Dendroclimatic Reconstruction with Time Varying Predictor Subsets of Tree Indices

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(Manuscript received 16 April 1996, in final form 31 July 1996)

ABSTRACT

Tree-ring site chronologies, the predictors for most dendroclimatic reconstructions, are essentially mean-value functions with a time varying sample size (number of trees) and sample composition. Because reconstruction models are calibrated and verified on the most recent, best-replicated part of the chronologies, regression and verification statistics can be misleading as indicators of long-term reconstruction accuracy. A new reconstruction method is described that circumvents the use of site chronologies and instead derives predictor variables from indices of individual trees. Separate regression models are estimated and cross validated for various time segments of the tree-ring record, depending on the trees available at the time. This approach allows the reconstruction to extend to the first year covered by any tree in the network and yields direct evaluation of the change in reconstruction accuracy with tree-ring sample composition. The method includes two regression stages. The first is to separately deconvolve the local climate signal for individual trees, and the second is to weight the deconvolved signals into estimates of the climatic variable to be reconstructed. The method is illustrated in an application of precipitation and tree-ring data for the San Pedro River Basin in southeastern Arizona. Extensions to larger-scale problems and spatial reconstruction are suggested.

1. Introduction

Networks of tree-ring sites have proved valuable for extending climatic records on most of the world's continents (Stockton et al. 1985). Dendroclimatic reconstructions are usually generated by a regression model in which the predictors are site chronologies—indices of annual ring width averaged over several trees at a collection site (e.g., Fritts et al. 1979; Stockton and Meko 1983; Stahle and Cleaveland 1992). The trees in a chronology typically have different starting years, so that a site chronology is a mean-value function with a time varying sample size. Calibration and verification statistics measuring the accuracy of climatic reconstruction are computed for the most recent period, when the sample size is generally highest and the chronology most representative of the hypothetical ''true'' population tree-ring variation at the site. Such statistics are known to overestimate the accuracy of reconstruction when applied to the more poorly replicated early part of the tree-ring record (Wigley et al. 1984). The ''subsample signal strength'' (SSS), a statistic derived from the theory of the average of correlated variables, can be used to estimate the bias in the regression R^2 for a climatic reconstruction model (Wigley et al. 1984). This application of the SSS is strictly valid, however, only if the strength of climatic signal is similar for the various trees at a site. For heterogeneous site types, large microsite differences—in moisture availability and exposure, for example—could be associated with large tree to tree differences in climatic content of the ring sequences. If the climatic signal happens to be strong in only a few trees, increasing the sample size could dilute rather than enhance the strength of the climatic signal in the site chronology and invalidate the use of the SSS in assessing the drop in reconstruction accuracy over time.

In this paper a dendroclimatic reconstruction method is proposed that exploits the tree-specific climatic signal in tree-ring data and gives a direct estimate of the time variation of reconstruction accuracy. A departure from conventional reconstruction methods is that the regression predictors are derived from indices of individual trees instead of site chronologies. A separate reconstruction model is calibrated and verified for each year or group of years in the tree-ring record, using tree-ring data from only the trees living at the time. The time coverage of reconstruction is maximized by this approach because the reconstruction can extend to the earliest year of data for the oldest tree at any site.

The calibration–verification of multiple reconstruction models to accommodate predictor data subsets whose composition varies in time is not new in dendroclimatology. A similar approach has previously been applied to deal with site chronologies with different

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starting years (Young 1994). In the extension to individual trees, tree to tree differences in the dynamic response of growth to climate are allowed for by a two-stage regression procedure. The first stage is lagged regression to deconvolve the local climatic signal from the growth indices of individual trees. The result of this stage is essentially a time-filtered tree index. The second stage is principal components regression to weight the time-filtered indices for groups of trees into estimates of the climatic variable to be reconstructed.

The method as described in this paper applies to the following reconstruction scenario: a set of tree indices and climatic time series is available for some geographical region; the objective is reconstruction of a single ''regional'' climatic time series; and all tree indices and climatic series overlap for a common period, to be used as a calibration period. The model is described and its application illustrated for tree-ring data and precipitation data for the San Pedro River Basin in southern Arizona. Possible extension to spatial regression and to tree-ring datasets that do not uniformly overlap the climate–tree-ring calibration period is then suggested.

2. The model

Three sets of data are required to implement the model: ${}_p\mathbf{y}_1$, a p-year time series of the regional climate variable whose long-term reconstruction is the goal; ${}_m\mathbf{W}_n$, a matrix of tree indices, or ring-width indices, for m years at n trees; and ${}_p\mathbf{C}_n$, a matrix of ''local'' climate variables for p years at the n tree locations. Trees sampled at the same location (e.g., at a conventional tree-ring ''site'') could be assigned the same local climate variable; thus, some columns of ${}_p\mathbf{C}_n$ might be identical. The modeling procedure, illustrated in Fig. 1, consists of three main steps, followed by cross-validation. Step A is a time filtering of each tree index to deconvolve its local climate signal. The filter weights for this operation are the coefficients of a multiple linear regression equation of the local climate variable on lagged values of the tree index. The filtered series resulting from substitution of long-term tree indices into the equation is referred to as a ''single-site reconstruction'' (SSR). Time coverage by the SSRs will generally differ from tree to tree, depending on the date of the first measured ring and the number of start-up values lost in the lagged regression.

Step B is the identification of k different tree subsets, one of which can be associated with each year of the tree-ring record. For example, the beginning years of the record might be represented by the smallest possible subset, consisting of a single tree, and the last few years by a subset of hundreds of trees. The k subsets of SSRs are different possible predictor data subsets for spatial models to reconstruct the regional climate variable.

Step C is spatial filtering of the SSRs to combine climatic information from the spatially distributed trees into an estimate of the regional climate variable. The equations to weight the SSRs are derived by principal components regression (PCR) of the regional climate variable on principal component (PC) scores of the SSRs. Separate models are estimated for the k different predictor data subsets. Because the lagged response of tree growth to climate has already been adjusted for in generation of the SSRs, these final regression models do not include lagged predictors.

