graduate students. Cody Moser completed his Ph.D. in May 2011 while Tate Geren and Ross Ogle completed their Master’s degree(s) in December 2010.


The research is currently under review in the *Journal of the American Water Resources Association* (pages 3 thru 30 below) and is in preparation for submittal to *Tree Ring Research* (pages 31 thru 51 below).

The results of the research made several contributions including the improvement of reconstructions of precipitation in the Tennessee Valley and the first successful reconstructions of streamflow in the Tennessee Valley. Literature review, data, methods, results and conclusions are provided below.
ABSTRACT

A considerable record of past climate has been reconstructed for the southwestern United States (U.S.), but little knowledge exists about the history of climate in the southeastern part of the country. We investigate the dendroclimatic potential of a critical flood control and hydropower region in the southeastern U.S. (Tennessee Valley) using climate division precipitation and regional tree-ring chronology datasets. Predictors (i.e., tree-ring chronologies) are pre-screened using correlation (p ≤ 0.05) with regional precipitation to ensure a practical and reliable reconstruction. Model calibration was based on the period 1895–1980 and a rescaling technique was applied to create the reconstruction. Tennessee Valley spring-summer (May–July) precipitation was reconstructed from 1692 to 1980 (289 years) using a stepwise linear regression model. The reconstruction model explains 56% of the variance in spring-summer precipitation records while the reduction of error (RE) statistic indicates valuable information exists in the reconstruction. The Weibull technique, which is frequently used in the field of hydrology, was applied to the field of dendroclimatology to visualize problematic areas (i.e., frequency regimes) of the climate reconstruction. The Weibull analysis illustrates that the Tennessee Valley reconstruction model developed generally underestimates extreme precipitation and

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overestimates average precipitation. The reconstruction reveals 15 drought periods in which Tennessee Valley spring-summer rainfall was below average for at least three consecutive years. The longest May–July drought occurred over 10 consecutive years (1827–1836). Instrumental records indicate that the two most recent droughts rank second and third in severity in the past three centuries. The reconstruction provides valuable climatic variability information that can be used to assess current conditions and manage water resources in the region. This information is especially valuable given the reservoir operation of the Tennessee Valley Authority (TVA).

(KEY TERMS: Tennessee Valley; dendrochronology; tree rings; precipitation; climate variability; water supply; time series analysis.)

INTRODUCTION

Dendroclimatology is the science of extracting climatic information from the annual growth layers of woody plants, and assumes that these growth layers contain the environmental conditions under which they were formed (Fritts, 1971; Hughes et al., 1982). 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 (Meko et al., 1995). Since all forest sites are not equally influenced by interannual variations in the regional climate, dendroclimatologists search for the particular marginal forest sites where precipitation and temperature variations strongly limit tree growth (Stahle and Cleaveland, 1992). The recovery of valid climate information from tree-ring data relies upon the regular formation of distinctive annual-growth layers, the selection of trees from climate-sensitive forest sites, and on the
accurate cross-dating of annual rings to their exact year of formation (Douglass, 1941; Stokes and Smiley, 1968; Fritts, 1976).

Annual tree-ring data are uniquely suited for high-resolution climate reconstructions and have been widely used to reconstruct climatic conditions and atmospheric oscillations. Valuable reconstructions of drought (Girardin et al., 2006; Cook et al., 2007; D’Arrigo et al., 2008), climate indices (Cook et al., 2002; Gray et al., 2004; Braganza et al., 2009), precipitation (Stahle and Cleaveland, 1994; Dettinger et al., 1998), streamflow (Meko et al., 2007; Watson et al., 2009; Barnett et al., 2010), and temperature (Wiles et al., 1998; Yadav et al., 1999; Cook et al., 2000) provide important baseline information for evaluating current trends in climate and for placing possible future changes within a historical context. Given the great age and extensive spatial coverage of tree-ring chronologies in the temperate latitudes of the Northern Hemisphere, tree rings can provide one of the best sources of information on natural climate fluctuations to measure the anticipated climate changes of the future (Stockton et al., 1985; Stahle and Cleaveland, 1992). Moisture-sensitive trees species are ideal in dendroclimatic research and the arid and semi-arid conditions of the southwestern U.S. offers the opportunity to create statistically skillful tree-ring reconstructions of climate variables. However, in the southeastern U.S., many misconceptions still linger among scientists that tree-ring research simply is not possible 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 (Grissino-Mayer, 2009).

While dendroclimatology has a long history in the southwestern U.S., the science in the southeastern U.S. has been discontinuous, largely because the forests of the region are more mesic and have been extensively cleared or impacted by management practices (Grissino-Mayer, 2009). Although misconceptions still exist regarding the applicability of dendroclimatology in
the Southeast, tree rings in the region have been used to investigate the relationships between climate and tree-growth. Using seven tree-ring chronologies, Phipps (1983) reconstructed April–August streamflow in Virginia. Tainter et al. (1984) used dendrochronology to investigate red oak species decline within the western North Carolina Nantahala Mountains. The 1,000-year spring-summer precipitation reconstruction created by Stahle and Cleaveland (1992) was found to replicate most of the multidecadal variability apparent in the available instrumental rainfall data within North Carolina, South Carolina, and Georgia. These studies form the foundation to dendroclimatology in the southeastern U.S. However, it is evident that very little dendroclimatology research has been conducted within the southeast U.S. during the past 20 years.

