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An objective approach for classifying precipitation patterns to study climatic effects on tree growth

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Abstract

This study applied the simple, quantitative method of statistical cluster analysis to the task of objectively classifying precipitation patterns over northern California into paternally homogeneous regions. The statistical clustering results were then combined with geographical information to generate regional precipitation indices and study the relationship between precipitation levels and tree growth over specific areas. Generating regional indices replaces the often-used practice of associating growth rates with precipitation data from a single, 'remote' weather station, a station located outside the tree growth plot. Use of regional precipitation information generated in this manner can significantly improve the accuracy of growth predictions. © 2000 Elsevier Science B.V. All rights reserved.

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1. Introduction

The influence of climate on tree growth has been studied by a number of authors (Holdaway, 1990; Graumlich, 1991; Little et al., 1995; Wensel and Turnblom, 1998; Yeh, 1997). Climatic data are usually supplied by the U.S. National Oceanic Atmospheric Administration or a state's water resource department, based on information recorded at the weather station nearest to each tree growth plot (Holdaway, 1990; Graumlich, 1991; Little et al., 1995). Ideally, of course, climate and tree growth would both be recorded in the same plot, but individual weather stations are rarely located in every growth plot. Some studies (Woollons et al., 1997; Snowdon et al., 1998) used estimated values of climatic variables that were computed from mathematical surfaces for different climate elements of a region. These surfaces were derived by using advanced smoothing splines techniques (Wahba and Wendelberger, 1980) and a network of weather stations for an area of interest. The surfaces are then interrogated to estimate values of climatic variables at any chosen latitude/longitude of that area.

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However, these methods must depend on the existence of frequent, long-running and reliable weather stations in forest regions; unfortunately, not many afforested areas have these. Also, additional errors may be introduced by the fitting process, particularly when they are interrogated to within very short distance.

Most often, researchers obtain climatic data from the weather station that is the shortest distance away from a growth plot, but topography should also be considered. Climate is closely related to the topographic factors that influence air circulation patterns, moisture transportation, and sunshine (Koeppe and De Long, 1958). Thus, if a mountain peak separates a growth plot from its nearest weather station, the climate at the plot might be very different from the climate at the station; more reliable climatic information for that plot might come from a station located a little farther away, but on the same side of the mountain as the plot (Felton, 1965; Elford, 1970). This type of climatic idiosyncrasy is very likely to obscure the relationship between growth and climate when the climatic data are gathered from just one 'remote' weather station (any station located outside a growth plot regardless of distance from the plot).

Blasing et al. (1981) reported that where growth sites were remote from weather stations, a good statistical argument can be made for using regional climatic averages instead of data from a single local station. The question arising from this argument is how to define the region to be assessed. In studying relationships between growth and climate, growth plots and weather stations situated across the same geographic area can constitute one region, and the similarity or dissimilarity of data gathered from those stations can be compared to generate regional climatic information.

The purpose of the current study is to apply the quantitative method of cluster analysis (Johnson and Wichern, 1988; Everitt, 1993) to the data collected for a growth-climate study by Wensel and Turnblom in 1998 in order to objectively classify precipitation patterns into paternally homogeneous regions. The statistical clustering technique has been used in such diverse fields as psychology, zoology, biology, botany, sociology, artificial intelligence, and information retrieval (Anderberg, 1973). It also has been used with principal component or factor analysis for meteorological data including several climatic variables or multiple factors such as climate, physiography, soil, and vegetation to delineate climatic zones for use in site classification related studies (van Groenewoud, 1984; Rauscher, 1984; Denton and Barnes, 1988; Briggs and Lemin, 1992). However, this objective and simple process (Kalkstein et al., 1987) is new to growth-climate studies in northern California. Using this method, attempts will be made to group weather stations based on similar (statistically the same) relative precipitation patterns. An average pattern for each group will then be obtained and used to represent all the stations in that group. This study is part of a project to provide background precipitation information for a tree growth-climate study (Wensel and Turnblom, 1998).

In the 1998 growth-climate study by Wensel and Turnblom, climatic data were taken from weather stations that were originally set up to measure precipitation in order to predict water flow in the California rivers and canals. Only 77 of these weather stations were distributed across the same area as the tree growth plots. However, these 77 stations were not located adjacent to the tree growth plots, but regional average precipitation patterns over the study area had been generated. With this precipitation information, periodical growth projections obtained from a growth model that excludes climatic factors were post-adjusted for climate changes between periods.

2. Data source

In the current study, we are interested in the relative annual precipitation of a 'water year', the period from 1 October through 30 September. For example, the water year 1990 begins 1 October 1989, and ends 30 September 1990. Data for the current study were provided by James Goodridge, California Department of Water Resources (retired).

