DENDROCLIMATOLOGY IN THE

NORTHEASTERN UNITED STATES

by

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# ABSTRACT

Canonical correlations and regressions were calculated between a set of 7 tree-ring width chronologies and a set of 12 temperature or 15 precipitation records from the northeastern United States. The regressions calibrated 38.5% of the winter temperature variance, 26.5% of the winter precipitation variance, and 20.9% of the spring precipitation variance in the dependent period, 1905-1960. The regression equations were then applied to the 275-year record of the 7 tree-ring chronologies to obtain estimates of past temperature and precipitation. Reconstructions were tested for statistical verification with climatic data not used in the regressions, and the series that showed highest verification in each season was selected for further study. The best winter temperature reconstruction passed 50% of the verification tests, the best winter precipitation reconstruction passed 12.5% of the tests, and the best spring precipitation reconstruction passed 26.8% of the tests. The reconstructions of the stations which passed the most verification tests in each season were averaged, and the regional averages were smoothed and plotted. These are presented as a first, tentative approximation of past climate.

# CHAPTER 1

# INTRODUCTION

Climate is a topic of increasing concern and relevance today, as we move from a relatively complacent period of ample rain and warm temperatures to a period of more variability--more floods, more droughts, severe winters (Bryson and Hare 1974). The large number of people on the globe, coupled with our dependence on food from the earth, requires an increased knowledge of climate, of both its effect on us and the range of its variation. This latter need is hampered by the relatively short span of systematic meteorological observing, 100 years or less, including largely the time period of low climate variability. Extension of our knowledge of climate back through time via proxy series enables us to more wisely predict future climatic possibilities, and thus help in planning food and energy resource needs.

Tree rings have already served as a source of proxy data in determining hydrologic and climatologic histories (Stockton 1975; LaMarche 1978). The ability to assign actual calendar dates to each ring of certain tree species' growth allows for studies into the yearly environmental conditions necessary for that growth. By comparing patterns of growth of climatically sensitive trees with patterns of environmental conditions for the same years, a relationship may be derived and applied to past years for which no written records of those environmental conditions exist.

The southwestern United States has long been a center for dendroclimatic studies, in part because of the strongly limiting effect of climate on tree growth in areas of low precipitation and high evaporation and temperature. Extensive multivariate statistical methods have been applied to grids of tree-ring widths from this area and various climatic and hydrologic parameters, providing verifiable records of past climate. Most reconstructions have centered on western North America (e.g., Stockton and Meko 1975), but others have included an area from the North Pacific to the eastern United States (Blasing and Fritts 1976; Fritts, Lofgren and Gordon 1979). Inclusion of available tree-ring data from these outer areas should theoretically improve the reliability of the entire grid of reconstructions.

Eastern North American trees, however, do not demonstrate as strong a link to climate as do trees in the semi-arid west. For instance, intra-site competition for moisture and/or light may at a given time be limiting to growth and may obscure the influence of climate in the growth rings (Cook 1976). Relationships between tree growth and climate in the east have long been sought (see review in Cook 1976), but early failures were discouraging, and tree-ring studies were not pursued. Present-day applications of multivariate statistical techniques to eastern U. S. tree rings has thus been hampered by a lack of tree-ring collections and a lack of interest and/or belief in their success; all now are increasing. Recent studies indicate that a climatic relationship to tree growth in the east may be more readily obtainable with new technical and statistical methods (Cook and Jacoby 1977, Conkey in press). The present study was undertaken to provide some first experimentation with recently developed statistical methods on currently available tree-ring data from the northeast.

The objective of this thesis is to describe a set of canonical correlations and regressions between 7 tree-ring width chronologies and meteorological records of 12 temperature and 15 precipitation stations. Reconstructions of 275 years of past climate for each station are derived by applying the regression equation to the entire ring-width series. The resulting temperature and precipitation estimates are compared with meteorological data withheld from the canonical analysis to provide an independent check of reconstruction reliability. Interpretations of the canonical models and of individual station reconstructions are a crucial part of this preliminary study. It is hoped that such evaluation will aid in the development of working techniques best suited to dendroclimatology in humid areas.

## CHAPTER 2

## DATA

Tree-ring chronologies from seven northeastern United States sites (DeWitt and Ames 1978) were chosen for use in this study (Figure 1). They range from northern Vermont to southeastern New York State, and include one deciduous species, chestnut oak (Quercus prinus L.), and four conifers, red spruce (Picea rubens Sarg.), eastern hemlock (Tsuga canadensis (L.) Carr.), pitch pine (Pinus rigida Mill.), and white pine (Pinus strobus L.), from varying elevations and ecological settings. Chronology length and identification, location and site specifics, and publication information are found in Table 1. Each chronology contains 26 or more tree cores, which were dated and measured according to Laboratory of Tree-Ring Research techniques (Stokes and Smiley 1968; Fritts 1976, p. 246-252). The measured ring widths were standardized, deriving indices which are comparable among cores and among sites, as the individual trends due to growth are removed. This was accomplished by fitting exponential, polynomial, or straight-line curves to each time series and dividing each year's width by the value of the fitted curve (Fritts 1976, p. 254-268). Core indices were then averaged to produce the chronologies used in this study.

Fifteen climatic stations were selected for maximum length, completeness of record, and apparent homogeneity. The stations range from Burlington, Vermont in the north, to Philadelphia to the southwest, and east to Eastport, Maine so that they cover an area large enough to


Figure 1. Location of Tree-ring Sites and Climatic Stations, New England, U.S.A. -- Letters are tree-ring sites and correspond to the rows in Table 1. Numbers are climatic stations and correspond to rows in Table 2. ◉ indicates temperature and precipitation data. ● indicates precipitation data only.

Table 1. Tree-ring Site Characteristics.

| | Site Name and Chronology Identification | Geographical Location and Elevation in Meters | Species, Common Name | Site Description | Length of Chronology | Collectors,[1] References |
|---|---|---|---|---|---|---|
| A. | Camel's Hump, Vermont | 44°19'N<br>72°54'W<br>975-1036 m | *Picea rubens*<br>red spruce | spruce-fir forest with white birch.<br>deep organic duff on thin glacial till. | 1635-1971 | T. Siccama[1] (1974)<br>DeWitt & Ames (1978) |
| B. | Nancy Brook, New Hampshire | 44°6'53"N<br>71°23'24"W<br>872 m | *Picea rubens*<br>red spruce | spruce forest, some balsam fir.<br>15° slope, south-facing.<br>well-drained, shallow soil on thin glacial till over schist. | 1561-1971 | T. Siccama & H. Fritts[1]<br>DeWitt & Ames (1978) |
| C. | Livingston, Massachusetts | 42°38'N<br>72°59'W<br>427 m | *Picea rubens*<br>red spruce | spruce mixed with hardwoods, no new-growth spruce.<br>30°-35° slope, north-facing.<br>deep organic duff on glacial till over schist. | 1697-1971 | T. Siccama & H. Fritts[1]<br>DeWitt & Ames (1978) |
| D. | Shawangunk Mt., New York | 41°44'N<br>74°14' and 16'W<br>335 m, 396 m | *Pinus rigida*<br>pitch pine | open pine stand.<br>little or no slope.<br>soil sparse on rocky site, xeric. | 1622-1973 | E. R. Cook[1] (1976) |
| E. | Shawangunk Mt., New York | 41°46'N<br>74°09'50"W<br>305-396 m | *Pinus strobus*<br>white pine | Both chronologies from same site:<br>pine and hemlock with white and black birch, mountain laurel, blueberry bushes. | 1626-1973 | E. R. Cook[1] (1976) |
| F. | Shawangunk Mt., New York | 41°46'N<br>74°09'50"W<br>305-396 m | *Tsuga canadensis*<br>eastern hemlock | 20°-50° slope, west-southwest facing.<br>soil only at base of trees on loose, impermeable talus. | 1636-1973 | E. R. Cook[1] (1976) |
| G. | Shawangunk Mt., New York | 41°46'15"N<br>74°10'W<br>213-305 m | *Quercus prinus*<br>chestnut oak | oak stand with mountain laurel, huckleberry, blueberry.<br>0°-40° slope, west-facing.<br>dry, steep upper slopes and exposed ridge tops, soil $\leq$ 20" depth. | 1690-1973 | E. R. Cook[1] (1976) |

[1]Collectors are noted by superscript 1.

Table 2. Climatic Data Stations Used, Sources, and Length of Record.

| Station Name, Location | ID | Temperature Source* | Temperature Length | Precipitation Source* | Precipitation Length |
|---|---|---|---|---|---|
| 1. Eastport, ME | 01732426 | UMO | 1874-1975 | WWR | 1887-1960 |
| 2. Burlington, VT | 04321081 | TRL | 1891-1972 | TRL | 1872-1972 |
| 3. Portland, ME | 01736905 | TRL | 1872-1972 | TRL | 1872-1972 |
| 4. Concord, NH | 02721683 | TRL | 1871-1972 | TRL | 1859-1972 |
| 5. Albany, NY | 03050042 | TRL | 1900-1970 | TRL,WWR | 1826-1970 |
| 6. Amherst, MA | 01920120 | RB | 1836-1976 | RB | 1836-1975 |
| 7. Blue Hill, MA | 01920736 | TRL | 1886-1972 | TRL | 1886-1972 |
| 8. Hartford, CT | 00623451 | WB | 1905-1976 | WB | 1905-1976 |
| 9. Mohonk Lake, NY | 03055426 | ERC | 1896-1973 | ERC | 1896-1973 |
| 10. New Haven, CT | 00635266 | WWR | 1796-1960 | WWR | 1873-1960 |
| 11. Block Island, RI | 03710896 | WWR | 1881-1960 | WWR | 1881-1960 |
| 12. NYC Central Park, NY | 03045801 | TRL | 1871-1972 | TRL | 1826-1972 |
| 13. St. Johnsbury, VT | 04317054 | | | WWR | 1894-1960 |
| 14. Hanover, NH | 02723850 | | | WWR | 1867-1960 |
| 15. Philadelphia, PA | 03636878 | | | WWR | 1820-1960 |

*UMO = University of Maine, Orono; WWR = World Weather Records (1927, 1934, 1947, 1959, 1965); TRL = Laboratory of Tree-Ring Research, University of Arizona, Tucson; RB = R. Bradley, University of Massachusetts, Amherst; WB = U.S. Weather Bureau; ERC = E. Cook (1976). All material now on file at the Laboratory of Tree-Ring Research.

encompass the tree-ring sites (Figure 1). Twelve of the stations have records of both temperature and precipitation, the other three have only precipitation. Lengths of the recorded data range from 72 to 165 years. Beginning and ending years and sources are noted in Table 2.

# CHAPTER 3

# METHODS

## Eigenvector Analysis

Multiple time series of tree-ring chronologies or climatic data can be viewed as a matrix in space and time, with columns representing the spatial array of n chronologies or climatic stations, the variables, and the rows representing the observations for y years. Within such groups of similar data, the series are usually highly correlated with one another, and it is sometimes helpful to transform the data into a new set of variables called eigenvectors which are uncorrelated, or orthogonal, to one another. Calculation of the eigenvectors is made from an n x n matrix of correlation coefficients among the n variables. The transformed data still take the form of an n x n matrix, but the columns are now eigenvectors, and the rows are elements or weights of those eigenvectors, giving a relative expression of the importance of each variable (e.g., chronology) to that eigenvector. A subsequent correlation matrix of these new variables would be an identity matrix, containing ones along the diagonal for perfect correlation, and zeros in the off-diagonal elements.

Each eigenvector is associated with a scalar, called an eigenvalue, which is proportional to the percent of the total variance that is explained by that eigenvector. The new variables are arranged so that the first eigenvector represents the highest percentage of the variance, and the second, the next highest, until all of the variance is explained in the n variables. The smaller eigenvectors, especially where intercorrelation among the original variables is quite high, often explain very little of the total variance. These may be omitted in regression studies, to reduce the number of predictors or predictands and thus maintain a maximum number of degrees of freedom.

The n x n eigenvector matrix, ${}_nE_n$, is multiplied by the original data, ${}_nF_y$, to obtain a transformed data set of amplitudes, A (also called principal component scores), as follows:

$$ {}_nE_nF_y = {}_nA_y \tag{3.1} $$

These amplitudes, derived from the eigenvectors, make up the new time series which are now orthogonal to one another, but which together nonetheless represent all of the original variance. In this study, eigenvectors were calculated separately for the tree-ring chronologies and for temperature and precipitation data in different seasons. While this is a useful step for some of the subsequent calculations used here, the eigenvectors themselves can reveal meaningful relationships among the variables.

## Response Functions

Tree growth may be influenced by any of a large number of climatic variables, including temperature averages or precipitation totals for many months before and during the growing season. To determine which of the months and climatic variables are important to tree-ring growth, multiple regression, or a modified form called response function analysis, is used (Fritts 1976, p. 363-370, 377-405). Largely a descriptive tool, response functions aid in determining climate variables later chosen for reconstruction efforts.