Several assumptions are made in applying the model. The tree indices ${}_m\mathbf{W}_n$ are assumed to have been adjusted for removal of the growth trend (Cook et al. 1990b). Each column of ${}_p\mathbf{C}_n$ is assumed to be a time series of a climate variable governing or strongly influencing growth variations of the tree in the corresponding column of ${}_m\mathbf{W}_n$. Climatic series must, therefore, have been paired with or otherwise grouped beforehand to match up with individual trees. This pairing might be accomplished by distance weighting the station climate series to tree locations, by averaging over climate stations nearest each tree or by simply pairing each tree with its nearest climate station. The tree-ring series, local climate series, and regional climate series are assumed to overlap for a p-year calibration period and to contain no missing data for that period. Relaxation of these assumptions is discussed later.

The climate series ${}_p\mathbf{y}_1$ and ${}_p\mathbf{C}_n$ might or might not be of the same type, depending on the application. In large-scale climatological application, for example, ${}_p\mathbf{y}_1$ might be an index of atmospheric circulation and ${}_p\mathbf{C}_n$, might be the annual or seasonal precipitation interpolated for tree locations over a continent. For a basin-scale hydrologic study, ${}_p\mathbf{y}_1$ might be basin-average precipitation and ${}_p\mathbf{C}_n$ might be station precipitation series paired with individual trees scattered over the runoff producing parts of a watershed. The steps in the modeling procedure are described in more detail below.

a. Time filtering—Single-site reconstructions

The climate–tree-growth system is dynamic in that past, as well as the current year's, climate can influence the current year's ring width. The time filtering operation described here is intended to reverse the effects of the filtering of climate by this natural system. Each local climate series (column of ${}_p\mathbf{C}_n$) is regressed on lagged values of its paired tree index (corresponding column of ${}_m\mathbf{W}_n$) for the p-year overlap period. The estimated regression equation is used as the time filter for the tree index. The filter is optimal in a least squares sense in maximizing the explained variance of the local climate series from a sequence of values of the tree index.

An initial decision in the regression design is the number of positive and negative lags to include as potential predictors. An upper limit for this number might be guessed from prior knowledge of the lag properties of the tree-growth system—for example, that needles are retained for a specific number of years. Another approach might be trial and error modeling, increasing the number of lags until the regression residuals are

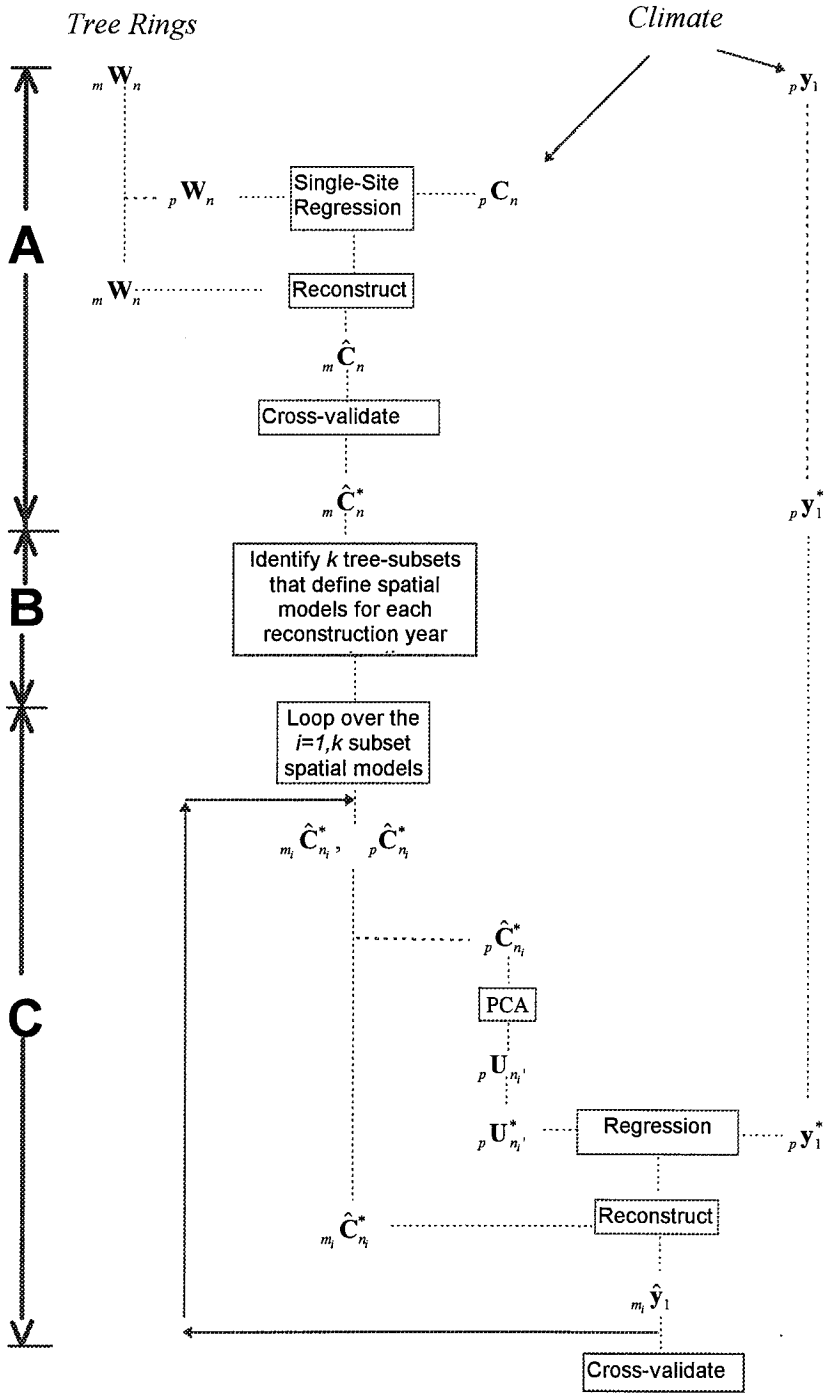

FIG. 1. Flowchart summarizing reconstruction steps. Refer to text for definitions. Superscript "*" attached to a variable (e.g., ${}_p\mathbf{y}_1$ to ${}_p\mathbf{y}^*_1$) indicates standardization by subtraction of calibration-period mean and division by calibration-period standard deviation.