There were 77 weather stations within the study area for which the California Department of Water Resources had data complete enough to be included in the current study. These stations, listed in Appendix A (see Table 2), fall into the region roughly between the longitudes of -123° and $-119^\circ 50'$ and between the latitudes of $37^\circ 80'$ and 42° (Fig. 1). These are the lands around the Central Valley, within the region bounded by the Coast Range on the west and the Sierra Nevada

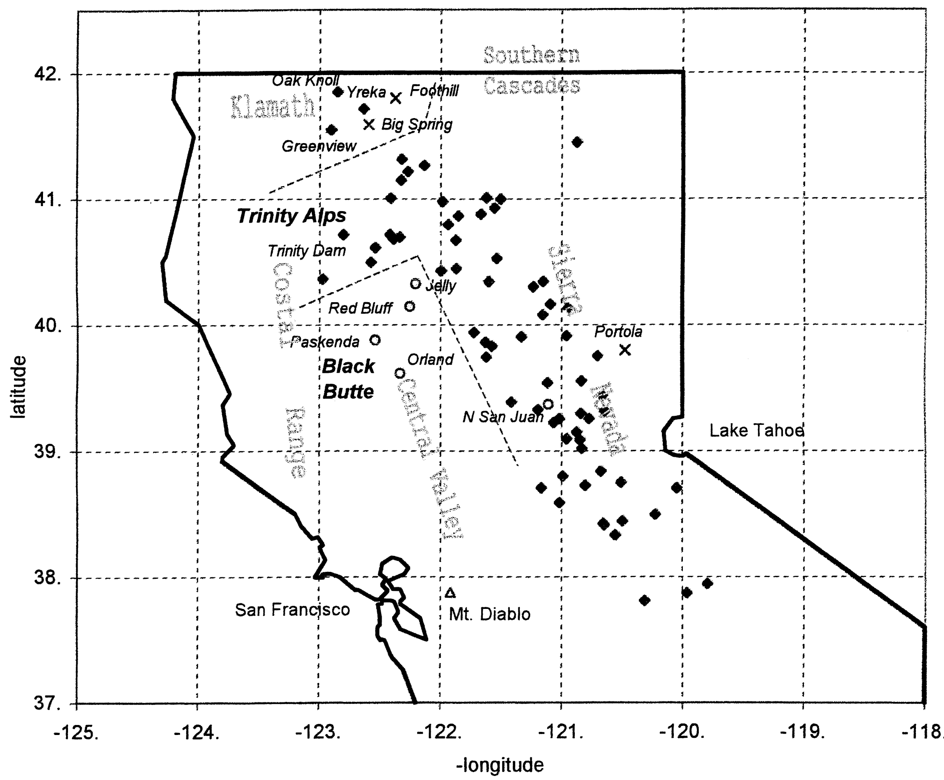

Fig. 1. Location of stations in each of the three 'statistical' clusters of weather stations indicated by the symbols ○, x, ◆.

on the east. The northern end of the valley is bounded by the Cascade Range and the Klamath Mountains. Much of the northeastern area of this region is a huge plateau with relatively little precipitation (Felton, 1965). The stations in the current study are distributed over a wider latitudinal and longitudinal range than the area covered in the corresponding growth rate study (Wensel and Turnblom, 1998). This expansion of the study area ensures that the climatic information representing each of the 1998 growth plots will be included in the current calculations.

At each station, we used measurements of annual total precipitation that had been taken over the 24-year period from 1970 to 1993, the same period for which tree growth data were available.

Since the goal of the 1998 growth rate study was to measure the fluctuation in tree growth from year to year, in the current study we wanted to measure the fluctuation in relative precipitation from year to year. Thus, precipitation measurements at each station were standardized, based on the average over all years investigated at that station. That is, for precipitation P_{it} for station i in year t, the precipitation index, Z_{it} is computed by the usual standardization equation:

$$Z_{it} = \frac{P_{it} - \overline{P}_i}{\sigma_i} \qquad (1)$$

where $\overline{P}_i$ is the average, σ_i the standard deviation of all measurements at station i for $i = 1,2,\ldots,77$ and $t = 1,2,\ldots,24$. The average and standard deviation of the precipitation for each station is given in Appendix A (see Table 2).

3. Cluster analysis

Cluster analysis is a technique used to place objects into groups or clusters based on statistical similarities of their properties. This technique makes no assumptions about the number of groups or the structure of those groups. Instead, groups are formed based on similarities in variable patterns. Therefore, objects in a given cluster tend to be statistically similar to each other in some sense, and objects in different clusters tend to be dissimilar (Johnson and Wichern, 1988).

