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PILOT STUDY OF LATEWOOD-WIDTH OF CONIFERS AS AN INDICATOR OF VARIABILITY OF SUMMER RAINFALL IN THE NORTH AMERICAN MONSOON REGION

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ABSTRACT

The variability of the North American Monsoon System (NAMS) is important to the precipitation climatology of Mexico and the southwestern United States. Tree-ring studies have been widely applied to climatic reconstruction in western North America, but as yet, have not addressed the NAMS. One reason is the need for highly resolved seasonal dendroclimatic information. Latewood-width, the portion of the annual tree ring laid down late in the growing season, can potentially yield such information. This paper describes a pilot study of the regional summer precipitation signal in latewood-width from a network of five *Pseudotsuga menziesii* chronologies developed in the heart of the region of NAMS influence in Arizona, USA. Exploratory data analysis reveals that the summer precipitation signal in latewood is strong, but not equally so over the full range of summer precipitation. Scatter in the relationship increases toward higher levels of precipitation. Adjustment for removal of inter-correlation with earlywood-width appears to strengthen the summer precipitation signal in latewood-width. To demonstrate a possible application to climatic reconstruction, the latewood precipitation signal is modelled using a nonlinear model—a binary recursive classification tree (CT) that attempts to classify summers as dry or not dry from threshold values of latewood-width. The model identifies narrow latewood-width as an effective predictor of a dry summer. Of 14 summers classified dry by latewood-width for the period 1868–1992, 13 are actually dry by the instrumental precipitation record. The results suggest that geographical expansion of coverage by latewood-width chronologies and further development of statistical methods may lead to successful reconstruction of variability of the NAMS on century time scales. Copyright © 2001 Royal Meteorological Society.

KEY WORDS: classification tree; climate reconstruction; dendroclimatology; monsoon; precipitation; North America

1. INTRODUCTION

The North American Monsoon System (NAMS), characterised by a rapid shift in positions of the Pacific and Bermuda highs, development of an upper level anticyclone over the southern United States, and other circulation changes in June or early July, governs the summer precipitation regime over large areas of northern Mexico and southwestern United States (Bryson and Lowry, 1955; Namias, 1955; Carleton, 1986; Higgins *et al*., 1998). Variation of the NAMS on time scales longer than the instrumental record is poorly understood. Tree-ring indices of total ring-width have been demonstrated to effectively integrate moisture conditions over seasons, and have been applied to reconstruct summer (June, July, August average) Palmer Drought Severity Index (PDSI) at gridpoints over the continental United States (Cook *et al*., 1999). This reconstruction, while accurate over much of the southwestern United States, is of limited use for studying the variability of the NAMS because the seasonal window of moisture response of PDSI is too broad. PDSI for a given month or season depends partly on previous months' moisture

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conditions through soil-moisture storage and autoregressive terms in the computation algorithm (Palmer, 1965). Summer PDSI, therefore, reflects moisture conditions not just in summer, but also in the preceding winter and spring. In contrast, the window of climate response of an effective NAMS indicator must be restricted to the summer months.

Perhaps the most promising tree-ring variable for large-scale application to the study of the NAMS is the latewood-width of drought-sensitive conifers. Earlywood and latewood describe wood of differing density typically formed early and late in the growing season of a tree. Earlywood is the first-formed portion of the growth ring, characterised by large cells with thin walls, and lower density wood. Latewood is the later-formed portion, characterised by smaller cells with thick walls, and higher density wood (Hoadley, 1990). The size and density differences are imparted by differences in rates and durations of cell processes (Larson, 1969; Jagels and Telewski, 1990). In some tree species, including *Pseudotsuga menziesii* (Douglas fir), the transition between earlywood and latewood is readily recognizable as a sharp change from lighter to darker wood (Kozlowski and Pallardy, 1997). Latewood holds the greatest potential for studying summer precipitation and the NAMS. A positive relationship between latewood-width and growing-season precipitation has been reported in correlation studies for various conifer tree species growing in widely differing climate regimes. Examples include *Pinus ponderosa* in central Arizona (Douglass, 1919), *Pinus palustris* in western Florida (Lodewick, 1930), *Pinus echinata* in Arkansas (Schulman, 1942), *Pinus sylvestris* in Germany (Spurk, 1997), and *Pseudotsuga menziesii* in Mexico and southwestern United States (Cleaveland, 1983, DW Stahle, personal communication), and on a plantation in Great Britain (Chalk, 1951).