suitably independent in time and uncorrelated with the predictors. The lags appropriate for the model are likely to depend on whether the tree indices in ${}_m\mathbf{W}_n$ have been prewhitened beforehand—for example, by autoregressive moving average (ARMA) modeling (Cook et al. 1990a). Prewhitening essentially removes low-order autocorrelation from the tree indices, which should reduce multicollinearity of the predictors in the lagged regression models. Lagged predictors are thus less likely to enter as important predictors in the models, and the

model structure is simplified. Significant cross correlations are still possible, however, between the prewhitened tree indices and the local climate variable, especially if the climate variable is itself autocorrelated (Meko and Graybill 1995).

If lags from $-L$ to L yr from the year of climate are specified as potential tree-ring predictors, the model for a tree is

$$c_t = b_0 + \sum_{i=1}^{2L+1} b_i w_{\tau+i} + e_t, \quad (1)$$

where c_t is the local climate variable in year t, b_0 is the regression constant, b_i is the regression coefficient on a current or lagged value of the tree-ring index, $w_{\tau+i}$ is the tree-ring index in year $\tau + i$, τ is $t - L - 1$, a relative year index, and e_t are regression residuals.

The predicted values of the local climate data are estimated from the fitted model

$$\hat{c}_t = \hat{b}_0 + \sum_{i=1}^{2L+1} \hat{b}_i w_{\tau+i}. \quad (2)$$

The model is fit stepwise such that lagged tree indices are entered in decreasing order of contribution to the reduction of residual variance. Entry of variables is stopped when the addition of another variable fails to increase the adjusted squared coefficient of multiple determination R_a^2 (Weisberg 1985).

The long-term tree-ring data are substituted into the equation to get estimates of the local climate variable at each tree for the full length of the tree-ring series (possibly minus one or more start-up years in lagging). The resulting reconstruction, scaled by subtracting the calibration-period mean and dividing by the calibration-period standard deviation, is a single-site reconstruction. The regression procedure is repeated for all trees, and the SSRs are stored in a matrix ${}_m\hat{\mathbf{C}}^*{}_n$.

A suite of statistics, adequately described elsewhere, is available for assessing the accuracy of the reconstruction models (Gordon 1982). An important part of this assessment is the verification of each model's performance using data not used in model calibration. The verification method used here is cross validation, in which each observation is successively withheld, a model is estimated on the remaining observations, and a prediction is made for the omitted observation. The model performance is then judged by the agreement of the predicted climate with the observed climate for the complete set of deleted observations (Michaelsen 1987). Agreement can be quantified by the average prediction error, as computed from the predicted residual sum of squares (Weisberg 1985). The reduction of error statistic, also based on the residual error sum of squares, can be used to assess the relative skill of reconstruction—relative to simply substituting the calibration-period mean as the reconstructed value in each year (Gordon 1982).

A slight modification of Michaelsen's (1987) cross-validation procedure was necessary for the reconstruction method proposed in this paper because of the use of lagged predictors in the SSR models. A ''leave one out'' strategy is not suitable because tree-ring data used in model estimation would also be used in the prediction for the omitted observation. For a symmetrical lag of $\pm L$ yr in the SSR models, $r = 4L + 1$ values centered on the cross-validation estimate must be omitted to ensure that there is no overlap of the tree-ring data used to fit a reconstruction model with data used to generate the cross-validation prediction.

b. Tree subset identification

The second step in the model is to identify the different tree subsets that each year of the tree-ring record can be associated with. The starting row of valid entries (nonmissing data) in the matrix of single-site reconstructions ${}_m\hat{\mathbf{C}}^*{}_n$ will generally vary for reasons described previously. Let $I = \{1, 2, \ldots, m\}$ be the set of row numbers, representing years, of ${}_m\hat{\mathbf{C}}^*{}_n$, and $J = \{1, 2, \ldots, n\}$ be the set of column numbers, representing trees, in ${}_m\hat{\mathbf{C}}^*{}_n$. Each year of ${}_m\hat{\mathbf{C}}^*{}_n$ can be associated with a column subset of J, indicating the trees available for a reconstruction of the regional climate variable in that year. The same subset of trees might apply for several years, such that only k of the m possible subsets are unique.

The unique subsets of trees, denoted by $\{H_j \in J, j = 1, \ldots, k\}$, identify k different predictor data subsets for later use in reconstructing the regional climate variable. The corresponding groups of years of the tree-ring record before the calibration period for which the subset models apply can be denoted by $\{L_i \in I, i = 1, \ldots, k\}$.

Let m_i and n_i be the numbers of rows (years) and columns for the ith subset model, ${}_{m_i}\hat{\mathbf{C}}^*{}_{n_i}$ be the submatrix of single-site reconstructions prior to the calibration period, and ${}_p\hat{\mathbf{C}}^*{}_{n_i}$ be the corresponding submatrix for the p-year calibration period. The matrices ${}_p\hat{\mathbf{C}}^*{}_{n_i}$ and ${}_{m_i}\hat{\mathbf{C}}^*{}_{n_i}$ are the calibration-period predictor data and reconstruction period predictor data applicable to the ith spatial reconstruction model.

c. Spatial filtering

The SSRs derived by lagged regression in step A and grouped in step B are weighted by principal components regression into estimates of the regional climate series ${}_p\mathbf{y}_1$. This second regression stage is ''spatial filtering'' in that the regression weights are applied to functions of spatially distributed variables. PCR is adopted to convert the original set of predictors into a smaller set of orthogonal predictors.