A data set including objects, each of which has multiple variables, is translated into coordinates in a multi-dimensional Euclidean space, and Euclidean distances (the most commonly used distance measure) are computed. A Euclidean distance between two p-dimensional objects (observations), x and y, is defined algebraically as

$$d(x,y) = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + \ldots + (x_p - y_p)^2}$$

or in terms of vectors by

$$d(x,y) = \sqrt{(x-y)^{\mathrm{T}}(x-y)}$$

where

$$x = [x_1, x_2, \ldots, x_p]^{\mathrm{T}} \quad \text{and} \quad y = [y_1, y_2, \ldots, y_p]^{\mathrm{T}}$$

Although precipitation is the only variable being used here, it is a multiple variable with the precipitation for each year being a separate variable.

In this study, each station has 24 years of precipitation measurements to investigate. Therefore, the precipitation data have 24 variables for each of the 77 stations and those variables are translated into coordinates in 24-dimensional Euclidean space. In computing the Euclidean distance between two clusters, any one of several algorithms can be used. The distance measure (McQuitty, 1957; Anderberg, 1973; Ray, 1982; Johnson and Wichern, 1988; SAS Institute Inc., 1988; Everitt, 1993) used in this study is derived from average linkage and is shown mathematically as follows.

$$A_{\mathrm{KL}} = \frac{\sum_{i \in C_{\mathrm{K}}} \sum_{j \in C_{\mathrm{L}}} d(x_i, x_j)}{N_{\mathrm{K}} N_{\mathrm{L}}}$$

where, for cluster K and L, C_{K} and C_{L} are the lists of items, N_{K} and N_{L} the number of items, respectively, and $d(x_i, x_j)$ the distance measure between item i of cluster K and item j of cluster L.

The clustering process starts from n clusters (the number of the objects in the data set), successively groups the two closest clusters together, and eventually ends with a single cluster.

4. The number of clusters

Numerous criteria have been proposed to determine the number of clusters in a data set (Dubes and Jain, 1979; Milligan, 1981; Perruchet, 1983). The procedure for deciding on the appropriate number of clusters using each criterion is referred to as a 'stopping rule' when applied to the results of hierarchical clustering methods (Milligan and Cooper, 1985). The three criteria used for this study are the cubic clustering criterion (CCC), the pseudo F, and the squared pseudo Student's t (see below), all computed by SAS (Sarle, 1983; SAS Institute Inc., 1988).

One recommended stopping rule is to select a cluster number with a local peak value of CCC or F (values before and after the peak would be lower), or a value before a high value of t^2. This study selected a cluster number based on these three statistics and a consensus among them (SAS Institute Inc., 1988).

5. Results and discussion

The 77 stations were analyzed using the clustering method described above. A clustering report shows which stations or clusters are being clustered together at each step of the clustering process. The process takes 76 (77-1) steps to arrive at one single cluster.

Using average linkage, the process was stopped at step 74 and three clusters were distinguished using the three statistics (CCC, pseudo F, and pseudo Student's t^2) with an obvious peak of F and followed by a high value of t^2. Fig. 1 shows the locations of stations for each statistically defined cluster. (In Fig. 1 only the stations discussed below are labeled. To label all stations would make the figure unreadable). The final three clusters were named for the three regions covered: the Black Butte; Klamath; and Sierra Nevada clusters.

The Black Butte cluster covers the area east of the Coast Range and west of the Central Valley. To form this cluster, the Paskenta and Orland stations were joined into one cluster first, Red Bluff and Jelly stations were joined later, and those two clusters were joined and stayed a single cluster until the process was stopped. This statistical clustering reflected the geographical locations of these stations.

For the Klamath cluster in the northwest, the statistical analysis grouped Oak Knoll, Yreka, Greenview and Trinity Dam stations into the Sierra Nevada cluster late in the process before it was stopped. However, Big Spring and Foothill were grouped into one cluster and remained a single cluster until the process was stopped. This statistical finding brought us to consider the possibility that the Klamath area should be split into two statistical regions, with Big Spring and Foothill representing one part and all the other stations in the Klamath area representing the other part. However, an examination of the Big Spring and Foothill locations relative to the major drainage in the Klamath area suggested that geographical factors justified including these two stations in the Klamath area, even though they added more variance to the cluster.

The early statistical steps in forming the Sierra Nevada cluster of 68 stations showed a similarity among the Sierra Nevada stations south of latitude 40°, with 29 stations forming a cluster. As clustering continued, the 11 stations in the Trinity Alps area west of longitude 122° were added to the Sierra Nevada group.

In the final stage of clustering, the Portola and the North San Juan stations (statistically each was grouped with other stations) were forced into the Sierra Nevada group at the end of the analysis, even though their statistics were different from all other stations in the group. Of course, this adds to the amount of statistical variation shown within this cluster, but their inclusion is consistent with the geographical grouping of stations in this area. Fig. 2 shows the final distribution of stations in each cluster.

