10

Dendroclimatology

10.1 Introduction

Variations in tree-ring widths from one year to the next have long been recognized as an important source of chronological and climatic information. In Europe, studies of tree rings as a potential source of paleoclimatic information go back to the early 18th century when several authors commented on the narrowness of tree rings (some with frost damage) dating from the severe winter of 1708–9. In North America, Twining (1833) first drew attention to the great potential of tree rings as a paleoclimatic index (for a historical review, see Studhalter 1955). However, in the English-speaking world, the "father of tree-ring studies" is generally considered to be A. E. Douglass, an astronomer who was interested in the relationship between sunspot activity and rainfall. To test the idea of a sunspot–climate link, Douglass needed long climatic records and he recognized that ring-width variations in trees of the arid south-western United States might provide a long, proxy record of rainfall variation (Douglass 1914, 1919). His efforts to build long-term records of tree growth were facilitated by the availability of wood from archaeological sites, as well as from modern trees (Robinson 1976). Douglass' early work was crucial for the development of dendrochronology (the use of tree rings for dating) and for dendroclimatology (the use of tree rings as a proxy indicator of climate).

Although much work has been carried out since these early pioneering studies, the greatest strides in dendroclimatology have been made in the last 10–15 years, largely as a result of the work of H. C. Fritts and associates at the Laboratory of Tree Ring Research in the University of Arizona, Tucson; much of this work has been documented at length in the excellent book by Fritts (1976). Latest developments, including discussion of recent dendroclimatic studies of the Southern Hemisphere, are discussed in the volume edited by Hughes *et al.* (1982).

10.2 Fundamentals of dendroclimatology

A cross section of most temperate forest trees will show an alternation of lighter and darker bands, each of which is usually continuous around the tree circumference. These are seasonal growth increments produced by meristematic tissues in the cambium of the tree. When viewed in detail (Fig. 10.1) it is clear that they are made up of sequences of large, thin-walled cells (earlywood) and more densely packed, thick-walled cells (latewood). Collectively, each couplet of earlywood and latewood comprises an annual growth increment, more commonly called a tree ring. The mean width of a ring in any one tree is a function of many variables, including the tree species, tree age, availability of stored food within the tree and of important nutrients in the soil, and a whole complex of climatic factors (sunshine, precipitation, temperature, wind speed, humidity, and their distribution through the year). The problem

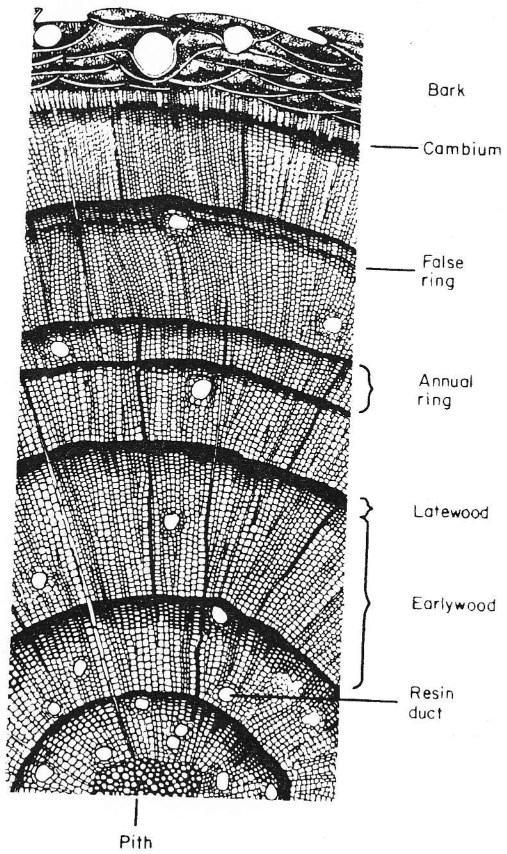


Figure 10.1 Drawing of cell structure along a cross-section of a young stem of a conifer. The earlywood is made up of large and relatively thin-walled cells (tracheids); latewood is made up of small, thick-walled tracheids. Variations in tracheid thickness may produce false rings in either earlywood or latewood (after Fritts 1976).

Fig 2.3

facing dendroclimatologists is to extract whatever climatic signal is available in the tree-ring data and to distinguish this signal from the background "noise." Furthermore, the dendroclimatologist must know precisely the age of each tree ring if the climatic signal is to be chronologically useful. From the point of view of paleoclimatology, it is perhaps useful to consider the tree as a filter or transducer which, through various physiological processes, converts a given climatic input signal into a certain ring-width output which is stored and can be studied in detail, even thousands of years later (e.g. Yapp & Epstein 1977, Fritts 1976).

Climatic information has most often been gleaned from interannual variations in ring width, but recently there has been a great deal of work on the use of density variations, both inter- and intra-annually (Sec. 10.4). Significant advances have also been made in studying isotopic variations in wood as a proxy of temperature variation through time (Sec. 10.5). These different approaches are complementary and can be used independently to check paleoclimatic reconstructions based on only one of the methods, or collectively to provide an extremely accurate reconstruction (Schweingruber *et al.* 1978).

10.2.1 *Sample selection*

In conventional dendroclimatological studies, where ring-width variations are the source of climatic information, trees are sampled in sites where they are under stress; commonly, this involves selection of trees which are growing close to their extreme ecological range. In such situations, climatic variations will greatly influence annual growth increments. In more beneficent situations, perhaps nearer the middle of a species range, or in a site where the tree has access to abundant ground water, tree growth may not be noticeably influenced by climate, and this will be reflected in the low interannual variability of ring widths (Fig. 10.2). Such tree rings are said to be complacent. There is thus a spectrum of possible sampling situations, ranging from those where trees are extremely sensitive to climate to those where trees are virtually unaffected by interannual climatic variations. Clearly, for useful dendroclimatic reconstructions, samples close to the sensitive end of the spectrum are favored as these would contain the strongest climatic signal. However, it is now clear that climatic information may also be obtained from trees which are not under obvious climatic stress, providing the climatic signal common to all the samples can be successfully isolated (LaMarche 1982). For example, ring widths of New England deciduous and coniferous trees have been used to reconstruct the history of drought in the area since AD 1700 (Cook & Jacoby 1977) and, recently, reasonably good paleoclimatic reconstructions have been achieved using Tasmanian mesic forest trees (LaMarche & Pittock 1982). For isotope dendroclimatic studies (Sec. 10.6) the sensitivity requirement is not

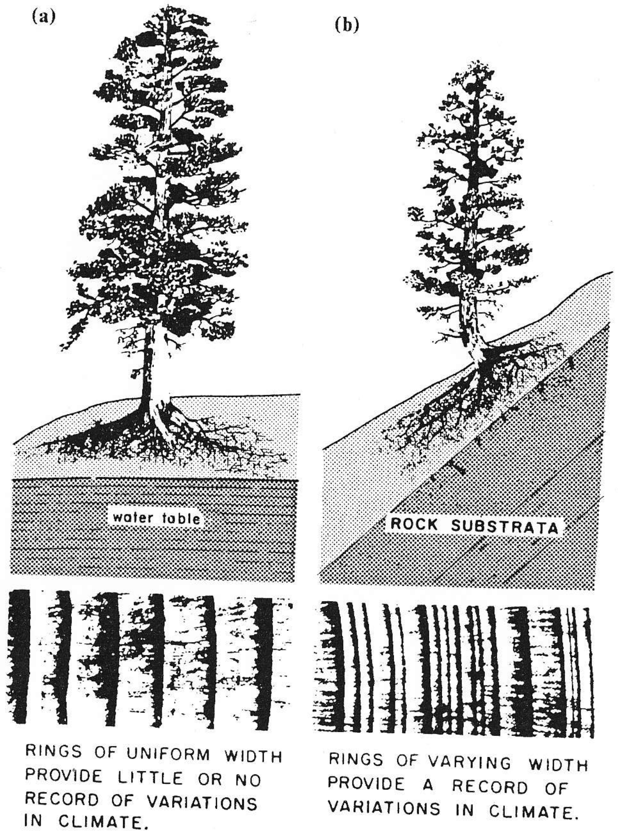


Figure 10.2 Trees growing on sites where climate seldom limits growth processes produce rings that are uniformly wide (a). Such rings provide little or no record of variations in climate and are termed *complacent*. Trees growing on sites where climatic factors are frequently limiting produce rings that vary in width from year to year depending on how severely limiting climate has been to growth (b). These are termed *sensitive* (from Fritts 1971).

critical and it would, in fact, be preferable to use complacent tree rings for analysis (Gray & Thompson 1978). Sensitivity is also less significant in densitometric studies (Sec. 10.5).

Commonly two types of climatic stress are recognized, moisture stress and temperature stress. Trees growing in semi-arid areas are frequently limited by the availability of water, and ring-width variations primarily reflect this variable. Trees growing near to the latitudinal or altitudinal treeline are mainly under growth limitations imposed by temperature and hence ring-width variations in such trees contain a strong temperature signal. However, other climatic factors may be indirectly involved.