The reader is referred elsewhere for general information on PCR as a reconstruction method in dendroclimatology (Cook et al. 1994). The use of PCR in the context of the proposed reconstruction method is outlined in Fig. 1 and described briefly below.

Several steps are repeated k times within a loop for each of the k spatial models. The single-site reconstructions ${}_p\hat{\mathbf{C}}^*_{n_i}$ are converted to orthogonal principal component scores using principal components analysis (PCA). Only n_i' of the n_i eigenvectors are retained, where $n_i' \leq n_i$, based on an eigenvalue of 1 or other criterion for deleting higher-order eigenvectors (Cook et al. 1994). The transformation is given by

$$ {}_p\mathbf{U}_{n_i'} = {}_p\hat{\mathbf{C}}^*_{n_i}\mathbf{E}_{n_i'}, \tag{3} $$

where ${}_p\mathbf{U}_{ni}'$ are the PC scores and ${}_{n_i}\mathbf{E}_{ni}'$ are the n_i' most important eigenvectors (sorted by order of eigenvalue) of ${}_p\hat{\mathbf{C}}^*_{n_i}$. Because the columns of ${}_p\hat{\mathbf{C}}^*_{n_i}$ are standardized variables, it makes no difference whether the eigenvectors are computed on the correlation matrix or the covariance matrix.

The PC scores are standardized to unit standard deviation by dividing by the square roots of their eigenvalues (Cook et al. 1994):

$$ {}_p\mathbf{U}^*_{n_i'} = {}_p\mathbf{U}_{n_i'}\mathbf{T}_{n_i'}, \tag{4} $$

where ${}_{n_i'}\mathbf{T}_{n_i'}$ is a diagonal matrix with inverses of square roots of the eigenvalues of the n_i' important eigenvectors along the diagonal.

To eliminate the need for a constant term in the regression equations, as a convenience, the regional climate variable is standardized to zero mean and unit standard deviation

$$ {}_p\mathbf{y}^*_1 = 1/s({}_p\mathbf{y}_1 - {}_p\bar{\mathbf{y}}_1), \tag{5} $$

where s is the calibration-period standard deviation (scalar) of ${}_p\mathbf{y}_1$ and ${}_p\bar{\mathbf{y}}_1$ is a constant vector of the calibration-period mean of ${}_p\mathbf{y}_1$. The standardized regional climate variable is then regressed on the standardized PC scores of tree indices using stepwise multiple linear regression. Because the predictors are orthogonal and have equal variances, the order of entry of predictors is specified by the relative sizes of the regression coefficients. A t test (Mardia et al. 1979) is used to determine whether the regression coefficient for a PC score is significant at the 95% level, and nonsignificant predictors are omitted from the prediction equation. This equation is

$$ {}_p\hat{\mathbf{y}}^*_1 = {}_p\mathbf{U}^*_{n_i'}\hat{\mathbf{A}}_1, \tag{6} $$

where ${}_{n_i'}\hat{\mathbf{A}}_1$ is a vector whose elements are estimated regression coefficients if the corresponding PC score in ${}_p\mathbf{U}^*_{n_i'}$ has been included as a predictor and are zero if not.

The prediction equation is expressed in terms of the original predictors (single-site reconstructions) instead of the PC scores:

$$ \begin{aligned} {}_p\hat{\mathbf{y}}^*_1 &= {}_p\mathbf{U}^*_{n_i'}\hat{\mathbf{A}}_1 \\ &= {}_p\mathbf{U}_{n_i'}\mathbf{T}_{n_i'}\hat{\mathbf{A}}_1 \\ &= ({}_p\hat{\mathbf{C}}^*_{n_i}\mathbf{E}_{n_i'})\mathbf{T}_{n_i'}\hat{\mathbf{A}}_1. \end{aligned} \tag{7} $$

The precalibration-period SSRs are substituted into the regional regression equation to get the long-term reconstruction for the subset reconstruction period

$$ {}_{m_i}\hat{\mathbf{y}}^*_1 = ({}_{m_i}\hat{\mathbf{C}}^*_{n_i}\mathbf{E}_{n_i'})\mathbf{T}_{n_i'}\hat{\mathbf{A}}_1, \tag{8} $$

Finally, the predicted values for the calibration period and the earlier period are transformed to units of the regional climate variable by multiplying by the calibration-period standard deviation and adding back the calibration-period mean:

$$ {}_p\hat{\mathbf{y}}_1 = s({}_p\hat{\mathbf{y}}^*_1) + {}_p\bar{\mathbf{y}}_1 \tag{9} $$

and

$$ {}_{m_i}\hat{\mathbf{y}}_1 = s({}_{m_i}\hat{\mathbf{y}}^*_1) + {}_{m_i}\bar{\mathbf{y}}_1, \tag{10} $$

where s and ${}_p\bar{\mathbf{y}}_1$ are defined as before, and ${}_{m_i}\bar{\mathbf{y}}_1$ is a constant vector of length m_i of the calibration-period mean of ${}_p\mathbf{y}_1$.

The final step is cross validation of the PCR models, which is accomplished as described previously for the SSR models.

3. Example

The method described above is illustrated in a reconstruction of cool-season (November–April) precipitation for the San Pedro River Basin (SPRB) in southeastern Arizona (Fig. 2). The input data consist of precipitation records for 12 stations (Table 1) and tree-ring indices for 16 trees in mountain ranges flanking the SPRB (Table 2). Two tree species are represented: *Pinus ponderosa* (2 trees), and *Pseudotsuga menziesii* (14 trees). The beginning years of the tree-ring series range from 1270 to 1723, and the ending years from 1987 to 1994. In the terminology of the previous sections, the regional series to be reconstructed is the 12-station-mean precipitation and the local climate series for the single-site reconstructions are averages of precipitation over one to seven stations grouped with each tree (Table 2). The calibration period for all regression models is 1916–68, when precipitation records sampling various parts of the basin were most complete.

