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Precipitation Variation in the Pacific Northwest (1675–1975) as Reconstructed from Tree Rings

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Abstract. Long-term records of precipitation variation for three regions within the Pacific Northwest are reconstructed based on ring-width data from drought-sensitive conifers. Precipitation reconstructions are derived using multiple regression models that predict variation in annual precipitation as a function of standardized and prewhitened tree-ring chronologies. The precipitation reconstructions indicate that droughts similar in magnitude and duration to those observed in the 1920s and 1930s have occurred frequently, at least once per century, in the past. The timing of drought episodes varies spatially, most notably during the nineteenth century. During the first half of the nineteenth century, precipitation was above average in Washington and northern Oregon but below average in southern Oregon and northern California. During the latter half of the nineteenth century, southern Oregon and northern California experienced above average precipitation while Washington and northern Oregon experienced repeated droughts. In contrast, severe, single-year drought events (1973, 1929, 1899, 1839, 1739, 1721, 1717) have affected the Pacific Northwest as a whole, reflecting the scale and persistence of the circulation features that cause such extreme events.

Key Words: dendroclimatology, Pacific Northwest, precipitation variation, drought.

RECENT droughts (Namias 1983) as well as high lake levels (Kay and Diaz 1985) in the western United States raise questions as to the probability of such events recurring in the future. Long-term records of precipitation reconstructed from tree-ring data shed light on this question by providing an assessment of both the nature of low-frequency variation in precipitation and the frequency of extreme events. By delimiting the full range of climatic variability observed in the past, such long-term reconstructions of climate aid in defining climatic scenarios of the future.

During the 1930s researchers sought relationships between tree-ring records and precipitation with the hope of uncovering evidence of cyclic behavior that would allow them to explain and predict droughts (Davis and Sampson 1936; Keen 1937; Antevs 1938). Since that time quantitative models that predict precipitation or drought indices from tree rings have been derived for semi-arid regions of the western U.S. (Stockton and Meko 1983; Meko, Stockton, and Boggess 1980; Fritts, Lofgren, and Gordon 1979) as well as for the more mesic regions of the eastern U.S. (Blasing and Duvick 1984; Cook and Jacoby 1977; Stahle, Cleaveland, and Hehr 1985). Despite this far-ranging research, the most recent analysis of the precipitation history of the Pacific Northwest based on intensive sampling of trees in this region dates to the 1930s. The present study makes use of recently collected tree-ring data from Washington, Oregon, and northern California to reconstruct annual precipitation for three regions within the Pacific Northwest. These reconstructions provide new long-term information on the spatial coherence of precipitation variation in this region.

Data

Tree-Ring Data

Forty-one tree-ring chronologies from drought-sensitive conifers in Washington, Oregon, and northern California (Fig. 1) were developed using standard procedures (Fritts 1976). Two increment cores were collected from each of 9 to 25 trees of the same species at each site. After the cores were

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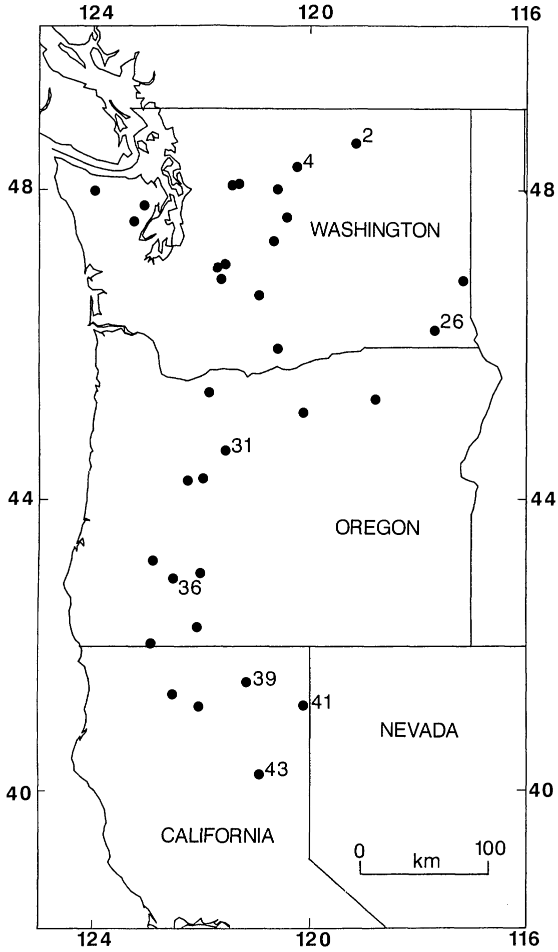

Figure 1. Location of tree-ring chronologies from drought-sensitive conifers considered as candidate predictor variables in regression equations predicting precipitation. Numbered sites are chronologies that are included in one of the final models.

cross-dated to insure that the correct calendar year was assigned to each ring, the ring widths were measured to the nearest 0.01 mm. Species sampled included Douglas fir (*Pseudotsuga menziesii*), ponderosa pine (*Pinus ponderosa*), jeffrey pine (*P. jeffreyi*), sugar pine (*P. lambertiana*), whitebark pine (*P. albicaulis*), subalpine larch (*Larix lyallii*), and western larch (*Larix occidentalis*).