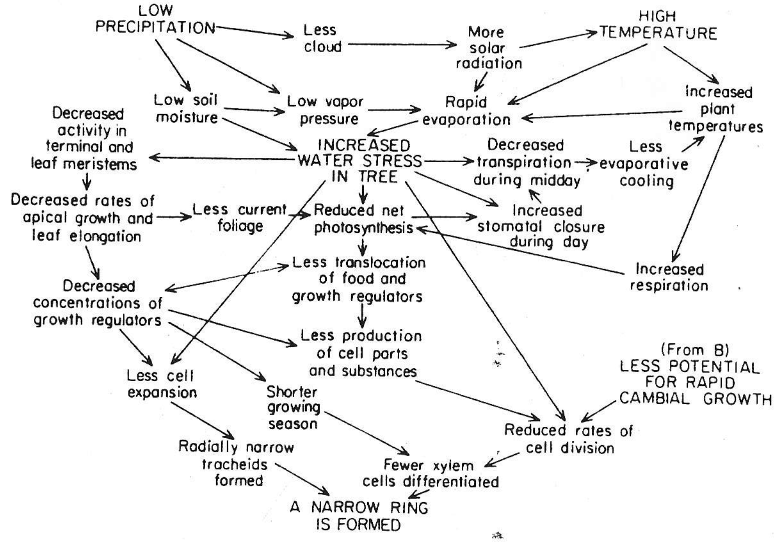


Figure 10.3 A schematic diagram showing how low precipitation and high temperature during the growing season may lead to the formation of a narrow tree ring in arid-site trees. Arrows indicate the net effects and include various processes and their interactions. It is implied that the effects of high precipitation and low temperature are the opposite and may lead to an increase in ring widths (from Fritts 1971).

Biological processes within the tree are extremely complex (Fig. 10.3) and similar growth increments may result from quite different combinations of climatic conditions. Furthermore, climatic conditions *prior* to the growth period may "precondition" physiological processes within the tree and hence strongly influence subsequent growth (Fig. 10.4). For the same reason, tree growth and food production in one year may influence growth in the following year, and lead to a strong serial correlation or autocorrelation in the tree-ring record. Tree growth in marginal environments is thus commonly correlated with a number of different climatic factors in both the growth season (year t_0) and in the preceding months, as well as with the record of prior growth itself (generally in the preceding growth years, t_{-1} and t_{-2}). Indeed in complex dendroclimatic models, tree growth in subsequent years (t_{+1}, t_{+2}, etc.) may also be considered, since they also contain climatic information about year t_0. This will be discussed in more detail in Sections 10.2.4 and 10.3.

Trees are sampled radially using an increment borer which removes a core of wood (generally 4 mm in diameter), leaving the tree unharmed. It is important to realize that dendroclimatic studies are unreliable unless an adequate number of samples are recovered; two or three cores should be taken from each tree and at least 20–30 trees should be sampled at an

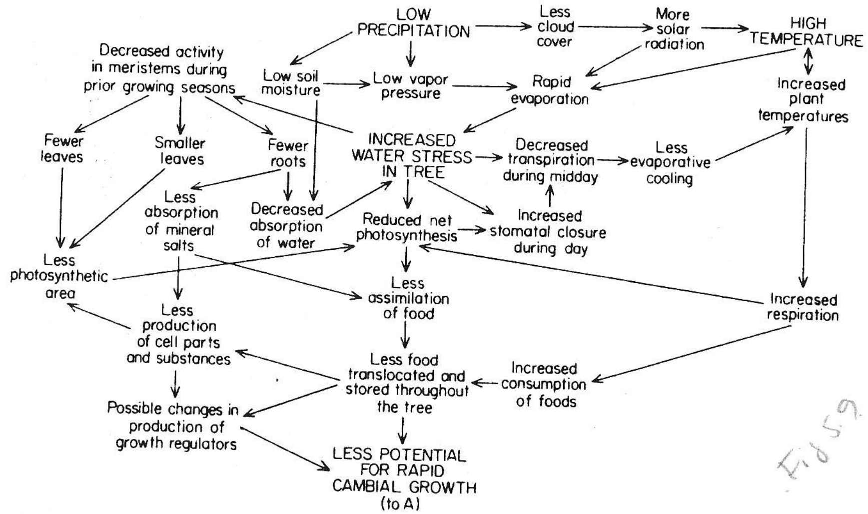


Figure 10.4 A schematic diagram showing how low precipitation and high temperature *before* the growing season may lead to a narrow tree ring in arid-site trees (from Fritts 1971).

individual site, though this is not always possible. Eventually, as discussed below, the cores are used to compile a master chronology of ring-width variation for the site and it is this that is used to derive climatic information.

10.2.2 *Cross dating*

For tree-ring data to be used for paleoclimatic studies, it is essential that the age of each ring be known precisely. This is necessary in constructing the master chronology from a site where ring widths from modern trees of similar age are being compared, and equally necessary when matching up sequences of overlapping records from modern and archeological specimens to extend the chronology back in time (Stokes & Smiley 1968). Great care is needed because occasionally trees will produce false rings or intra-annual growth bands, which may be confused with the actual earlywood/latewood transition (Fig. 10.5). Furthermore, in extreme years some trees may not produce an annual growth layer at all, or it may be discontinuous around the tree, or so thin as to be indistinguishable from adjacent latewood (i.e. a partial or missing ring). Clearly, such circumstances would create havoc with climatic data correlation and reconstruction, so careful cross dating of tree-ring series is necessary. This involves comparing ring-width sequences from each core so that characteristic patterns of ring-width variation (ring-width "signatures") are correctly matched (Fig. 10.6). If a false ring is present, or if a ring is missing, it will thus be immediately apparent. The same procedure can

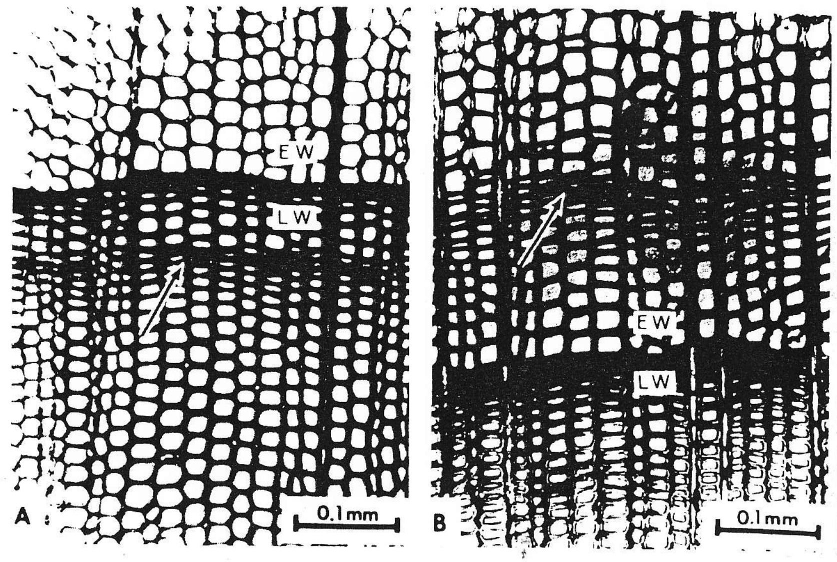


Figure 10.5 Annual growth increments or rings are formed because the wood cells produced early in the growing season (earlywood, EW) are large, thin-walled, and less dense, while the cells formed at the end of the season (latewood, LW) are smaller, thick-walled, and more dense. An abrupt change in cell size between the last-formed cells of one ring (LW) and the first-formed cells of the next (EW) marks the boundary between annual rings. Sometimes growing conditions temporarily become severe before the end of the growing season and may lead to the production of thick-walled cells within an annual growth layer (arrows). This may make it difficult to distinguish where the actual growth increment ends, which could lead to errors in dating. Usually these intra-annual bands or false rings can be identified, but where they can not the problem must be resolved by cross dating (after Fritts 1976).

be used with archeological material; the earliest records from living trees are matched or cross dated with archeological material of the same age and the procedure is repeated many times over to establish a thoroughly reliable chronology. In the south-western USA, the ubiquity of beams or logs of wood used in Indian pueblos has enabled chronologies of up to 2000 years to be constructed. In fact, accomplished dendrochronologists can accurately date wood used in dwellings by comparing their tree-ring widths with master chronologies for the area (Robinson 1976). Similar chronologies are being established in western Europe; Baillie (1977), for example, has used beams of wood from historical and archeological sites to establish an oak chronology for northern Ireland back to AD 1001. In the Netherlands, studies of oak panels used for paintings up to AD 1650, and even wooden sculptures, have provided cross-datable material (Eckstein *et al.* 1975). Tree stumps recovered from Holocene bogs have also been cross dated, forming a "floating chronology," fixed in time by