The differences in precipitation patterns across these three regions can be explained topographically. The Black Butte cluster is situated in the upper west portion of the great Central Valley, where it is surrounded by mountains to the east, north, and west. The Coast Range forms the western boundary here, and these mountains have first lien on the moisture-bearing winds from the Pacific. As a result, precipitation is

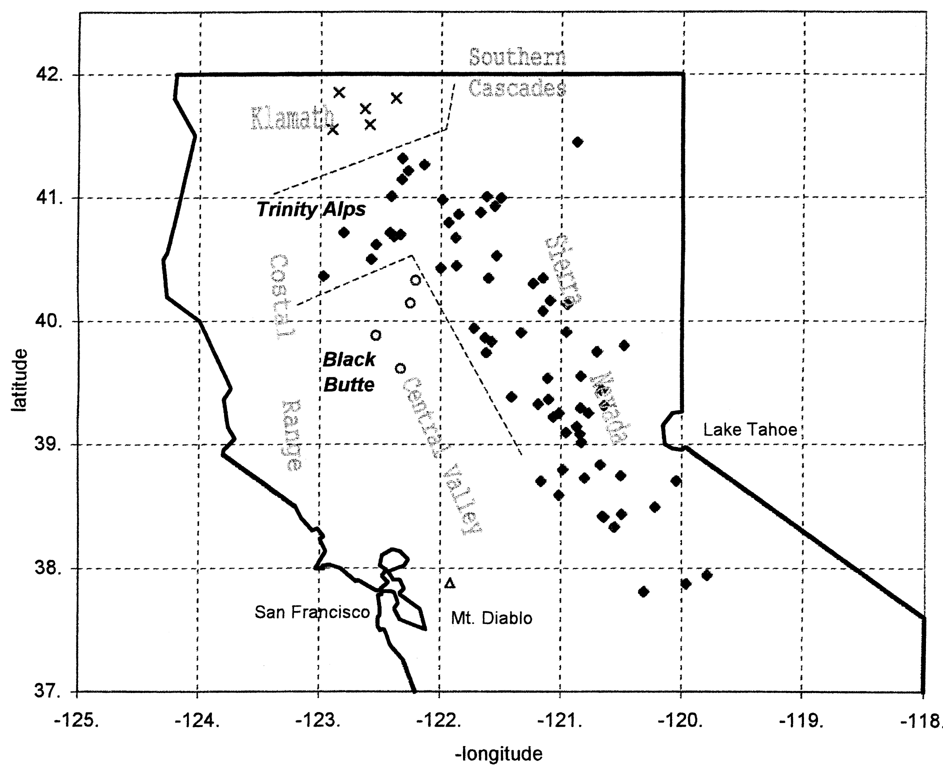

Fig. 2. Distribution of each final cluster of weather stations indicated by ○, x, ◆.

much lighter in the Black Butte area than in the coastal area or the Sierra Nevada. The Klamath cluster is located in an open area and stations here receive much less annual precipitation than those in mountainous areas. Although this cluster is surrounded by mountains on three sides, the stations are very close to the eastern side of the Coast Range, lying in the rain shadow of the mountains. Stations in the Sierra Nevada cluster are situated in mountain areas where precipitation is abundant. This is a land of heavy rains and snows that provide a vast resource of water for irrigation, power production, and domestic and industrial uses.

Among the three regions, differences in the annual precipitation amounts (received mostly during wet winter seasons) can lead to difference in the lengths of precipitation-falling periods. For example, more rainfall days are needed for a high-rainfall area to achieve its higher annual precipitation average. Therefore, precipitation distribution patterns may be different among three regions. The use of an average precipitation pattern may provide more reliable information than of one single station. On the other hand, using more regions, three in this case, may supply more detailed climate information than using one large region. Fig. 3 shows the yearly average precipitation pattern of each cluster representing each corresponding region. The yearly index values (see Eq. (1) above) for each group are given in Appendix A (see Table 3).

Applying these results to the growth study, Wensel and Turnblom (1998) grouped the growth plots into the same three regions. Within each region and for each major species (species most heavily represented on each growth plot), growth variation from period to period was projected by a growth model that considers only biological and cultural factors, and this model was calibrated for a period with atypical climate