In the single-site regressions, each local climate series was regressed stepwise on its paired tree index, lagged -1, 0, and $+1$ yr from the year of climate. Note that including the lag $t - 1$ tree-ring index as a predictor for the climate in year t does not imply a violation of physical causality. The negative lag is included because the climatic interpretation of the ring width anomaly in year t is conditional on the ring width anomaly in year $t - 1$. For example, even if precipitation is normal in year t, the ring in year t might be wider than normal because of carryover food storage from an unusually moist year year $t - 1$.

Predictors were entered stepwise until an additional predictor failed to increase the adjusted R^2. The single-site regression models are summarized in Table 3. A simple no-lag model was selected for 10 of the 16 trees; both positive and negative lags were represented in other

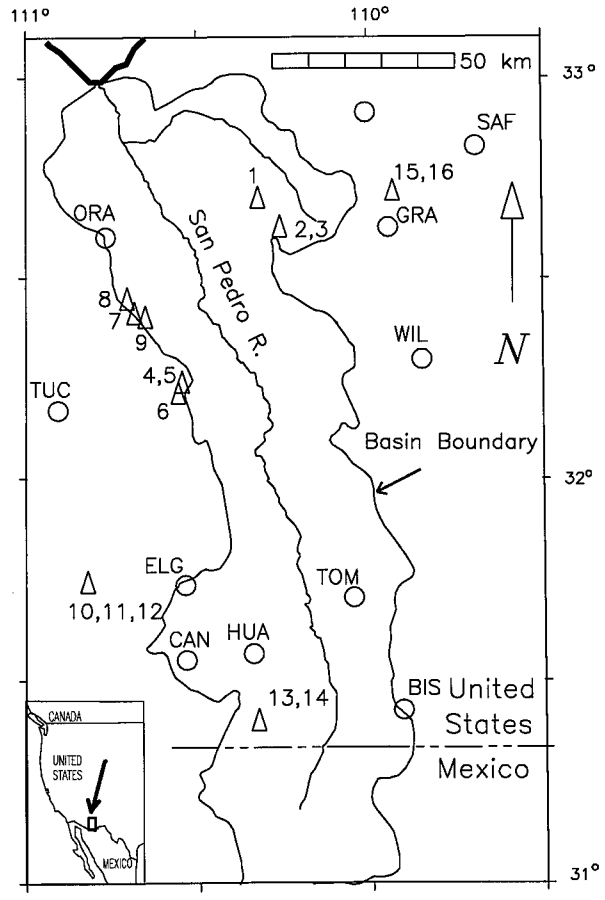

FIG. 2. Map showing locations of trees and precipitation stations in or near the San Pedro River Basin. Precipitation stations (circles) are labeled by a three-letter code as in Table 1. Tree locations (triangles) are numbered as in Table 2.

trees' models. Tree 5 apparently has a 1-yr delay in climate response. The strength of local climate signal varies greatly among trees, as indicated by the regression R^2 values and overall F of the equations. Variance explained ranges from 1% to 44% and overall F from 0.35 to 34.25. The computed overall F is significant at the 0.05 confidence level for 14 of the 16 trees. Tree 14, which explains only 1% of the climate variance and has an overall F lower than expected by chance, was deleted from the tree-ring dataset before proceeding to the PCR modeling. Except for tree 14, the reduction of error statistic from cross validation is positive for the SSR models, indicating some skill of reconstruction (Table 3).

Subset identification (step B in Fig. 1) yielded 15 different tree subsets for the years prior to the calibration period (Table 4). The earliest subset, for 1271–1465, consists of just a single tree. The second subset, for 1466–1531, consists of 2 trees. Sample size gradually increases, up to a 15-tree subset for the period 1724–1915. The actual makeup of the subsets can be identified by referring back to Table 1 and Table 3. For example,

TABLE 1. Precipitation stations for sample application.

Code[a]	Station name	Station ID[b]
1-TOM	Tombstone	02078619
2-BIS	Bisbee	02070768
3-CAN	Canelo	02071231
4-ELG	Elgin	02072797
5-FAI	Fairbank	02072902
6-SAN	San Rafael Ranch	02077555
7-HUA	Ft. Huachuca	02073120
8-TUC	Tucson	02078815
9-GRA	Ft. Grant	02073110
10-WIL	Wilcox	02079334
11-ORA	Oracle[c]	02066116
12-SAF	Safford	02077388

[a] Letter code is used on map in Fig. 2; all stations in southern Arizona; common period of data coverage is 1916–68.
[b] Station identification (U.S. Weather Bureau).
[c] Oracle 2 Southeast (02066119) for years 1950–68.

tree 16 has a start date of 1271, tree 15 joins the dataset in 1466, and tree 10 joins in 1532.

Each predictor subset listed in Table 4 corresponds to a PCR model to reconstruct the regional-average precipitation. As described previously, the PC scores of the single-site reconstructions are the predictors in these models. Although a purely objective criterion (e.g., eigenvalue greater than 1.0) could be used to screen PCs to be included in the pool of potential predictors, such a criterion would be overly restrictive in the early part of the tree-ring record, when the predictor dataset is not in need of reduction. For the sample application, the ''eigenvalue of 1'' criterion was adopted with the following modifications: 1) as long as 7 or fewer trees

TABLE 2. Grouping of climate stations with trees for single-site reconstructions.