Our first objective evaluates the dendroclimatic potential in the Tennessee Valley using tree-ring chronologies. Blasing et al. (1981) attempted the first tree-ring reconstruction within the Tennessee Valley. Updating the reconstruction will provide valuable graphical and statistical information about regional climatic drivers and patterns. We hypothesize that the research of Blasing et al. (1981) can be improved statistically, spatially, and graphically with the incorporation of modern statistical software, visualization tools, and mapping capabilities. Next, a Weibull exceedance probability technique is applied. The presented Weibull technique is a new contribution to the field of dendroclimatology. The method can be used to visualize problematic areas of a climate reconstruction and determine the validity of a reconstruction. Finally, we examine the long-term hydrologic variability in the Tennessee Valley and determine drought phases based on the reconstruction. Analyzing the multidecadal variability of precipitation on a timescale longer than the instrumental record provides valuable water availability information to Tennessee Valley water resource planners and managers.
SITE DESCRIPTION

The Tennessee Valley Authority (TVA) operates and maintains water resources in the Tennessee Valley. TVA works to support economic development and serves as an environmental steward of the nation’s fifth largest river system. Dams operated by TVA store the water needed to generate clean, efficient electric power and help prevent hundreds of millions of dollars in flood damage. Our study area encompasses eastern Tennessee and western North Carolina (Figure 1) within the Southern Appalachian region and the Great Smoky Mountains National Park (GSMNP). The crest of the Smoky Mountains forms the boundary between Tennessee and North Carolina and elevations range from 250 to 2,000 meters (NPS, 2010). GSMNP has a moderate climate, typified by mild winters and hot, humid summers. GSMNP experiences more annual rainfall (90 to 180 cm) than anywhere else in the country except the Pacific Northwest and the relative humidity in the park during the growing season is about twice that of the Rocky Mountain region (NPS, 2010). Both of these climatic factors provide exceptional growing conditions. Almost 95% of the GSMNP is forested, and about 25% of that area is old-growth forest making it one of the largest blocks of deciduous, temperate, old-growth forests in North America (NPS, 2010).

DATA AND METHODS

Tree-Ring Chronologies

Tree-ring chronology data are available from the International Tree-Ring Data Bank (ITRDB, 2010) (http://www.ncdc.noaa.gov/paleo/treering.html). Datasets are maintained by the National Oceanic and Atmospheric Administration (NOAA) Paleoclimatology Program and the World Data Center for Paleoclimatology. Available data include ring width measurements, wood
density measurements, and site chronologies. Tree-ring chronology datasets within and around the eastern Tennessee Valley were collected. All ring width series were uniformly processed and standardized using the ARSTAN program (Cook, 1985). Conservative detrending methods (negative exponential/straight line fit or a cubic spline two thirds the length of the series) were used to combine all series into a single site chronology (Cook et al., 1990). Low-order autocorrelation in the chronologies that may, in part, be attributed to biological factors (Fritts, 1976) was removed, and the resulting residual chronologies were used for analysis. Because the reconstruction length and moisture sensitivity of eastern U.S. tree species was unknown at the time of data collection, approximately 70 regional chronologies were collected (Figure 1).

Precipitation

NOAA provides monthly climatic datasets (i.e., temperature, precipitation, and Palmer Drought Severity Index) for each U.S. climate division. 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. Four climate divisions were used in our study; two located in Tennessee (Eastern and Cumberland Plateau) and two within North Carolina (Southern Mountains and Northern Mountains) (Figure 1).

Identifying Similar Precipitation Regions

We use a rotated principal components technique similar to Timelsena and Piechota (2008) to regionalize the climate division precipitation datasets. Principal components analysis (PCA) is a widely used technique in meteorology and climatology (Baeriswyl and Rebetz, 1997)
and is sometimes used to reduce the size of climate datasets without losing critical information. Spatial regionalization based on the principal components of climate variables is called S-Mode PCA (Richman, 1986). Following Timelsena and Piechota (2008), a principal component factor loading cutoff value of 0.6 was used to establish statistically similar climatic regions. As an alternative to reconstructing the precipitation for each climate division, S-Mode PCA determines if regional precipitation can be reconstructed, thus providing increased value. Blasing et al. (1981) concluded that it was generally true that division data, and 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. S-Mode PCA results provided the basis for the regionalization of the reconstruction area.

**Seasonal Reconstruction**

We use correlation between various seasons for regional (as identified by PCA) precipitation and yearly residual with measurements for tree-ring chronologies (in and adjacent to the precipitation region) to identify the precipitation season most influential to tree growth and therefore most suitable for reconstruction. 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 (Chen and Popovich, 2002). Due to varying climatological and biological influences in the region, a 95% (positive) significance level ($p \leq 0.05$) was chosen. Blasing et al. (1981) discovered tree rings in the region contain the highest moisture signal with May-June precipitation. We consider the relationship between tree growth and ten different precipitation seasons of various durations. Three-month seasonal
precipitation periods investigated include January–March, April–June, May–July, July–September, and October–December. Six-month seasonal precipitation periods include January–June, April–September, and July–December. May-June and annual precipitation are also considered. We retain significant, positive r-values for analysis.

Reconstruction Methodology

Model calibration and verification in the region was based on the period from 1895 to 1980 (n = 86). 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 (Blasing et al., 1981). Following the procedure of Woodhouse et al. (2006), the F-level for a predictor had a maximum p-value of 0.05 for entry and 0.10 for retention in our stepwise regression model.

Next, the ability of the variables to predict precipitation was tested using a split sample calibration-verification scheme (Meko and Graybill, 1995; Woodhouse, 2003). 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. The split sample scheme is an alternative method to calibrate and verify models and will confirm or deny the results from stepwise regression.
Graumlich (1987) and Grissino-Mayer et al. (1989) discovered that the final climatic reconstruction has less variability than the original climate data used in the regression analysis. In our study, predicted values from the regression model were rescaled to have the same variance as the instrumental record. First, the mean of the predicted series was subtracted from each predicted value. Next, each centered observation was multiplied by a scaling factor, $k$, defined as:

$$k = \frac{s_x}{s_p}$$

(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. The rescaling method results in a more realistic climate reconstruction without affecting the overall skill of the model.

Statistics calculated to assess model skill and proficiency include overall variance explained ($R^2$), $R^2$-predicted, reduction of error (RE), and the Durbin-Watson statistic. While $R^2$ 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. RE accounts for differences in magnitudes between observed and predicted values by testing the ability of the regression model to estimate precipitation compared to estimates based on the calibration period mean. $R^2$-predicted was calculated from the Predicted REsidual Sums of Squares (PRESS) statistic. PRESS is based upon a leave-one-out cross-validation in which a single year or observation is removed when fitting the model. As a result, the prediction errors are independent of the predicted value at the removed observation (Garen, 1992). The Durbin-Watson statistic was used to check for autocorrelation in the residuals. For model validation, it was imperative that the predictor chronologies and
reconstruction residuals contained similar autocorrelation structures. Root mean square error (RMSE), a measure of the differences between predicted and observed values, was also calculated and provided an additional measure of model skill.