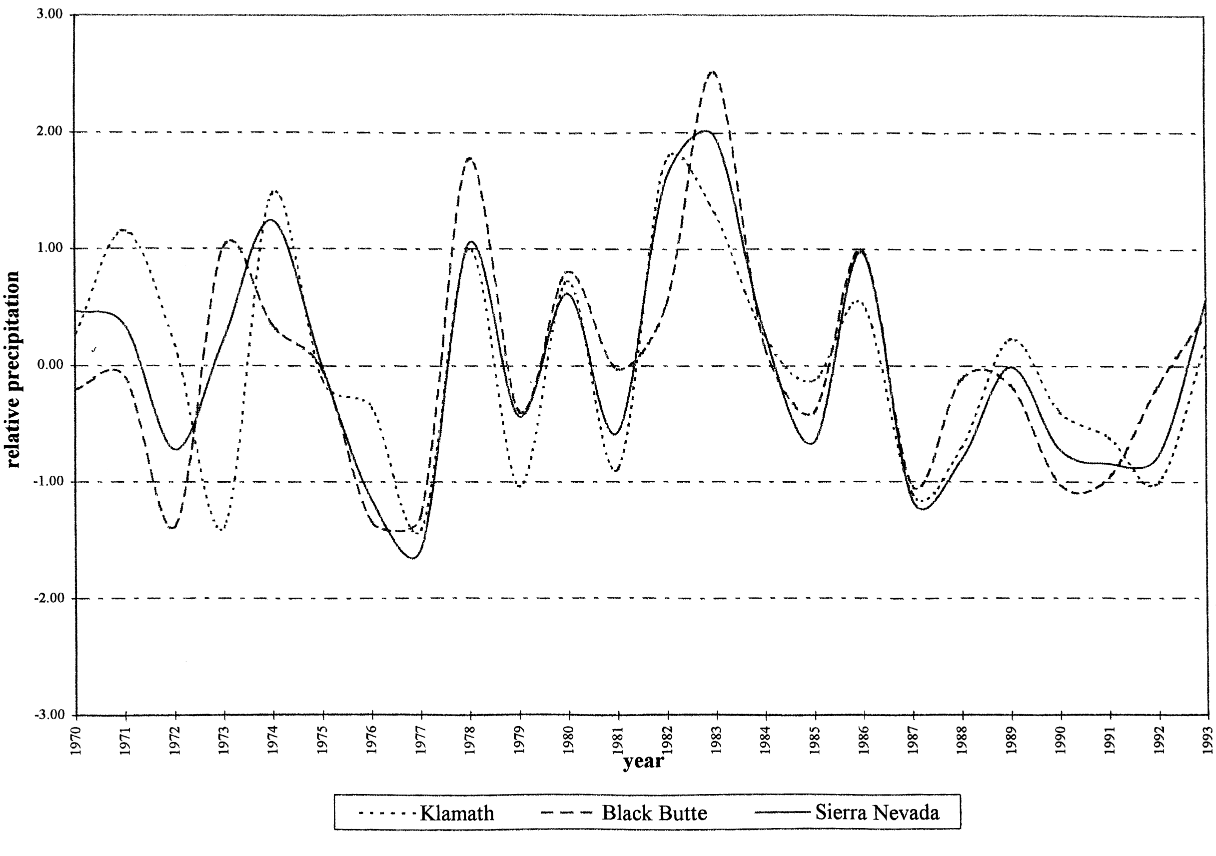

Fig. 3. Trend of relative precipitation by region.

conditions. This method assumes that growth prediction errors would be the same if climate conditions were the same for calibration and projection periods. Based on this assumption, the difference in growth prediction errors between period one (calibration period) and period two (projection period) was associated with the precipitation change from periods one to two. The estimate of the adjustment ratio, $\hat{f}$, for growth prediction was then determined by

$$\hat{f}(\mathrm{SP}, \overline{Z}_1, \overline{Z}_2) = 1 + \beta_{\mathrm{SP}}(\overline{Z}_2 - \overline{Z}_1) \quad (2)$$

where SP is the species, $\overline{Z}_1$ and $\overline{Z}_2$ the standardized levels of precipitation at the weather stations in the corresponding region (refer to Eq. (1)) for the two periods averaged and β a species-specific coefficient that was estimated from data by associating the difference in growth prediction errors with the precipitation difference between the two periods.

The resulting estimates for the coefficient β are displayed in Table 1. For six major species within each of the three regions, only 5 out of 18 tests were not significant. These widely different values of β across the three regions and between species indicate significant effects of precipitation on the tree growth over the area studied.

Using these coefficients to adjust the growth model's predictions, the prediction errors for period two (projection period) were brought much closer to that of period one (calibration period) because the growth variation due to precipitation was removed. Details of the methodology used to find the relational coefficients (β) are described by Wensel and Turnblom's study (1998). No comparison was made between the current result and a process of grouping growth plots with weather stations that share a common location, aspect, slope, elevation, etc. Had the current method not produced weather statistics that proved to be useful for relating changes in growth to precipitation these other criteria might have been considered.