In both the original and modified forms of regression, correlations of each of n climatic variables (predictors) with tree growth at one site for y years (the predictand) are calculated, deriving a single predictive equation from those climate variables which show significant partial correlation with growth, by a method called "least squares" (Beyer 1968, p. 39, 45-63). But the climate variables are usually highly correlated with one another, and intercorrelation among them may cause over- or under-representation of a given climatic pattern within the predictive equation derived from the unmodified form of multiple regression. In calculating the response function, data are first transformed into orthogonal eigenvectors, thereby avoiding the problem of intercorrelation. Selection of climatic variables into the predictive equation can therefore depend on each orthogonal variable's relationship to tree growth alone.

Since the smaller eigenvectors (those with small eigenvalues) often represent very little of the total climatic variance, they may safely be excluded before the regression analysis. Use of fewer predictor variables results in both a maximum number of degrees of freedom retained in the final regression and a reduced amount of error. In addition, a stepwise variable selection procedure includes only those variables showing good intercorrelation by checking for large F-ratios (Beyer 1968, p. 23, 304-329) at each step of the regression.

One property of yearly ring widths, especially for mesic eastern United States sites (Cook 1976), is that growth of one year may be highly correlated with conditions for x number of previous years, a relationship described by the statistic of "serial correlation" (Fritts 1976, p. 257). This is calculated as a Pearson's product-moment correlation (Beyer 1968, p. 9), r, between a time series and itself at one (autocorrelation) or more lags. Thus, a predictive equation that includes a measure of growth as a predictor may describe a larger part of the overall growth variance, giving added information about persistence in possible climate-growth relationships. In response functions calculated in this study at each tree-ring site, three years of growth indices prior to each year _t_ of the calibration period were included. Other predictors were a selected set of the amplitudes of the larger eigenvectors of recorded temperature and precipitation for 14 to 16 months previous to and including each growing season of year _t_. The stepwise procedure selected and tested variables one by one as they were entered into regression. Because the three variables of prior growth are intercorrelated, the stepwise selection of predictor variables is necessary.

Response functions were calculated for each of the seven tree-ring sites in this study. The analyses at the four sites on Shawangunk Mountain, New York (Figure 1, chronologies D-G), involved 16 months of temperature and precipitation (May of year _t-1_ through August of year _t_) from the Mohonk Lake climatic station (Figure 1, station 9; Cook 1976). The response functions of the three other sites (Figure 1, chronologies A-C); Appendix A) included 14 months of temperature and precipitation

(June of year t-1 through July of year t) from regionalized averages of climatic stations from the appropriate regions as found in the Decennial Census (U. S. Weather Bureau 1963): northeastern Vermont region for Camel's Hump, northern New Hampshire region for Nancy Brook, and western Massachusetts region for the Livingston chronology.

## Canonical Correlation and Regression

In order to reconstruct past climate from a long series of tree rings, a predictive equation must be developed for the statistical relationship between climate and tree growth for the time period of overlap. There are, in this study, two sets or matrices of data, time series of tree-ring chronologies and climatic stations; therefore, canonical correlation and regression were used (Glahn 1968). The predictive equation for multiple linear regression, used in response functions, can only estimate one single variable from another set of variables. By using canonical correlation and regression, however, it is possible to estimate several variables from another set of variables. The process of canonical analysis is analogous to an eigenvector analysis, except that the orthogonal canonical vectors are extracted not from the correlations within a given set, but rather according to correlations between two different data sets.

A four-part correlation matrix, R, is calculated from the two sets of data, A and B, where $R_{AA}$ is the submatrix containing correlations among the variables of set A, $R_{BB}$ is the same from set B, $R_{AB}$ contains those correlations between the A and B sets of variables, and $R_{BA}$ is that submatrix's transpose. The canonical correlations are derived from these four submatrices by calculating the "latent roots", $\lambda$, as follows:

$$(R_{BB}^{-1} \cdot R_{BA} \cdot R_{AA}^{-1} \cdot R_{AB} - \lambda I) = 0 \quad , \tag{3.2}$$

where I is an identify matrix (Clark 1975). The latent roots, $\lambda$, which are analogous to eigenvalues, are the squares of the canonical correlations. There are as many canonical correlations as there are variables in the smaller of the two sets, A or B.

Canonical variates, or vectors, are derived from the covariation between sets A and B. For every canonical variate in set A, there is a paired variate in set B to which it is correlated. That correlation squared is $\lambda$, and it describes the percent of the variance of the set A variate that is correlated with its paired variate in set B. A variate is otherwise uncorrelated with every other variate in both sets of data. The canonical variates have associated weights ("canonical weights") for each variable in the two data sets, formulating a matrix much like the eigenvector matrix. This canonical variate matrix is multiplied by the original standardized data matrix to produce canonical scores. Like eigenvector amplitudes, the scores make up the new time series which are used in subsequent calculations.

The canonical scores of each variate from the predictor data set are regressed on the scores of the paired variate in the predictand set, in decreasing order of the variate $\lambda$ values. An F-ratio significance test (e.g., Beyer 1968, p. 23, 304-329) is made at each variate step to determine whether the variance due to regression of the new variate pair is greater than that expected by chance. In the version used here, all variate pairs are regressed and tested by the appropriate F-ratio level, and the predictive equation is formulated with the "beta-weights" from all canonicals that precede and include the last significantly passing step. The beta-weights are similar to regression coefficients in a multiple linear regression, but the latter are scaled only to the variance of the predictand; whereas the normalized beta-weights are scaled to the total variance of both data sets, describing the relative relationships among the objects in the two sets. The predictive equation, described by the beta-weights, is then used to reconstruct past climate for each year for which there are tree-ring data.

Canonical correlations can be calculated either with original standardized data or with selected eigenvector amplitudes extracted from the original data. Use of amplitudes would be especially valuable where the number of variables is large and data reduction is needed. In this case, the predictions of past climate are correspondingly made in terms of eigenvector amplitudes; these are then transferred to actual climatic estimates by multiplying the amplitudes back by their associated eigenvectors. In this analysis, both eigenvector and non-eigenvector methods were used, but since higher correlations and percent variances were obtained by calculating the canonicals directly from the original standardized data, the non-eigenvector method and its results are emphasized.

This study includes regression estimates of precipitation totals or temperature averages for groups of months representing winter and spring from combinations of tree-ring indices for years _t_, _t-1_, _t+1_, and

and t+2, where t is the year being reconstructed. This was done because of a lagging characteristic of tree growth: the climate of one year may affect the growth of trees for several years after, as the tree integrates the effects of favorable or poor conditions over more than one growing season, through effects of bud set, cone yield, stored foods, etc. This phenomenon is demonstrated here by relatively high values of serial correlation and by results of the response functions (Appendix A, Fritts 1976). The relationship between tree growth and climate thus is better represented by the inclusion of several years of tree growth for each year of climate.

Regressions were calculated over a 56-year calibration period, 1905-1960, the period of overlap for the records of all climatic stations and the tree-ring chronologies. Temperature and precipitation values were reconstructed for the length of the tree-ring record at all seven sites combined, 1697-1971.

## Verification

Statistical reconstructions of past climate are estimates, based on a percent calibrated variance often much less than 100%. The variance in the predictors and predictands present during the calibration (or dependent) period may be different in amount or frequency from the variance present in the years prior to it. Some statistical models may reconstruct past climate more accurately than others. Thus, a very important part of the calibration and reconstruction procedures is verification of the pre-calibration period estimates with data which were not used in the original calibration. This verification can be accomplished by matching the climatic reconstructions with: 1) independent meteorological observations, either from the same stations used in the original analysis or from others nearby; 2) historical records or individual observations; or 3) other proxy data, such as independent tree-ring chronologies or recent-period pollen profiles.

The reconstructions in this study have primarily been tested with independent meteorological observations. The reconstructed temperature and precipitation values at individual stations are matched with actual instrumented measurements at the same or nearby stations, for the independent time period prior to 1905, and statistics of the association are calculated. Many of the climatic stations in the eastern U. S. have continuous records which are considerably longer than the 56-year calibration period (Table 2), providing a large body of independent meteorological observations for such verification. New Haven, for example, has winter temperature records from 1797 to 1905, or 109 years of independent data.

Five statistical tests which measure the association between the reconstructed and actual series are calculated for those stations with at least five years of independent data. Any given reconstructed series may be expected to pass 5% of the tests by chance alone.

The sign test is the least rigorous of the five tests. A first-differenced series is constructed by subtracting the value of year <u>t-1</u> from the value of year <u>t</u>; thus, it emphasizes the high-frequency component of the climatic series. The sign test of the first-differenced series matches the direction of change, negative or positive, in the reconstructed and actual series from one year to the next, disregarding the magnitude of that change (Fritts 1976, p. 329-331). A sign test is also calculated using the sign of the departures from the mean. It differs from the first-differenced sign test in that it examines the agreement at all frequencies. Those cases which are on the same side of the mean are counted and the numbers compared, and the number of agreements versus the number of oppositions are tested for significance (Beyer 1968, p. 398). This sign test is difficult to pass, because large and small departures from the mean are given equal weight. Thus, even if most of the large departures match between the two series, the test will fail if a number of departures close to the mean fall on the wrong side of the mean.

However, the magnitude of agreement of the large departures can be assessed using the product mean test. The departures from the actual and reconstructed series are multiplied in each year, the means of the negative (opposing) and positive (agreeing) products are calculated, and the difference between the means is tested with Student's t-test (Beyer 1968, p. 24, 282-283) for significance. A significantly higher positive product mean than negative mean thus indicates closer agreement in the larger departures (Fritts 1976, p. 331-332).

The correlation coefficient (Beyer 1968, p. 9, 389-390) is a commonly-used test of coherence integrated over all frequencies, measuring both the number of cases which agree between two series as well as the relative degree of correspondence. It emphasizes the large deviations from the mean relative to the small ones; as such it is a finer test of agreement between the two series than the combined departure sign test and the product mean t-test. However, it does not consider differences in the means of the two samples (Fritts 1976, p. 332).

The final test is the "reduction of error" (R.E.) and is the most rigorous of the tests used here (Fritts 1976, p. 333). It is a measure similar to the correlation coefficient, but it is affected by the difference between the means of the two series as well as the departures from their respective means. Because values of the R.E. are bounded by +1 and $-\infty$, such that absolute values of the negative R.E.'s may be much greater than the positive ones, one very bad yearly estimate may affect the mean R.E. enough to offset several good estimates. Significance levels are difficult to ascertain. Since the theoretical expectation for random numbers is a negative value (J. H. Hunt, personal communication, 1979), any positive R.E. is an encouraging sign of agreement between the two series.

In this study, nine calibration models that exhibited the highest percent variance calibrated were tested for verification.

## Error Analysis

Each tree-ring chronology in this study is an average of standardized ring widths from 2 samples, or increment cores, per tree from 13 to 23 trees at each site. But only a small number of these cores extend as far back as the 1600's, and the maximum number of cores is not attained until after 1850. Change in sample number through time will influence the strength of the climatic signal in the chronologies, such that a higher error will be introduced into the climatic reconstructions during periods of fewer samples.

An approximation of the error due to small sample size can be calculated as the standard error of the mean,

$$\varepsilon_x = \frac{k}{\sqrt{n}} \quad , \tag{3.3}$$

where the constant, k, is the standard deviation of the individual core indices for a particular year. The equation assumes that each core represents a single individual in the population. This may be averaged over m chronologies:

$$\varepsilon_{x_i} = \frac{\sum_{i=1}^{m} \frac{k}{\sqrt{n_i}}}{m} \quad . \tag{3.4}$$

This type of chronology error is propagated throughout the calculation of the calibrations and reconstructions (Bevington 1969, p. 56-65). Here we assume that the derived coefficients of the regression equation are themselves without error.

The regression equation is of the form:

$$y = f(x) \quad , \tag{3.5}$$

where the independent variable, x, may be composed of several years of tree-ring data (see p. 15, this thesis). For instance, a model incorporating three years of tree-ring indices, from years <u>t-1</u> (designated as B), <u>t</u> (I), and <u>t+1</u> (F), has an x composed of B + I + F for each year of climate, y. Thus Equation 3.5 can be expanded to:

$$y = \alpha + \sum_{i=1}^{m} (\beta_{B_i} B_i + \beta_{I_i} I_i + \beta_{F_i} F_i) \quad , \tag{3.6}$$

where $\beta$ is the beta-weight, or regression coefficient, associated with each chronology, i, for a given climatic relationship (see p. 15, this thesis). Because the variables in this case are normalized, the scalar, $\alpha$, is zero.

The error of y is proportional to the error in the B, I, and F independent variables, and its square is calculated by summing the squared products of the errors in each variable times the effect that variable has on the final value of y (the partial derivatives):

$$\varepsilon_y^2 = \sum_{i=1}^{m} \left( \varepsilon_{B_i}^2 \left(\frac{\partial y}{\partial B_i}\right)^2 + \varepsilon_{I_i}^2 \left(\frac{\partial y}{\partial I_i}\right)^2 + \varepsilon_{F_i}^2 \left(\frac{\partial y}{\partial F_i}\right)^2 \right) \tag{3.7}$$

(Bevington 1969, p. 57). The difference in n among the B, I, and F variables of each chronology for a given year is insigificant, so that the errors on those variables may all be expressed as $\varepsilon_{x_i}^2$. Setting k equal to 1 in Equation 3.4 facilitates the derivation of a relative chronology error that is inversely proportional to $\sqrt{n}$. Thus, the square of each chronology's error, $\varepsilon_{x_i}^2$, is $\frac{1}{n_i}$. The partial derivative of y with respect to each of the variables in Equation 3.6 is calculated to be the constant, $\beta_{B_i}$, $\beta_{I_i}$, and $\beta_{F_i}$. Equation 3.7 then simplifies to:

$$\varepsilon_y = \sqrt{\sum_{i=1}^{m} \left( \frac{1}{n_i} (\beta_{B_i}^2 + \beta_{I_i}^2 + \beta_{F_i}^2) \right)} \quad . \tag{3.8}$$

Equation 3.8 may be used to derive an estimate of the error due to sample size within a given climatic reconstruction. This error may be calculated for selected years throughout the record as sample size increases, to examine the relative change in error through time. Such a technique is used in this study to explore anomalous peaks and troughs in the early years of a climatic reconstruction, where sample numbers are low, and climatic signal correspondingly weakened.