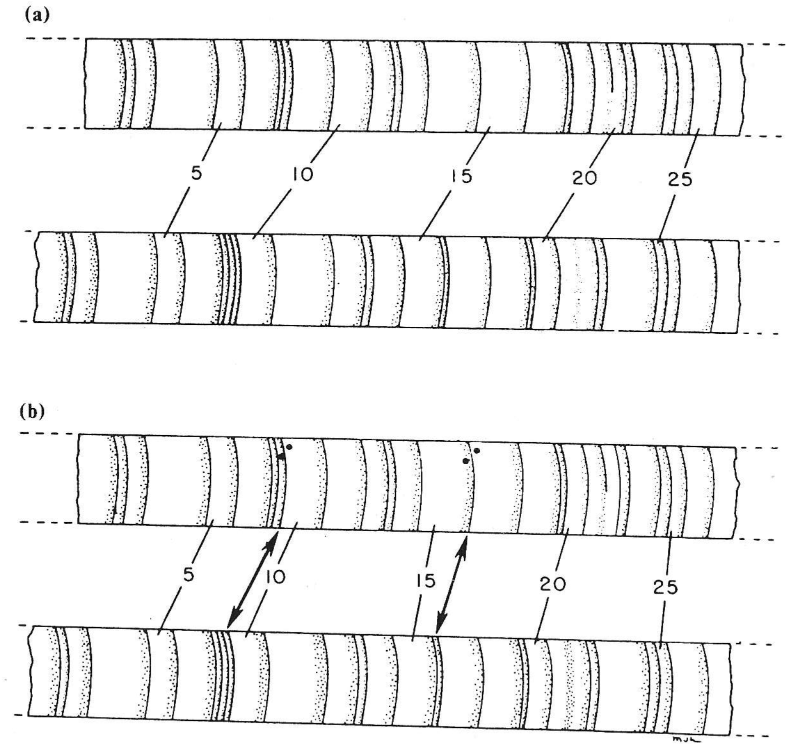


Figure 10.6 Cross dating of tree rings. Comparison of tree-ring widths makes it possible to identify false rings or where rings are locally absent. For example, in (a), strict counting shows a clear lack of synchrony in the patterns. In the lower specimen of (a), rings 9 and 16 can be seen as very narrow, and they do not appear at all in the upper specimen. Also, rings 21 (lower) and 20 (upper) show intra-annual growth bands. In (b), the positions of inferred absence are designated by dots (upper specimen), the intra-annual band in ring 20 is recognized, and the patterns in all ring widths are synchronously matched (after Fritts 1976).

^{14}C dating only, at present (e.g. Pilcher *et al.* 1977). Finally, cross-dating techniques have been most successfully applied to very old living trees (bristlecone pines) and wood fragments from adjacent dead tree stumps. In this way, a chronology extending over 7000 years has been established (Ferguson 1970) which is considered to be so accurate that radiocarbon dates on bristlecone pine samples of known age are used to calibrate the radiocarbon timescale (see Sec. 3.2.1.5).

10.2.3 Standardization of ring-width data

Once the chronology for each core has been established, individual ring widths are measured and plotted to establish the general form of the data (Fig. 10.7a). It is common for time series of ring widths to contain a

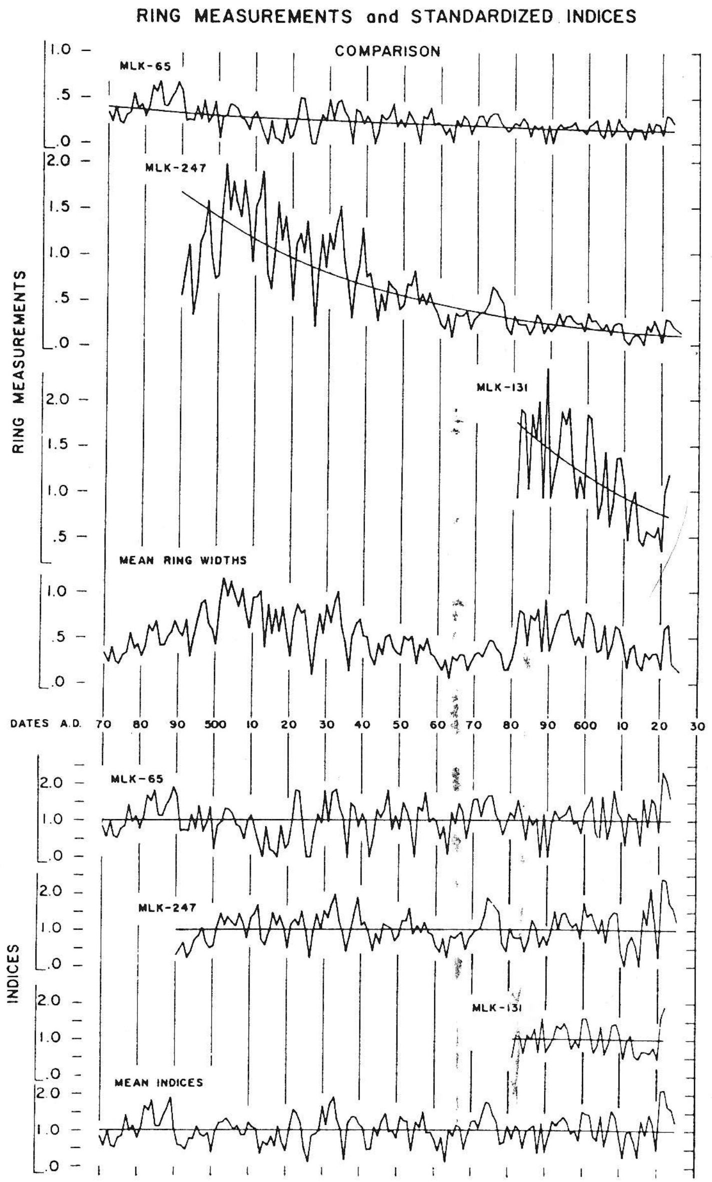


Figure 10.7 Standardization of ring-width measurements is necessary to remove the decrease in size associated with increasing age of the tree. If the ring widths for the three specimens shown in the upper figure are simply averaged by year, without removing the effect of the tree's age, the mean ring-width chronology shown below them exhibits intervals of high and low growth, associated with the varying age of the samples. This age variability is generally removed by fitting a curve to each ring-width series, and dividing each ring width by the corresponding value of the curve. The resulting values, shown in the lower half of the figure, are referred to as indices, and may be averaged among specimens differing in age to produce a mean chronology for a site (lowermost record) (from Fritts 1971).

function resulting entirely from the tree growth itself, with wider rings generally produced during the early life of the tree. In order that ring-width variations from different cores can be compared, it is first necessary to remove the growth function peculiar to that particular tree. Only then can a master chronology be constructed. Growth functions are removed by fitting an exponential or polynomial curve to the data (Fig. 10.7a) and dividing each ring-width value by the "expected" value on the growth curve. This standardization procedure leads to a new time series of ring-width indices, with a mean of one and a variance which is fairly constant through time (Fritts 1971). Ring-width indices are then averaged, year by year, to produce a master chronology for the sample site, independent of growth function and differing sample age (Fig. 10.7b). Averaging the standardized indices also increases the (climatic) signal to noise ratio. This is because climatically related variance, common to all records, is not lost by averaging, whereas non-climatic "noise," which varies from tree to tree, will be partially cancelled in the averaging process. It is thus important that a large enough number of cores be obtained initially to help enhance the climatic signal common to all the samples.

Standardization is an essential prerequisite to the use of ring-width data in dendroclimatic reconstruction but it poses significant methodological problems. Consider, for example, the ring-width chronologies shown in Fig. 10.8. Drought-sensitive conifers from the south-western United States characteristically show ring-width variations like those in Figure 10.8a. For most of the chronology a negative exponential function, of the form $y = ae^{-by} + k$, fits the data well. However, this is not the case for the early section of the record, which must be either discarded or fitted by a separate mathematical function. Obviously, the precise functions selected will have an important influence on the resulting values of the ring width indices. In the case of deciduous trees, the growth curve is often quite variable and unlike the negative exponential values characteristic of arid-site conifers. In such cases (Fig. 10.8b) a polynomial function is fitted to the data and individual ring widths are divided by the local value of this curve to produce a series of ring-width indices. In the case of polynomial functions, given a large enough number of coefficients, it is theoretically possible to describe the raw data quite precisely, which would, of course, remove all the climatic information. It is therefore necessary to restrict the number of coefficients to the minimum; in practice, additional coefficients are not included unless they reduce the variance of the ring-width data by at least a further 5% (Fritts 1976), though this cut-off point is quite arbitrary.

Further problems arise when complex growth functions are observed, such as those in Figure 10.8c. In this case it would be difficult to decide on the use of a polynomial function (dashed line) or a negative exponential

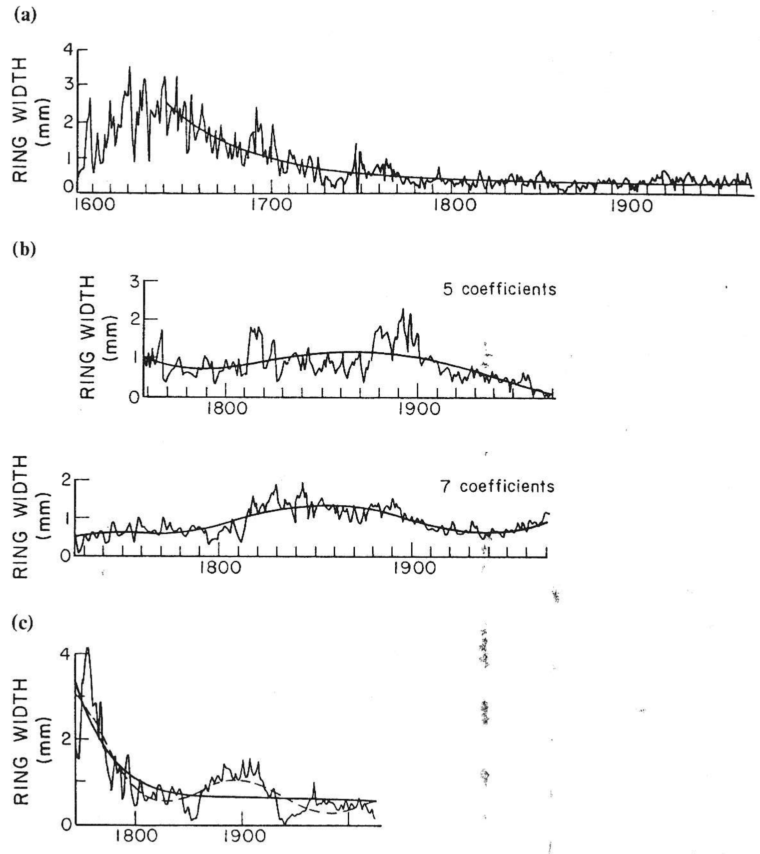


Figure 10.8 Some problems in standardization of ring widths. In (a) most of the tree-ring series can be fitted by the exponential function shown. However, the early part of the record must be discarded. In (b) the two ring-width series required higher-order polynomials to fit the lower frequency variations of each record (the greater the number of coefficients for each equation, the greater the degree of complexity in the shape of the curve). In (c) the series could be standardized using either a polynomial (dashed) or exponential function (solid line). Depending on the function selected and its complexity, low-frequency climatic information may be eliminated. The final ring-width indices depend very much on the standardization procedure employed (examples selected from Fritts 1976).