Tree-ring data commonly exhibit high variance at low frequencies (i.e., long-term variation) that is unrelated to long-term variation in climate and that needs to be removed from the tree-ring data before such data are used to reconstruct climate. Long-term variation in tree-ring data has two components: (1) a quasi-deterministic component related to forest stand dynamics and the changing geometry of the growing tree and (2) a stochastic component related to the persistence of climatic effects in one year on the physiological status of the tree in ensuing years. Two different procedures were used to attempt to eliminate the part of the long-term variation in the tree-ring data that is independent of current year climatic variation. The deterministic portion of the long-term variation was removed by fitting negative exponential or polynomial curves to the ring-width series. Trends shared in common at a site were not removed by the curve-fitting procedure because these common trends in the tree-ring data are thought to be generated by large-scale variation in climate (Fritts 1976). The detrended ring-width series were then summed across each site to form a ring-width chronology for that site.

The stochastic portion of the long-term variation in tree-ring chronologies is generated by autoregressive processes in which the effect of climate in a given year is propagated into following years by affecting the food reserves, bud formation, and general vigor of the tree (Fritts 1976). This stochastic component was removed from the data by fitting autoregressive-integrated-moving-average (ARIMA) models (Box and Jenkins 1976) to the tree-ring chronologies (Table 1). ARIMA models were fit to the chronologies based on the time series characteristics of the chronologies during the period of the observed climatic data (1899–1975). This procedure is based on the assumption that the form of biological persistence in the tree-ring data has not changed through time and can be adequately modeled using the twentieth-century observations. Any long-term variation remaining in the earlier portions of the series after the biological persistence is removed is attributed to long-term climatic variation (Meko 1981).

The tree-ring data used in the following analyses are thus prewhitened series in which the deterministic and stochastic sources of long-period variation have been removed. Complete information on site characteristics and a listing of each chronology is available in Graumlich (1985).

Precipitation Data

Monthly precipitation records for 13 stations in Washington, Oregon, and California extend back to 1899 (Fig. 2). Two of the 13 stations had a combined total of 10 years of missing data. These missing data were estimated using stepwise

Table 1. Results of Autoregressive Models

Site[a]	Site name	Spp.[b]	Model[c]	ϕ	δ
2	Aenes Mt.	PP	AR(1)	0.691	0.320
2	Bear Creek	PP	AR(1)	0.686	0.323
26	Indian Ridge	PP	AR(1)	0.519	0.500
31	Castle Rocks	PP	AR(1)	0.774	0.233
36	Abbot Creek	DF	AR(1)	0.530	0.491
39	Damon's Butte	PP	ARI(1,1)	−.334	—
41	Black Cone	PP	AR(1)	0.558	0.440
43	Greenville Saddle	PP	AR(1)	0.420	0.602

[a] Site numbers identify locations shown in Figure 1. Only those sites included as predictor variables in a final reconstruction model are listed.

[b] Species: DF, Douglas fir (*Pseudotsuga menziesii*); PP, ponderosa pine (*Pinus ponderosa*).

[c] AR(1) is a first order autoregressive model of the form $z_t = \phi z_{t-1} + \delta + u_t$ and ARI(1,1) is an integrated first order autoregressive model of the form $z_t = (1 + \phi)z_{t-1} - \phi z_{t-2} + u_t$ where z_t is the value of the tree-ring series for the current year (t); z_{t-1} is the value of the tree ring series for the previous year ($_{t-1}$); z_{t-2} is the value of the tree-ring series for two years previous (t-2);

ϕ is the coefficient for autoregressive terms;

δ is a constant;

μ_t is the residual series at time t (i.e., the ''prewhitened'' tree-ring series).

regression with adjacent stations as candidate predictor variables. The explained variance (R^2) of the regression equations ranged from 0.57 to 0.63, indicating that the adjacent station records were adequate predictors of the missing data. Annual precipitation series were then formed by summing precipitation for the months January to August and adding that sum to the sum of monthly values for September to December of the previous year. This method of summing monthly precipitation values results in annual values in which the ending month coincides with the termination of growth by the trees.