CHAPTER 4

# RESULTS

## Preparation for Canonical Analysis

### Eigenvector Analysis of the Tree-ring Data

Eigenvectors were extracted from the seven by seven correlation matrix of the seven tree-ring chronologies. The weights of the first three most important eigenvectors are plotted in Figure 2. Possible climatic and ecological relationships among the chronologies may be traced by examining the size and sign of the weights of these eigenvectors.

The first and most important eigenvector, accounting for 30.3% of the variance, has weights which are all of the same sign, signifying, perhaps, that all seven chronologies do vary together. However, the three conifer chronologies in New York State (Table 1, D, E, and F) have the highest weights, indicating that they resemble one another more often than they do the other chronologies. If one also considers the latitudes of the sites, the size of the weights of all seven chronologies form a gradient, from site A, Camel's Hump in northern Vermont, which has the lowest weight and is farthest north, to the four New York State sites which have the highest weights and are the farthest south. Such a pattern may indicate that, in addition to the proximity of the New York chronologies, climatic differences encountered in latitudinal changes

Figure 2. First Three Eigenvectors of Tree Growth. -- Eigenvectors are extracted from the correlation matrix of seven tree-ring chronologies from the northeastern United States. The three eigenvectors together represent 65.5% of the total variance of the chronologies.

A = Camel's Hump spruce
B = Nancy Brook spruce
C = Livingston spruce
D = New York pitch pine
E = New York white pine
F = New York hemlock
G = New York oak

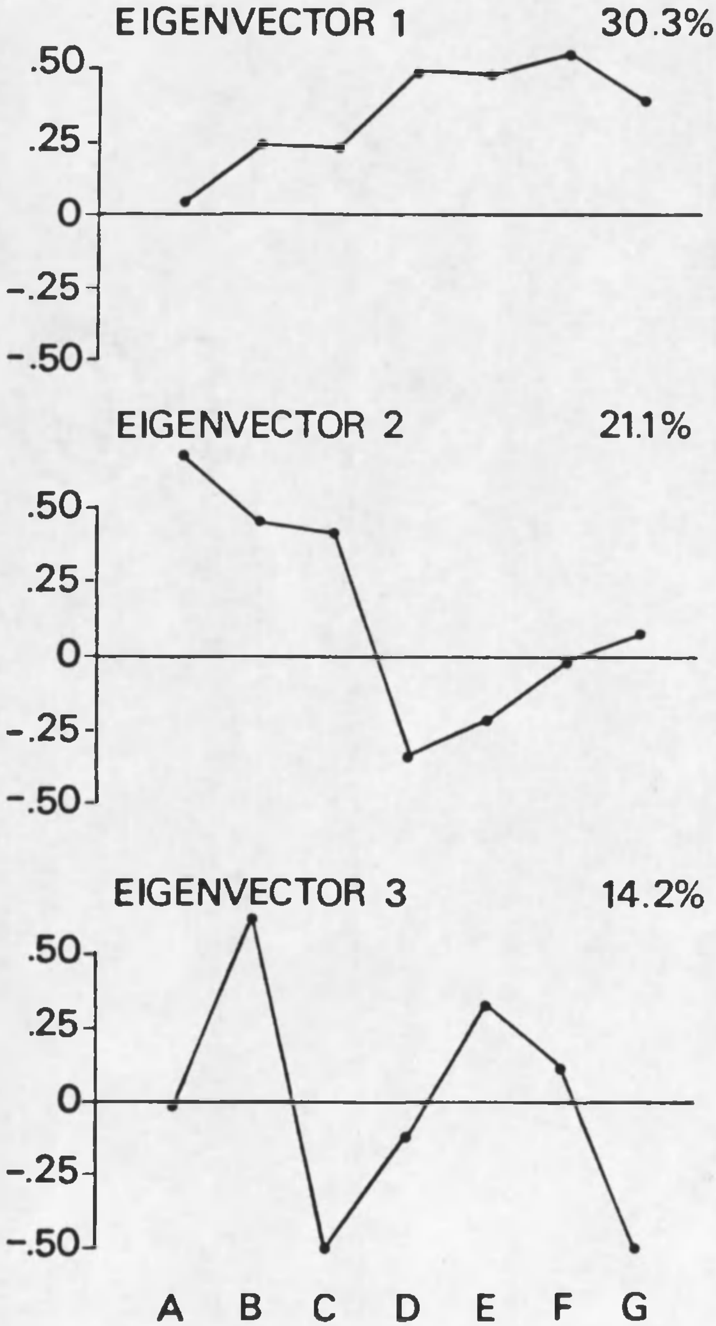


Figure 2. First Three Eigenvectors of Tree Growth.

are also reflected by this major mode of covariance among the chronologies.

The second eigenvector describes 21.1% of the total variance. The three red spruce chronologies in the north, Camel's Hump (Table 1, A), Nancy Brook (B), and Livingston (C), have positive weights, in contrast to the negative weights for the pine chronologies in New York State (D,E). This suggests that the second most important mode of variation among these seven chronologies is ecological and climatological, differentiating between the climatic responses of the two most highly represented species, spruce and pine. The hemlock (F) and oak (G) chronologies in New York State have weights near zero, indicating that this eigenvector is of little importance to their variance.

The third eigenvector reduces an additional 14.2% of the variance. High positive versus high negative values of the weights differentiate between chronologies of like species (Nancy Brook and Livingston, both spruce) and also between chronologies from the same area (New York State white pine and oak). This suggests that this third eigenvector is related to some sort of difference within species or within climatically similar areas. Any "climatic" information here may be of a more local nature, indicating how the same species may respond differently at different sites in the case of the two spruce chronologies, or how different microclimates allow pine or oak to grow in the same area. Camel's Hump and the New York State pitch pine and hemlock have weights near zero and thus are of little importance in this eigenvector.

Eigenvectors 4 through 7 reduce smaller amounts of the total variance and, with the increasing effect of the constraint of orthogonality, the structure of their weights has less physical meaning. The first three eigenvectors, however, do appear to express different kinds of relationships among the seven chronologies, and they account for 65.5% of the tree-growth variance. These first three eigenvectors were used as predictors in those canonical correlations calculated with eigenvector amplitudes.

## Determining Climatic Seasonality

Ring widths integrate climatic conditions on a seasonal, and not necessarily a monthly, basis. The response functions of the seven tree-ring chronologies (Appendix A, Cook 1976) indicate those months in which the trees respond directly or inversely to climate (temperature or precipitation). A change from a positive growth response to climate of one month to a negative response in the next month represents a shift in the growth relationship to climate for the tree, a change in the tree's requirements from, and response to, the environment.

Positive (+) and negative (-) responses, significant at the 95% level, were tabulated over the seven chronologies' response functions for each month (Table 3). The combined responses of the chronologies to monthly temperature and precipitation were therefore designated as primarily positive, primarily negative, or zero (equal or no response). Groups of consecutive months to which the trees responded mainly positively or negatively were postulated to represent climatic seasons for this group of sites and these species. Thus, the responses to

Table 3. Significant Response Function Results.[1]

| Sites | J | J | A | S | O | N | D | J | F | M | A | M | J | J |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | Months of Temperature | | | | | | | | |
| A. Camel's Hump | – | – | – | – | | + | | + | | | | + | – | + |
| B. Nancy Brook | – | – | | | | + | | | | | | | | + |
| C. Livingston | – | – | | | | + | + | | | | | | | |
| D. NY pitch pine | | + | + | + | | – | | | | | | – | | |
| E. NY white pine | | | | + | – | – | | | | | | – | – | |
| F. NY hemlock | – | | | | | | | + | | + | | – | | |
| G. NY oak | | + | | + | | | | | | | – | – | – | – |
| # positive/ # negative | 0/4 | 2/3 | 1/1 | 3/1 | 0/1 | 3/2 | 1/0 | 2/0 | 0 | 1/0 | 0/1 | 1/4 | 0/3 | 2/1 |
| | | | | | | Months of Precipitation | | | | | | | | |
| A. Camel's Hump | – | + | | | | | | | | | | | | |
| B. Nancy Brook | – | + | | + | – | | + | – | | | | | | + |
| C. Livingston | | | + | | + | | | | | – | | | | – |
| D. NY pitch pine | | | | | | | + | + | | | | | + | + |
| E. NY white pine | | | + | | + | + | | | | – | | + | + | |
| F. NY hemlock | + | + | + | + | | | + | | | | | + | + | + |
| G. NY oak | | + | + | + | | | | – | | | | + | + | + |
| # positive/ # negative | 1/2 | 4/0 | 4/0 | 3/0 | 2/1 | 1/0 | 3/0 | 1/2 | 0 | 0/2 | 0 | 3/0 | 4/0 | 4/1 |

[1]Positive (+) and negative (–) correlations, significant at the 95% level, between tree growth and climate variables.

temperature were primarily positive in the winter months of November, December, January, and March (no significant response in February), suggesting a winter season from November through March. The responses to April, May, and June shift to largely negative, suggesting that these three months constitute a spring season. Precipitation responses indicate a break in sign of response between December and January, splitting up the November to March winter, but the choice of a spring season of April through June (with or without July) is supported.

Instrumented climatic data were also examined to see if such tree-growth "seasons" were reflected in any shifts in actual regional climatic regimes. Comparison of monthly mean precipitation of the 15 climatic stations (Table 2) shows very little change in mean from one month to the next, and their large standard deviations overlap greatly, indicating no significant difference among the monthly means over the 15-station grid. Monthly temperature means and standard deviations show the opposite extreme, with relatively small standard deviations about the 12-station means and little overlap of means from one month to the next. Thus, actual data, especially for precipitation, do not immediately suggest seasonal breaks in these climatic statistics.

Two eigenvector analyses were made of the monthly data from all the climatic stations, one analysis with precipitation and the other with temperature. Variables were for correlations among the 12 months of the year, January to December, in both cases. It was theorized that the major mode of variance, the first eigenvector in each case, might indicate months which varied together, with all negative or positive eigenvector weights for several consecutive months suggesting a climatic season. The first eigenvector of temperature (Figure 3A), which reduced 23% of the total temperature variance, has all positive weights except for August. The January and December weights are near zero, perhaps indicating a statistical end effect of the problem design. Temperature thus seems to be remarkably coherent over the 12-station grid, except for August, and for October with its near-zero weight; variations from month to month are relatively consistent. The first eigenvector of precipitation (Figure 3B), which reduced 17% of the total precipitation variance, is more varied. The most marked changes in sign occur between the weights of March and April, between June and July, and August and October versus September. This suggests a frequent change in the precipitation patterns from month to month except for April through June, and October and November.

The response function-based choice of April, May, and June as spring is thus supported by climatic data. Climatic data neither support nor contradict the chosen winter of November through March. The most practical compromise appeared to be climatic seasons of November through March, and April through June. Some other seasons and groups of months for winter and spring were considered and results examined, but none of these exhibited as promising calibration results as the above seasons.

## Canonical Analysis

Combinations of tree-ring chronologies were used as predictors of different climatic variables in canonical correlation and regression.