**Weibull Exceedance Probability**

The Weibull equation is the most efficient formula for computing plotting positions for unspecified distributions (Viessman and Lewis, 2003).

\[
P = \frac{m}{(n+1)}
\]

(2)

P is an estimate of the probability of values being equal to or greater than the ranked value, \(m\) is the rank of descending values, and \(n\) is the number of values. Weibull exceedance probability plots provide water managers comprehensive estimates of average precipitation, flows, and extreme events. We calculate the Weibull distribution separately for the reconstruction and observed datasets. Our novel approach plots the Weibull distributions together and provides a visualization tool for the accuracy of the reconstruction model over the full range of precipitation values during the calibration period (1895 to 1980). The evaluation of reconstructed precipitation values before the instrumental record was based on the errors associated with the Weibull plot. The presented Weibull technique may be applied to compare any two time-series of similar lengths (i.e., observed and modeled).
RESULTS

Seasonal Reconstruction and Identification of Similar Precipitation Regions

Similar to Blasing et al. (1981), our correlation analysis between seasonal precipitation data and regional chronologies indicates tree-ring sensitivity to climate conditions from spring-summer moisture. DendroClim 2002 from Biondi and Waikul (2004) indentifies a significant correlation with May, June, and July precipitation, with May and June showing the strongest moisture signal. Henderson and Grissino-Mayer (2009) found positive relationships between spring-summer precipitation and tree growth in the Southeastern Coastal Plain and Stahle and Cleaveland (1992) found that April–June precipitation had the strongest relationship with tree growth in North Carolina, South Carolina, and Georgia, which further confirm our results. Large quantities of tree-ring chronologies were statistically significant with May-June, April–June, and May–July precipitation (Figure 2). The three-month precipitation seasons of January–March, July–September, October–December and six-month season of July–December were insignificant (i.e., very few moisture sensitive chronologies). Several tree-ring chronologies were significant with respect to the precipitation seasons of January–June, April–September and January–December (annual). However, this was observed because these periods contain the highly sensitive period of April through July within their time-series, making these periods unsuitable to reconstruct. May–July contains a stronger moisture signal compared to April–June. Rather than reconstructing May-June precipitation as performed in Blasing et al. (1981), we elect to reconstruct May–July precipitation because reconstructing a three-month season provides more climatic variability and temporal information. May-June precipitation reconstructed in Blasing et al. (1981) accounts for 15–20% of total annual precipitation while 25–35% of total annual precipitation occurs in May–July.
Correlation analysis indicates that all four climate division precipitation datasets are highly related (significant at p < 0.01) to each other. Following Timilsena and Piechota (2008), S-Mode PCA reveals that all four climate division precipitation datasets also exceed the factor loading cutoff value of 0.6. Therefore, the four climate divisions were merged (averaged) similar to Woodhouse (2003). The reconstruction region contains 42 tree-ring chronologies that were significant with May–July precipitation (Figure 2). To further investigate and better understand the dendroclimatic potential of the southeastern U.S., tree-ring chronologies that were significant (95%) with spring-summer precipitation were analyzed by species (Figure 3). Within the southeastern U.S., the ITRDB contains more oak chronologies than any other species. Approximately 60% of the oak chronologies in the region were significant with May–July precipitation. While fewer bald cypress and hemlock chronologies have been cored in the region, they contain a similar moisture signal (~60%). All tulip and cedar chronologies in the region contain a significant spring-summer moisture signal although very few (less than 5) of these species have been collected. Spruce and pine species contain the weakest moisture signal in the region (Figure 3).

Calibration and Verification of the Reconstruction Model

A spring-summer (May–July) precipitation reconstruction dating back to 1692 was most feasible in this region. We base feasibility on the balance between reconstruction length and predictability of the calibration model. Five tree-ring chronologies (Table 1) within and around the reconstruction region were retained in the stepwise regression model. The Scotts Gap chronology is a tulip poplar, Mt. Collins a spruce, and the Land Between the Lakes an oak species. Two Bald Cypress chronologies (Lassiter Swamp and Black River) from Stahle and
Cleaveland located near the Atlantic coast were also retained in the reconstruction model (Figure 1). Although the five chronologies are not all located within our reconstruction region, the stepwise regression results indicate that this was the set of chronologies that best reflects the regional climate conditions and also influence spring-summer precipitation in the region.

Model calibration and verification results in our study significantly exceed those of Blasing et al. (1981). The overall variance explained in regional May-June precipitation from the Blasing et al. (1981) calibration model never exceeded 29%. Our Tennessee Valley spring-summer reconstruction model explained 56% of the total variance (Figure 4). Predicted precipitation values were correlated at $p \leq 0.001$ with instrumental values from 1895 to 1980. The Durbin-Watson statistic for the regression model was 2.15, indicating no signs of autocorrelation and validating the use of residual chronologies. Residuals from the regression equation display no trends with the predictor variables and were approximately normally distributed, meeting the assumptions of multiple linear regression. The calibration model had a reduction of error value of 0.50, indicating valuable information exists in the reconstruction, and the RMSE of the rescaled ($k = 1.34$) calibrated reconstruction model was 5 centimeters (14% of the mean). Model statistics (Table 2) were calculated using the rescaled reconstruction.

Results from the split sample method confirm the findings of stepwise regression. Overall variance explained was similar to that of stepwise linear regression. The period from 1895 to 1937 resulted in better model calibration and verification (65% of the variance explained), compared with 40% of the variance being explained using the period from 1938–1980. These results suggest that tree growth had an improved response to May–July precipitation during 1895–1937 in the region. The Weibull plot (Figure 5) shows that the reconstruction model generally underestimates extreme precipitation (wet and dry) and overestimates average
precipitation. The average absolute difference between reconstructed and observed spring-summer precipitation for the Weibull plot was 3.5%, confirming a reasonably accurate and realistic reconstruction.