Blasing, Duvick, and West (1981) have demonstrated that tree-ring chronologies show stronger relationships with regionally averaged climatic data than with data from a single station. Climatic data averaged over several stations represent regional conditions whereas single station records may reflect localized phenomena or microclimatic influences at that station. Regionally averaged climatic data will thus show stronger relationships with tree-ring chronologies, especially when the tree-ring collection sites are located at some distance from precipitation stations as in this study. In order to form regional precipitation indices, three groups of stations were identified by loadings obtained from a principal component analysis of the correlation matrix of the annual precipitation data (Dyer 1975). A varimax rotation of the components was used to maximize the correlation of the components with the individual station records. The three groups include five stations in southeastern Oregon and northern California (''Southern Valleys''), five stations in eastern Washington and northeastern Oregon (''Columbia Basin''), and three stations in western Washington and northwestern Oregon (''Western Lowlands'') (see Table 2). Precipitation indices were formed for each region by averaging the standardized annual precipitation series within the station groups defined by the principal component analysis.

Methods

Regression models were derived to predict each series of precipitation indices as a function of the prewhitened tree-ring chronologies. The model-building process included:

(1) deriving several ''preliminary'' models in which approximately two-thirds of the available observations were used to determine the ''best subset'' of candidate predictor variables;

(2) cross-validating each preliminary model (i.e., evaluating the model's ability to predict those ''independent'' observations withheld from initial model building);

(3) choosing, on the basis of cross-validation results, the best preliminary model for each precipitation series and reestimating the coefficients for the ''full data-set model'' using all available observations;

(4) checking the adequacy of the full data-set model using regression diagnostic statistics; and

(5) evaluating the correspondence between the

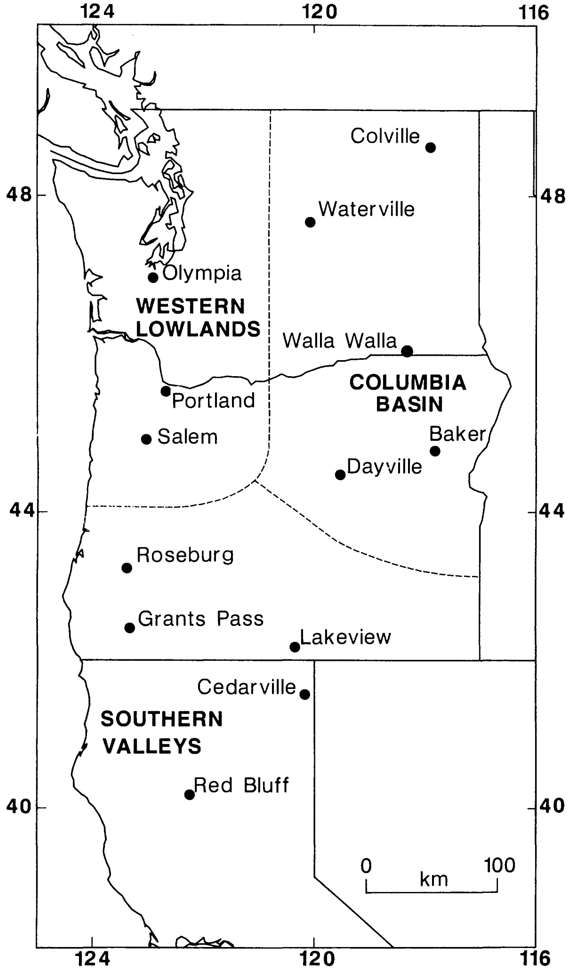

Figure 2. Precipitation stations in the Pacific Northwest with records extending back to 1899. Principal components analysis was used to group the stations into three regional groups: the Western Lowlands, the Columbia Basin, and the Southern Valleys.

observed and predicted precipitation series in the frequency domain through cross-spectral analysis.

Each of these steps is described below.

Choosing Predictor Variables

Cross-correlation functions and bivariate scatter plots for pairs of tree-ring chronologies and precipitation series were examined to assess (1) which group of the chronologies was significantly correlated with each annual precipitation series, (2) the significance of lagged relationships between the tree-ring chronologies and precipitation series, and (3) the presence of outliers in the data. The "best subset" regression procedure (Draper and Smith 1981) was used to choose predictor variables for each precipitation series. The best subset regression procedure evaluates models containing all possible combinations of candidate predictor variables, ranging in number from one to the total number of candidate predictor variables. The major criterion for choosing a model was minimization of Mallow's Cp statistic where

$$Cp = RSSp/s^2 - (n\text{-}2p)$$

and $RSSp$ is the residual sum of squares from a model containing all p parameters, p is the number of parameters in the model, s^2 is the residual mean square from the equation containing all possible predictors, and n is the number of observations (Draper and Smith 1981, 299). The value of the Cp statistic is a function of both the explained variance of a given model and the number of predictors included in that model. By choosing a model with Cp less than or equal to p, the probability of artificially inflating the explained variance or of omitting important predictor variables is minimized (Draper and Smith 1981). When two or more models exhibited comparable values of the Cp statistic, the model that included the longest chronologies was chosen as the best model.