Tree no.[a]	Code[b]	Site name	Climate stations[c]
1	DCY15A	Douglas Canyon	8, 9, 10, 11, 12
2	PAD04A	Paddys River Pine	8, 9, 10, 11, 12
3	PDF07A	Paddys River	8, 9, 10, 11, 12
4	M118A	Mica Mountain	8
5	NSF032	North Slope Fir	8
6	TSE121	Tucson Side East	8
7	BWF091	Bear Wallow Fir	8, 11
8	RRG01B	Red Ridge	8, 11
9	GMF021	Green Mountain Fir	8, 11
10	SRH021	Santa Rita High	3, 4, 5, 6, 7
11	SRH102	Santa Rita High	3, 4, 5, 6, 7
12	SRH191	Santa Rita High	3, 4, 5, 6, 7
13	MIP3A	Miller Peak	1, 2, 3, 4, 5, 6, 7
14	MIP12A	Miller Peak	1, 2, 3, 4, 5, 6, 7
15	CMP10B	Camp Point	9, 10, 12
16	CMP02C	Camp Point	9, 10, 12

[a] As numbered on map in Fig. 2.
[b] Site code–tree number–core, as designated by researchers who collected the samples. First three characters refer to site, last character to core, and middle characters to tree; for example, DCY15A is core A of tree 15 at site DCY, and M118A is core A of tree 8 at site M11.
[c] Climate stations used for single-site reconstructions, numbered as in Table 1.

TABLE 3. Summary of single-site reconstructions.[1]

Site no.[a]	Period[b]		Regression coefficients[c]				Calibration[d] Accuracy statistics			Verification[e]	
			c	$t-1$	t	$t+1$	R^2	F	p value	r^2	RE
1	1697	1991	2.07	0.00	3.40	0.00	0.28	19.35	0.0001	0.22	0.24
2	1659	1991	1.43	0.00	3.84	0.00	0.40	34.25	0.0000	0.34	0.35
3	1717	1990	1.64	−1.00	5.13	0.00	0.44	19.71	0.0000	0.37	0.38
4	1711	1985	3.43	0.00	1.42	0.00	0.04	2.23	0.1412	0.01	0.03
5	1660	1986	1.97	0.00	0.00	3.19	0.14	8.32	0.0057	0.05	0.05
6	1685	1986	2.64	0.00	2.01	0.00	0.13	7.42	0.0088	0.10	0.12
7	1646	1986	4.15	0.00	3.10	0.00	0.08	4.66	0.0357	0.03	0.03
8	1682	1992	5.21	0.00	4.55	−2.84	0.13	3.63	0.0338	0.06	0.07
9	1560	1985	4.05	−1.61	4.53	0.00	0.22	6.85	0.0023	0.18	0.20
10	1532	1984	3.42	0.00	2.02	−1.13	0.14	4.14	0.0217	0.06	0.07
11	1601	1985	3.54	0.00	2.91	−1.86	0.38	15.04	0.0000	0.27	0.28
12	1639	1985	1.17	0.00	3.88	0.00	0.38	31.67	0.0000	0.34	0.36
13	1724	1992	3.34	0.00	1.12	0.00	0.07	3.86	0.0548	0.03	0.04
14	1714	1992	4.15	0.00	0.38	0.00	0.01	0.35	0.5559	0.02	−0.01
15	1466	1989	2.75	0.00	1.44	0.00	0.09	4.83	0.0325	0.04	0.05
16	1271	1989	2.28	0.00	1.74	0.00	0.07	3.78	0.0573	0.04	0.07

[a] As in Table 2 and on map in Fig. 2.
[b] Starting and ending years of single-site reconstruction.
[c] Estimated regression constant and coefficient at indicated lags from year of climate.
[d] Decimal proportion of explained variance; overall F and its p value.
[e] Squared correlation between reconstructed and observed climate; reduction of error statistic.

were available, all PCs were included in the pool of potential predictors, and 2) when more than 7 trees were available, the potential predictors included the seven PCs with highest eigenvalues plus any other PCs with eigenvalues exceeding 1.0. A PC score was selected from this pool as a predictor in the final model only if a t test indicated that the predictor's regression coefficient differed from zero at the 0.05 confidence level (Mardia et al. 1979).

TABLE 4. Summary of principal components regression models.

Model no.[a]	Period[b]		Number of variables[c]			Calibration–verification statistics[d]			
			N_t	N_p	N_u	R^2	r^2	RE	RMSE
1	1271	1465	1	1	1	0.09	0.06	0.09	2.156
2	1466	1531	2	2	1	0.13	0.09	0.11	2.129
3	1532	1559	3	3	1	0.17	0.12	0.13	2.101
4	1560	1600	4	4	1	0.23	0.18	0.19	2.025
5	1601	1638	5	5	3	0.45	0.25	0.22	1.992
6	1639	1645	6	6	3	0.53	0.31	0.31	1.868
7	1646	1658	7	7	2	0.49	0.25	0.24	1.965
8	1659	1659	8	7	3	0.59	0.46	0.46	1.662
9	1660	1681	9	7	2	0.55	0.45	0.46	1.661
10	1682	1684	10	7	2	0.55	0.43	0.43	1.696
11	1685	1696	11	7	3	0.62	0.45	0.46	1.662
12	1697	1710	12	7	2	0.54	0.38	0.38	1.771
13	1711	1716	13	7	4	0.57	0.44	0.45	1.677
14	1717	1723	14	7	4	0.62	0.51	0.52	1.558
15	1724	1915	15	7	2	0.58	0.51	0.53	1.554

[a] Model number, sequentially from earliest to most recent model period.
[b] Starting and ending years of model periods.
[c] Number of trees (N_t), number of PCs in pool of potential predictors (N_p), and number of PCs included as predictors in final model (N_u).
[d] Regression R^2 for calibration, squared correlation between observed and reconstructed climate, reduction of error statistic, and root-mean-square error for cross validation.

The 15 PCR models are summarized in Table 4. The maximum number of potential predictors for any model is seven, and the maximum number in any final reconstruction model is four. The most recent reconstruction model, for 1724–1915, includes only two PCs as predictors. Regression R^2 for the PCR models ranges from 0.09 for the earliest, single-tree, model to 0.62 for two of the later models.