6. Conclusions

Cluster analysis enabled us to assess the similarity and dissimilarity in precipitation amounts among

Table 1
Estimated parameter of Eq. (2) by species and region for the fitting half of the data set

Species	Region	Number of trees (plots)[a]	$\hat{\beta}$[b]	RMSE
Ponderosa Pine	Main	2160 (153)	0.24457	0.59565
	Klamath	269 (11)	0.51206	0.67569
	Black Butte	154 (22)	0.07438	0.46771
Sugar Pine	Main	367 (99)	0.11601	0.57600
	Klamath	67 (10)	0.16700	0.43201
	Black Butte	53 (19)	0.00000	0.38297
Cedar misc.	Main	1308 (147)	0.25249	1.10038
	Klamath	73 (13)	0.36894	0.80555
	Black Butte	29 (11)	0.00000	0.70772
Douglas-fir	Main	874 (104)	0.23912	0.43833
	Klamath	282 (18)	0.28473	0.42022
	Black Butte	128 (21)	0.07995	0.34493
White Fir	Main	2142 (166)	0.15275	0.61576
	Klamath	275 (15)	0.12747	0.43626
	Black Butte	60 (13)	0.00000	0.30590
Red Fir	Main	49 (11)	0.13871	0.38887
	Klamath	4 (2)	0.00000	0.22278
	Black Butte	10 (2)	0.00000	0.17342

[a] Use of trees could be challenged for want of independence, so number of plots were utilized as degrees of freedom to test the significance of β_i.

[b] Coefficients shown as '0.00000' were not significantly different from zero so they were set equal to zero.

weather stations, and allowed us to define subgroups of stations that reflected the geographical location of those stations. Combining the cluster results with knowledge of the geographical location of each station enabled us to divide the northern interior of California into three regions and to compute a relative precipitation index for each region.

It is true that some stations within these subgroups reported precipitation patterns that were clearly different from the patterns at neighboring stations. In a different type of study, attention might need to be given to assessing the details of these differences. However, in this study we chose to group these stations with their neighbors, thereby adding variability to the combined group.

This analysis presents one way to study the relationship between growth and climate without reliance on climatic data from a single, remote weather station that may or may not share the same climate as the growth plot. The use of group averages like these obtained through cluster analysis does prevent expression of the plot-to-plot variation in microclimates within a given region. However, we believe that the clustering process provides more reliable precipitation information than one single station can provide for growth-climate studies in which weather stations are not located in the growth plots. Furthermore, the clustering method supplies more detailed information than does an average that has been calculated across a larger region.

Appendix A.

Table 2 give the analysis of the mean and standard deviation for 77 stations and Table 3 the yearly precipitation index values for each group/area.

Table 2
Gives the mean and standard deviation for each of the 77 stations used in the analysis (statistics for 1970–1993)

Station	County	Longitude	Latitude	Elevation (m)	Average annual precipitation, P_i (cm)	Standard deviation, σ_i
Bangor	Butte	−121.41	39.390	229	85.85	29.35
BigSpring 4E	Siskiyou	−122.59	41.592	901	27.36	8.32
Bowman Dam	Nevada	−120.66	39.445	1630	164.30	57.63
Buckhorn	Shasta	−121.85	40.867	1149	161.59	57.02
BucksPH	Plumas	−121.33	39.911	536	168.52	61.20
Burney	Shasta	−121.67	40.883	957	66.32	23.35
Canby	Modoc	−120.87	41.450	1314	37.95	10.64
CanyonDam	Plumas	−121.09	40.171	1388	93.19	36.66
CaribouPH	Plumas	−121.15	40.086	910	105.41	39.08
Castle Craggs	Shasta	−122.32	41.148	618	191.34	70.55
Chester	Plumas	−121.23	40.306	1379	80.66	28.34
Cohassett 1NNE	Butte	−121.72	39.945	969	146.94	52.08
Colfax	Placer	−120.95	39.099	737	117.11	43.32
ColgatePH	Yuba	−121.19	39.331	178	101.39	33.67
Coloma	El Dorado	−120.98	38.801	235	80.51	30.39
Darrah Sp	Shasta	−122.00	40.432	297	73.61	20.89
Deer Cr Forbay	Nevada	−120.83	39.300	1359	176.18	69.79
DeSablaPH	Butte	−121.63	39.867	829	161.73	56.68
Downieville	Sierra	−120.83	39.559	882	152.49	53.69
Drum PH	Placer	−120.77	39.258	1040	166.94	65.58
Dunsmuir	Siskiyou	−122.27	41.217	738	150.21	56.37
Early Intake	Tuolumne	−119.96	37.875	718	84.18	31.83
ElectraPH	Amador	−120.67	38.838	218	75.92	29.14
Folsom	Sacramento	−121.16	38.707	107	61.37	24.47
Foothill Sch	Siskiyou	−122.37	41.803	902	42.49	9.63

Table 2 (*Continued*)