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

The stepwise linear regression model was used to reconstruct May–July Tennessee Valley precipitation for the years of the tree-ring record, dating back to 1692 (Figure 6). The full precipitation reconstruction average was 36 centimeters. Based on the calibrated model and validation statistics, the reconstruction accurately replicates the annual variability apparent in instrumental rainfall data ($r = 0.75$). Instrumental records can be evaluated in the context of a longer period based on climate reconstructions. This is useful in determining whether planning based on the instrumental record incorporates the range of variability and extremes that is representative of long-term natural variability (Woodhouse, 2003). Extreme 5, 10, and 25-year periods were calculated using percentage of overall normal for the reconstruction and recent instrumental records (Table 3). In all cases, the reconstruction revealed more variability in May–July precipitation has occurred compared to what has been observed in instrumental records. The largest difference was found in the 5-year driest periods. While the driest 5-year period based on instrumental records was 16.5% below normal, the driest 5-year period based on the reconstruction was nearly 26% below normal.

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 (Woodhouse, 2003). We define a drought as a period of at least three consecutive
years in which the spring-summer precipitation was below the overall (i.e., reconstruction) average. Following the procedure in Woodhouse (2003), 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 a seasonal average severity. One drought occurred in the late 1600s (Figure 7). Six droughts occurred in the 1700s including the most severe drought in the past three centuries (1724–1726) during which the May–July precipitation was nearly 30% below normal. Six droughts also occurred in the 1800s, including the longest spring-summer drought (a duration of ten years from 1827–1836) in the past three centuries. Because the reconstruction ends at 1980, droughts occurring in the past century were broken into two groups: (1) droughts based on the reconstruction (1900–1980) and (2) droughts based on recent instrumental records (1981–2008). Similar to droughts based on the reconstruction, droughts based on instrumental records were determined using the long-term reconstruction mean. A total of four droughts occurred during the past 110 years, two based on the reconstruction period and two based on recent instrumental data. The two most recent May–July droughts (1985–1988 and 2006–2008) were ranked second and third in terms of drought severity in the past 300 years (Figure 7). Since the reconstruction model generally underestimates extreme low precipitation values based on the Weibull plot, it should be noted that droughts were most likely slightly less severe than what is shown in Figure 7.

CONCLUSIONS AND FUTURE WORK

We evaluated the dendroclimatic potential in the Tennessee Valley using precipitation and tree-ring chronologies. Although our reconstruction was not as robust as those found in the western U.S., it exceeds previous research efforts and can provide regional water managers with
a visual tool to analyze current and future spring-summer precipitation patterns and extremes within the Tennessee Valley. A Weibull technique new to the field of dendroclimatology was presented and provides a visualization tool for a climate reconstruction. The reconstruction reveals that variability in 1700s and 1900s precipitation had slightly more variability than 1800s precipitation. Furthermore, droughts occurred with similar frequency in each century.

The climatic and biological persistence within the southeastern U.S. makes it difficult to create an accurate climate reconstruction because tree growth is likely driven by a number of environmental variables. Future work may investigate the dendroclimatic potential of reconstructing other regional climate parameters, including temperature. Our results suggest that tree growth in the southeast U.S. is affected by numerous limiting factors, which is an important observation, but causes a problem because an accurate reconstruction of a single climate variable is challenging. Value would be found in the collection of more recent samples from tree species found to contain a significant response to precipitation in our research. Many of the chronologies in the region available on the ITRDB were last cored in the 1980s, making it difficult to compare the recent change in climate with climate of past centuries. It is anticipated that subsequent reconstruction studies will find value in this work by using our study as a foundation when evaluating past climate in the Tennessee Valley.

ACKNOWLEDGEMENTS

This research is sponsored by the University of Tennessee, the USGS 104B, and the Oak Ridge National Laboratory JDRD program. The authors wish to thank the many contributors to the International Tree-Ring Data Bank for the tree-ring chronologies used in our study.
LITERATURE CITED


FIGURE 1. Location Map. The reconstruction region and all southeastern U.S. tree-ring chronologies are shown.
FIGURE 2. Seasonal Correlation Results. A 95% significance correlation level is used. Precipitation is reconstructed for spring-summer (May–July).
FIGURE 3: Tree-Ring Chronology Species Distribution in the Southeastern U.S. The black bar represents the total number of tree-ring chronologies collected and analyzed in our study. The gray bar represents the number of tree-ring chronologies that are correlated at 95% significance with May–July precipitation.
FIGURE 4. Tennessee Valley Calibration Model. The regression model explains 56% of the variance in spring-summer precipitation.
FIGURE 5. Tennessee Valley Weibull Distribution for May–July Precipitation. The reconstruction model generally underestimates extreme (high and low) precipitation and overestimates average precipitation.
FIGURE 6. May-June-July Tennessee Valley Precipitation Reconstruction (Smoothed with a Five-Year Filter). Values are plotted against the long-term (full reconstruction) mean, with periods of below-average precipitation shown in red and periods of above-average precipitation shown in blue. Recent instrumental May–July (1981–2008) precipitation is shown in gray. The change in total number of samples in the five chronologies used in the reconstruction is shown by the line at the bottom (right hand y-axis).
FIGURE 7. Tennessee Valley Spring-Summer Droughts in the Past Three Centuries. The length of each bar represents drought severity while the width represents drought longevity. The most severe drought occurred from 1724 to 1726 and the longest drought occurred from 1827 to 1836. Black bars represent droughts found using the reconstruction. Droughts occurring from 1981 to 2008 are shown in gray and are based on observed data.
TABLE 1. Tree-Ring Chronologies used for the Tennessee Valley Precipitation Reconstruction. Listed chronologies are found to be correlated at 95% with spring-summer precipitation in the region and have an adequate period of record to create the reconstruction.