Cross-Validation of the Models

Cross-validation procedures for regression models evaluate how well a model predicts new values of the independent variable (Montgomery and Peck 1982; Gordon 1982). Cross-validation of the preliminary regression models included assessment of the accuracy of the model's predictions of new observations and evaluation of the stability of the regression coefficients when estimated with different subsets of the data. The available data were randomly assigned to two subsets: (1) the "estimation" or "calibration" data, comprising approximately two-thirds of the total number of observations (i.e., years), were used to build preliminary regression models, and (2) the "prediction" or "verification" data, consisting of the remaining years, were used to study the predictive ability of the model. All the cross-validation trials were performed on three different randomly chosen subsets of observations so that a fortuitous division of the observations would not bias the assessment of the model's skill in predicting new observations (Montgomery and Peck 1982).

The correspondence between the predictions of each preliminary model and the verification data was measured using the correlation coefficient (*r*) and the reduction of error statistic (*RE*) (Fritts 1976). The *RE* statistic, widely used by dendrochronologists, is defined as

$$RE = 1.0 - \sum_{i=1}^{n} \frac{Y_i - (\bar{Y})(\hat{Y}_i - \bar{Y})}{(Y_i - \bar{Y})^2}$$

where n is the total number of observations in the prediction data, Y_i is the i^{th} observation of the dependent variable, $\hat{Y}$ is the estimated predicted value for observation i, and $\bar{Y}$ is the mean of the predicted variable for the "calibration" data. A positive value of the *RE* statistic indicates that the predictions made by the model are more accurate than a prediction based solely on the mean of the observed data and that the model is thus useful for reconstructing climate.

The predictor variables in the preliminary model having the highest *RE* and *r* values were taken to be the best predictors of precipitation. To reduce the variance of the estimates of the coefficients, the coefficients were reestimated using all available observations and thereafter referred to as full data-set models.

Regression Diagnostic Statistics

Regression diagnostic statistics were calculated to assess the extent to which the statistical assumptions underlying ordinary least squares (OLS) estimation were violated and to identify data points that are either unusual with respect to the majority of the data or inordinately influential in determining estimates (Weisberg 1980; Cook and Weisberg 1982). The two statistical assumptions underlying OLS regression estimation that have the greatest potential for degrading the regression estimates are (1) that the regression errors are independent, identically normally distributed random variables with a mean of zero and constant variance equal to σ^2; and (2) that the regression model is correctly specified, implying that the correct predictors are included in the model and that the relationship between independent and dependent variables is linear (Johnston 1972; Graumlich 1985). Violations of these assumptions may result in regression estimates that are inefficient (i.e., biased or not minimum variance) and sensitive to deletion of small numbers of observations (Graumlich 1985; Johnston 1972; Judge et al. 1980).

Table 2. Rotated Component Loadings for Precipitation Stations[a]

Stations	Rotated components 1	2	3
Southern Valleys			
Cedarville, Calif.	0.84	0.08	0.12
Lakeview, Oreg.	0.82	0.30	0.14
Grants Pass, Oreg.	0.78	0.31	0.36
Roseburg, Oreg.	0.64	0.26	0.57
Red Bluff, Calif.	0.61	0.46	−0.22
Columbia Basin			
Waterville, Wash.	0.05	0.84	0.30
Baker, Oreg.	0.35	0.79	0.10
Colville, Wash.	0.25	0.77	0.26
Walla Walla, Wash.	0.26	0.68	0.40
Dayville, Oreg.	0.61	0.65	−0.04
Western Lowlands			
Portland, Oreg.	0.06	0.20	0.83
Salem, Oreg.	0.30	0.04	0.88
Olympia, Wash.	0.20	0.22	0.84
Percent total variance	50.3	16.0	8.9

[a] Stations are grouped into regions according to the strength of their correlation with each factor.

Several diagnostic procedures were used to assess whether any of the assumptions underlying OLS regression analysis were violated (Graumlich 1985). Normal probability plots of the residuals (Weisberg 1980, 133) were examined to determine if the residuals appeared normal. Plots of the residuals against time and the lag-one autocorrelation coefficient were inspected to assess whether the residuals were independent. These types of plots show a random scatter of points if the variance of the residuals is constant and unrelated to the variance of the predicted variable. Plots of the residuals vs. the predicted variable were also examined. These types of plots show distinctive patterns if the variance is nonconstant or if a nonlinear relationship exists between the predictor and predicted variables (Weisberg 1980, 121).