Latewood is particularly suitable for studying the NAMS because the area of influence of the NAMS overlaps the distributions of several tree species with a reported warm-season precipitation signal in latewood. The influence on precipitation in the United States is particularly strong in Arizona and New Mexico, where the monthly precipitation distribution is strongly bimodal, and in many places, dominated by a summer peak.

The application of latewood data to climatology has been hampered by a shortage of developed chronologies and a lack of knowledge about the statistical and time series properties of latewood. In this paper, we report on a pilot study to explore the regional-scale summer precipitation signal in a set of recently developed *Pseudotsuga menziesii* chronologies from a part of Arizona, USA, strongly influenced by the NAMS. We address some statistical problems with extracting the precipitation signal, and demonstrate a probabilistic approach to reconstruction of occurrence of dry summers.

2. DATA AND METHODS

2.1. Precipitation

The study area is the United States portion of the San Pedro River Basin (SPRB), a semi-arid basin with an area of about 9800 km^2 in southeastern Arizona (Figure 1). Elevations range from 590 m along the San Pedro River to more than 2900 m in highest parts of the flanking mountains. Annual precipitation ranges from 290 mm on the valley floors to more than 630 mm in the higher elevations (Sellers and Hill, 1974).

To derive a regional summer-precipitation series for calibration with tree-rings, monthly precipitation data for 39 stations in southern Arizona and New Mexico were downloaded from the western region Climate Centre (WRCC, 2000). The network includes all stations in or near the SPRB with at least 30 years of record, plus selected long-term stations from surrounding areas. Station locations are plotted in Figure 1. The data span the period 1866–1999, but time coverage varies by station. July and August contribute, on average, more than 40% of the annual total annual precipitation at the stations in the SPRB. This summer rainy period is normally preceded by an extremely dry late spring. For example, at Tombstone (Figure 1), the mean annual precipitation is 352 mm (1887–1999), the mean July–August total is 172 mm, and the mean May–June total is only 17 mm.

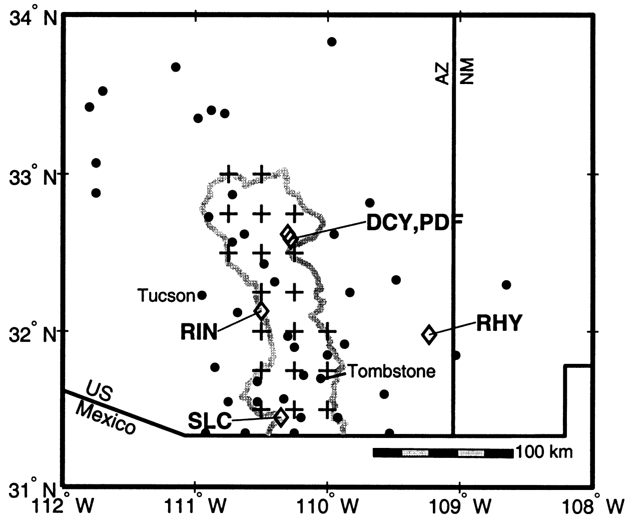

Figure 1. Map showing data locations. Tree-ring sites marked by diamonds, precipitation stations by dots, and gridpoints for interpolation of regional precipitation by plus signs. Boundary of the SPRB shaded light grey

To emphasise the larger-scale precipitation variations, station data were converted into regional monthly precipitation by a method described by Jones and Hulme (1996). For a given month and year, standardised station anomalies of monthly precipitation were interpolated to evenly spaced gridpoints in the SPRB by inverse-distance weighting. The five nearest stations to a gridpoint were used in the interpolation—fewer if five stations were not available for a month/year. Long-term means and standard deviations were interpolated to gridpoints using the same scheme as the standardised anomalies, and were applied to restore the gridpoint-anomaly time series to original precipitation units. Regional precipitation was then computed by averaging over gridpoints (Figure 1) and the regional monthly data were seasonalized into various monthly groupings. We define the July–August total for the purposes of this study as summer precipitation.