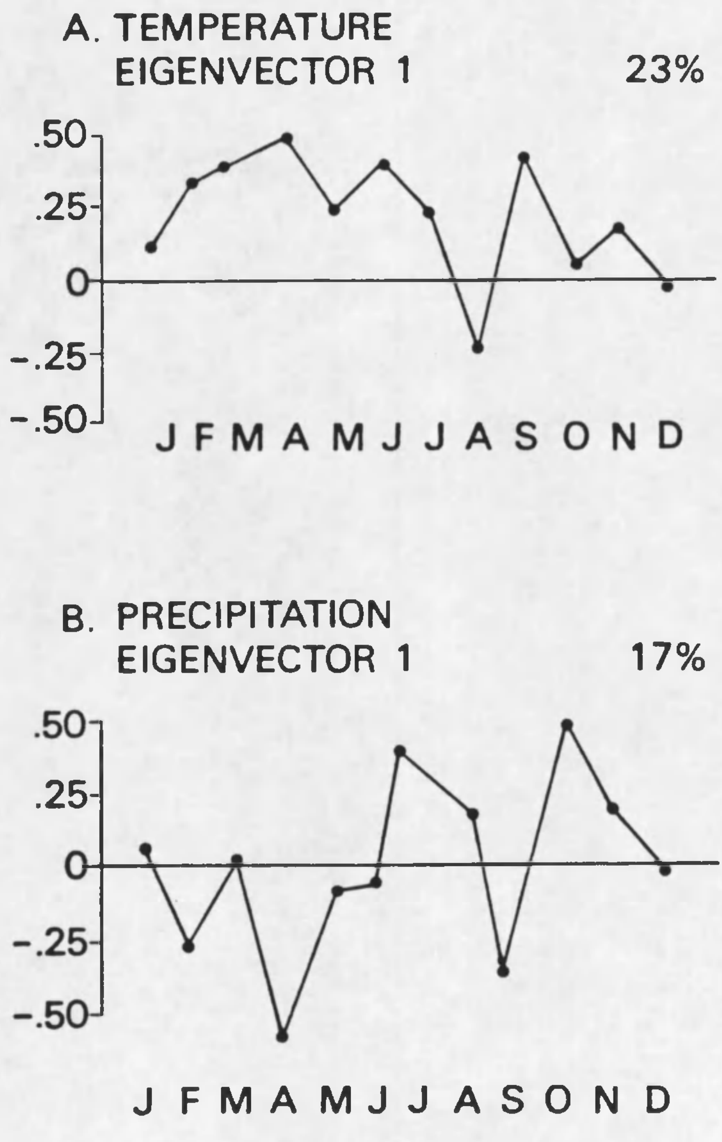


Figure 3. Weights of the First Eigenvector Each of Actual Monthly Temperature (A) and Precipitation (B). -- The variables in each analysis are the 12 months of the year, from January through December. Letters identifying eigenvector weights (J - D) correspond to the first letter of each month.

The predictors were tree-growth indices for years t-1 (designated hereafter as B), t (I), t+1 (F), and t+2 (FF), which were used in varying combinations to predict climate for each year t. Predictands were temperature averages or precipitation totals for different seasons. Two types of analysis were made: 1) tree-ring indices were used as predictors of temperature or precipitation; and 2) eigenvectors of the tree-ring indices and climatic data sets were extracted, and their amplitudes were used as predictors and predictands. The reconstructed amplitudes of climate were then translated back into "real world" variables of temperature or precipitation by multiplying the amplitudes by the associated eigenvector. Table 4 lists, by season and climatic variable, the 47 calibrations that were obtained. Analyses were conducted using the "winter" and "spring" seasons of temperature and precipitation as predictands, and I, I+F, B+I, B+I+F, and B+I+F+FF combinations of tree growth as predictors.

Fourteen of those models listed in Table 4 calibrated more than 15% of the variance by entering canonical variates with significant F-ratios. Table 5 lists these 14 models in order of high to low percent of predictand variance calibrated for each climatic variable and season.

Twice as many models were calibrated with eigenvector amplitudes of predictors and predictands than with the original tree-ring and climatic data (Table 4), and yet the models using original data calibrated much more of the total variance than their comparable amplitude models. Only three of the 14 models appearing in Table 5 were calculated with

Table 4. Results of Canonical Regressions.

| Regression Model Name[1] | Months In Season[2] | Variable | Model # In Tables 5 & 6 | Last Significantly Passing Canonical Step | % Variance Calibrated At That Step | F-level (All Significant At 95% Level) | Maximum % Variance Regardless Of Significance |
|---|---|---|---|---|---|---|---|
| Ie | DJF | T | | 2 | 13.3 | 2.78 | 13.5 |
| IFe | DJF | T | | 1 | 9.7 | 2.47 | 19.3 |
| IFe | NDJFM | T | | 1 | 1.9 | 2.56 | 19.5 |
| BIe | DJF | T | | 1 | 1.7 | 2.33 | 18.2 |
| BIFe | DJF | T | | none | | | 23.5 |
| BIFe | NDJFM | T | | 1 | 7.7 | 2.06 | 27.4 |
| BIFe[3] | NDJFM | T | 4 | 2 | 26.6 | 4.79 | 27.4 |
| BIFe[4] | DJF | T | | none | | | 38.1 |
| BIF-FFe | DJF | T | | none | | | 25.9 |
| I | NDJFM | T | 5 | 5 | 21.2 | 2.26 | 21.6 |
| IF | NDJFM | T | 3 | 7 | 29.1 | 1.71 | 29.9 |
| BI | NDJFM | T | 2 | 6 | 36.5 | 1.78 | 38.4 |
| BIF | NDJFM | T | 1 | 6 | 38.5 | 1.95 | 46.7 |
| Ie | DJF | R | | 1 | 4.7 | 4.17 | 5.7 |
| IFe | DJF | R | | 1 | 4.9 | 2.60 | 9.8 |
| BIe | DJF | R | | 1 | 7.7 | 2.18 | 14.9 |
| BIe | NDJFM | R | | 1 | 6.5 | 3.15 | 13.5 |
| BIFe | DJF | R | | none | | | 18.0 |
| BIFe | NDJFM | R | | 2 | 14.2 | 1.91 | 18.8 |
| BIFe[4] | NDJFM | R | | none | | | 34.2 |
| BIF-FFe | DJF | R | | none | | | 26.4 |
| I | NDJFM | R | | 3 | 8.0 | 2.33 | 9.9 |
| IF | NDJFM | R | 7 | 5 | 20.4 | 2.13 | 25.2 |
| BI | NDJFM | R | 8 | 4 | 16.4 | 2.79 | 22.1 |
| BIF | NDJFM | R | 6 | 6 | 26.5 | 1.84 | 34.9 |
| Ie | MAMJ | T | | none | | | 5.9 |
| IFe | MAMJ | T | | none | | | 7.2 |
| BIe | MAMJ | T | | none | | | 16.0 |
| BIe | AMJ | T | | none | | | 12.2 |
| BIe | AMJJ | T | | none | | | 15.9 |
| BIFe | MAMJ | T | | none | | | 18.5 |
| BIF-FFe | MAMJ | T | | none | | | 19.3 |
| I | AMJJ | T | | 2 | 6.1 | 2.92 | 9.5 |
| IF | AMJJ | T | | 2 | 12.8 | 4.28 | 22.9 |
| BI | AMJJ | T | | 1 | 9.4 | 3.80 | 22.3 |
| BIF | AMJJ | T | 9 | 3 | 15.5 | 1.65 | 33.5 |

Table 4, Continued.

| Regression Model Name[1] | Months In Season[2] | Variable | Model # In Tables 5 & 6 | Last Significantly Passing Canonical Step | % Variance Calibrated At That Step | F-level (All Significant At 95% Level) | Maximum % Variance Regardless Of Significance |
|---|---|---|---|---|---|---|---|
| Ie | MAMJ | R | | 1 | 2.3 | 3.36 | 3.9 |
| IFe | MAMJ | R | | 1 | 8.8 | 3.44 | 11.9 |
| BIe | MAMJ | R | | 1 | 8.2 | 3.14 | 11.5 |
| BIFe | MAMJ | R | | 2 | 14.9 | 2.34 | 19.5 |
| BIFe | AMJJA | R | | none | | | 16.8 |
| BIFe | AMJ | R | 13 | 2 | 17.8 | 1.97 | 20.9 |
| BIF-FFe | MAMJ | R | 14 | 2 | 17.8 | 1.93 | 23.5 |
| | | | | | | | |
| I | AMJ | R | | 4 | 12.2 | 2.53 | 13.2 |
| IF | AMJ | R | 12 | 6 | 18.9 | 2.60 | 22.7 |
| BI | AMJ | R | 10 | 4 | 20.9 | 3.86 | 28.7 |
| BIF | AMJ | R | 11 | 3 | 19.7 | 2.39 | 37.9 |

[1]Model names (B, I, F, FF) are described in text; in addition, those followed by an "e" were derived with selected eigenvector amplitudes of the original data sets, whereas those with no suffix were calculated with the original, untreated data sets.

[2]Months in seasons are designated by the first letter of each month, listed consecutively.

[3]This eigenvector model contained an experimental weighting scheme for F-ratio values at each canonical step. Based, in part, on its success in this study, the procedure was adopted for use in later studies (Blasing, Lofgren, and Carter 1978).

[4]Eigenvector amplitude models wherein seven or all tree-ring eigenvector amplitudes were used against a selected set of eigenvector amplitudes of temperature or precipitation.

Table 5. Summary of Canonical Analysis Results.[1]

| Model Number | Model Name | Climatic Variable | Months in Season | Percent Variance Calibrated | F-ratio for All Included Canonicals |
|---|---|---|---|---|---|
| 1 | BIF | T | NDJFM | 38.5 | 1.95 |
| 2 | BI | | | 36.5 | 1.78 |
| 3 | IF | | | 29.1 | 1.71 |
| 4 | BIFe[2] | | | 26.6 | 4.79 |
| 5 | I | | | 21.2 | 2.26 |
| | | | | average = 30.4 | |
| 6 | BIF | R | NDJFM | 26.5 | 1.84 |
| 7 | IF | | | 20.4 | 2.13 |
| 8 | BI | | | 16.4 | 2.79 |
| | | | | average = 21.1 | |
| 9 | BIF | T | AMJJ | 15.5 | 1.65 |
| 10 | BI | R | AMJ | 20.9 | 3.86 |
| 11 | BIF | | | 19.7 | 2.39 |
| 12 | IF | | | 18.9 | 2.60 |
| 13 | BIFe | | | 17.8 | 1.97 |
| 14 | BIF-FFe | | MAMJ | 17.8 | 1.93 |
| | | | | average = 19.0 | |

[1]Includes only those analyses with a percent variance calibrated ≥ 15.0%. Model name, climatic variable, and months in season abbreviations are as in Table 4.

[2]Eigenvector model incorporating experimental weighting scheme for F-ratios (Blasing et al. 1978).

Table 6. Verification Results by Model.

| A | B | C | D | E | F | G | H | I | J | K | L | M |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | % Verification Tests Passed | | | | | | % Climate Stations Passing One or More Tests |
| Model Number | Model Name | Variable | Months in Season | % Variance Calibrated | # Climate Stations Tested | Total | 1st Diff. Sign Test | Departure Sign Test | Product Mean t-test | Correlation | % RE >0 | |
| 1 | BIF | T | NDJFM | 38.5 | 10 | 50.0 | 80 | 10 | 60 | 50 | 30 | 90 |
| 2 | BI | | | 36.5 | | 40.0 | 50 | 10 | 50 | 50 | 0 | 90 |
| 3 | IF | | | 29.1 | | 22.5 | 60 | 0 | 0 | 30 | 20 | 70 |
| 6 | BIF | R | NDJFM | 26.5 | 14 | 12.5 | 7 | 7 | 21 | 14 | 14 | 21 |
| 7 | IF | | | 20.4 | | 10.7 | 7 | 7 | 14 | 14 | 21 | 29 |
| 8 | BI | | | 16.4 | | 10.7 | 7 | 7 | 21 | 7 | 21 | 21 |
| 10 | BI | R | AMJ | 20.9 | 14 | 3.6 | 14 | 0 | 0 | 0 | 7 | 14 |
| 11 | BIF | | | 19.7 | | 7.1 | 7 | 0 | 21 | 0 | 14 | 29 |
| 12 | IF | | | 18.9 | | 26.8 | 43 | 7 | 36 | 21 | 14 | 57 |
| | | | | | AVERAGE % BY TEST: | | 27 | 5 | 24 | 18 | 16 | |

[1]Model number and name, climatic variable, and months in season abbreviations are as in Tables 4 and 5.

eigenvector amplitudes ("e"), and none of them had the highest percent variances calibrated for that season.

The BIF model for winter temperature, model 1, calibrated the most variance, at 38.5%. Model 2 calibrated 36.5%, model 3 calibrated 29.1%, model 4 calibrated 26.6%, and model 5 calibrated 21.2% of the variance. Model 4 is an eigenvector model which incorporated an experimental weighting scheme for the F-ratio values (Blasing et al. 1978). One winter precipitation model, model 6 (BIF), calibrated 26.5% of the variance. The others calibrated 20.4% and 16.4% of the variance. Individual spring temperature and precipitation models did not calibrate as much of the variance as winter models, with model 10 (BI) for precipitation having the highest calibrated variance at 20.9%. All other spring models calibrated less than 20%.

The highest average value of calibrated variance was for winter temperature models (Table 5, 1 to 5), at 30.4%, followed by winter precipitation models (6 to 8) at an average of 21.1%. Spring models of precipitation (10 to 14) averaged 19.0%, higher than the one model of spring temperature (model 9) at 15.5%.

All of the winter temperature and precipitation models in Table 5 (1 to 8) include climatic data from five months, November through March; none of the models using a shorter winter season of December through February calibrated as much as 15% of the variance (Table 4). Spring precipitation models (10 to 14), however, calibrated more variance with a shorter season of April through June than with the longer combinations of April through July, March through June, or April through August (Table 4).

Tables 4 and 5 also indicate that the "larger" tree-growth models, those involving two or three years of tree-ring indices (BIF, BI, or IF), calibrated more variance than the I model alone. This is not a surprising result, for each of the tree-ring chronologies used here has high serial correlation, indicating that the trees integrate the effects of climate into several years' growth.