Outliers, or single observations that do not follow the trend of the majority of the data, may exert a disproportionate influence on the regression estimates. Two statistics were used to identify single observations that unduly influenced the regression equation and that were thus considered for deletion. The "Studentized" residual (Weisberg 1980, 105) was used to measure the relative size of each residual, and Cook's distance quantified the change in the regression estimates when a given case was deleted (Weisberg 1980, 108).

Frequency Domain Fidelity

Ideally, the reconstruction of a climatic variable accurately captures not only the mean and variance but also the true frequency characteristics (i.e., the relative dominance of long- and short-period variance) of the observed climatic series (Stockton 1975; Cook and Jacoby 1983). Tree-ring data commonly exhibit a greater concentration of variance at long periods as compared to climatic data, and the ARIMA transformations discussed earlier allow removal of that long-term variance before the tree-ring data are used in regression equations to predict climate. Cross-spectral analysis, in which the correspondence between the observed and reconstructed precipitation data is assessed at different frequencies (Jenkins and Watts 1968), was used to determine how effective the ARIMA transformation had been in removing the nonclimatic long-term variance from the tree-ring data. The results of the cross-spectral analysis, specifically the squared coherency spectra, indicate which frequency characteristics of precipitation data were best reconstructed by the tree-ring data. The squared coherency between the observed and reconstructed precipitation data ranges from zero to one and is analogous to the square of the correlation coefficient for the two series calculated at each frequency.

Results

Regression Models

Cross-correlation functions of pairs of tree-ring chronologies and precipitation series revealed that lagged correlations between these variables were rarely significant, and, therefore, lagged chronologies were not included as candidate predictor variables in the regression models. The relationships between chronologies and precipitation series were linear, and no bivariate outliers were present in the data.

Each of the preliminary models for each series had *RE* values greater than zero and showed a significant correlation (*r*) between the observed and predicted values. The regression coefficients and statistics for the best preliminary model and for the full data-set model for each precipitation series (Table 3) were very similar, indicating that the model coefficients are stable over the period of observed climate.

Regression diagnostic statistics did not indicate that any of the major assumptions underlying OLS regression analysis were violated by the full data-set models. Normal probability plots of the residuals indicated that the residuals were approximately normally distributed, and plots of the residuals vs. the predicted variables exhibited a random scatter of points. The residuals were statistically independent. In each of the three full data-set models, one observation (i.e., one year) was identified as a multivariate outlier and deleted. The regression estimates were then recalculated (reported as "final model" in Table 3).

The resulting final reconstructions are less variable than the original series. This is expected when the regression fit is less than perfect and the resulting sum of squares attributable to regression ("explained variance") is less than the sum of squares of the dependent variable. As a result, the variance of the reconstruction will always be less than the variance of the observed data. The three reconstructions were rescaled in order to make the variance equivalent to that in the observed series.

Frequency Domain Fidelity

For both the Columbia Basin and the Southern Valleys, the highest coherence between reconstructed and observed precipitation is at low frequencies or at periods equal to 5 years or more (Fig. 3a,b). In addition, the coherency spectra show values significantly different from zero ($p = .05$) at periods of approximately 2.0 and 2.5 years for both regions. For the Western Lowlands, the overall level of coherence is lower than that for the other two regions. The highest coherence for the Western Lowlands centers on periods approximately equal to 2.5 and 5.0 years (Fig. 3c).

Thus, the regression models for the Columbia Basin and the Southern Valleys most accurately capture the long-term variation in the observed data. Multiyear wet or dry episodes will be well reconstructed for these two series, but the magnitude of year-to-year fluctuations in precipitation should be interpreted with more caution. The coherency spectrum for the Western Lowlands indicates that the correspondence between observed and reconstructed precipitation is lower than that for the other two regions. The precipitation reconstruction for the Western Lowlands shows significant coherence with observed data only at short (2–6 year) time scales: longer-term trends in the reconstruction may not be real.