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<tr>
<th>Chronology</th>
<th>State</th>
<th>Span</th>
<th>Species</th>
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<td>Scotts Gap</td>
<td>TN</td>
<td>1686-1980</td>
<td><em>Liriodendron tulipfera</em> L.</td>
</tr>
<tr>
<td>Lassiter Swamp</td>
<td>NC</td>
<td>1527-1984</td>
<td><em>Taxodium distichum</em> L.</td>
</tr>
<tr>
<td>Mt. Collins</td>
<td>TN</td>
<td>1658-1986</td>
<td><em>Picea rubens</em> S.</td>
</tr>
<tr>
<td>Land Between The Lakes</td>
<td>KY</td>
<td>1692-2005</td>
<td><em>Quercus stellata</em> W.</td>
</tr>
<tr>
<td>Black River</td>
<td>NC</td>
<td>367-1985</td>
<td><em>Taxodium distichum</em> L.</td>
</tr>
</tbody>
</table>


<table>
<thead>
<tr>
<th>Calibration Model</th>
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<td>Calibration Period</td>
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<tr>
<td>( r )</td>
</tr>
<tr>
<td>( R^2 )</td>
</tr>
<tr>
<td>( R^2 ) (predicted)</td>
</tr>
<tr>
<td>RE</td>
</tr>
<tr>
<td>RMSE (cm)</td>
</tr>
<tr>
<td>Durbin-Watson</td>
</tr>
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</table>

TABLE 3. Extreme Spring-Summer Precipitation Periods in the Tennessee Valley. The wettest and driest 5, 10, and 25-year periods are shown for the instrumental record and the reconstruction. In all cases, the reconstruction reveals that more variability in spring-summer precipitation has occurred compared to what has been observed in recent instrumental records. Values are in percentage of May–July normal.

<table>
<thead>
<tr>
<th># of Years</th>
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<th>Reconstruction (1692-1894)</th>
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<tr>
<td></td>
<td>Dry</td>
<td>Wet</td>
</tr>
<tr>
<td>5</td>
<td>-16.5</td>
<td>18.0</td>
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<tr>
<td>10</td>
<td>-11.1</td>
<td>9.7</td>
</tr>
<tr>
<td>25</td>
<td>-5.4</td>
<td>6.5</td>
</tr>
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TREE-RING RECONSTRUCTIONS OF
STREAMFLOW FOR THE TENNESSEE VALLEY

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ABSTRACT

This study used USGS streamflow data from 11 gages within the Tennessee Valley and regional tree-ring chronologies to analyze the dendroclimatic potential of the region and create seasonal flow reconstructions. Prescreening methods included correlation, chronology end date, and temporal stability analysis of predictors to ensure practical and reliable reconstructions. Seasonal correlation analysis revealed that large numbers of regional tree-ring chronologies were significantly correlated (p ≤ 0.05) with May-June-July streamflow. Stepwise linear regression was used to create the May-June-July streamflow reconstructions. Nine of the 11 streamflow reconstructions were considered statistically skillful ($R^2 \geq 0.40$). Skillful reconstructions ranged from 208 to 301 years in length and were statistically validated using leave-one-out cross validation, the sign test, and comparison of the distribution of low flow years. The long-term streamflow variability was analyzed for the Nolichucky, Nantahala, Emory, and SF Holston stations. The reconstructions revealed that while most of the western U.S. was experiencing some of its highest flow years during the early 1900s, the Tennessee Valley region was experiencing very low flow. Results reveal the potential benefit of using tree-ring chronologies to reconstruct hydrologic variables in the southeastern U.S. by demonstrating the ability of proxy-based reconstructions to provide useful data beyond the instrumental record.

Keywords: Tennessee Valley, tree-ring, reconstruction, streamflow, dendroclimatology
INTRODUCTION

Water planners and managers can make more accurate decisions based on information provided by expanding hydrologic records. Tree rings have been widely used as a proxy to reconstruct hydrologic variables in the western U.S. (Woodhouse 2003; Meko et al. 2007; Watson et al. 2009; Barnett et al. 2010). Relatively little dendroclimatological research has been conducted within the southeastern U.S. during the past 20 years when compared to the number of studies conducted in the southwestern, northwestern, and Rocky Mountain regions of the U.S. 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, a lack of trees that are long-lived, and the absence of climatically sensitive patterns of tree rings to facilitate crossdating (Grissino-Mayer 2009). Furthermore, a lower priority is put on hydrologic reconstructions in the southeastern U.S. due to abundant water supplies.

The limited number of streamflow reconstructions for the southeastern U.S can be explained by a number of factors. Tennessee Valley Authority (TVA) dam construction has limited the number of undisturbed streams in the region. The region’s natural topography divides the area into many small catch basins and obstructs rainfall pathways within watersheds. The effects of the topography may explain why the proximity of a tree-ring chronology to a streamflow gage is not always indicative of a statistically significant streamflow-tree-growth relationship. In addition, the southeastern U.S. receives more precipitation than most parts of the country, especially when compared to the western U.S., providing less motivation for water quantity studies. Furthermore, the lack of streamflow gage and tree-ring
datasets spanning cooperative lengths contributes to the difficulty of obtaining long calibration windows.

Although misconceptions still exist regarding the applicability of dendroclimatology in the Southeast, tree rings in the region have been used to investigate the relationships between climate and tree-growth. Blasing et al. (1981) found that tree-rings were a good predictor of May-June precipitation for East Tennessee. Phipps (1983) reconstructed Occoquan River monthly summer streamflow in Virginia, finding June streamflow to be the strongest predictand. Stahle and Cleaveland (1992) created a 1,000-year spring-summer precipitation reconstruction within North Carolina, South Carolina, and Georgia that was found to replicate most of the multidecadal variability apparent in the available instrumental rainfall data. More recent studies have found strong climate signals in tree-ring patterns from Texas to Florida to Virginia and sites further inland (Henderson and Grissino-Mayer 2009; Speer et al. 2009; DeWeese et al. 2010; Harley et al. 2011), confirming the potential ability to develop a more extensive network of sites for spatial reconstructions of past climate.