## Verification

### Model Evaluation

Verification tests were calculated for the three reconstructions which reduced the highest amount of calibrated variance for winter temperature and for winter and spring precipitation. Other models appeared to have too little variance calibrated to attempt verification. Data from the independent period, prior to the years of data used in the calibration, from 10 of the temperature stations or 14 of the precipitation stations were compared with each model's reconstructed climate at those stations. Albany temperature and Hartford temperature and precipitation records were of inadequate length (<5 years) for meaningful analysis.

Model 1, the BIF winter temperature model that calibrated the highest variance, verified very well, passing 50% of the verification tests (Table 6, column G), and model 2, BI, was next with 40% of the tests passed. These percentages are, respectively, 12% and 2% higher than verification of the best winter temperature reconstruction obtained by H. C. Fritts and others (personal communication, 1979), using tree-ring chronologies from western North America and climate for the entire

United States. Model 12, a spring rainfall IF, passed 26.8% of the verification tests, a percentage that is 15% higher than Fritts' best spring rainfall model verification. Other verification percentages fall below Fritts' results for comparable seasons. These verifications (Table 6) range from model 3 of winter temperature, which passed 22.5% of the tests, to model 10 of spring rainfall, passing only 3.6% of the tests, the only percentage in Table 6 that is below the 5% expected by chance.

Columns H to K of Table 6 show the above percentages broken down by test. Average values over all 9 models indicate that the first difference sign test passed most frequently, at 27%, followed by the product mean t-test (24%), the correlation (18%), and the departure sign test (5%). All except the departure sign test are substantially above that expected by chance alone.

The first difference sign test (column H) was passed consistently by those models (1, 2, 3, and 12) which had high verification overall. That is, the models which verified well did so, at least, at the high-frequency range of their variance. Although the departure sign test (column I) passed few times, the product mean t-test (column J) passed much more frequently, indicating that the agreements in sign between departures were greatest when the departures from the mean were large. The small departures from the mean approximate average conditions, regardless of sign, but the significantly passing product mean t-test indicates that the larger reconstructed departures are essentially correct.

Like the departure sign test, the product mean t-test and the correlation (column K) measure coherence at all frequencies. The correlation, in particular, takes the magnitude of that coherence into account. Both tests were frequently passed by most of the models with highest verification (1, 2, and 12), an encouraging indication that the low as well as high frequencies were correct in these models. Model 3 passed none of the departure sign tests or product mean t-tests; this model apparently did well primarily in the high-frequency domain, but failed to consistently match the large departures from the mean.

Column L in Table 6 includes the percentage of cases in which the reduction of error (R.E.) is positive. These are not included in the total percentage of verification tests passed (column G) because the significance level is not known (J. H. Hunt, personal communication, 1979). Because of the similarity of the derivation of the correlation coefficient and of the more rigorous R.E. (Fritts 1976, p. 332-333), it is reasonable that those stations with a positive R.E. might also have significant correlations. Exceptions occur where the number of years tested is small and degrees of freedom are too few for a significant correlation, but where there is enough coherence in the mean for a positive R.E. Five of the six precipitation models do show percentages of positive R.E. values either equal to or greater than percentages of significant correlations. Winter temperature models, however, show a drop from the number of significant correlations to the number of positive R.E.'s; even though correlations are good, the mean is not always matched, perhaps because of climate- and/or urban growth-caused trends in the temperature data.

Column M (Table 6) notes the percentages of stations passing at least one of the four tests of verification (columns H to K). The winter temperature models verify the highest percentages of stations; 70% to 90% of those tested pass at least one test. Precipitation models have lower percentages of stations passing; they are perhaps less consistent over the larger grid than the temperature models.

The 9 models chosen for verification were those calibrating the highest percent variances in each season. These were thought to be most likely to verify best, as they explained the most variance. However, this relationship did not always hold up: models 1 and 2 did display the highest calibrated variances and the highest verifications, but model 12 calibrated only 18.9% of the variance and passed 26.8% of the tests, whereas model 10 calibrated 20.9% of the variance and passed only 3.6% of the verification tests. Winter precipitation model 6 calibrated an encouraging 26.5% of the variance, but passed only 12.5% of the tests. H. C. Fritts and his co-workers have also found this apparent inconsistency in their analysis of models originally selected for high percent calibrated variances (personal communication, 1979). Often, those with lower calibrated variances verify better, providing a more accurate picture of past climate. Thus, some of the models which calibrated low percentages of variance might well have passed verification tests.

## Station Evaluation

The verification results from Table 6 are also broken down by individual climatic stations (Table 7). The climatic stations are ranked according to the number of tests they passed in each of the three

Table 7. Verification of Individual Climatic Stations for Three Models Per Season.

| | Station | % Tests | # Years |
|---|---|---|---|
| Winter Temperature | Amherst | 67 | 69 |
| | New Haven | | 109 |
| | New York City | 58 | 34 |
| | Concord | 50 | 34 |
| | Blue Hill | 42 | 19 |
| | Eastport | 25 | 31 |
| | Burlington | | 14 |
| | Portland | | 33 |
| | Block Island | 17 | 24 |
| | Mohonk Lake | 0 | 9 |
| | AVERAGE: | 38% | |
| Winter Precipitation | Mohonk Lake | 67 | 9 |
| | Blue Hill | 25 | 19 |
| | St. Johnsbury | 17 | 11 |
| | Philadelphia | | 85 |
| | Portland | 8 | 33 |
| | Amherst | | 69 |
| | New Haven | | 32 |
| | New York City | | 79 |
| | Eastport | 0 | 18 |
| | Burlington | | 33 |
| | Concord | | 46 |
| | Albany | | 79 |
| | Block Island | | 24 |
| | Hanover | | 88 |
| | AVERAGE: | 11% | |
| Spring Precipitation | Amherst | 42 | 69 |
| | St. Johnsbury | 25 | 11 |
| | Hanover | | 38 |
| | Concord | 17 | 46 |
| | Albany | | 79 |
| | New York City | | 79 |
| | Eastport | 8 | 18 |
| | Burlington | | 33 |
| | Blue Hill | | 19 |
| | Philadelphia | | 85 |
| | Portland | 0 | 33 |
| | Mohonk Lake | | 9 |
| | New Haven | | 32 |
| | Block Island | | 24 |
| | AVERAGE: | 13% | |

climatic variable groups. Results from three models are included in each seasonal group: models 1, 2, and 3 of winter temperature; models 6, 7, and 8 of winter precipitation; and models 10, 11, and 12 of spring precipitation. The number of years available at each station for such independent testing is also indicated.

Of the three groups, the winter temperature models passed the most tests, at an average of 38%, and at the most number of stations, 9 out of the 10 tested. Amherst and New Haven passed the most tests, at 67%. These two stations also have the most number of years for verification testing, and it is encouraging that the reconstructed series maintained a close resemblance to the actual series over long periods of time. New York City passed the next highest percentage of tests, at 58%, followed by Concord (50%), Blue Hill (42%), Eastport, Burlington, and Portland (25%), and Block Island (17%). Mohonk Lake passed no tests in its short (9 years) independent period.

Winter precipitation models did least well, averaging 11% of the tests passed. As opposed to the winter temperature results, Mohonk Lake passed the most tests, at 67%, again with 9 years of independent data. The other stations passed many fewer tests, with Blue Hill passing 25%; St. Johnsbury and Philadelphia 17%; and Portland, Amherst, New Haven, and New York City passing only 8%. The remaining 6 stations passed no tests.

Spring precipitation models averaged slightly more passing verification tests than winter precipitation, at 13%, and all except 4 stations passed at least 1 test. As with winter temperature, Amherst again passed the highest percentage of tests, 42%; followed by St. Johnsbury and Hanover at 25%; Concord, Albany, and New York City passing 17%; and Eastport, Burlington, Blue Hill, and Philadelphia at 8%. The 4 remaining stations passed no tests.

Comparisons can be made of the stations' results within and among each of the three groups (Table 7). The percentage of tests passed and rank of each station can be compared from group to group, creating at least three possible patterns: 1) a station may be similarly ranked in all three groups, 2) there may be a distinction in its rank between temperature models and precipitation models, and 3) it may be ranked differently in each one of the three groups.

Those stations which are ranked similarly among the three groups include Eastport, Burlington, and Portland, which are on the lower end of the ranked stations in every model group. Block Island was even less successful in all three groups of models. Because these stations showed similar inability to accurately reconstruct any of the climatic variables or seasons, reasons for failure to verify may be related to the stations' placement relative to the tree-ring sites. All four stations lie outside the area of greatest concentration of tree-ring sites. In addition, three of the four are on the Atlantic Coast, perhaps reflecting more maritime conditions than those to which the trees respond.

The second ranking pattern occurred where a station verified noticeably better with one climatic variable than with the other. New Haven, New York City, and Concord all verified the temperature reconstructions very well, ranging from 50 to 67% tests passed. But averages of the verification percentages of the two seasons of precipitation show that New York City passed 12.5% of the tests, Concord 8.5%, and New Haven only 4%. These stations are close to the area of tree-ring site concentration, and their success in verifying temperature is encouraging enough to include them in future temperature analyses. But in some way the precipitation data at these three stations did not successfully reflect the moisture conditions to which the trees respond, perhaps because of inhomogeneities in the precipitation records.

The third pattern occurred where a station was ranked differently among the three climatic variables and seasons, especially when there was a marked contrast between the two seasons of precipitation. Blue Hill, for example, passed 42% of the winter temperature tests, ranked well with 25% of the winter precipitation tests, but dropped to 8% of the spring precipitation tests. Amherst did very well in winter temperature and spring rainfall, but poorly in winter precipitation; and Mohonk Lake passed no tests in winter temperature or spring rainfall, but passed 67% of the tests in winter precipitation. Some of the stations with only precipitation data also showed a contrast between the two seasons: Albany passed none of the winter tests, but passed 17% of the spring tests; and Hanover passed no winter tests, but 25% of the spring tests. Because the relationship is not consistent between the seasons of precipitation data, the station data themselves may not be at fault. If a station did well with any of the tree variables, the placement of the station in relation to the tree-ring sites would not be suspect. Perhaps, then, the differences in verification ability arise from the modeling of the tree-growth/climate relationship. There may be changes in the relationship of the tree growth to the climatic station from season to season that were not adequately calibrated by the grid of tree-ring sites or the modeling procedures used. In some cases, the results may also be influenced by the fact that temperature is spatially more coherent than precipitation and may therefore be easier to reconstruct. The lack of individual station verification, especially for precipitation records for which calibrations and verifications were low, may not necessarily implicate bad station data. On the other hand, an effort to improve calibrations and verifications should include close analysis of the climatic data to assure homogeneity and applicability.

## Additional Verification

Climatic data from stations not included in the calibrations may also be used for independent verification of reconstructions. Diaz (1978) recently compiled long (1854-1977), continuous records of temperature and precipitation at Cooperstown, N.Y. These records are used here to test the reconstruction of winter temperature (model 1) at Albany, a station 100 km to the east, and the reconstructions of winter temperature (model 1) and winter precipitation (model 6) at Mohonk Lake, a station 130 km to the southeast. Simple sign tests (Fritts 1976, p. 329) and correlations were calculated between the reconstructed series and the Cooperstown record. Test results (Table 8) are presented for years equivalent to the pre-calibration and calibration periods.

Because correlations were significant (at the 99% level) between the Cooperstown data and actual observations from Albany (temperature,

Table 8. Additional Verification of Winter Reconstructions Using Climatic Data Not Included in the Calibrations.

| | | SIGN TEST[1] | | | CORRELATION | |
|---|---|---|---|---|---|---|
| | | 1856-1905 | 1906-1960 | 1856-1970 | 1855-1905 | 1906-1960 |
| COOPERSTOWN TEMPERATURE | ALBANY reconstructions (model 1) | 17/50[2] | 19/55[2] | 38/115[3] | .42[3] | .44[3] |
| | actual T | | | | | .80[3] |
| | MOHONK LAKE reconstructions (model 1) | 18/50 | 20/55 | 43/115[3] | .37[3] | .48[3] |
| | actual T | | | | | .89[3] |
| COOPERSTOWN PRECIPITATION | MOHONK LAKE reconstructions (model 6) | 25/50 | 18/55[2] | 51/115 | -.14 | .23[2] |
| | actual R | | | | | .46[3] |

[1]The number of non-agreeing cases over the total cases compared.
[2]Significant at the 95% level.
[3]Significant at the 99% level.

r = .80) and Mohonk Lake (temperature, r = .89; precipitation, r = .46), and because the Albany record includes only 5 years and the Mohonk Lake record only 9 years of independent data, the Cooperstown series appeared to be a likely source of verification data for the climatic reconstructions at these stations. Correlations between the Albany temperature reconstruction and Cooperstown actual data were .44 for the calibration period and .42 for the pre-calibration period, both significant at the 99% level. Sign tests for each period passed at the 95% level, and at the 99% level over the total record (Table 8). The Mohonk Lake temperature reconstruction also correlated significantly (99% level) with the Cooperstown record, at .48 during the calibration period and .37 in the pre-calibration period. The sign test failed by one value to reach the 95% level of significance in the pre-calibration and calibration periods, but passed at the 99% level over the total record (Table 8). Cooperstown-Mohonk Lake precipitation verification tests were less successful. A calibration period correlation of .23 was significant at the 95% level, but much lower than temperature correlations, and the pre-calibration period correlation of -.14, negative and close to zero, indicated no relationship. The sign test passed at the 95% level during the calibration period, but failed in the pre-calibration period and over the total record (Table 8).