The ability of the reconstruction models to predict regional climate data not used in the model calibration was checked with cross validation, successively omitting sequences of five observations from the calibration dataset and estimating the regression model on the remaining observations. The results of cross validation are summarized by the squared correlation coefficient between actual and predicted data, the reduction of error statistic, and the root-mean-square error of prediction (Table 4).

The accuracy of reconstruction generally increases with the number of available trees (Fig. 3). Periods of large vertical separation of the R^2 and reduction of error (RE) curves in the bottom plot of Fig. 3 indicate poor model verification. The period of best reconstruction, as indicated by a combination of high R^2 and high RE, is restricted to the years beginning with the mid-1600s. Models before 1600 verify fairly well, but explain little variance. Models from 1600 to the mid-1600s explain much more variance than earlier models, but verify poorly, possibly indicating overfitting of the models.

The reconstruction and its associated uncertainty as measured by the root-mean-square error (RMSE) for the

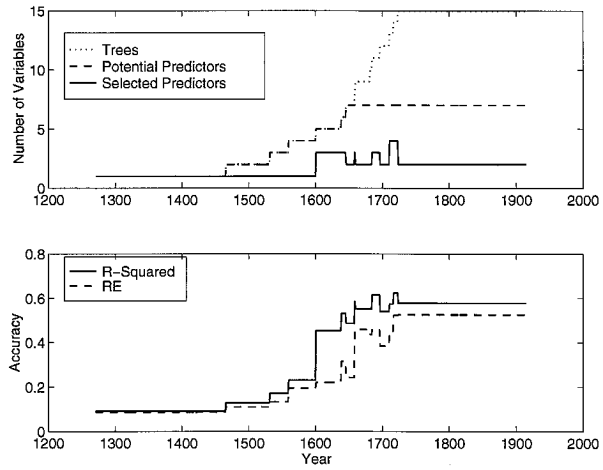

FIG. 3. Variation of predictor datasets and accuracy of reconstruction with time. Predictor datasets vary in the number of trees available, the number of PC scores included as potential predictors, and, the number included in the final model (top). Calibration and verification accuracy are measured by the regression R^2 and the reduction of error statistic (bottom).

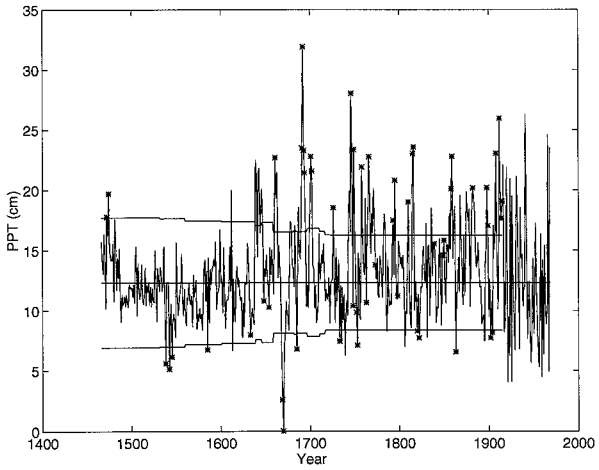

FIG. 4. Reconstructed cool-season precipitation in the San Pedro River Basin, 1466–1968. Error bars are ±1.0 root-mean-square error of reconstruction based on cross validation. Asterisks mark regression estimates classified as extrapolations versus extrapolations by a simple ellipsoidal approximation to the interpolatory region (Weisberg 1985). The earliest, least reliable, segment of the reconstruction (1271–1465) has been omitted from the plot to improve readability.

period after 1466 are plotted in Fig. 4. The error bars are conservative in that the RMSE was computed from the cross-validation data. The earliest part of the reconstruction (1271–1465) has been omitted from the plot to improve readability; the reconstruction model for that period is based on only one tree and explains only 9% of the climate variance (Table 4). The vertical compression of the reconstructed series and expansion of the error bars in the earliest part of the reconstruction reflect a weakened climatic signal. The signal before 1600, in particular, is weak not only because few trees are available as predictors, but because the trees available have relatively weak signals for the climate variable of interest (single-site R^2 values in Table 3).

An unavoidable dilemma with regression methods, as applied to paleoclimatic reconstructions, is that the most interesting climatic interpretation is likely to focus on predicted values classified as extrapolations rather than interpolations (Weisberg 1985). The regression equation cannot be assumed to apply to such extrapolations, which result from tree-ring data outside the multivariate cloud of tree-ring data for the calibration period. Such extrapolations are scattered throughout the plotted series in Fig. 4; in fact, most of the reconstructed values more than one root-mean-square error greater or less than the calibration-period mean are extrapolations. The additional uncertainty inherent in these extrapolations should be acknowledged in climatic interpretations of reconstructions.

This example is intended solely to illustrate the reconstruction method, and for clarity of illustration uses only a few of the available tree-ring collections from the SPRB. The reconstructions summarized in Figs. 3 and 4 should, therefore, not be considered the most accurate possible for the basin.

4. Discussion

The expansion of error bars and vertical compression of reconstructed values toward the earliest part of the record (Fig. 4) is the expected pattern for the following circumstances: 1) sample size increasing with time, 2) the trees containing a common signal reflecting climate, and 3) the signal strength being reasonably similar among trees. In the limit, the earliest part of such a reconstruction might approach a horizontal line equal to the calibration-period mean and the error bars (RMSE) might exceed the standard deviation of the observed predictand. In such a case, the early part of the reconstruction should of course be discarded. Less likely, but plausible, is that the essential climate signal might be contained by a few very old, climatically sensitive trees. If so, the error bars might narrow toward the early part of the tree-ring record, and the researcher might consider redoing the entire reconstruction using just the small subset of old trees.