The first objective of this research was to analyze the dendroclimatic potential of a critical flood control and hydropower region in the southeastern U.S. (Tennessee Valley) using streamflow and regional tree-ring chronology datasets. Based on previous studies, we hypothesized that regional tree-growth would be significantly correlated with spring-summer streamflow. Our second objective was to create statistically skillful (based on overall variance explained and model stability) streamflow reconstructions for 11 gages within the Tennessee Valley. Our final objective was to examine the long-term hydrologic variability of Tennessee Valley streamflow on a timescale exceeding the instrumental record. Doing so may provide
valuable water availability information to Tennessee Valley water resource planners and managers.

DATA AND METHODS

**Streamflow (USGS)**

Unimpaired streamflow data for 11 gages within the Tennessee Valley were obtained from the United States Geological Survey (USGS) website via the National Water Information System (NWIS 2009). One of the most important components in a streamflow reconstruction is the accuracy and length of existing streamflow gage records. Although the USGS streamflow-gaging program began collecting streamflow data as early as 1887, not all of the USGS gage stations have the same period of record. Some USGS gage stations have missing data due to technical, mechanical, or otherwise unknown reasons. The USGS gage stations that were used in this study contained no missing data and most of the stations had at least 40 years of data to compare with regional tree-ring chronologies. Although these rivers are located in close proximity (Figure 1), the elevation and drainage area of each station is unique (Table 1). Cumulative flow in million cubic meters (MCM) was used.

**Tree-Ring Chronologies (ITRDB)**

Tree-ring chronology datasets within and around the southeastern U.S. were retrieved from the International Tree-Ring Data Bank (ITRDB) (Grissino-Mayer and Fritts 1997), which is maintained by the National Oceanic and Atmospheric Administration (NOAA) Paleoclimatology Program. All ring width series were uniformly processed and standardized using the AutoRegressive STANdardization (ARSTAN) program (Cook 1985). Conservative detrending methods (negative exponential/straight line fit or a cubic spline two thirds the length of the series) were used to combine all series into a single site chronology (Cook et al. 1990). Low-order autocorrelation in the chronologies that may in part be attributed to
biological factors (Fritts 1976) was removed by autoregressive modeling, and the resulting residual
chronologies were used for analysis. The residual chronology type has been found appropriate (rather
than the standard chronology type which retains autocorrelation) when modeling hydrologic variables in
the western U.S. (Woodhouse 2003; Meko et al. 2007; Watson et al. 2009; Barnett et al. 2010) and the
southeastern U.S. (Crockett et al. 2010). We initially examined 102 chronologies across 12 states (Figure
1) for the strength of their responses to Tennessee Valley streamflow.

Predictor Prescreening Methods

Three prescreening methods were used to identify the most suitable tree-ring
chronologies to use as predictors for the reconstruction models. First, a date screen was used.
Many of the tree-ring samples within the southeastern U.S. were last collected during the early
1980s. We used the year 1980 as the cutoff date for initial predictor pool tree-ring
chronologies, and removed any chronologies cored before 1980 from analysis.

Next, we inspected correlation coefficients between various streamflow seasons and
residual tree-ring chronologies (in and adjacent to the Tennessee Valley) to identify the
streamflow season most influential to tree growth and therefore most suitable for
reconstruction. One of the most important aspects of the seasonal correlation analysis was to
determine a consistent streamflow season to reconstruct for all 11 of the streamflow gages.
Based on similar studies in surrounding regions, we hypothesized that a strong relationship
would be found between tree growth and spring-summer (April–August) streamflow (Blasing et
al. 1981; Phipps 1983; Stahle and Cleaveland 1992). However, numerous streamflow seasons of
various lengths were analyzed for completeness. We considered the relationship between tree
growth and ten different streamflow seasons of various durations. Three-month seasonal
precipitation periods investigated included January–March, April–June, May–July, July–September, and October–December. Six-month seasonal precipitation periods include January–June, April–September, and July–December. May-June and annual precipitation were also considered. We retained significant (p ≤ 0.05), positive r-values for analysis.

The last pre-screening method involved temporal stability analysis. Temporal stability analysis consisted of performing a 30-year moving correlation window, similar to Biondi et al. (2004), between the various streamflow seasons and residual tree-ring widths. Chronologies containing negative 30-year correlation values with seasonal flow were considered unstable and removed from analysis. Stability analysis ensured that reliable and practical streamflow reconstructions were generated.

Reconstruction Methodology

Model calibration windows were controlled by the date that streamflow was first collected at each gage station. While all calibration windows ended at 1980, the beginning dates of the calibration windows ranged from 1919 to 1949 (Table 1). The ability of the statistically significant and stable moisture sensitive tree-ring chronologies to predict precipitation was tested using a forward and backward (standard) stepwise regression model. Standard stepwise regression adds and removes predictors as needed for each step. The model stops when all variables not in the model have p-values that are greater than the specified alpha-to-enter value and when all variables in the model have p-values that are less than or equal to the specified alpha-to-remove value. Following the procedure of Woodhouse et al. (2006), the alpha-level for a predictor chronology had to have a maximum p-value of 0.05 for entry and 0.10 for retention in our stepwise regression model.
Numerous statistical measures were used to establish the statistical skill of each streamflow reconstruction. $R^2$ explained the amount of variance being explained by each model. $R^2$-predicted was calculated from the Predicted REsidual Sums of Squares (PRESS) statistic. The PRESS statistic is based upon a leave-one-out cross-validation in which a single year or observation is removed when fitting the model. As a result, the prediction errors are independent of the predicted value at the removed observation (Garen 1992). The Variation Inflation Factor (VIF) indicates the extent to which multicollinearity is present in a regression analysis. Generally, a VIF value close to 1.0 indicates low correlation between predictors and is ideal for a regression model (O’Brien 2007). The Durbin-Watson (D-W) statistic was used to analyze the autocorrelation structure of model residuals. The sign test, a nonparametric procedure to count the number of agreements and disagreements between instrumental and reconstructed flow, was used for additional model validation.