function (solid line), and in either case the first few observations should perhaps be discarded. It is clear that this standardization procedure is not easy to apply and may actually remove important low-frequency climatic information. It is not possible, *a priori*, to decide if part of the long-term change in ring width is due to a coincident climatic trend. The problem is exacerbated if one is attempting to construct a long-term dendrochronological record, when only tree fragments or historical timbers are

available and the corresponding growth function may not be apparent. Such difficulties are less significant in densitometric or isotope dendroclimatic studies because there is little or no growth trend in the density and isotope data (Polge 1970, Schweingruber *et al.* 1979); it is thus likely that these approaches will yield more low-frequency climatic information than is possible in the measurement of ring widths alone.

10.2.4 *Calibration of ring-width data*

Once a master chronology of standardized ring-width indices has been obtained, the next step is to relate variations in ring-width data to variations in climatic data. This process is known as calibration, whereby a mathematical or statistical procedure is used to convert growth measurement into climatic estimates. If an equation can be developed which accurately describes instrumentally observed climatic variability in terms of tree growth over the same interval, then paleoclimatic reconstructions can be made using only the tree-ring data. A survey of the various methods which have been used to determine the tree growth–climate relationship indicates several different levels of complexity, each level involving more complex statistics (Table 10.1). In this section, a brief summary of each method is given to provide an overview of the various approaches. In Section 10.3, there follows a more detailed discussion of each method, with examples of how they have been applied to dendroclimatic reconstructions. For a more exhaustive treatment of the statistics involved, and more examples of how they have been used, the reader is referred to Fritts (1976 Ch. 7).

At the primary level of calibration (level I in Table 10.1) is the simple linear regression model with only two variables: growth indices and a climatic parameter, perhaps mean summer temperature. This approach

Table 10.1 Methods used to determine relationship between tree growth and climate.

Level	Number of variables of: Tree growth	Climate	Main statistical procedures used
I	1†	1†	Linear regression analysis
II	1†	*n*†	Multiple stepwise regression analysis
IIIa	1†	*n* (eigenvector)‡	Principal components and stepwise multiple regression analysis
IIIb	*n* (eigenvector)‡	1†	Principal components and multiple regression analysis
IV	*n* (eigenvector)‡	*n* (eigenvector)‡	Principal components and multiple canonical regression analysis

† Temporal array of data.
‡ Spatial and temporal array of data.

necessitates an assumption, *a priori*, that the climatic variable selected is the main one accounting for most of the variance in the tree-growth record. However, as discussed above, tree growth is generally too complex to be usefully equated with climate using only one variable. A more objective approach (level II in Table 10.1) is the use of multiple regression techniques to select from a variety of climatic variables those which are primarily responsible for variance in the tree-growth record (Ferguson 1977). This empirical approach allows the data to "speak for itself," and involves no *a priori* assumptions other than the selection of variables entered into the regression initially as possible predictors (or independent variables). The analysis results in an equation expressing the response of the tree (the dependent variable) to variations in the most important climatic variables, and this is known as a response function. In practice, response functions are always multivariate, reflecting the complexity of the tree growth – climate relationship.† One of the difficulties in multiple regression is the fact that climatic variables are themselves often highly intercorrelated. For example, July temperature and July precipitation may exhibit a strong negative correlation. In such a case it would be problematical to determine whether incorporating the variable for July temperature in a regression equation would truly reflect the relationship of the tree to temperature in that month or to precipitation amounts or to some combination of both. A way around this is to express the variance of the climatic data in terms of principal components or eigenvectors and to use these as predictors in the regression procedure (level IIIa). Principal components analysis involves statistical transformations of the original (intercorrelated) data set to produce a set of orthogonal (i.e. uncorrelated) eigenvectors (Grimmer 1963, Stidd 1967, Daultrey 1976). Each eigenvector is a variable which expresses part of the variance in the data set (which is usually expressed in terms of "departures from long-term averages" or anomaly patterns). There are as many eigenvectors as original variables, but most of the original variance will be accounted for by only a few of the eigenvectors. The primary eigenvectors can be thought of as preferred modes of distribution of the data set and account for most of its variance (Mitchell *et al.* 1966). Subsequent eigenvectors account for minor amounts of the remaining variance. The value or amplitude of each eigenvector will vary from year to year, being highest in the year when that particular combination of climatic variables which the eigenvector represents, is most apparent. Conversely, it will be lowest in the year when the inverse of this combination is most apparent in the data. By using eigenvector amplitudes as independent (prediction) variables in the stepwise regression procedure, a higher proportion of the dependent data variance can be accounted for by fewer variables than would be possible using the "raw" climatic data themselves.

†It is worth noting that level I calibrations may be used successfully *if* response function analysis indicates that the climatic variables influencing ring widths can be conveniently grouped. For example, white oak in Iowa responds to annual precipitation there in all 12 months of the year, according to response function analysis. Thus annual precipitation can be used in a straight-line regression, with growth indices from a white oak chronology as the independent variable (Blasing *et al.* 1981).

These methods have all focused on the relationship between tree growth on an individual site (as expressed in terms of the master chronology of ring-width indices) and its response to climate in the area. Similar methodology can be applied to studying the way in which a network of trees responds to a specific climatic, or climatically related, parameter. In this case, variance of the tree-growth data is expressed in the form of eigenvectors, each one thus representing a spatial pattern of growth variation (level IIIb, Table 10.1). Amplitudes of these eigenvectors are then used as independent variables in the multiple regression analysis. The resulting equation is termed a transfer function, whereby spatial patterns of growth records are "transferred" into climatic estimates.

Simple transfer functions express the relationship between *one* climatic variable and *multiple* growth variables. A more complex step (level IV in Table 10.1) is to relate the variance in multiple growth records to that in a multiple array of climatic variables. To do so, each data matrix, made up of data representing variations in both time and space, is converted into its principal components or eigenvectors; these are then related using multiple canonical correlation and regression techniques (Clark 1975). This involves identifying the variance which is common to individual eigenvectors in the two different data sets and defining the relationship between them. The importance of the technique is that it allows spatial arrays (maps) of tree-ring indices to be used to reconstruct maps of climatic variation through time. At present, these are the most complex models used in dendroclimatic reconstruction and result in the most sophisticated year-by-year paleoclimatic reconstructions ever obtained from proxy data (Fritts *et al.* 1979).

Before concluding this section on calibration, it is worth noting that tree-ring indices need not be calibrated directly with climatic data. The ring-width variations contain a climatic signal and this may also be true of other natural phenomena which are dependent in some way on climate. It is thus possible to calibrate such data directly with tree rings and to use the long tree-ring records to reconstruct the other climate-related series. In this way, dendroclimatic analysis has been used to reconstruct runoff records (Stockton 1975, Stockton & Boggess 1980), lake-level variations (Stockton & Fritts 1973), sea-surface temperatures (Douglas 1973), and even albacore tuna populations off the California coast (Clark *et al.* 1975). Some of these applications are discussed in more detail in subsequent sections.