Station	County	Longitude	Latitude	Elevation (m)	Average annual precipitation, P_i (cm)	Standard deviation, σ_i
Forest Hill	Placer	−120.83	39.021	972	125.09	47.83
GibsonHMS	Shasta	−122.41	41.010	437	171.31	67.51
Gold Run	Placer	−120.87	39.150	1012	140.60	54.52
GrassValley	Nevada	−121.06	39.226	821	129.01	47.35
Greenview	Siskiyou	−122.90	41.550	859	57.51	21.01
Greenville	Plumas	−120.94	40.140	1085	97.79	42.21
Harrison Gulch	Tehama	−122.97	40.367	826	92.56	34.55
Hat CrPH	Shasta	−121.55	40.933	919	47.37	15.72
Hetch Hetchy	Tuolumne	−119.78	37.945	1180	87.85	35.25
Igo 2W	Shasta	−122.57	40.501	332	108.10	36.52
Indian GRSP	Amador	−120.65	38.422	759	101.87	39.38
IowaHill	El Dorado	−120.84	39.089	931	125.81	44.94
Jelly	Tehama	−122.20	40.330	108	70.60	23.17
KilarcPH	Shasta	−121.87	40.678	808	119.41	36.91
LakeSpaulding	Nevada	−120.64	39.319	1571	179.61	67.01
Lehman Rch	Amador	−121.01	38.592	183	70.01	29.81
LookoutShaw	Modoc	−121.15	40.350	1372	54.55	17.43
Magalia 2N	Butte	−121.57	39.836	780	182.33	65.90
Manzanita Lake	Shasta	−121.53	40.533	1783	99.48	34.07
McAurtherBFSP	Shasta	−121.62	41.012	902	80.83	29.28
McCloud	Siskiyou	−122.13	41.267	1006	119.68	42.27
Mineral	Tehama	−121.60	40.350	1487	138.79	55.21
Moccosin	Tuolumne	−120.31	37.811	290	66.09	23.90
Mt Shasta City	Siskiyou	−122.32	41.317	1080	89.14	37.21
N SanJuan	Nevada	−121.10	39.371	634	121.14	38.58
NevadaCity	Nevada	−121.01	39.258	792	141.44	50.08
Oak Knoll RS	Siskiyou	−122.85	41.850	518	62.58	20.09
Orland French Rch	Glenn	−122.33	39.617	95	45.56	18.60
PacificHouse	El Dorado	−120.50	38.750	1049	123.07	49.38
Paradise	Butte	−121.62	39.750	543	135.82	46.03
Paskenta RS	Tehama	−122.53	39.883	230	58.60	23.25
PineGrove	Amador	−120.64	38.413	716	96.85	38.08
Pit Riv PH1	Shasta	−121.50	41.000	878	46.86	15.16
Pit Riv PH5	Shasta	−121.98	40.983	444	184.80	70.80
Placerville	El Dorado	−120.80	38.729	576	93.09	36.33
PlumasEureka	Plumas	−120.70	39.757	1583	160.24	63.94
Portola	Plumas	−120.47	39.805	1474	54.91	23.87
Quincy	Plumas	−120.95	39.917	1039	98.57	42.51
Railroad Flat	Calaveras	−120.55	38.333	829	90.87	35.05
Red Bluff	Tehama	−122.25	40.150	104	57.64	19.29
Redding 1W	Shasta	−122.33	40.700	207	118.14	42.03
RoundMtn	Shasta	−121.93	40.800	640	160.93	55.86
Salt Sp PH	Amador	−120.22	38.497	1128	115.50	43.35
ShastaDam	Shasta	−122.42	40.717	328	155.98	55.38
StrawberryV	Yuba	−121.11	39.543	1161	199.06	76.71
SummitCity	Shasta	−122.38	40.683	244	134.23	46.34
TigerCr PH	Amador	−120.49	38.440	718	115.30	43.71
TrinityDam	Trinity	−122.80	40.717	567	78.48	25.96
TwinLakes	Alpine	−120.04	38.706	2386	117.06	40.08
VoltaPH	Stasta	−121.87	40.450	671	87.16	24.28
Whiskeytown	Shasta	−122.53	40.617	399	153.75	59.39
Yreka	Siskiyou	−122.63	41.717	802	48.23	14.75

Table 3
Yearly precipitation index values for each group/area

Year	Klamath	Black Butte	Sierra Nevada	All stations
1970	0.27	−0.20	0.47	0.42
1971	1.16	−0.09	0.35	0.38
1972	0.18	−1.37	−0.72	−0.69
1973	−1.38	1.01	0.23	0.17
1974	1.48	0.34	1.25	1.22
1975	−0.12	−0.04	−0.01	−0.02
1976	−0.35	−1.34	−1.15	−1.11
1977	−1.41	−1.29	−1.58	−1.55
1978	1.00	1.78	1.05	1.09
1979	−1.03	−0.38	−0.43	−0.47
1980	0.73	0.81	0.62	0.63
1981	−0.89	−0.02	−0.57	−0.56
1982	1.74	0.52	1.59	1.55
1983	1.32	2.52	1.98	1.97
1984	0.26	0.18	0.30	0.29
1985	−0.12	−0.40	−0.66	−0.61
1986	0.53	1.00	0.98	0.95
1987	−1.10	−1.04	−1.16	−1.15
1988	−0.70	−0.12	−0.80	−0.76
1989	0.23	−0.16	0.00	0.00
1990	−0.39	−1.01	−0.72	−0.71
1991	−0.61	−0.96	−0.84	−0.83
1992	−1.00	−0.17	−0.77	−0.75
1993	0.22	0.45	0.58	0.55

References

Anderberg, M.R., 1973. Cluster analysis for applications. Academic Press, Inc. New York.