RESULTS

After the date screen, 72 of the 102 chronologies were retained and used for seasonal correlation analysis. Similarly to Blasing et al. (1981), the two-month period May-June contained the largest number of significant tree-ring chronologies for the majority of the 11 gages. Furthermore, the winter months never yielded a large number of highly correlated tree-ring chronologies. While the number of significant tree-ring chronologies was similar for the seasons of April–June and May–July, tree-growth contained a stronger moisture signal (higher correlation) with May–July streamflow when compared to April–June streamflow. Rather than reconstructing May–June streamflow as performed in Blasing et al. (1981), we reconstructed May–July streamflow because reconstructing a three-month season provides more information on temporal characteristics of climate variability over a longer season. The number of chronologies with positive, significant ($p \leq 0.05$) $r$-values after seasonal (May-June-July) correlation varied for each streamflow station and ranged from three (Watauga gage) to 35.
(NF Holston, Nolichucky, and Valley gages). Stability analysis removed the highest number (nine) of predictor pool tree-ring chronologies from the Valley gage, and the final number of chronologies that entered as initial predictors in the calibration models ranged from three (Watauga gage) to 34 (NF Holston gage).

For all of the streamflow gages, the most feasible calibration models and reconstructions were chosen (Table 2). We based feasibility on the length of the reconstruction, the overall variance explained of the model, and the predictability of the model. Nine of the 11 calibration models were considered statistically skillful \((R^2 \geq 0.40)\). The D-W test for autocorrelation in the residuals from regression showed that the autocorrelation was not significant for most of the models, indicating that the residuals are random and the models were appropriate (Draper and Smith 1981). However, the D-W value for the Nolichucky calibration suggested that the model had serial correlation, but results were not conclusive. VIF values for all models were within acceptable ranges and sign test results were significant \((p \leq 0.01)\) for 10 of the 11 calibration models.

Tree-ring chronologies, that were retained by at least one of the stepwise regression models, varied by location (Figure 1) and species (Table 3). The Knob Job chronology (Eastern red cedar) was retained by the highest number of calibration models (five). More oak chronologies are available on the ITRDB in the southeastern U.S. than any other species, and at least one oak chronology was retained in eight of the 11 models. While the Hampton Hills chronology (white oak) contained a strong moisture signal and was retained in four of the models, it only dated back to 1772, which limited the reconstruction length of those gages. Furthermore, many of the baldcypress tree-ring chronologies on the Atlantic coast previously found to contain a high moisture signal (Stahle and Cleveland 1992) were retained in many of our models.
We chose four streamflow stations (Nolichucky, Nantahala, Emory, and SF Holston) that had sufficient calibration windows (≥ 40 years) and covered a large spatial region of the Tennessee Valley (Figure 1) for analysis. These four calibration models (Figure 2) explained 42–52% of the variance in May-June-July streamflow records. The models generally captured the year-to-year trend and peaks of regional streamflow (Figure 2).

May-June-July streamflow reconstructions, smoothed with 5-year end year filters, were created for the Nolichucky, Nantahala, Emory, and SF Holston gages (Figure 3). Flow at the Nolichucky gages was reconstructed back to 1686, Nantahala (1679), and flow at the Emory and SF Holston gages was reconstructed back to 1772. The reconstructions revealed numerous wet and dry periods that varied slightly at each gage. The distribution of flow years in the lowest 10th percentile from 1772 to 1980 was analyzed for visual validation of the streamflow reconstructions (Figure 4). The distribution of low flow years across the four stations were fairly consistent from 1772 to 1910. The period from 1910 to 1940 revealed numerous dry years that matched favorably across the four stations. Stahle and Cleaveland (1992, 1994) also found relative dry periods in their reconstructions of North Carolina, South Carolina, and Georgia in spring-summer precipitation during this period. In the western U.S., specifically the Upper Colorado River Basin, the highest sustained flows in the last 500 years occurred in the early decades of the 20th century (Woodhouse et al. 2006). This period coincided with allocation of Colorado River flows. Our results show reveal that while most of the western U.S. was experiencing some of its highest flow years during the early 1900s, the Tennessee Valley region was experiencing very low spring-summer conditions.

Although our reconstructions were not as robust (in terms of length and explained variance) as those found in the western U.S., they can provide regional water managers with a visual tool to analyze current and future spring-summer streamflow patterns and extremes within the Tennessee Valley.
Climatic persistence from year to year and biological persistence in tree growth in the southeastern U.S. makes it challenging to create statistically skillful hydrologic reconstructions because tree growth is likely driven by a number of environmental variables. Value would be found in the collection of more recent samples from tree species found to contain a significant response to precipitation in our research. Many of the chronologies in the region available on the ITRDB were last cored in the 1980s, making it difficult to compare recent changes in climate with climate of past centuries.

ACKNOWLEDGEMENTS

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LITERATURE CITED


<table>
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<tr>
<th>Station</th>
<th>Description</th>
<th>State</th>
<th>Drainage Area (km²)</th>
<th>Elevation (m)</th>
<th>Start Date</th>
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<td>03528000</td>
<td>Clinch River above Tazewell</td>
<td>TN</td>
<td>3818</td>
<td>323</td>
<td>1920</td>
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<td>03524000</td>
<td>Clinch River at Cleveland</td>
<td>VA</td>
<td>1380</td>
<td>457</td>
<td>1921</td>
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<td>03540500</td>
<td>Emory River at Oakdale</td>
<td>TN</td>
<td>1979</td>
<td>232</td>
<td>1928</td>
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<td>03500000</td>
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<td>NC</td>
<td>363</td>
<td>612</td>
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<tr>
<td>03504000</td>
<td>Nantahala River near Rainbow Springs</td>
<td>NC</td>
<td>134</td>
<td>937</td>
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<td>03488000</td>
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<td>572</td>
<td>519</td>
<td>1921</td>
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<td>03465500</td>
<td>Nolichucky River at Embreeville</td>
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<td>NC</td>
<td>477</td>
<td>562</td>
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<tr>
<td>03473000</td>
<td>SF Holston near Damascus</td>
<td>VA</td>
<td>785</td>
<td>546</td>
<td>1932</td>
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<td>03550000</td>
<td>Valley River at Tomotla</td>
<td>NC</td>
<td>269</td>
<td>474</td>
<td>1919</td>
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<td>03479000</td>
<td>Watauga River near Sugar Grove</td>
<td>NC</td>
<td>239</td>
<td>795</td>
<td>1941</td>
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Table 2. May-June-July streamflow reconstruction statistics and Tree-Ring Chronologies (TRCs) used for each model.