The method proposed here can be extended to the problem of spatial reconstruction, or the reconstruction of spatially distributed fields of climate variables (Cook et al. 1994). Instead of a single predictand vector ${}_p\hat{\mathbf{y}}^*_1$, the model would include a matrix of predictands at many sites or grid points. This predictand matrix could be reduced, just as ${}_p\hat{\mathbf{C}}^*_{n_i}$ is by PCA, to some smaller number of orthogonal predictands. The reconstruction of these orthogonal predictands and the transformation back to original predictands at the sites or grid points would then follow directly according to orthogonal spatial regression, as described by Cook et al. (1994).

A complication in the extension of the proposed method to spatial regression for large-scale problems is the PCA reduction of the predictor data. For a continental-

scale problem, the tree-ring data might include hundreds of tree-ring sites and thousands of trees. The initial step in the reconstruction for such a dataset would be the estimation of thousands of single-tree regression models and the generation of the thousands of SSRs. The PCs of these thousands of SSRs would probably be so strongly biased by the uneven spatial distribution of the trees that the predictor variables for the PCR models would poorly represent the large-scale tree-growth variations over the study area. One possible approach is to impose an intermediate step of data reduction by averaging the SSRs over trees before proceeding to PCA. For example, SSRs could be averaged over trees according to membership in site chronologies as follows:

1) for each tree, represented by a column of ${}_m\mathbf{W}_n$ retain a tag identifying the chronology collection site;
2) proceed with the reconstruction as described previously through the identification of tree subsets H_j (see section titled ''Tree subset identification'');
3) for a given tree subset, average the SSRs over trees (columns of ${}_m\hat{\mathbf{C}}^*_n$) according to chronology collection site; and
4) proceed with the remaining steps of the reconstruction, but using the reduced-column matrix of averaged SSRs instead of the SSR matrix ${}_m\hat{\mathbf{C}}^*_n$.

In this modified method, the number of averaged SSRs, or the number of variables to be reduced to regional-climate predictors by PCA, is no larger than the number of chronology collection sites. A trade-off in the modification is the loss of flexibility in incorporating possible differences in the strength of the climate signal of different trees at a particular collection site.

Another complication in the extension to large-scale problems is the choice of local climate variables for the single-site reconstructions for trees distributed over a very large area and representing perhaps many different species. Precipitation was the variable used in the sample application—a hydrologic application for a relatively small watershed. In other applications, temperature as well as precipitation might be considered for the local climate variable. If a generalized drought response is expected, a derived variable (e.g., the Palmer Drought Index) incorporating the combined influence of precipitation and temperature on drought stress might be appropriate.

Alternative time series approaches are possible for deconvolving, or digitally filtering, the annual local climatic signal from the individual tree indices in the single-site regression modeling (step A, Fig. 1). One possibility is to remove persistence separately from the climate variable and the tree-ring series by ARMA modeling, reconstruct the climate residuals from the tree-ring residuals in a no-lag model, and build persistence back into the reconstruction using the ARMA climate model (Meko 1981; Stahle and Cleaveland 1988).

The method presented here could perhaps be modified to better take into account tree to tree differences in climate signal strength, as measured by the R^2 values from the single-site reconstructions (Table 3). One possibility is to skip the step of normalizing the SSRs to unit variance and to use the covariance matrix instead of the correlation matrix in the PCA (Fig. 1). Skipping the normalization risks, however, placing undue importance on SSRs whose local climate variables happen to have relatively large variance—as for example, precipitation for mountain stations. This problem could be circumvented by normalizing the SSRs to unit variance, but then scaling them by some function of the R^2 value before proceeding to PCA with the covariance matrix.

The assumption that all tree indices overlap the period covered by climatic data is seriously restrictive in excluding tree-ring data from remnant wood as well as tree-ring series from living trees whose most recent sections had to be discarded for some reason (e.g., poor crossdating or injury to the tree). An examination of this important problem is beyond the scope of this paper. A possible approach is to use in place of the remnant wood series in calibration a substitute or stand-in tree, whose ring width series does cover the calibration period. This stand-in tree might be identified by a similarity of its site characteristics to those of the remnant wood specimen, or by a similarity in statistical properties (e.g., variance or autocorrelation properties of tree indices). The SSR model for the remnant wood could be calibrated using the stand-in series and the earlier reconstruction generated by substitution of the remnant wood series into the regression equation. Such substitution is no more problematic than the generation of long-term climate reconstructions from site chronologies built by splicing together time series segments from living tree and remnant wood specimens (Cook et al. 1995).

The number of trees in the sample application is smaller than for most practical dendroclimatic problems. Cross validation can be computer intensive for much larger datasets. Cross validation of the SSR models for m trees and p calibration years requires estimation of $m*p$ regression models. Cross validation of the k PCR models then requires estimation of $k*p$ models. The total number of models to be estimated is $p*(k + m)$. For a problem with $p = 80$ calibration years, $m = 300$ trees, and $k = 200$ tree subsets, a total of 40 000 regression models must be estimated. Whether this requirement is a serious limitation to the method depends on the power of the available computer.

5. Conclusions

The proposed reconstruction method is most applicable to reconstruction scenarios in which the climate–tree-growth relationship is dynamic, strong in at least some trees, and variable from tree to tree. The main advantages over existing reconstruction methods are flexibility in accommodating tree-specific climate signals and improved estimation of the time variation of

reconstruction accuracy. The method has been described in the context of tree-ring data, but should be adaptable to other types of annually resolved, spatially distributed, paleoclimatic indicators with dynamic responses to climate.

No claim is made that reconstructions by the proposed method will generally be more accurate than those by existing methods using site chronologies, only that the assessment of accuracy is more direct.

Acknowledgments. Christopher Baison and Henri Grissino-Mayer provided ring-width series from the Rincon Mountains and Pinaleño Mountains for use in the sample application. The research was supported by U.S. Bureau of Land Management Cooperative Agreement A950-A1-0012 and National Park Service Award CA-8012-2-9001.

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