10.3 Dendroclimatic reconstructions

10.3.1 Models derived by stepwise multiple regression (level II)
Nearly all modern dendroclimatic studies involve the use of multivariate statistics to define the relationship between climate and tree growth (levels II and III in Table 10.1). In level II models, the basic equation (assuming linear relationships) is of the form

$$y_t = a_1x_{1'} + a_2x_{2'} + a_3x_{3'} \ldots + a_mx_{m'} + b,$$

where, in the case of response functions (Sec. 10.2.4), y_t is the tree growth index value for year t; b is a constant; $x_1, \ldots x_m$ are climatic variables in year t; and $a_1, \ldots, a_m$ are weights or regression coefficients assigned to each climatic variable in order to obtain the estimate of y_t. In effect, the equation is simply an expansion of the linear equation, $y_t = ax_t + b$, to incorporate a larger number of terms, each additional variable "accounting for" more of the variance in the ring-width data (Ferguson 1977). Theoretically, if all of the factors governing tree growth (including their interactions) could be considered, it would be possible to construct an equation to predict the value of y_t precisely. However, even in this situation the predicted value would only be a point at the center of a zone of probability since each regression coefficient in the equation has an associated standard error. As increasing numbers of variables are added to the multiple regression equation, so the zone of uncertainty in the calculation of y_t increases due to the additive effect of all the coefficient standard errors. There is thus little point in using a large number of independent variables to account for 100% of the variance in the tree-ring record because the confidence limits (or probability range) would be so large as to make the estimate virtually worthless. What is needed is an equation which uses the minimum number of climatic variables to account for the maximum amount of variance in the tree-ring record. Commonly, the procedure of stepwise multiple regression is used to achieve this aim (Fritts 1962, 1965). From a matrix of potentially influential climatic variables, the one which accounts for most of the tree-ring variance is selected; next, the variable which accounts for the largest proportion of the remaining variance is identified and added to the equation, and so on in a stepwise manner. Tests of statistical significance, as each variable is selected, enable the procedure to be terminated when a further increase in the number of variables in the equation results in an insignificant increase in variance explanation. In this way, only the most important variables are selected, objectively, from the large array of potentially important influences on tree growth. This approach was taken by Fritts *et al.* (1965) to interpret tree-ring records from south-western Colorado. A "great drought" at the end of the 13th century was

thought to have led to prehistoric people in the area abandoning their settlements and migrating to other regions. Several analyses were performed, using measurements of precipitation, maximum, minimum, and mean temperatures at nearby weather stations, averaged over varying time periods, as the independent (predictor) variables. In each case, the dominant control on tree growth in the area was precipitation, followed by maximum, mean, and minimum temperatures in order of importance. Furthermore, precipitation in the months prior to the growth season was most significant for growth whereas temperatures at the beginning of the growth season, and during the previous season, were significantly

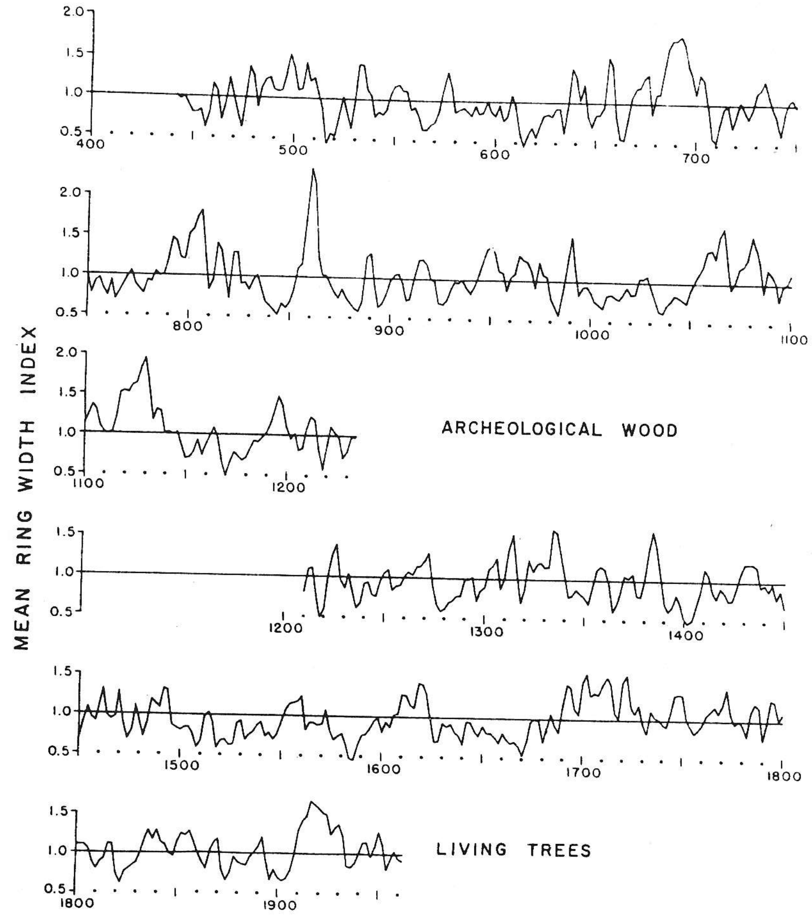


Fig 8.8

Figure 10.9 Five year running means of ring width indices from *Pseudotsuga menziesii* at Mesa Verde, Colorado, corrected for autocorrelation and plotted on every even year from AD 442 through 1962 (after Fritts *et al.* 1965).

(inversely) related to tree growth. Knowing this, long-term variations of tree growth in the area could be interpreted as being primarily a record of August to May precipitation, with low growth associated with low precipitation amounts and high temperatures. The record of ring-width indices (Fig. 10.9) appears to show that although the drought of the late 13th century was pronounced, it was no more significant than several other similar dry spells in the preceding and subsequent periods. It could thus be concluded the drought was only one of several factors contributing to settlement abandonment in south-western Colorado at this time.

10.3.2 *Models derived by principal components analysis and stepwise multiple regression (level III)*

One of the difficulties of using climatic data in stepwise multiple regression is that the variables are often highly intercorrelated, so it is difficult to separate the influence of two related variables. For example, high temperatures and low precipitation commonly occur together; if temperature is the first variable in a stepwise regression, the addition of a precipitation variable may not significantly increase the variance explanation, because much of the variability of precipitation has already been subsumed by the temperature variable. This difficulty can be overcome by the calculation of principle components or eigenvectors to represent the climatic data. As explained in Section 10.2.4, eigenvectors are uncorrelated transformations of the original data set, each accounting for a proportion of variance in the data (Daultrey 1976). Instead of using "raw" climatic data in the regression analysis, eigenvector amplitudes are used as the independent variables (Fig. 10.10). Once the regression coefficients have been calculated, the eigenvectors incorporated in the regression equation are mathematically transformed into a new set of n coefficients corresponding to the original (intercorrelated) set of n variables. These new coefficients are termed weights or elements of the response function and are analogous to the stepwise regression coefficients discussed earlier, except that there is a coefficient for each of the original climatic variables from which the eigenvectors were derived. An example of response function elements is shown in Figure 10.11. Collectively, these values represent the response of the tree to the combination of climatic conditions represented in the eigenvector. Thus, in the case of Figure 10.11a, the regression equation with only one variable (amplitudes of eigenvector 1) accounts for 36% ($R^2 \times 100$) of the variance of ring-width indices during the period of instrumental records. This first eigenvector represents a climatic condition in which tree growth is associated with below average temperatures in all months leading up to and including those in the growth season, and above average precipitation in all months. Note that the 95% confidence limits on these weights are small since they are based on only one variable. Figure 10.11b shows the

Fig 7.10

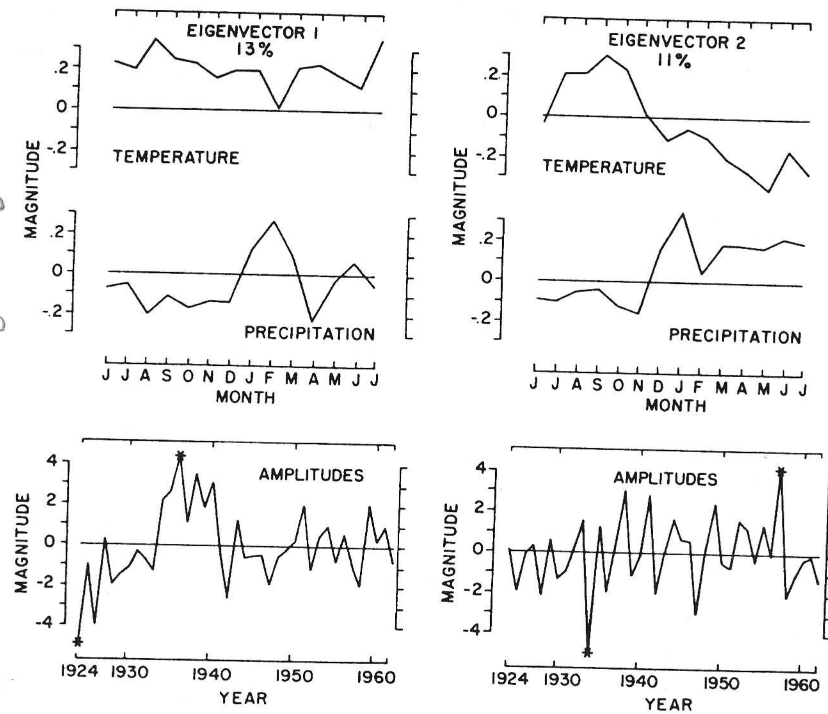


Fig 7.11

Figure 10.10 Magnitudes of the elements of the first and second eigenvectors of climate at Mesa Verde, southwestern Colorado, and their corresponding amplitude sets. In eigenvector 1 (which reduces 13% of the climatic variance) the eigenvector elements for temperature are all the same sign; the corresponding signs for ten elements for precipitation have the opposite sign. This arises because temperatures throughout the 14 month period are somewhat positively correlated with each other, but they are negatively correlated with precipitation for ten out of 14 months. In eigenvector 2 (which reduces 11% of the climatic variance) the eigenvector expresses a mode of climate in which the departures of temperature for July to November are opposite in sign to those for December to July. All elements for precipitation have signs opposite those for temperature, indicating a generally inverse relationship. The eigenvectors are multiplied with normalized climatic data to obtain the amplitude sets. Asterisks mark those elements with the largest positive and negative values, indicating a climatic regime for the year which most resembles the eigenvector in question (either positively or negatively) (after Fritts 1976).

response function weights resulting from an equation utilizing three eigenvector variables; these account for 67% of the tree-growth variance. Using this equation, ring-width indices are inversely related to temperature in most months, but positively correlated with precipitation. May of the growth year and September of the previous year are the only months for which temperature is positively and significantly related to growth. Note also that the wider 95% confidence limits span zero in many months, making interpretation very difficult. As more eigenvector vari-