The resulting regional summer precipitation time series and changing station density, 1868–1999, are plotted in Figure 2. The mix of available stations for a given month/year varies, depending on station openings and closures and missing data. The early part of the record is poorly determined because the

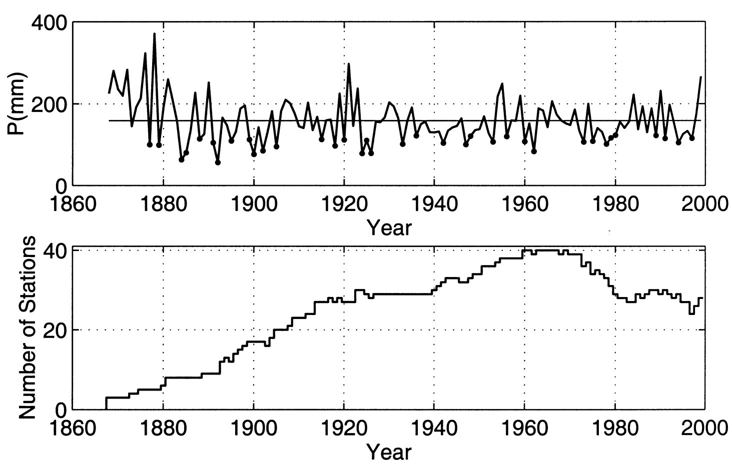

Figure 2. Time series plots of July–August total regional precipitation and precipitation station coverage. Dots mark dry summers ($p < 124$ mm)

station network is sparse, necessitating interpolation from distant stations. The earliest station record in the SPRB, Tombstone, begins in 1887. Thus, the unusual wet period before 1880 in the regional series is quite uncertain. The regional summer precipitation series ranges from 56.3 to 371.0 mm, and has a long-term mean of 159 mm. For tree-ring modelling, we focus on accuracy of classifying 'dry' summers, as defined by summer precipitation less than 124 mm. This threshold marks approximately the driest quarter of summers (27%, or 36 of 132) as dry. The threshold was chosen at a steep part of the cumulative probability histogram of precipitation to minimise years with ambiguous classification. The dry summers are marked by dots on the precipitation plot in Figure 2.

2.2. Tree-rings

Five *Pseudotsuga menziesii* partial ring-width (earlywood and latewood) tree-ring chronologies—four from the SPRB and one from 60 km to the east—were used in the study (Figure 1, Table I). The collections included at least eight trees suitable for partial-ring measurements at each site. Two core samples were extracted from each tree. We followed standard procedures for sample preparation and dating (Stokes and Smiley, 1968). Rings were measured to the nearest 0.01 mm, and earlywood/latewood boundaries of individual rings were identified visually under the microscope. Visual identification of boundaries can be done rapidly, and so, is feasible where many sites must be processed quickly; this is important if the method is to be extended to a network of many sites over the NAMS region. Moreover, spot checks indicated that, for our samples, visual identification of boundaries was repeatable from one technician to another. Available automated methods of identifying the earlywood–latewood boundary (e.g. X-ray densitomety, reflected-light image analysis) were considered impractical for our samples because of expense and requirements for specialised sample preparation (Jagels and Telewski, 1990; Sheppard *et al.*, 1996).

The separate ring components were then measured, and the sum checked for consistency against the previously measured total ring-width. Measured partial-ring-width series were converted to dimensionless growth indices by dividing the measured widths by the values of a smooth detrending line fit to the widths. The detrending line is intended to represent the gradual ring-width change over time associated with increasing tree size or age. Trend lines fit to the data were generally monotonic decreasing—negative exponential or straight line. A spline function was used to detrend some problematic series, but to avoid excessive filtering out of climatic information, we restricted the flexibility of the spline by specifying that the amplitude of frequency response (Cook and Peters, 1981) did not drop below 0.50 for wavelengths shorter than 100 years.