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<tr>
<th>Station</th>
<th>Reconstruction Date</th>
<th>$R^2$</th>
<th>$R^2_{(p)}$</th>
<th>D-W</th>
<th>VIF</th>
<th>Sign Test (Hit/Miss)</th>
<th>TRCs Retained</th>
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<td>Clinch TN</td>
<td>1752</td>
<td>0.45</td>
<td>0.34</td>
<td>1.87</td>
<td>1.1</td>
<td>49/12*</td>
<td>LH, LCT, KJ, FBS</td>
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<td>Clinch VA</td>
<td>1752</td>
<td>0.36</td>
<td>0.27</td>
<td>2.05</td>
<td>1.2</td>
<td>46/14*</td>
<td>KJ, LCT, LH</td>
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<td>Emory</td>
<td>1772</td>
<td>0.42</td>
<td>0.33</td>
<td>2.06</td>
<td>1.1</td>
<td>38/15*</td>
<td>HH, LBL, LS</td>
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<td>Little TN</td>
<td>1679</td>
<td>0.42</td>
<td>0.31</td>
<td>2.06</td>
<td>1.0</td>
<td>28/8*</td>
<td>KJ, PR</td>
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<td>Nantahala</td>
<td>1679</td>
<td>0.48</td>
<td>0.36</td>
<td>2.25</td>
<td>1.1</td>
<td>31/9*</td>
<td>KT, PC, PR</td>
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<td>NF Holston</td>
<td>1797</td>
<td>0.50</td>
<td>0.42</td>
<td>2.11</td>
<td>1.3</td>
<td>48/12*</td>
<td>SG, KJ, HH, HWFB</td>
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<td>Nolichucky</td>
<td>1686</td>
<td>0.52</td>
<td>0.43</td>
<td>1.55</td>
<td>1.1</td>
<td>45/15*</td>
<td>SG, LS, GM, KJ</td>
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<tr>
<td>Oconaluftee</td>
<td>1679</td>
<td>0.48</td>
<td>0.39</td>
<td>2.08</td>
<td>1.0</td>
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<td>SF Holston</td>
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<td>0.56</td>
<td>0.45</td>
<td>1.88</td>
<td>1.2</td>
<td>37/12*</td>
<td>KJ, PC, PW, HH</td>
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<td>Valley</td>
<td>1772</td>
<td>0.47</td>
<td>0.33</td>
<td>1.89</td>
<td>1.1</td>
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<td>Watauga</td>
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<td>0.12</td>
<td>0.03</td>
<td>1.39</td>
<td>1.0</td>
<td>23/17</td>
<td>HWFB</td>
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*a Calibration and reconstruction figures shown

*p ≤ 0.01
Table 3. Tree-ring chronologies retained in the stepwise regression models and used for the reconstructions.

<table>
<thead>
<tr>
<th>Code</th>
<th>Chronology</th>
<th>State</th>
<th>Species</th>
<th>Elevation (m)</th>
<th>Period</th>
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<td>BRSC</td>
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<td>SC</td>
<td>TADI</td>
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<td>551–1993</td>
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<td>FBS</td>
<td>Francis Beidler Swamp</td>
<td>SC</td>
<td>QULY</td>
<td>12</td>
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<td>GM</td>
<td>Grandfather Mountain</td>
<td>NC</td>
<td>PCRU</td>
<td>1800</td>
<td>1563–1983</td>
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<td>HH</td>
<td>Hampton Hills</td>
<td>NC</td>
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<td>108</td>
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<td>HWFB</td>
<td>Hen Wallow Falls B</td>
<td>TN</td>
<td>TSCA</td>
<td>218</td>
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<td>KJ</td>
<td>Knob Job</td>
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<td>JUVI</td>
<td>500</td>
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<td>KT</td>
<td>Kelsey Tract</td>
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<td>TSCR</td>
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<td>QUST</td>
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<td>PCPW</td>
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<td>TN</td>
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<td>300</td>
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<td>PR</td>
<td>Pearl River</td>
<td>MS</td>
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<td>QUAL</td>
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<td>Ramseys Draft Recollection</td>
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<td>TSCA</td>
<td>1000</td>
<td>1598–1982</td>
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<td>SG</td>
<td>Scotts Gap</td>
<td>TN</td>
<td>LITU</td>
<td>520</td>
<td>1686–1981</td>
</tr>
</tbody>
</table>

\(^a\)TADI = *Taxodium distichum*, QULY = *Quercus lyrata*, PCRU = *Picea rubens*, QUAL = *Quercus alba*, TSCA = *Tsuga Canadensis*, JUVI = *Juniperus virginiana*, TSCR = *Tsuga caroliniana*, QUST = *Quercus stellata*, QUPR = *Quercus Montana*, LITU = *Liriodendron tulipifera*. 
Figure 1. Location map showing the 11 USGS streamflow stations analyzed and all ITRDB tree-ring chronologies (TRCs) in the southeastern U.S.
Figure 2. May-June-July streamflow calibration models for (a) Nolichucky River (1921–1980), (b) Nantahala River (1941–1980), (c) Emory River (1928–1980), and (d) SF Holston (1932–1980). Observed (dark line), reconstructed (gray line).
Figure 3. May-June-July streamflow reconstructions for (a) Nolichucky River (1686–1980), (b) Nantahala River (1679–1980), (c) Emory River (1772–1980), and (d) SF Holston (1772–1980). Values have been smoothed with a 5-year end year filter. May-June-July instrumental streamflow values after 1980 are shown in gray. Also shown is the long-term mean for each record (dotted line).
Figure 4. Distribution of May-June-July flows in the lowest 10th percentile for the streamflow reconstructions from 1772 to 1980.