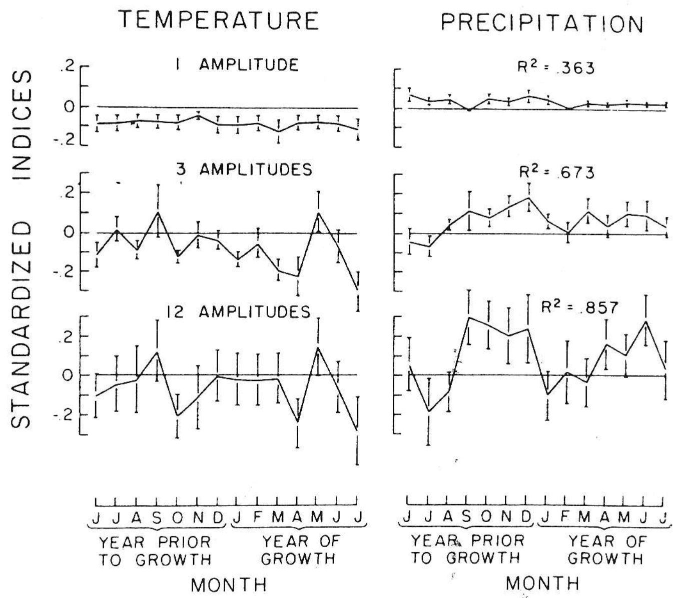


Figure 10.11 Response functions obtained from a stepwise regression analysis using amplitudes of eigenvectors to estimate a ring-width chronology representing six *Pinus ponderosa* sites along the lower slopes of the Rocky Mountains, Colorado. Steps with 1, 3, and 12 predictor variables are shown. Percentage variance reduced can be calculated by multiplying the R^2 value by 100. The regression coefficients for amplitudes are converted to response functions though when response functions are complex, as in this example, a linear combination of many eigenvectors is needed to obtain the best fitting relationship (after Fritts 1976).

ables are added to the equation (Fig. 10.11c) the percentage explanation increases, but the confidence limits increase also and the exact relationship of each response function element to tree growth becomes more uncertain. Ideally then, one would aim to achieve an equation with the minimum number of eigenvectors and the maximum percentage explanation.

As an example of how these complex calculations can be used for paleoclimatic reconstruction, consider the work of LaMarche (1974). LaMarche studied ring-width variations of bristlecone pines in the White Mountains of California. Here, the tree occupies a distinct altitudinal range, on the flanks of the mountains. Ecological studies indicate that trees at the upper and lower forest borders respond differently to climate, so analysis of ring widths in both sites may yield paleoclimatic information unobtainable from either record alone. In order to quantify the tree ring–climate relationship at each site, local climatic data was expressed in terms of eigenvectors and used as independent variables in

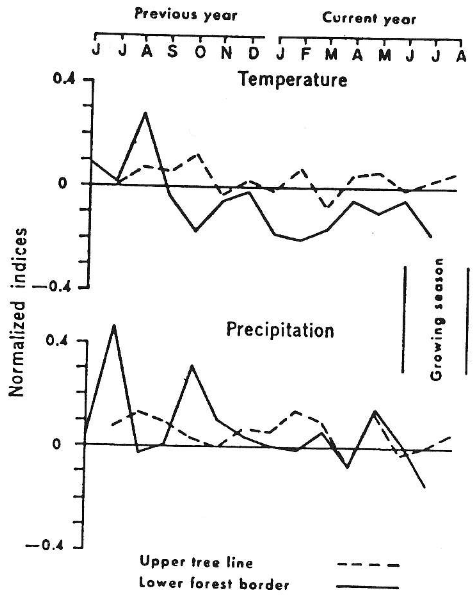


Figure 10.12 Effect of climate on tree-ring width in bristlecone pines (*Pinus longaeva*) of the White Mountains (California) shown by response functions of trees at the upper treeline (dashed line) and lower forest border (solid line). The response functions relate normalized ring-width indices to temperature and precipitation over a 14 month period prior to and including the growing season. The generally positive effect of high temperatures on ring width at the upper treeline contrasts with a predominantly negative effect at the lower forest border. Precipitation is favorable to growth at both sites (after La Marche 1974).

a stepwise multiple regression analysis of ring-width variations. Specifically, monthly and mean temperature and monthly precipitation data from nearby weather stations, for the period from June of the year prior to the growth increment to August of the growth year (30 variables in all), were used to obtain the climate eigenvectors (LaMarche & Stockton 1974). The resulting response functions are shown in Figure 10.12. The width of annual rings in low altitude bristlecone pines is largely dependent on moisture, as shown by the positive effect of precipitation in nearly all months considered, and the negative effect of temperature in most months. High precipitation in the previous summer and autumn and in the current spring favors growth of a wide ring during the short summer growing season. High temperatures lead to depletion of soil moisture and drought stress in the trees, resulting in lower net productivity. By contrast, trees at the upper treeline are less limited by moisture availability and are more directly dependent on monthly temperatures in almost all months (Fig. 10.12). Thus, tree-ring indices from the upper treeline may be interpreted as a record of temperature, whereas tree-ring

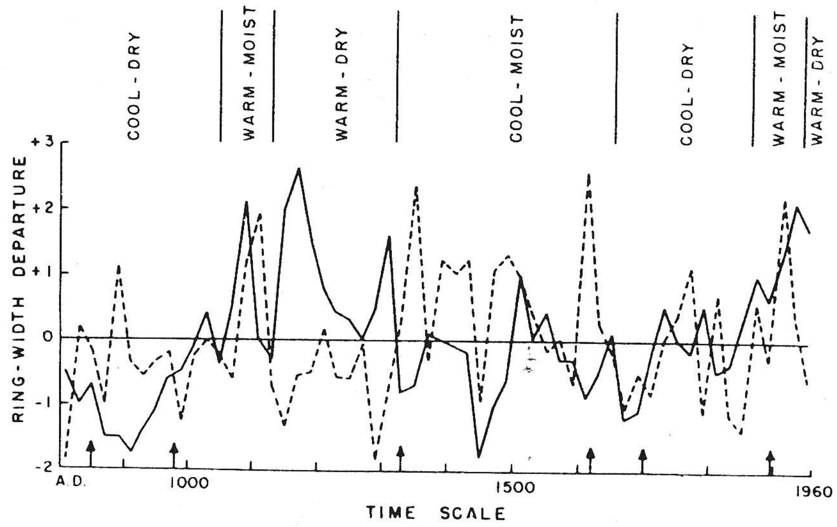


Figure 10.13 Growth of *Pinus longaeva* on lowest forest border (....) and upper treeline (—) sites of the White Mountains, California, and the precipitation and temperature anomalies inferred from the departures in ring width. Data expressed as 20 year averages of standardized normal values. Arrows show dates of glacial moraines in nearby mountains (after LaMarche 1974).

indices from the lower treeline can be considered to be an index of precipitation. Together, then, the ring-width indices enabled combinations of periods of above and below average temperatures as well as above or below average precipitation to be identified (Fig. 10.13). It would appear that conditions similar to those of the last 30–40 years ("warm, dry") were last experienced in the period ~ AD1100–1300, apparently a time of widespread drought (Sec. 10.3.1). This was followed by a period of first "cool, moist," then "cool, dry" climate which collectively spanned a period of ~500 years. In this case, the differing response functions of trees at the upper and lower treelines provided more insight into paleoclimatic conditions than would have been possible using only one set of ring-width data.

In the above examples, ring width was the dependent variable in the multiple regression, with climatic variables (either "raw" or expressed by eigenvectors) used as independent or predictor variables. This may provide a strong mathematical model of ring-width variations but one still has to interpret the early tree-ring record in a qualitative manner. Thus LaMarche (1974) was only able to describe paleoclimates as, for example, "cooler and wetter" but not *how much* cooler or wetter. A more direct calibration of ring-width data is to make climate the dependent

variable with ring-width data the predictors. This is usually accomplished by utilizing a number of different ring-width series from a given area and expressing their variance by eigenvectors. These are then used in a stepwise multiple regression to derive an equation which accounts for most of the variance in the climatic variable selected. For example, Cook and Jacoby (1979) selected series of ring-width indices from six different sites in the Hudson Valley, New York, and calculated eigenvectors of their principal characteristics. These were then used as predictors in a multiple regression analysis with Palmer drought severity indices (Palmer 1965)† as the dependent variable. The resulting equation, based on climatic data for the period 1931–70, was then used to reconstruct Palmer indices back to 1694 when the tree-ring records began (Fig. 10.14). It would appear from this reconstruction that the drought of the early 1960s, which affected the entire north-eastern United States, was the most severe the area has experienced in the last three centuries. Further work in this region may provide independent verification of these estimates, using some of the early instrumental records which go back into the 18th century (e.g. Smith *et al.* 1981).