These preliminary tests of verification indicate a good relationship between Cooperstown actual records and reconstructions of winter temperature at both Albany and Mohonk Lake. This supports the climate as it is reconstructed by tree growth and suggests that the Cooperstown temperature record could be used for calibration in future analyses. The precipitation results are less strong, reflecting perhaps the lower ability of most of the winter precipitation reconstructions to verify (Table 6). Because precipitation is not as spatially coherent as temperature, the Cooperstown record may be less able to simulate precipitation at Mohonk Lake. Thus, lower verification is not surprising. However, the Mohonk Lake reconstructions verified well with the nine years of Mohonk Lake actual data (Table 7), and with Cooperstown from 1906 to 1960. The reconstruction thus does not maintain a close relationship to actual conditions prior to the calibration period, a situation which is not apparent without testing with a longer independent record, such as Cooperstown.

## Reconstructions

In each season, the model passing the highest percentage of verification tests was chosen for further study: model 1 of winter temperature, model 6 of winter precipitation, and model 12 of spring precipitation (Table 6). The 42 individual station reconstructions from these models were plotted and examined along with actual climatic data from each station for comparison. Inspection of these plots reveals some characteristics of the reconstructions that are not seen in the verification statistics. These characteristics possibly indicate inaccuracies in the original climatic or tree-ring data used in calibration, such that the final reconstructions may not consistently reproduce actual conditions. The winter temperature reconstruction of New Haven is presented here as an example of a problem which is largely due to the climatic data, and the winter precipitation reconstruction of Portland is discussed as an example of a tree-ring related problem. Finally, plots of reconstructions averaged over several stations for each season are presented as a first approximation of past climate in the northeast.

New Haven Winter Temperature

Actual and reconstructed winter temperature values at New Haven are plotted as departures from the calibration (1906-1960) mean for the years 1797 to 1970 (Figure 4). Year-to-year agreement on extremes and average values between the two series is good and is reflected in the high-frequency verification test results (Tables 6 and 7). However, there is a rising trend in the actual series (Figure 4, A) between the nineteenth and twentieth centuries that is not reconstructed (Figure 4, B). Thus, the independent period of the New Haven record is, on the average, cooler than either the reconstructed series during the same time period or the same meteorological record for the twentieth century. Less pronounced trends in actual climatic series other than New Haven are often apparent when the record extends back to the 1880's or earlier, such as at Eastport, Amherst, Blue Hill, Cooperstown, and New York City. But the difference between the actual and reconstructed means appears greatest at New Haven, and is perhaps best seen there because of the great length of the independent record.

There are at least three possible explanations for trends in the climatic record: 1) changes in observational circumstances such as changes in exposure, elevation, or location of the thermometers, changes in types of instruments, or changes in observation time or calculation

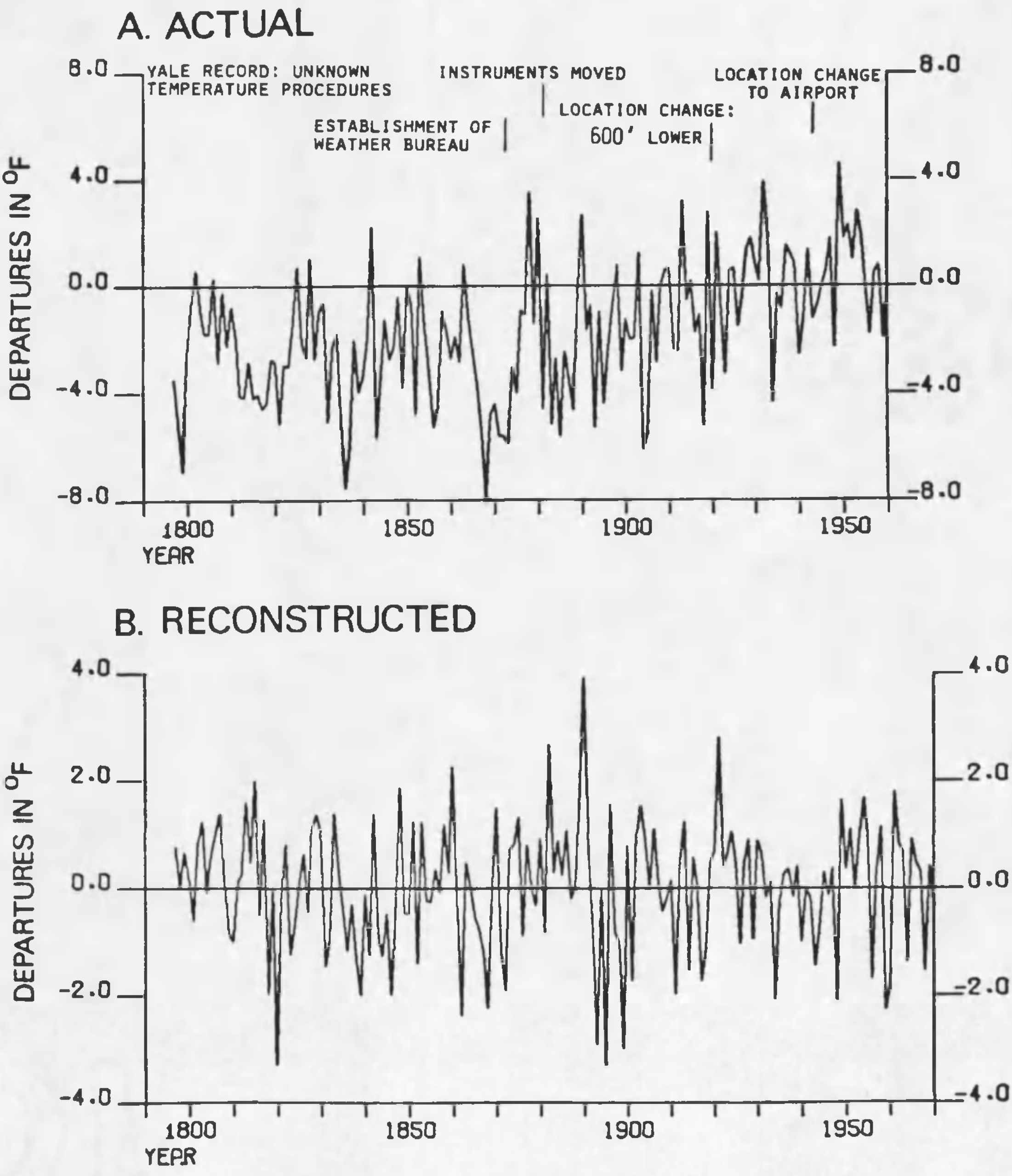


Figure 4. New Haven, Connecticut, Actual (A) and Reconstructed (B) Winter Temperature. -- Values are in degree Fahrenheit departures from the 1906-1960 mean of 34.8$^{\circ}$F. Reconstructions are from model 1. Recorded are location and instrumentation changes of the observed record as noted in station histories (U. S. Weather Bureau 1958).

of the daily values; 2) local environmental changes in the vicinity of the thermometers caused by changes in vegetative cover, by growth of cities with buildings and road paving, affecting wind currents and surface albedo, or by the addition of atmospheric pollutants, affecting solar radiation levels; and/or 3) actual change in macroclimatic conditions.

Since the start of the Weather Bureau administration of climatic records in the late 1800's, the "major" changes of instrumentation and station location have been recorded. Such changes made at New Haven are noted on Figure 4 (U. S. Weather Bureau 1958). But, according to Mitchell (1953), "minor" changes of instrumentation can also produce artificial shifts in temperature means. The history of such changes is unknown, but Mitchell (1953) estimates that deviations of up to ±2$^{\circ}$F may occur. In addition, any major or minor observational changes which occurred during the 76 years prior to Weather Bureau administration at New Haven are undocumented, and their effects on the data are unknown.

Human-induced local environmental changes associated with city growth produce the phenomenon of "urban heat islands" (Massachusetts Institute of Technology [M.I.T.] 1971). City build-up causes a gradual decrease in nocturnal radiation loss, thereby raising the minimum temperatures and with them, the mean daily temperatures. Chagnon (1976) estimates that winter temperatures are as much as 4$^{\circ}$F warmer in cities than in rural areas. In a study of the New Haven record, Mitchell (1953) demonstrated that winter temperatures were, on the average, 1$^{\circ}$F lower at the outlying airport weather station than at the discontinued downtown station. Such a large difference may be calibrated into the record as the change of station location is made. But the amount of gradual increase in temperatures at the downtown station prior to the move, as New Haven grew, remains undocumented.

Global warming from the mid-1800's until the early 1940's is proposed and discussed by Willett (1950) and Mitchell (1961), and such a change at New Haven itself is discussed by Landsberg (1949). The proposed warming is particularly pronounced in winter (Conover 1951, 1967; Landsberg 1967). Two of the station records which show a rising temperature trend that is less extreme than at New Haven, Amherst (R. Bradley, personal communication, 1977), and Blue Hill (Mitchell 1953, Putnins 1956, Conover 1967) have been carefully maintained or calibrated to minimize observational and/or local environmental effects. Thus, it is likely that winters have become more mild since the mid-1800's, but that other factors of observational techniques and local environmental changes have exaggerated the change in mean winter temperatures at New Haven (Mitchell 1953), thereby exaggerating the difference between the observed and reconstructed means at that station.

Even if the climatic records could be corrected for non-climatic trends, it still appears that the upward temperature trend is not well-matched by the reconstructions. This may be due to the reconstructions being of smaller amplitude, generally, than the actual data, because of the difference in the two series' variances. But, more importantly, failure of the tree-ring reconstructions to adequately match long-term trends may be due to a characteristic of the standardized tree-ring series themselves.

The seven tree-ring chronologies in this study were standardized (Fritts 1976, p. 254-268; Chapter 2, this thesis) by fitting a polynomial curve to each ring-width series in order to accommodate the widely varying periods of slow or fast growth common to mesic-area ring-width series. The polynomial curve fitting could have removed long-term climatic trends. A test of this hypothesis was made by fitting straight lines instead of polynomial curves to the ring widths from two sites, Camel's Hump and Nancy Brook. The resulting chronologies did have higher serial correlation than the polynomial chronologies and, overall, more trend was observed. But during the time period in question, there was no obvious visible trend in the straight-line chronologies that differed from the polynomial chronologies. Thus, in this case, the standardization procedure offers no immediately obvious explanation for deviation of reconstructed from actual temperatures. It is therefore likely that the observed difference in mean is largely due to the inaccuracies in the climatic data at New Haven.

### Portland Winter Precipitation

The complete reconstruction of winter precipitation at Portland is plotted in Figure 5A. Two noticeable peaks occur in 1754-55 and 1781-82. Less pronounced peaks at these times are seen in some other reconstructions, such as in winter precipitation of Hanover and Albany, in winter temperature of Hartford and Albany, and in spring precipitation of Hartford, Portland, Amherst, Blue Hill, Concord, Hanover, and Albany. Because the high values occur in both seasons and both climatic variables, and because available historical accounts of New England winters

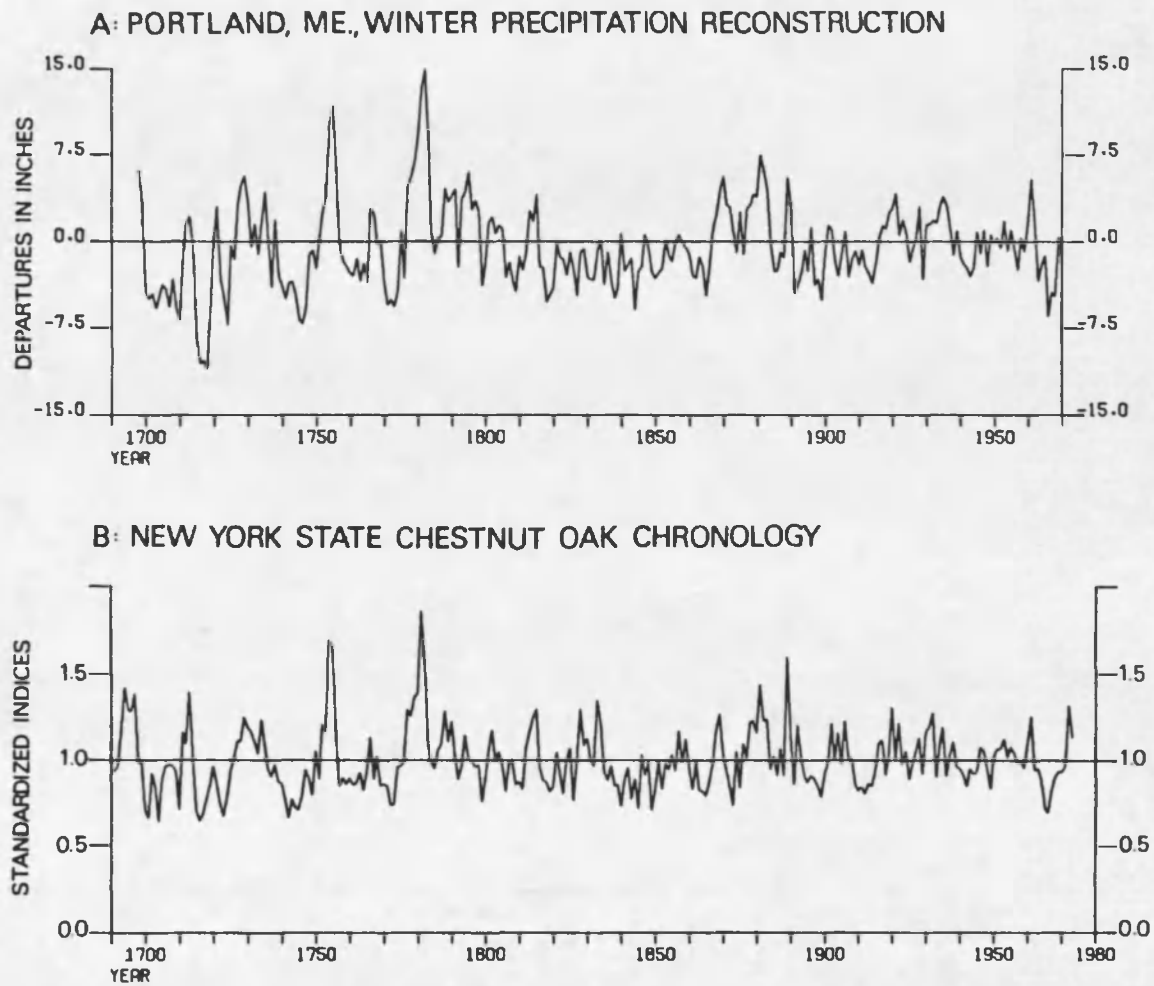


Figure 5. Portland, Maine Winter Precipitation Reconstructions (A) and Shawangunk Mountain, New York, Chestnut Oak Chronology (B). -- Precipitation is in inch departures from the 1906-1960 mean, 19.1 in. Chronology is in standardized indices.