Table 3. Regression results[a]

		Coefficients and statistics		
Region		Preliminary model	Full data-set model	Final model
Western Lowlands	Intercept	−0.101	−0.170	−0.560
	Site 31	1.828	1.812	2.003
	Site 36	−1.569	−1.313	−1.661
	Site 4	1.098	1.035	1.013
	R^2	0.27	0.21	0.24
	R^2a	0.23	0.18	0.21
	RE[d]	0.08	—	—
	r	0.34[b]	—	—
Columbia Basin	Intercept	−0.011	−0.035	−0.065
	Site 31	0.778	0.757	1.212
	Site 2	0.678	0.690	0.646
	Site 26	0.863	0.842	0.561
	R^2	0.29	0.27	0.29
	R^2a	0.25	0.25	0.26
	RE	0.25	—	—
	r	0.53[c]	—	
Southern Valleys	Intercept	−0.056	0.008	−0.014
	Site 39	0.681	0.803	1.073
	Site 41	1.206	1.318	1.330
	Site 43	0.051	−0.716	−1.071
	R^2	0.22	0.19	0.23
	R^2a	0.18	0.16	0.20
	RE	0.19	—	—
	r	0.49[c]	—	—

[a] Predictor variable names correspond to site numbers given in Table 1. R^2 is the explained variance of the regression equation and R^2a is the explained variance adjusted for the number of predictors in the model.

[b] Significant at the 95 percent level.

[c] Significant at the 99 percent level.

[d] Reduction of error (*RE*) statistics greater than zero are considered to indicate that the predictions of that model are better than predictions based on the mean of the observed series.

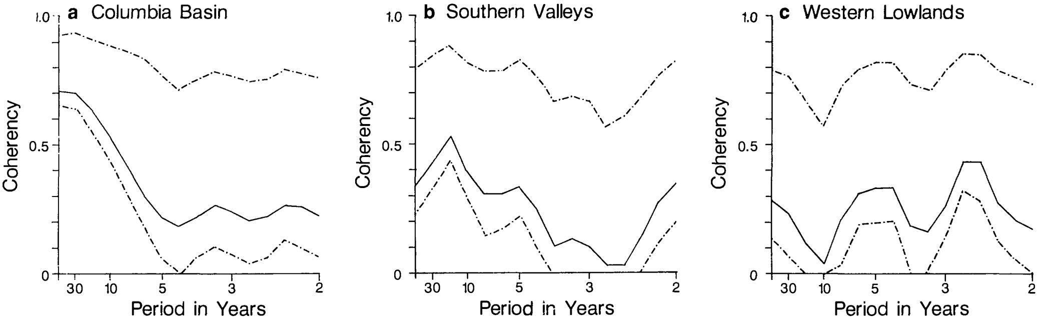

Figure 3. The squared coherency of (a) the Columbia Basin, (b) the Southern Valleys, and (c) the Western Lowlands observed and reconstructed precipitation series. A Parzen window with a truncation point of 15 lags was used to calculate the spectra; 95 percent confidence intervals were calculated according to Jenkins and Watts (1968).

Precipitation Reconstructions

The mean of the reconstruction for each region does not differ from the mean of the observed period (Fig. 4). Episodes of prolonged wet and dry conditions are evident, however, in all three reconstructions. In the Columbia Basin, droughts similar in magnitude to those of the 1920s and 1930s occurred from 1865 to 1895, in the 1840s, 1790s, 1780s, 1750s, and around 1680. Wet periods occurred from 1810 to 1835, 1740 to 1760, and 1695 to 1715. The timing of wet and dry