Calibration of the tree-ring records need not be in terms of a single climatic variable or climatic index. Tree rings containing a climatic signal can also be calibrated against other, climatically related time series, and some remarkable work along these lines has been accomplished. Stockton (1975) was interested in reconstructing long-term variations in runoff from the Colorado River Basin, where runoff records only began in 1896. As runoff, like tree growth, is a function of precipitation, temperature, and evapotranspiration, both during the summer and in the preceding months, it was thought that direct calibration of tree-ring widths in terms of runoff might be possible. Using 17 tree-ring chronologies from throughout the watershed, eigenvectors of ring-width variation were computed. Stepwise multiple regression analysis was then used to relate runoff over the period 1896–1960 to eigenvector amplitudes over the same interval. Optimum prediction was obtained using eigenvectors of ring width in the growth year (t_0) and also in years t_{-2}, t_{-1}, and t_{+1}, each of which contained climatic information related to tree growth in year t_0. In this way an equation accounting for 82% of variance in the dependent data set was obtained; the reconstructed and measured runoff values are thus very similar for the calibration period (Fig. 10.15). The equation was then used to reconstruct runoff back to 1564, using the eigenvector amplitudes of ring widths over this period (Fig. 10.16). The reconstruction indicates that the long-term average runoff for 1564–1961 was ~13

†Palmer indices are measures of the relative intensity of precipitation abundance or deficit and take into account soil-moisture storage and evapotranspiration as well as prior precipitation history. Thus they provide, in one variable, an integrated measure of many complex climatic factors.

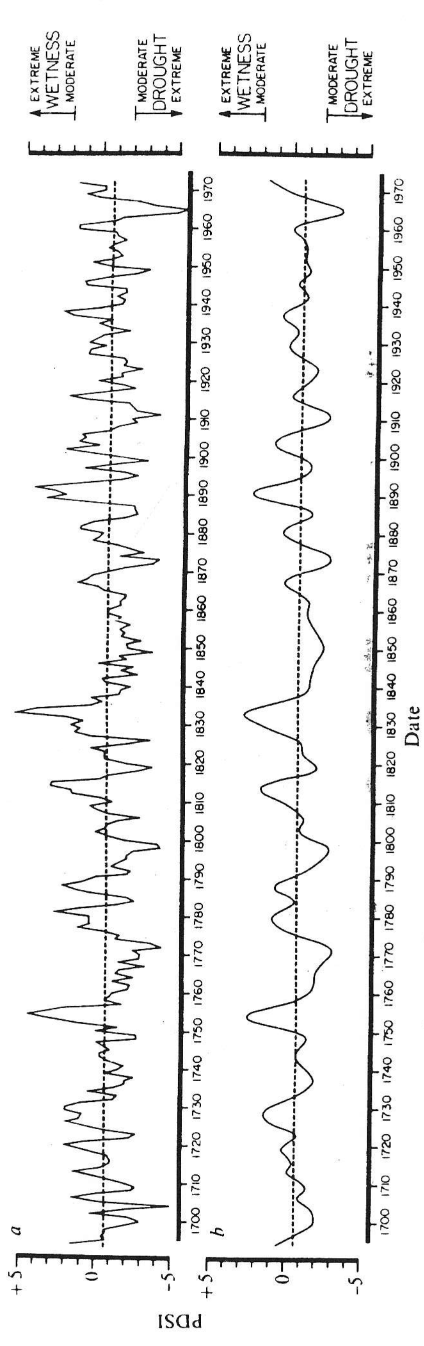


Figure 10.14 July Palmer drought indices for the Hudson Valley, New York, from 1694 to 1972 reconstructed from tree rings. (a) Unsmoothed estimates; (b) a low-pass filtered version of the unsmoothed series that emphasizes periods of ≥10 years (after Cook & Jacoby 1979).

million acre feet (~16 × 10^9 m^3), over 2 million acre feet (2.5 × 10^9 m^3) *less* than during the period of instrumental measurements. Furthermore, it would appear that droughts were more common in this earlier period than during the last century, and the relatively long period of above average runoff from 1905 to 1930 has only one comparable period (1601–21) in the last 400 years. Stockton argues that these estimates, based on a longer time period than the instrumental observations, should be seriously considered in river management plans, particularly in regulating flow through Lake Powell, a large reservoir constructed on the Colorado River. In this case, "dendrohydrological" analysis provided a valuable long-term perspective on the relatively short instrumental record. Similar work has been accomplished by Stockton and Fritts (1973), who used tree-ring eigenvectors calibrated against lake-level data to reconstruct former levels of Lake Athabasca, Alberta, back to 1810 (Fig. 10.17). Their reconstruction indicated that although the long-term average lake level is similar to that recorded over the last 40 years, the long-term variability of lake levels is far greater than could be expected from the short instrumental record. To preserve this pattern of periodic flooding, essential to the ecology of the region, the area is now artificially flooded at intervals which the dendroclimatic analysis suggests have been typical of the last 160 years.

10.3.3 Models derived by principal components and multiple canonical regression analysis (level IV)

The models discussed above involve either calculating the response of a single ring-width index series to a variety of climatic indices (i.e. a response function) or transferring ring-width variations from several sites into estimates of a single climatic or climate-related variable (i.e. a

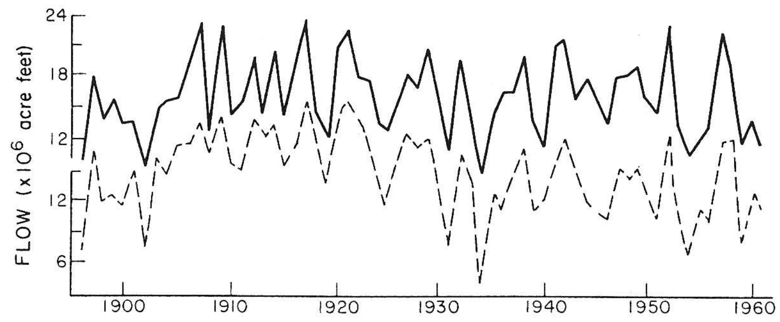


Figure 10.15 Runoff in the Upper Colorado River Basin. Reconstructed values (....) are based on tree-ring width variations in trees on 17 sites in the basin. Actual data, measured at Lee Ferry, Arizona, are shown for comparison (—). Based on this calibration period, an equation relating the two data sets was developed and used to reconstruct the flow of the river back to 1564 (Fig. 10.16) (after Stockton 1975).

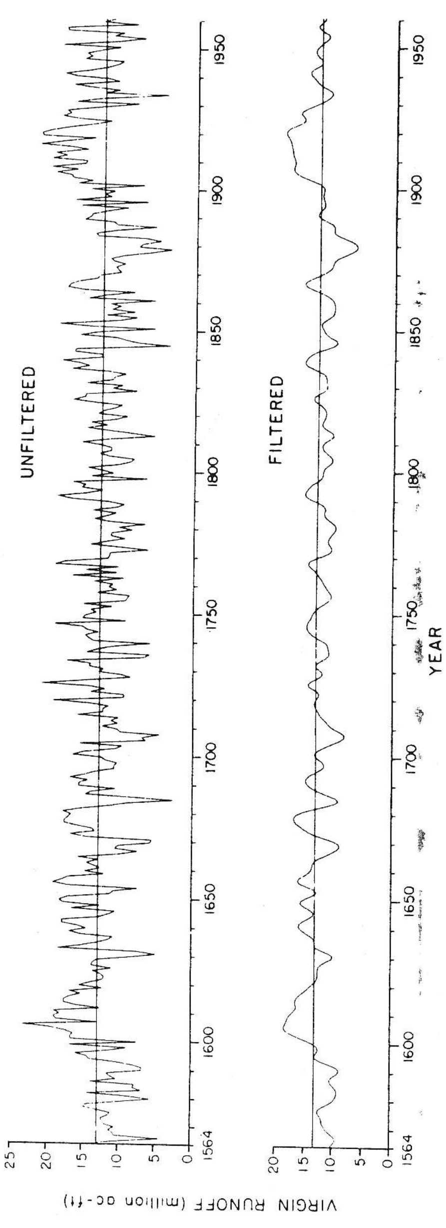


Figure 10.16 Annual virgin runoff of the Colorado River at Lee Ferry, as reconstructed using ring-width index variation, calibrated as shown in Figure 10.15. Growth for each year, and the three following years, was used to estimate river flow statistically. Smooth curve (below) represents essentially a 10 year running mean. Runoff in the period ~1905–25 was exceptional when viewed in the context of the last 400 years (after Stockton 1975).