The detrended series, or 'core indices', were merged by simple arithmetic averaging into a site chronology representing the latewood or earlywood growth variations at the site. The ability of this mean-value function to summarise the unknown population tree-growth variation at the site is degraded early in the record because of diminished sample size. The expressed population signal (EPS), as defined by Wigley *et al.* (1984) indicates that, for our chronologies, between three and 11 trees are needed for the expected correlation with the hypothetical population chronology to exceed 0.85. The sample size for the chronologies used in this study appears adequate for the period of calibration with climate records, which is the focus of this study, but needs to be increased in the period before the late 1800s for accurate climatic reconstructions (Table I). Note that the sample size for some latewood chronologies in Table I is less than that of the earlywood chronologies. We observed that latewood sometimes becomes extremely narrow, and variability decreases, as a tree reaches great age—more than a few hundred years. Thus, some cores suitable for earlywood indices could not be used for latewood indices. The earliest tree-ring series in our set begins in AD 1528, but the period of common coverage by all sites is restricted to AD 1791–1992.

The correlation is positive between latewood index (LWW) and earlywood index (EWW) at all sites ($r > 0.31$, $n > 207$, p-value < 0.01), suggesting that latewood-width is pre-conditioned by the tree vigour before the start of summer. The positive LWW–EWW correlation clearly cannot be attributed to inter-seasonal correlation in precipitation because the seasonal components of precipitation in the SPRB have a slight negative correlation. For example, the correlation coefficient between regional July–August

Table I. Site information on tree-ring chronologies

Code[a]	Site name	Period[b]		Location[c]			Sample depth[d]		
		First	Last	Latitude	Longitude	Elevation (m)	1800	1850	1900
SLC-E	Scheelite Canyon, Huachuca Mountains	1630	1995	31.4	110.3	1750	10	16	19
-L		1750	1995				*4	11	16
DLC-E	Douglas Canyon, Galiuro Mountains	1652	1993	32.6	110.3	2027	10	14	17
-L		1652	1994				9	14	17
PDF-E	Paddys River, Galiuro Mountains	1605	1994	32.6	110.3	2119	10	13	16
-L		1693	1993				*3	*4	8
RIN-E	Rincon Peak, Rincon Mountains	1791	1997	32.1	110.5	2774	*2	4	17
-L		1791	1997				*2	4	17
RHY-E	Rhyolite Canyon, Chiricahua Mountains	1528	1992	32.0	109.2	1828	4	8	16
-L		1528	1992				*4	8	16

[a] First three letters are site code, as in map in Figure 1; E and L denote earlywood and latewood.
[b] First and last years of tree-ring chronology.
[c] L and longitude in decimal degrees, elevation in metres.
[d] Number of trees in chronology in AD 1800, 1850, and 1900; * before number indicates sample size undesirably low as indicated by EPS < 0.85 (see text).

and preceding November–April precipitation is $r = -0.19$ ($n = 132$, p-value < 0.05). We attempted to adjust for the apparent pre-conditioning of latewood by adjusting LWW to remove its linear dependence on EWW using simple linear regression. LWW was regressed on EWW, and the residual with a constant of 1.0 added to restore the original mean, was defined as the 'adjusted' latewood index.

This simple adjustment resulted in increased correlation of latewood with summer precipitation at all sites (Table II). The largest increase in correlation is 0.48 to 0.62 at site DCY. The correlation between summer precipitation and LWW_{adj} is large and positive at each site. In contrast, summer precipitation is effectively uncorrelated with earlywood-width, and weakly correlated with total ring-width (Table II).

2.3. Classification tree (CT) model

The statistical model we chose to describe the relationship between dry summers and adjusted latewood-width index (LWW) is the binary recursive CT, which is described in detail by Clark and Pregibon (1992). This model was selected after exploratory data analysis indicated that the relationship between summer precipitation and adjusted latewood index is heteroscedastic and perhaps nonlinear. The CT model is suitable for modelling such relationships, and has the additional attributes for exploratory studies, such as ours, of allowing a mix of numeric and non-numeric predictors, and allowing predictors to be disregarded by the model if they are unimportant. The CT model is appropriate when a single response variable is to be modelled against one or more predictors. Mathematics and terminology of the CT are deferred to Appendix A.