Blasing, T.J., Duvick, D.N., West, D.C., 1981. Dendroclimatic calibration and verification using regionally averaged and single station precipitation data. Tree-Ring Bull. 41, 37–43.

Briggs, R.D., Lemin Jr., R.C., 1992. Delineation of climatic regions in Maine. Can. J. For. Res. 22, 801–811.

Denton, S.R., Barnes, B.V., 1988. An ecological climatic classification of Michigan: a quantitative approach. For. Sci. 34, 119–138.

Dubes, R., Jain, A.K., 1979. Validity studies in clustering methodologies. Patt. Recogn. 11, 235–254.

Elford, C.R., 1970. Climate of California. Climatography of the United States No. 60-4. U.S. Department of Commerce, Environmental Science Services Administration, Environmental Data Service, Silver Spring, Md.

Everitt, B., 1993. Cluster analysis. 3rd edn. Halsted press, Division of Wiley, New York.

Felton, E.L., 1965. California's many climates. Pacific books, Publishers, Palo Alto, California.

Graumlich, L.J., 1991. Subalpine tree growth, climate, and increasing CO_2: an assessment of recent growth trends. Ecology 72, 1–11.

Holdaway, M.R., 1990. Correlation analysis of tree growth, climate, and acid deposition in the Lake States. Res. Pap. NC-294. St. Paul, MN: U.S. Department of Agriculture, Forest Service, North Central Forest Experiment Station, 21 pp.

Johnson, R.A., Wichern, D.W., 1988. Applied Multivariate Statistical Analysis. Prentice-Hall, Simon & Schuster Inc.

Kalkstein, L.S., Tan, G., Skindlov, J.A., 1987. An evaluation of three clustering procedures for use in synoptic climatological classification. J. Clim. Appl. Meteorol. 26, 717–730.

Koeppe, C.E., De Long, G.C., 1958. Weather and Climate. McGraw-Hill Book Company, Inc. New York, Toronto, London.

Little, R.L., Peterson, D.L., Silsbee, D.G., Shainsky, L.J., Bednar, L.F., 1995. Radial growth patterns and the effects of climate on second-growth Douglas-fir (Pseudotsuga menziesii) in the Siskiyou Mountains, Oregon. Can. J. For. Res. 25, 724–735.

McQuitty, L.L., 1957. Elementary linkage analysis for isolating orthogonal and oblique types and typal relevancies. Educ. Psycholog. Measure. 17, 207–229.

Milligan, G.W., 1981. A discussion of procedures for determining the number of clusters in a data set. Paper presented at the meeting of the Classification Society, Toronto.

Milligan, G.W., Cooper, M.C., 1985. An examination of procedures for determining the number of clusters in a data set. Psychometrika 50 (2), 159–179.

Perruchet, C., 1983. Les epreuves de classifiabilite en analyses des donnees [Statistical tests of classifiability]. (Tech Rep. NT/PAA/ATR/MTI/810), Issy-Les-Moulinaux, France: C.N.E.T.

Rauscher, H.M., 1984. Homogeneous macroclimatic zones of the Lake States. USDA Forest service, North Central Experiment Station, St. Paul, Minn.

Ray, A.A. (Ed.), 1982. SAS user's guide: Statistics. Cary, North Carolina: SAS institute.

Sarle, W.S., 1983. Cubic clustering criterion. (Tech. Rep. A-108), Cary, NC.: SAS Institute.

SAS Institute Inc., 1988. SAS/STAT user's guide. release 6.03 edition. SAS Institute Inc., Cary, NC.

Snowdon, P., Woollons, R.C., Benson, M.L., 1998. Incorporation of climatic indices into models of growth of Pinus radiata in a spacing experiment. New Forests 16, 101–123.

van Groenewoud, H., 1984. The climatic regions of New Brunswick: a multivariate analysis of meteorological data. Can. J. For. Res. 14, 389–394.

Wahba, G., Wendelberger, J., 1980. Some new mathematical methods for variational objective analysis using splines and cross validation. Mon. Weather Rev. 108, 1122–1143.

Wensel, C.L., Turnblom, E.C., 1998. Adjustment of estimated tree growth rates in northern California conifers for changes in precipitation levels. Can. J. For. Res. 28, 1241–1248.

Woollons, R.C., Snowdon, P., Mitchell, N.D., 1997. Augmenting empirical stand projection equations with edaphic and climatic variables. For. Ecol. Manage. 98, 267–275.

Yeh, H.Y., 1997. The relationship between tree diameter growth and climate for the six major species in the northern California. Ph.D. Thesis, University of California, Berkeley.