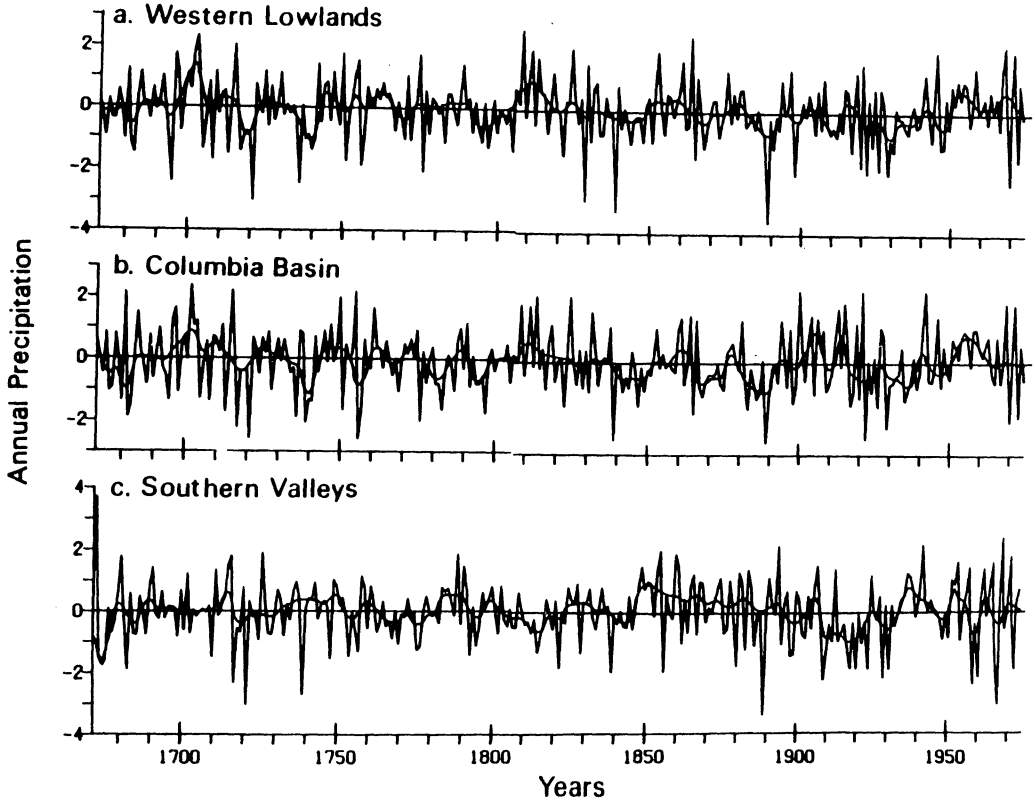

Figure 4. Reconstructed indices of precipitation for (a) the Western Lowlands, (b) the Columbia Basin, and (c) the Southern Valleys. The smoothed estimates emphasize low frequency variations in the data (periods > 8 years).

episodes is similar between the Columbia Basin and the Western Lowlands series except that the duration of droughts is less in the Western Lowlands. In the Southern Valleys, dry episodes occurred from 1795 to 1830 and 1760 to 1785; the period 1850–95 was uniformly wet with the exception of a very severe drought in 1889.

The frequency of severe drought years shows variation through time. Severe single-year droughts occurred relatively frequently during the period 1703 to 1757 in the Western Lowlands and the Columbia Basin (Table 4 and Fig. 4). Six of the 20 most severe droughts in the reconstructed precipitation record for the Western Lowlands and 8 of the 20 most severe droughts in the Columbia Basin occurred during this 55-year period. Such a high frequency of severe single-year droughts during the eighteenth century is not seen in the record from the Southern Valleys where the greatest frequency of severe drought years occurs during the twentieth century.

Discussion

Comparison With Other Proxy Precipitation Records

The most extensive early study of the relationship between tree growth and precipitation in the Pacific Northwest is that of Keen (1937), who used 265 stump sections of ponderosa pine from five localities in eastern Oregon to construct a composite chronology extending back to 1268 A.D. During the period of overlap between Keen's study and this one, Keen's chronology shows periods of lower than average tree growth from 1840 to 1852, 1755 to 1760, and 1739 to 1743, and higher than average tree growth from 1855 to 1870, 1800 to 1820, 1765 to 1777, and 1745 to 1755 (Fig. 5).

Keen's samples came from both the Columbia Basin and the Southern Valleys regions defined in this study. His tree-ring calendar thus represents an average of tree growth across areas exhibiting

Table 4. The 20 most severe drought years[a] from 1675 to 1975 for three regions within the Pacific Northwest based on tree-ring reconstructions of annual precipitation

Ranking	Western Lowlands	Columbia Basin	Southern Valleys
1	1889	1889	1889
2	1839	1721	1967
3	1721	1756	1721
4	1829	1839	1739
5	1736	1922	1959
6	1695	1717	1717
7	1970	1929	1909
8	1776	1739	1929
9	1898	1776	1961
10	1929	1970	1839
11	1922	1736	1856
12	1756	1682	1973
13	1926	1973	1924
14	1920	1797	1931
15	1751	1713	1683
16	1708	1865	1920
17	1973	1757	1918
18	1865	1783	1822
19	1713	1751	1880
20	1683	1883	1675

[a] The years are ordered starting with the most severe drought year in the reconstructed record.

different patterns of observed precipitation variation as indicated by the principal component analysis of precipitation data presented earlier (Table 2). Evidence for contrasting patterns of growth between Keen's northern and southern sites is contained in his Figure 3 which shows opposing tree growth between sites in east-central and southeastern Oregon. Keen's record will therefore show agreement with the tree-ring-based reconstructions when similar precipitation anomalies simultaneously occurred in both the Columbia Basin and the Southern Valleys. In fact, all of Keen's periods of low tree growth agree with reconstructed droughts in both areas during the 1840s, late 1750s, and early 1740s (Figs. 4 and 5). The common features of the tree-ring reconstructions and Keen's tree-ring calendar are climatic events of regionwide significance, whereas differences between the records may represent times of contrasting precipitation anomalies in the northern and southern portions of the Pacific Northwest.