The predictand for our application of the model is the binomial variable representing occurrence or non-occurrence of a dry summer, as defined previously. The potential predictors for the model are (1) a five-site-mean adjusted latewood index, and (2) a categorical variable indicating whether any of the five sites has wider than normal latewood. The five-site-mean was selected as a simple summary tree-ring variable to emphasise the common latewood-width signal at the various sites. The use of such a mean-value function is supported by a bivariate correlation analysis and consideration of the spatial heterogeneity of summer precipitation variations in the region. For the common period of tree-ring data (1791–1992), the inter-site correlation of adjusted latewood-width ranges from 0.31 to 0.76. The lowest of these bivariate correlations is significantly greater than zero (p-value < 0.0001), even if allowance is made for adjustment of effective sample size for autocorrelation in the individual time series (Dawdy and Matalas, 1964; Mitchell *et al*., 1966). The inter-site correlations in latewood-width are consistent with the inter-station correlation in summer (July + August) precipitation. For example, the correlation coefficient between summer precipitation at Tucson and Tombstone (1898–1992) is 0.42. The separation distance of these stations is similar to the distances between pairs of widely spaced tree-ring sites used (Figure 1).

An initial, overfit, CT was developed, as described in Appendix A. The tree was then simplified using cross-validation to identify the level of complexity (number of terminal nodes) beyond which the model fails to yield improved accuracy of prediction of observations not used in calibration (Clark and Pregibon,

Table II. Correlation between SPRB summer precipitation and ring-width-index variables for five tree-ring sites in southeastern Arizona

Site[a]	n (year)[b]	Correlation[c]			
		EWW	LWW	LWW_{adj}	TW
SLC	107 (1889–1995)	−0.01	0.40	0.44	0.14
DCY	105 (1889–1992)	−0.05	0.48	0.60	0.07
PDF	105 (1889–1993)	−0.04	0.44	0.54	0.06
RIN	109 (1889–1997)	−0.10	0.56	0.64	0.17
RHY	104 (1889–1992)	−0.08	0.48	0.53	0.15

[a] Tree ring sites, coded as in Table I.
[b] Number of years and period for correlation computation.
[c] Product-moment correlation between precipitation and tree-ring indices.

1992). We used a leave-one-out, or procedure in which each observation is successively withheld, the tree is developed on the remaining observations, and the model is applied to classify the withheld observations. The procedure is analogous to cross-validation in a regression model as describe by Michaelsen (1987). As a diagnostic tool to summarise the cross-validation we use a plot of total cross-validation tree deviance against number of terminal modes in the model.

3. RESULTS AND DISCUSSION

3.1. Strength of linear relationship

A scatterplot of summer precipitation against five-site-mean adjusted latewood index, x, reveals several interesting features of the latewood precipitation signal (Figure 3). First, the relationship summarised by a simple linear model is quite strong: regression R^2 is 0.45, which is respectably high for a dendroclimatic relationship, especially considering the spatial heterogeneity of summer precipitation anomalies and unlikelihood that scattered station data accurately mirror the precipitation variations at the tree-ring sites.

Second, the relationship is heteroscedastic—characterised by increasing scatter at higher precipitation. Third, the pattern of scatter hints at nonlinearity, with diminished tree-ring response at higher precipitation. Finally, as indicated by the open circles, dry summers and narrow five-site-mean latewood usually go along with the absence of wider than normal latewood at any of the five sites. This last observation led us to consider the categorical variable N_w as a candidate predictor variable for a dry summer, where $N_w = 1$ if no sites have wide latewood, and $N_w = 2$ if at least one site has wide latewood.

3.2. CT modelling

A CT model, as described previously, and in more detail in Appendix A, was fit to the precipitation and latewood data with the objective of testing the ability to predict whether a summer is dry (regional $p < 124$ mm) from adjusted latewood at the five sites. A model was fit to the data for the 125-year period 1868–1992, and then simplified using cross-validation. Potential predictors for the model were x and N_w, representing the five-site-mean adjusted latewood index and the presence or absence of any wide-latewood sites.