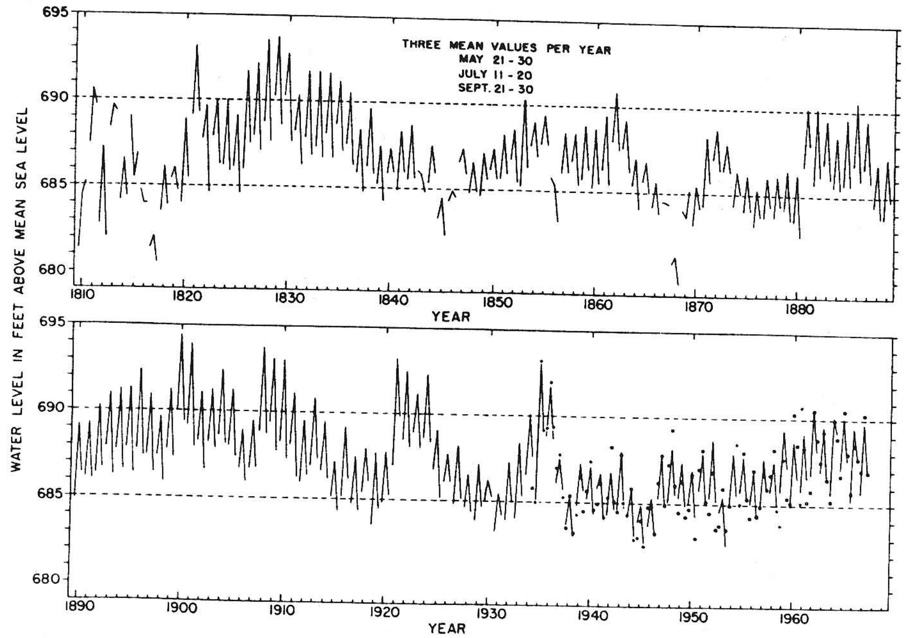
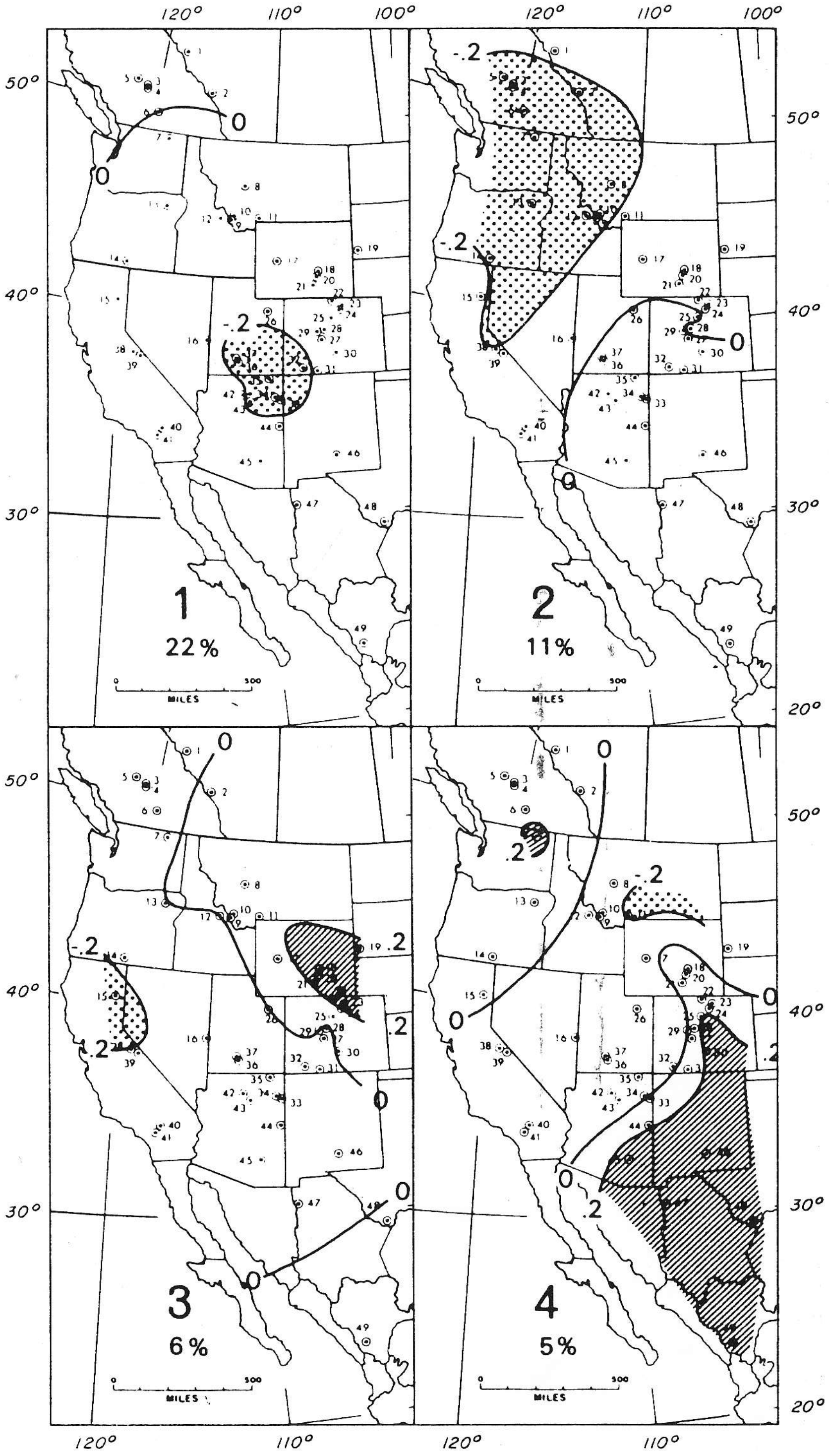
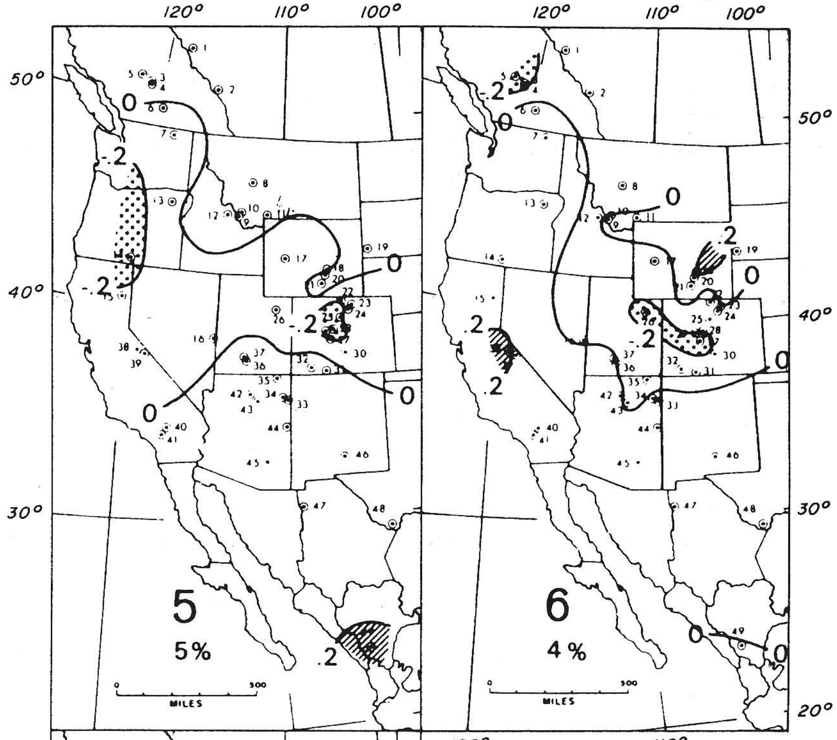


Figure 10.17 Levels of Lake Athabasca, Alberta, Canada, as reconstructed from tree-ring data. Tree rings indicate that prior to 1935 there was greater variability in lake levels during May and July, but there was less variability in lake levels for September than during the recent calibration period. Dots indicate actual lake levels used for calibration. Lines connect the three estimates from tree rings, representing mean lake level for May 21–30, July 11–20, and September 21–30. Points are not connected over the winter season, as calibrations of levels for the frozen lake could not be made (from Stockton & Fritts 1973).

transfer function). At the next level of complexity, a spatial array of tree-ring data is used to reconstruct the spatial distribution of a climatic parameter. This type of analysis has been termed dendroclimatography (Fritts 1976) and was first attempted by Fritts *et al.* (1971) in order to reconstruct variations in sea-level pressure over much of the Northern Hemisphere. Earlier work had shown that, although trees in different parts of western North America responded differently to climate (as indicated by individual response functions), spatial patterns of tree-growth anomaly were quite similar to spatial patterns of precipitation anomaly over the same region and time period (Fig. 10.18; LaMarche & Fritts 1971a). This suggested that anomalous large-scale weather patterns of particular years were associated with tree-growth anomaly patterns for the same years. Large-scale pressure anomaly patterns (as indicators of the anomalous weather patterns) might, therefore, be estimated from corresponding spatial patterns of tree-growth anomaly. To investigate this idea, Fritts *et al.* (1971) used multiple canonical regression analysis to





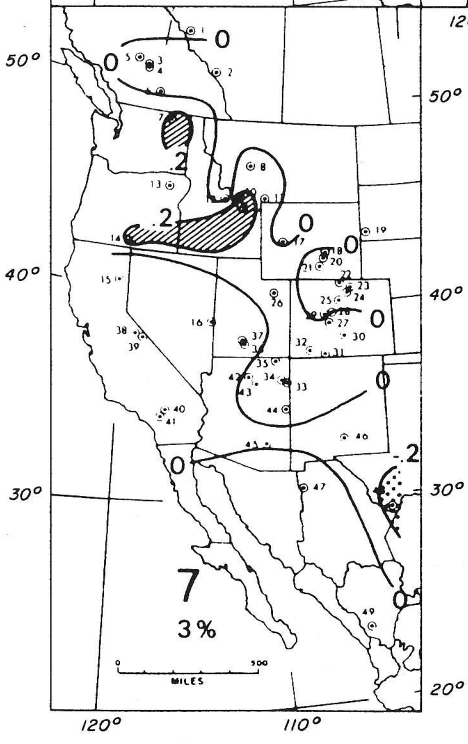


Figure 10.18 Characteristic anomaly patterns of tree growth at a network of 49 sites across the western United States based on the period 1700–1962. Each eigenvector represents a fraction of the variance in the tree-ring data set (shown as a percentage at lower left). Eigenvector 1 accounts for most variance, eigenvector 7 the least. Collectively they account for 56% of variance in the data (after Fritts 1976).

Fig 9.1