give no support for great warmth or high precipitation in these years (Ludlum 1966), a non-climatic cause is sought. The effort is concentrated on the Portland reconstruction (Figure 5A) because its peaks are proportionately higher than in any other reconstruction.

Figure 5B is a plot of the standardized indices of the New York State chestnut oak chronology. This series, too, shows peaks in 1754-55 and 1781-82 and, overall, greatly resembles the Portland reconstruction (Figure 5A). During the calibration period of 1906-1960, the partial correlation between the oak chronology and actual winter precipitation at Portland is higher than any other climate-tree growth correlation in that season. The reason for the high, positive correlation is not clear, as Portland and the New York State oak site are far from one another (350 km) and are in contrasting environments of the coast and inland mountains. Beta-weights (or regression coefficients, see p. 15, this thesis) for the Portland reconstruction, derived in part from that high correlation, are also largest for the oak chronology (Table 9). Thus, the reconstruction of Portland winter precipitation is highly dependent on the shape of the oak chronology.

The oak chronology displays greater variance in the early part of the series relative to later years, and the two peaks, early in the record, are thus much higher than later extremes in the series. This decrease in variance through time may be due, in part, to the gradual increase in sample size as cores from younger trees are added to the chronology. Table 10 shows the core numbers from all 7 chronologies for years in which significant increases occur. The total number of cores

Table 9. Portland, Maine, Winter Precipitation Beta-weights.[1]

| SITES | Beta-Weights β | | |
| --- | --- | --- | --- |
| | B | I | F |
| A Camel's Hump | -.1311 | .0099 | -.1313 |
| B Nancy Brook | -.1690 | .0281 | -.0164 |
| C Livingston | .1299 | .0020 | -.0308 |
| D NY pitch pine | .0181 | .1886 | -.1096 |
| E NY white pine | .2508 | -.1496 | -.0176 |
| F NY hemlock | -.1485 | -.3033 | .1454 |
| G NY oak | .2545 | .4246 | -.0129 |

[1]Beta-weights (regression coefficients) for reconstruction of winter precipitation at Portland, Maine using BIF model 6.

Table 10. Core Numbers Per Chronology for Selected Years of the Tree-ring Record.

| CHRONOLOGY \ YEAR | 1700 | 1720 | 1750 | 1780 | 1800 | 1820 | 1850 | 1900 | 1960 |
|---|---|---|---|---|---|---|---|---|---|
| Camel's Hump | 6 | 8 | 9 | 13 | 18 | 27 | 33 | 36 | 36 |
| Nancy Brook | 7 | 10 | 13 | 20 | 23 | 28 | 28 | 28 | 28 |
| Livingston | 1 | 3 | 6 | 14 | 17 | 20 | 24 | 26 | 24 |
| NY pitch pine | 7 | 7 | 15 | 19 | 22 | 29 | 32 | 32 | 32 |
| NY white pine | 12 | 14 | 19 | 23 | 25 | 25 | 32 | 32 | 32 |
| NY hemlock | 12 | 15 | 20 | 23 | 25 | 25 | 30 | 30 | 30 |
| NY oak | 2 | 3 | 7 | 16 | 26 | 30 | 40 | 46 | 46 |
| TOTALS | 47 | 60 | 89 | 128 | 156 | 184 | 219 | 230 | 228 |

in all chronologies (bottom row) shows a five-fold difference between 1700 and 1900, and the oak chronology has 23 times as many cores in 1900 as in 1700.

Chronology error due to sample size can be calculated from Equation 3.4 (p. 20). The error in all 7 chronologies is plotted through time in Figure 6 (solid line) and is compared to the error of the oak chronology alone (dashed line). The difference in error of all 7 chronologies in 1700 is 2.8 times that of 1900; for the oak chronology alone, this difference is 4.7 times.

This type of chronology error is propagated throughout the calculation of the calibrations and reconstructions, according to Equation 3.8 (p. 21). Figure 7 is a plot of the estimated error due to sample size in all 7 chronologies (solid line), translated into the reconstruction of winter precipitation at Portland, based on the beta-weights in Table 9. The reconstruction error in 1700 is thus 3.2 times the error in 1900.

The error in the oak chronology, we have seen, is relatively high in the early part of the record, and the link between the chronology and the Portland reconstruction is strong. To approximate the contribution of this chronology's high error to the error of the reconstructed series, the propagated error of the Portland reconstruction was recalculated (Equation 3.8) without the beta-weights associated with the oak chronology (Figure 7, dashed line). The error in the reconstruction in 1700, without the oak, would drop to 2.2 times the error in 1900, indicating that the oak chronology accounts for approximately 40% of the error in the early years of the Portland reconstruction.

Figure 6. Relative Chronology Error Due to Sample Size, Plotted as a Function of Time. -- Values are derived from Equation 3.4. The solid line represents seven chronologies. The dashed line represents New York State oak chronology.

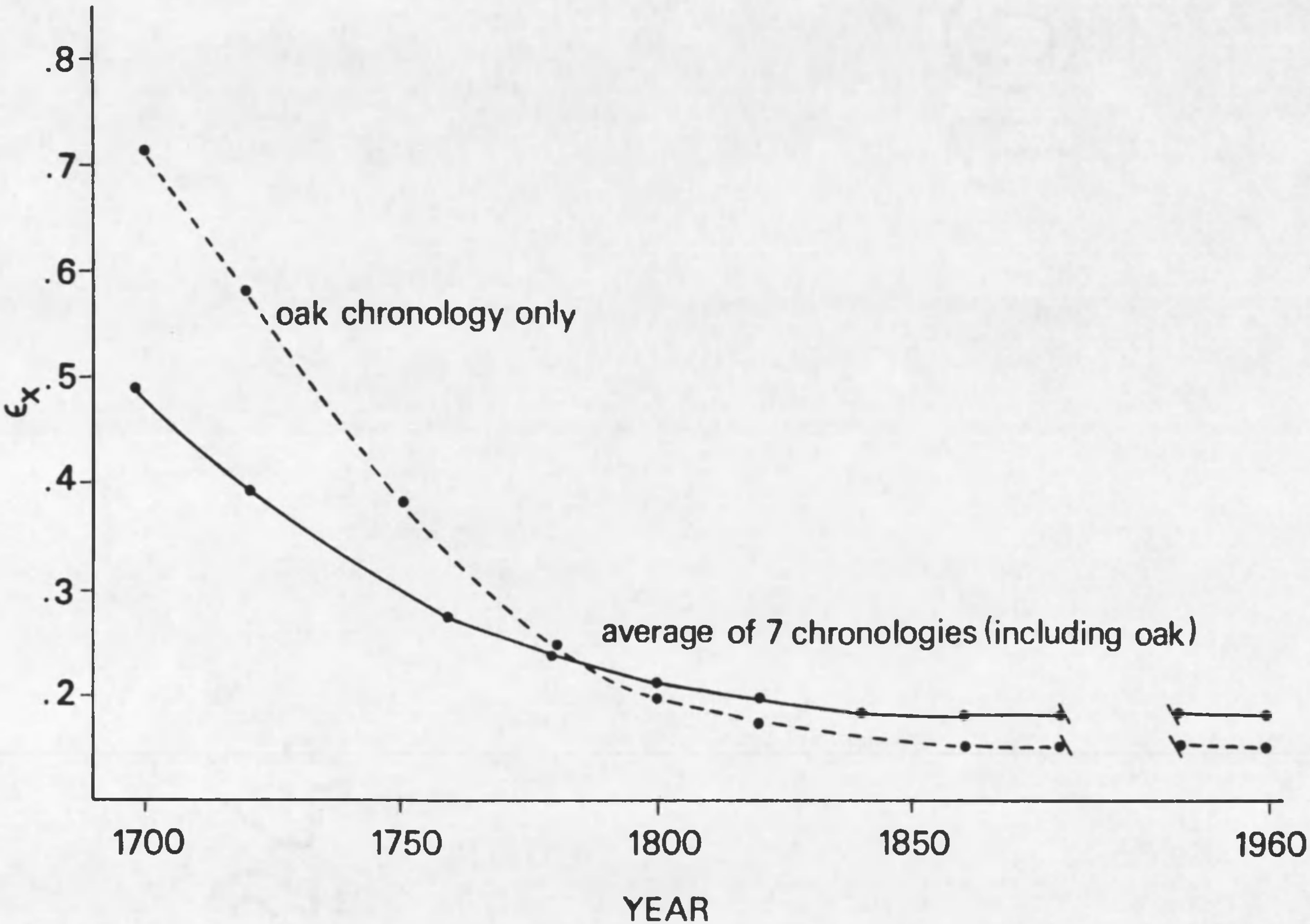


Figure 6. Relative Chronology Error Due to Sample Size, Plotted as a Function of Time.

Figure 7. Estimate of the Relative Error Due to the Effect of Sample Size on the Reconstruction of Winter Precipitation, Portland, Maine. -- Values are derived from Equation 3.8. The solid line represents seven chronologies. The dashed line represents six chronologies; the weights for the New York State oak chronology have been removed.

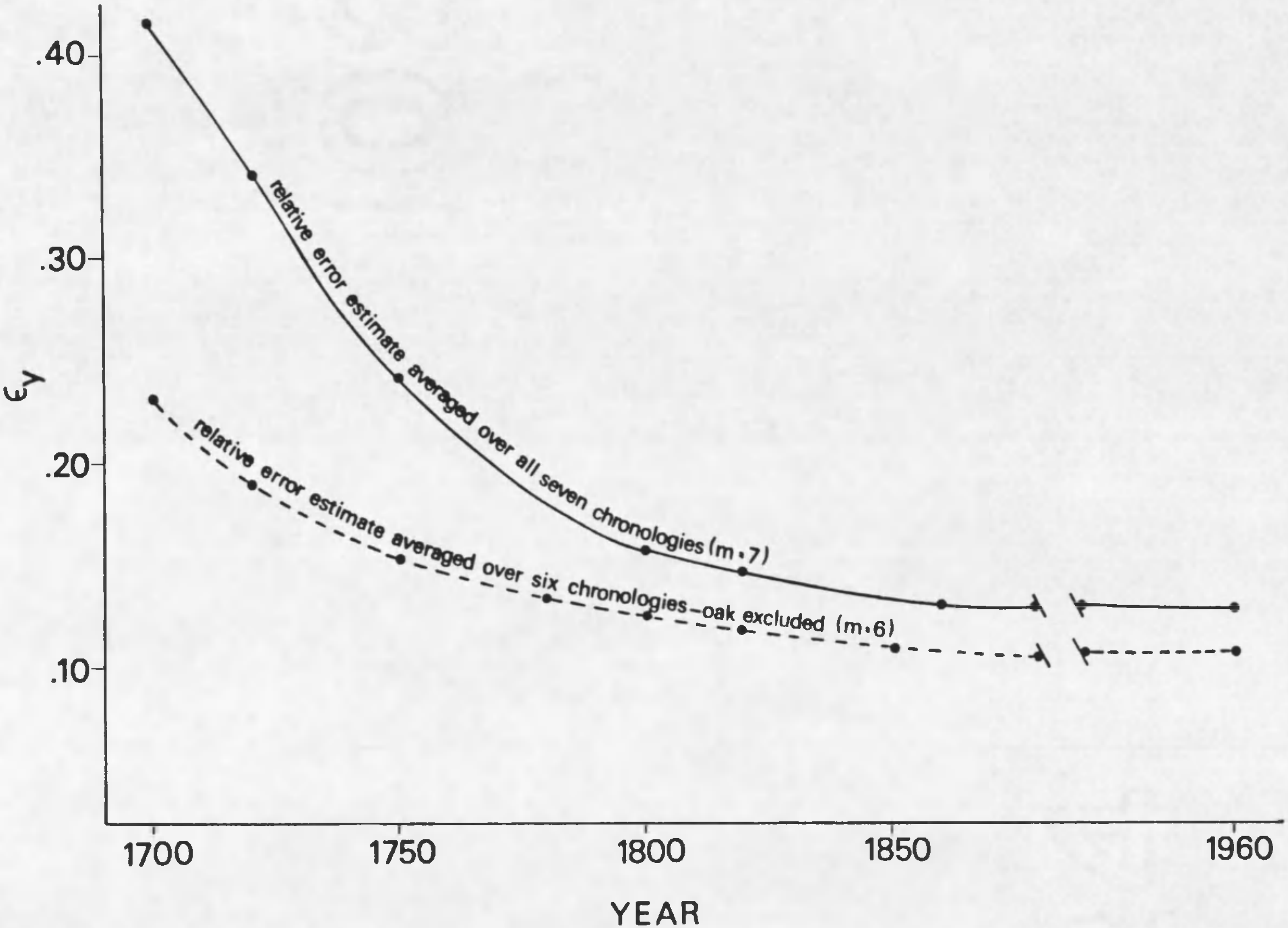


Figure 7. Estimate of the Relative Error Due to the Effect of Sample Size on the Reconstruction of Winter Precipitation, Portland, Maine.