The final estimated CT, after simplification by cross-validation, is sketched in Figure 4. The tree indicates remarkably high skill of identifying dry summers from a low threshold value of x. The root node

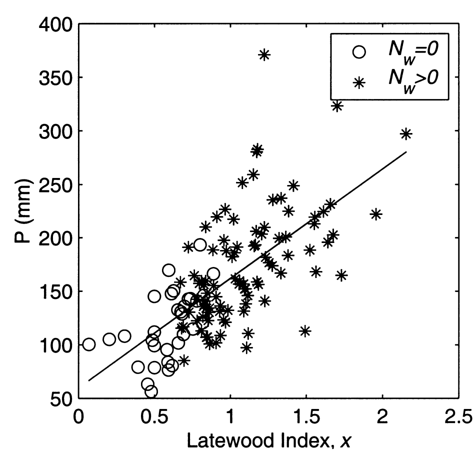

Figure 3. Scatter plot of summer precipitation against five-site-mean adjusted latewood index for SPRB. Circles mark years in which latewood was wider than normal at none of the five sites

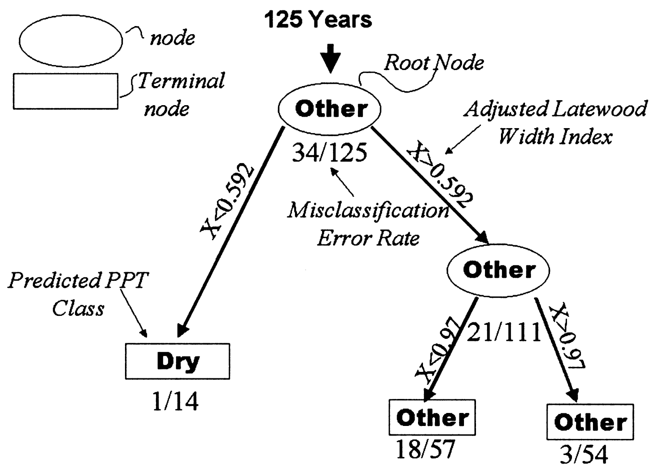

Figure 4. Sketch of final estimated CT. Predicted precipitation (PPT) classes are associated with nodes. Years are classified as having dry summers or not ('other') depending on the value of the mean adjusted latewood index, x

contains all 125 observations, with empirical probability $34/125 = 0.272$ that the summer is dry and $91/125 = 0.728$ that the summer is not dry. The prediction at the root node is, therefore, 'other', or not dry, with a misclassification probability of 34/125.

All splits in the model are on x. The categorical predictor N_w fails to enter the model, probably because its information on precipitation is not independent of the information contained in x. The latewood-width index can roughly be interpreted as a decimal fraction of normal growth, with 1.0 being normal, 0.50 half of normal, etc. The first split is on a latewood-width index of $x = 0.592$, with narrower latewood indicating a dry summer and wider latewood otherwise. This simple rule classifies 14 years as dry summers, with only one year misclassified. The secondary split in the right-hand branch of the tree indicates that normal-width latewood is a good indicator that summer was not dry: of 54 years with $x > 0.97$, only three had a dry summer.

The CT is essentially a reconstruction model in that tree-ring data for years before the precipitation record began can be 'dropped down' the tree in Figure 4 to get a probability that the summer was dry. If p_m is the misclassification error rate for a terminal node, the probability that summer was dry is $(1 - p_m)$ for a node labelled 'dry' and p_m for a node labelled 'other'. To illustrate the application of the model, the latewood data for years prior to the calibration period were entered into the model to reconstruct the probability of a dry summer back to 1791, the earliest year for which we have latewood-width data at all sites.

A summary bar plot shows time series variation in probability of dry summer (Figure 5). The discrete levels in the plot correspond to the terminal nodes in the CT (Figure 4). Dots have been plotted at the top of Figure 5 to mark years of actual dry summers. Note that the 1 year out of 14 incorrectly identified as dry is 1873, the first dry summer in the calibration period. As mentioned previously, the low station density makes the regional series uncertain then. Regional summer precipitation in 1873 was below normal (145 mm versus 159 mm), though not below the 124 mm 'dry summer' threshold. Interesting features of the reconstruction are the three consecutive dry summers in 1823–1825 and the unusually extended periods of low probability of dry summers in the 1840s and 1860s. Considering both the highest probability class and the intermediate class, the period from the early 1880s to the early 1890s stands out for high interannual persistence of dry summers. The extremely wet years 1876 and 1878 in the regional precipitation series (Figure 2) fall into the lowest probability class of a dry summer.