Additional information on the precipitation history of southeastern Oregon is contained in records of lake level variations, which, like tree growth variations, are governed by variation in precipitation, evaporation, and groundwater supplies. One of the best long records of lake level variation in the study area comes from Goose Lake, located 10 km south of Lakeview, Oregon. Harding (1965) and Phillips and Van Denburgh (1971) derived a time series of Goose Lake water level variation since 1831 from accounts of early explorers and settlers (Fig. 5). A major feature of the record is the interval of low lake levels from 1835 to 1860, with the minimum levels occurring around 1850. High stands occurred in 1868 and in 1910, with overflow into the Pit River from 1868 to 1881. The lake level data corroborate the Southern Valleys precipitation reconstruction in indicating a period of relatively wet conditions in the latter half

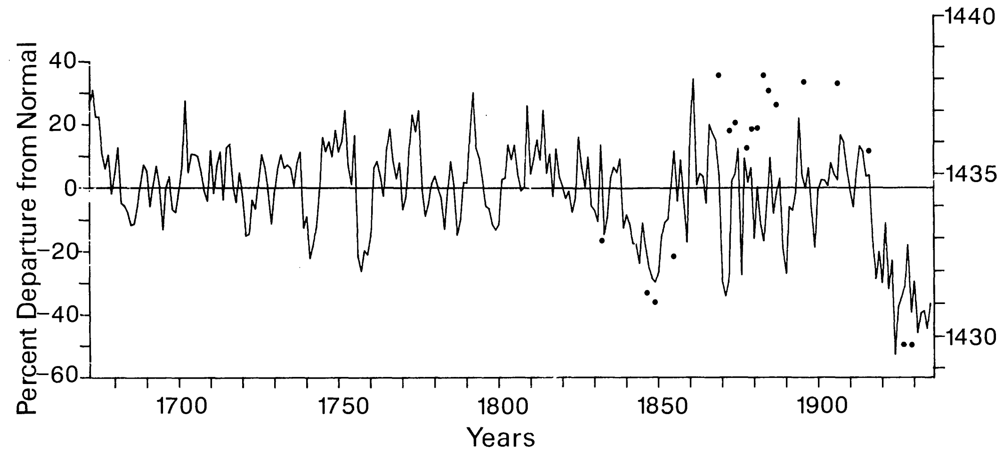

Figure 5. A comparison of Goose Lake water levels (circles) with standardized tree-ring departures (solid line) for five sites in eastern Oregon. Tree-ring data redrafted from Keen (1937). Levels of Goose Lake compiled from Harding (1965) and Van Denburgh (1971).

of the nineteenth century that was both preceded and followed by periods of drought.

Spatial Variation in Precipitation Histories

Similarities and contrasts in the long-term precipitation history of the three regions defined by this study can be understood using analogs based on observed synoptic climatology. The majority of the precipitation in the Pacific Northwest falls during the cool season (Bryson and Hare 1974). Cool season droughts occur when high pressure ridges block cyclonic activity from the Pacific and displace storm tracks northward into British Columbia (Namias 1983). The size and persistence of the pressure features can cause these extreme events to affect large areas. Extreme drought years (1973, 1929, 1889, 1839, 1739, 1721, 1717) show great spatial homogeneity: six of the ten most extreme droughts in the Columbia Basin and in the Southern Valleys occurred simultaneously in both regions.

Contrasting north-south patterns in annual precipitation occur because the intensity of summer drought and the magnitude and frequency of winter storms are governed by latitudinal variation in the position of large-scale pressure features. The severity of summer drought is correlated with the northward extent of the Pacific subtropical high pressure cell (Pittock 1977), whereas cool season precipitation is governed by the southward displacement of the polar jet stream (Pike 1972). The precipitation reconstructions indicate that north-south contrasts in the timing of wet and dry episodes were especially common in the nineteenth century. The wet period from 1810 to 1835 in the Columbia Basin and Western Lowlands is a time of drought in the Southern Valleys, and the wet episode from 1850 to 1890 in the Southern Valleys coincides with a drought in the Columbia Basin and Western Lowlands.

Conclusions

Tree-ring-based precipitation reconstructions for three regions in the Pacific Northwest show episodes of drought that differ in timing and duration among the three regions. The timing of drought episodes in the Western Lowlands coincides with the timing of those in the Columbia Basin, but the droughts in the Western Lowlands are often of lesser duration than are those in the Columbia Basin. Drought episodes vary in timing from north to south: long-term variation in precipitation in the Southern Valleys is often out of phase with that in the Columbia Basin and Western Lowlands. In contrast to the long-term precipitation trends, single-year drought events show remarkable spatial homogeneity, implying that severe dry years are caused by circulation features of sufficient size and persistence to affect the Pacific Northwest as a whole. Such extreme drought events were more frequent during the early eighteenth century and during the twentieth century than during the intervening decades.

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