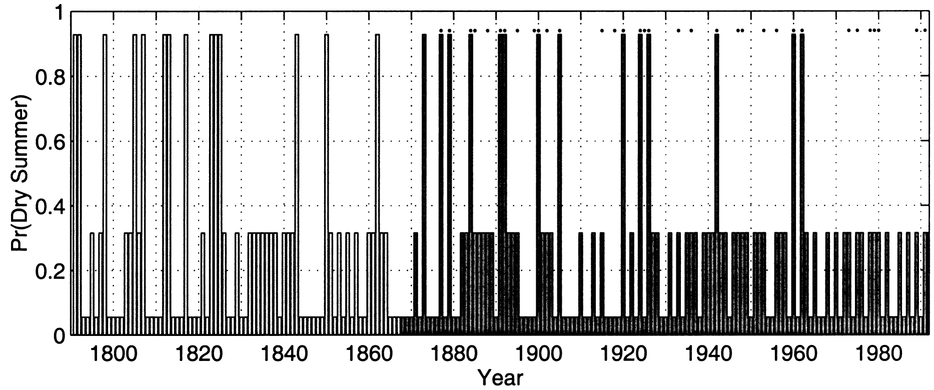

Figure 5. Bar chart of tree-ring reconstructed probability of a dry summer. Analysis period 1791–1992. Calibration period (1868–1992) bars shaded dark, and bars for earlier year light. Dots near top of figure mark dry summers ($p < 124$ mm) in calibration period as given by instrumental precipitation. Probability denoted by 'Pr'

4. CONCLUDING REMARKS

This pilot study for a small watershed in southeastern Arizona indicates that the regional summer precipitation signal is strong in *Pseudotsuga menziesii* latewood-width, and that the seasonal window of response is narrow enough to expect to capture a signal related to the July–August peak influence of the NAMS. Adjustment of latewood-width for removal of its linear dependence on earlywood-width sharpens the latewood signal for summer precipitation. The results suggest that larger scale application to reconstructing variability of the NAMS is possible. Spatial domain and density of tree-ring site coverage are likely to be critical to such application. We have focused on narrow latewood and its association with dry summers. The results suggest that additional useful information on summer precipitation can be gleaned from the full range of latewood-width variation. For example, we found that wider-than-normal latewood at any site is a good indicator that the summer was not dry. Testing of alternative statistical models, including other types of nonlinear models, to extract the summer precipitation signal from latewood-width is recommended.

We emphasise that many statistical and logistical problems remain in the application of latewood-width to reconstruction of the variability of the NAMS. The main logistical problem is development of more latewood-width chronologies. Sites distributed over the main NAMS influence region, including northern Mexico, are needed to extend inferences beyond the narrow regional perspective. Such chronologies can be developed from existing wood samples stored from earlier collections, but not without problems. We mentioned in referring to the sample sizes in Table I that sometimes only a subset of cores at a site is suitable for computation of latewood indices. The best expression of latewood with large interannual variability in our samples seems to be in the first 250 years of growth. If this is a general property of latewood-width of Douglas fir in the NAMS region, an age-stratified sampling scheme might be needed to capture a robust latewood-width signal over a long time period.

The rapid identification of the earlywood–latewood boundary can perhaps be made less subjective than in this study. Regardless, rigorous tests of the repeatability of identification for samples of varying quality of expression of latewood are needed. Alternative semi-quantitative techniques based on visual quantitative assessment of cell dimensions, X-ray densitometry or reflected light image analysis should also be explored.

ACKNOWLEDGEMENTS

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APPENDIX A. CT MODEL

The binary recursive CT model belongs to the general family of classification and regression trees (CART) described by Clark and Pregibon (1992). The predictand for the CT is categorical, with an observation falling into any of K possible levels, and is assumed to be multinomially distributed. For example, consider a predictand with two possible levels, indicating summer dry (level 1) or otherwise (level 2). An observation can be written as a vector of length two, with elements depending on the level of the observation. If y denotes an observation, and the observation falls in the first level, $y = \{1, 0\}$; and if the observation falls in the second level, $y = \{0, 1\}$.

The data are partitioned recursively into increasingly homogeneous subsets according to rules defined on the values of the predictors. Each subset is associated with a set of probabilities for level of the predictand. The subsets of observations produced by the partitioning are called *nodes*. The top, or 'root', node contains all observations. The partitioning begins when this root node is split using a rule on one of the predictors, resulting in two smaller subsets. The root node in this case is the *parent* node and the two resulting lower nodes the *children* nodes. The children nodes are, in turn, split, each resulting in two additional nodes, and so forth. The CT can be diagrammed as an inverted 'tree', with nodes expanding downward. The last nodes resulting from the splitting are the *terminal nodes*.

The partitions, or *splits*, are chosen such that the resulting subsets are as homogeneous as possible, as measured by the *deviance*. Let the total number of observations in the data set be N_T and at the jth node be N_j. For now, consider the computations at a single node j. The empirical probability of an observation falling in level k is

$$p_k = N_k/N_j \tag{1.1}$$

where N_k is the number of observations in level k at node j. Let the vector $\mu_j = \{p_1, p_2, \ldots, p_K\}$ denote the probability that an observation y_i falls in each of the possible levels. Because y must fall in one of the levels, $\Sigma_{\text{all } k}\, p_k = 1$.

The *deviance of an observation* y_i describes its similarity to other observations at the node, and is defined as minus twice the log likelihood,

$$D_i(\mu_j;\ y_i) = -2 \sum_{k=1}^{K} y_{ik} \log(p_k) \tag{1.2}$$

where y_{ik} is 0 or 1, depending on whether or not the observation is in level k. The summation is restricted to levels with at least one observation at the node (i.e. levels with non-zero p_k at the node) to avoid log(0). Each observation falls into some level k, and makes the contribution $-2\log(p_k)$ to the deviance. If all observations at the node fall into the same level the deviance of each observation is zero, as $p_k = 1$ and $-2\log(1) = 0$. Otherwise, the contribution of the observation to the deviance is positive.

The *deviance of a node* describes the similarity of the observations at the node, and is defined as the sum of the deviances of the observations at the node:

$$D_j(\mu_j;\ y) = \sum_{\text{all } i} D_i(\mu_j;\ y_i) \tag{1.3}$$

If all observations in the node fall in the same level, the node is called 'pure', and the deviance at the node is zero.

The *tree deviance* is the sum of the deviances of the terminal nodes of the tree

$$D_T = \sum_{j \in J} D_j \tag{1.4}$$

where D_T is the tree deviance and J is the set of terminal nodes, and the *residual mean deviance* is the tree deviance divided by the sample size adjusted for the number of terminal nodes

$$\bar{D} = D_T/(N_T - N^*) \tag{1.5}$$

where $\bar{D}$ is the residual mean deviance of the tree and N^* is the number of terminal nodes. The residual mean deviance is a summary measure used to describe the accuracy of the tree in classifying the data.

If the set of observations at the node is split into two subsets, following a left (L) and right (R) split, a deviance can be computed as above for each of the 'children' nodes. The *net deviance of the children nodes* is the sum of the node deviances for the left and right splits:

$$D(\mu_{\mathrm{L}}, \mu_{\mathrm{R}}; y) = \sum_{L} D(\mu_{\mathrm{L}}; y_i) + \sum D(\mu_{\mathrm{R}}; y_i) \tag{1.6}$$

In fitting the tree, candidate children nodes are generated for all possible partitions on each predictor variable. The chosen split is that which maximises the change in deviance, defined as

$$\Delta D = D(\mu; y) - D(\mu_{\mathrm{L}}, \mu_{\mathrm{R}}; y) \tag{1.7}$$

where $D(\mu; y)$ is the deviance of the parent node. Unless the parent node is pure, splitting will result in some reduction of deviance. At some point, however, the gain becomes small to justify the increased complexity of the tree. Two alternative rules used for ending the splitting procedure are to stop when (1) the node deviance is less than some small fraction of the root node deviance (e.g. 1%), or (2) when splitting results in a node with too few observations (e.g. <10).

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