The earlier of the two anomalous peaks in the oak chronology, in 1754-55, is at a time of low number of cores, and the oak indices may indeed be inflated by the small sample size alone. The second peak, in 1781-82, occurs when the number of cores has increased to 16, lowering the expected error due to sample size to less than twice the error in 1900. None of the other chronologies, all coniferous, show peaks at these times, so that a difference in this oak chronology may be due to differences between deciduous and non-deciduous tree responses to climate or to local site conditions, in addition to lowered reliability from smaller sample size. Because of the high dependence of the Portland reconstructed winter precipitation on the oak chronology, errors in that chronology from sample size or other growth characteristics are transmitted almost directly into the reconstruction. The resulting anomalous peaks of reconstructed precipitation in 1754-55 and 1781-82 appear exaggerated in relation to the rest of the reconstruction and, in later periods, to actual precipitation totals. This Portland/oak chronology anomaly seems to be an extreme example of problems that may occur in reconstructing climate from tree-ring series, problems which may be exaggerated by the small number of chronologies and climatic stations used in this study.

### Averaged Reconstructions of Each Season

Those climatic stations showing the highest verification percentages for each season (Table 7) were averaged to create a generalized reconstruction of each climatic variable and season. These values were then filtered with a low-pass digital filter (Fritts 1976, p. 268-271) and are plotted in Figure 8. In this way, periods of warm versus cold or wet versus dry common to the reconstructions over the New England region can be seen. In addition, the actual temperature or precipitation low-pass filtered series are shown as circles for the calibration period of 1905 or 1906 to 1960 (Figure 8).

These reconstructions represent a first approximation of past climatic conditions in New England, and they are subject to revision as basic data are added and techniques are improved.

Figure 8A is the averaged and filtered reconstruction of winter temperature at Amherst, New Haven, New York City, Concord, Blue Hill, and Albany. The averaged plot shows well-pronounced periods of cooler or warmer than average temperatures. The reconstruction begins with falling temperatures, and the first decade of the eighteenth century shows cooler than average temperatures. The early teens were suddenly warmer, and an equally rapid temperature decrease is reconstructed before 1720. Temperatures remained cool until 1750, with a period of more average winter temperatures during the 1730's. The 1750's show a rise in temperature, dropping again to more average conditions by 1760 to 1770. The 1780's show the warmest temperatures of the entire 300 years, gradually cooling until the 1790's. Gradual warming then is reconstructed, reaching cool to average conditions in the first decade of the nineteenth century, and then rapidly rising to a warm peak in the early teens. Temperatures then fell to below average before 1820, rising to more average conditions by the end of the 1820's and into the early

Figure 8. Averaged Reconstructions of Winter Temperature (A), Winter Precipitation (B), and Spring Precipitation (C). -- Line plots are reconstructions, circles are values of actual temperature or precipitation. Each reconstructed and actual series is treated with a low-pass filter, and the values are plotted as departures from the calibration period mean.

A. November-March temperatures (model 1) from six stations: New Haven, Amherst, Blue Hill, Concord, Albany, and New York City.

B. November-March precipitation (model 6) from four stations: Blue Hill, Mohonk Lake, Philadelphia, and St. Johnsbury.

C. April-June precipitation (model 12) from five stations: Amherst, Concord, Hanover, Albany, and St. Johnsbury.

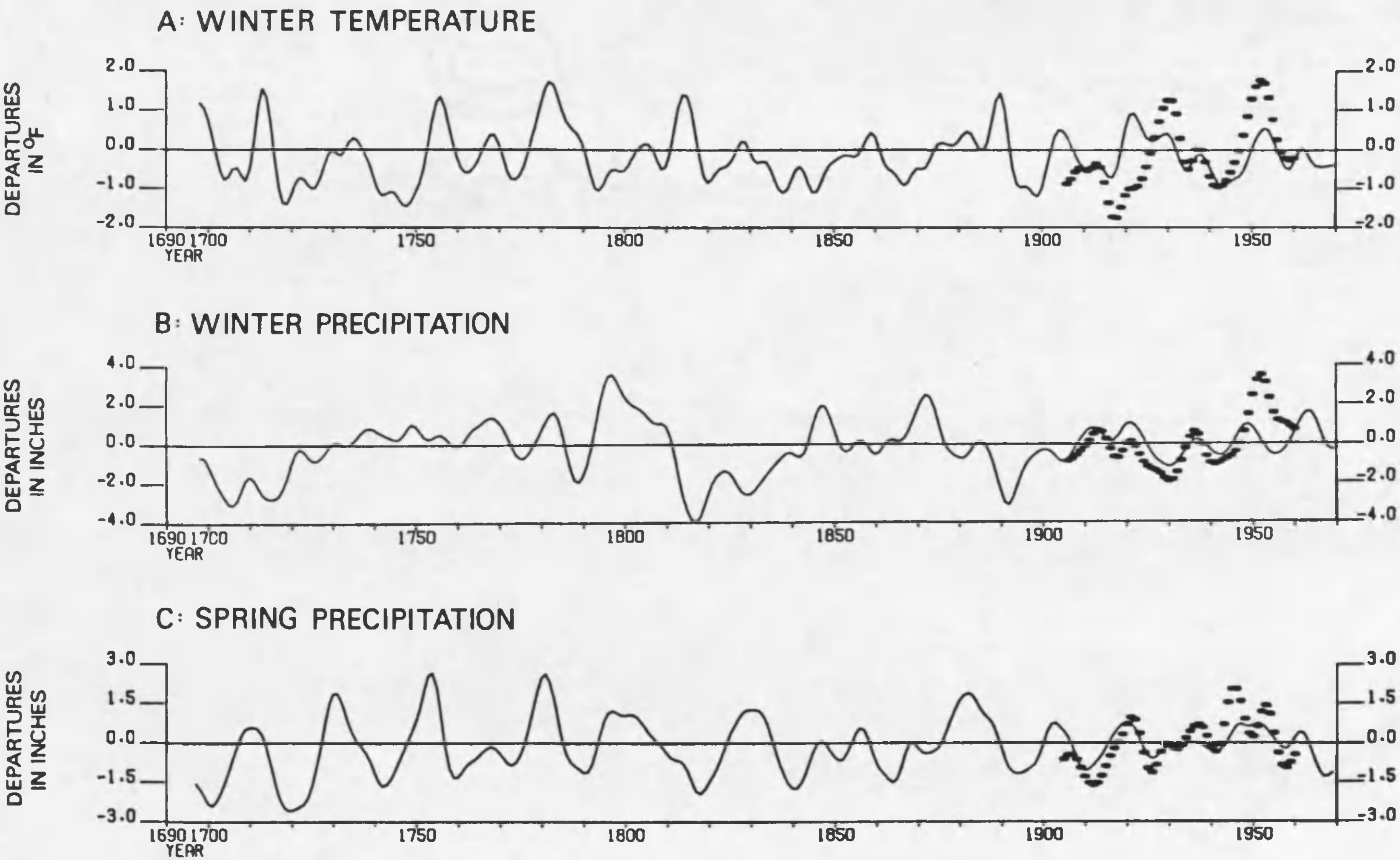


Figure 8. Averaged Reconstructions of Winter Temperature (A), Winter Precipitation (B), and Spring Precipitation (C).

1830's. Cool conditions were again reconstructed, lasting through the 1830's and 40's, when a gradual warming began which reached maximum warmth in the late 1850's and then again in the 1890's. An abrupt cooling is reconstructed during the final decade of the nineteenth century, with warming and then cooling in the 1900's to match the actual temperatures in the early teens. A period of very low actual temperatures in the late teens is underestimated by the reconstructions. The 1920's are reconstructed to have been warmer than average and are much warmer than the actual temperatures. A recorded peak of warmth in the late 1920's and early 1930's is underestimated by the reconstructions, but the period of near average to cooler conditions in the 1930's and early 1940's is well-matched. A gradual increase in temperature is seen in both series for the 1940's to early 1950's, although the reconstruction remains a conservative estimate of the peak. Average conditions return in both series by the late 1950's, and the estimated series ends by showing a slow cooling.

Figure 8B is the averaged and filtered reconstruction of winter precipitation at Mohonk Lake, Blue Hill, St. Johnsbury, and Philadelphia. There is an overall trend of low to average reconstructed precipitation in most of the eighteenth century, with a dry spell in the 1780's turning to very wet by the 1790's. Precipitation then drops to extreme dryness in the early nineteenth century. The curve rises to two peaks in the 1840's and 1870's and dips to another low in 1890-91. The twentieth century is reconstructed to show smaller deviations from average precipitation.

The early 1700's show dry winters, with slightly increasing moisture in 1710, but with another period of low moisture in the teens. Precipitation increased gradually and is reconstructed as average during most of the 1730's, 1740's, and 1750's. The 1760's show increased precipitation, decreasing to below average in the middle 1770's, increasing by 1780-81, and sharply decreasing by the end of the 1780's. A rapid increase in precipitation is reconstructed for the early 1790's, peaking in 1797-98 with the highest precipitation in the entire reconstruction. A gradual decrease in precipitation is then reconstructed, culminating in the most extreme dry period of the record by 1817-18. Precipitation then increased until the early 1820's, decreasing again by the late 1820's, and then increasing slowly until the mid-1840's when above average precipitation is again reconstructed. Near average conditions occurred during the 1850's to the mid-1860's, becoming wetter than average in the later 1860's and early 1870's. Drier conditions returned, culminating in a second extreme reconstructed low precipitation in the early 1890's. Precipitation is reconstructed to increase during the later 1890's, dipping again in the mid-1900's, returning to above average conditions along with the actual values by the teens. Actual precipitation then decreased more than is reconstructed, and the slight increase in the late teens is overestimated. Both reconstructed and actual series show a gradual drying from 1920 to 1930, although the actual amounts remained below the reconstructed. Increasing rainfall in the 1930's is seen in both series, followed by a decrease in precipitation in the late 1930's, again slightly underestimated by the reconstructions.

A rise in precipitation is reconstructed for the late 1940's, coming before and remaining a conservative estimate of the actual peak. A slight drying is indicated in the early 1950's for both series, although the reconstruction shows increasing precipitation in the late 1950's while the actual figures continue to decline. The end of the estimated series shows an early 1960's rise and later decline of winter precipitation.

Figure 8C is the averaged and filtered reconstruction of spring precipitation at Amherst, St. Johnsbury, Hanover, Concord, and Albany. Reconstructed spring rainfall in the eighteenth century shows a more regular oscillating pattern than the other reconstructions, with periods of dry springs centering on 1702, 1720 (the driest period of the entire record), the early 1740's, 1760, 1775, and 1790. Wetter springs were reconstructed centering on 1710, the early 1730's, with highest overall peaks occurring in the early 1750's and 1780. The 1795-1808 period is reconstructed to be above average in rain, gradually decreasing to a 1818 low. Rainfall is then shown to increase until the 1830's, decreasing again to 1840. An increase in rainfall is reconstructed for the 1840's, with more average conditions then prevailing until the late 1850 1850's. Another drying is reconstructed by the mid-1860's, gradually turning wet into the late 1870's and early 1880's. Drier than average springs were reconstructed in the mid-1890's, increasing in the early 1900's, and decreasing again by 1910. A gradual increase in raininess is reconstructed until 1920, going along with actual values, with a return to below and near average conditions in both reconstructed and actual, lasting until the mid-1930's. Here the actual precipitation is higher than the reconstructed, but both are near average by 1950. Peaks of higher than average rainfall reconstructed for the mid-1940's and early 1950's are lower than the actual peaks, and both series show decreasing rainfall until the late 1950's. The reconstructed series then shows a slight increase and then a gradual decrease in rain until the end of the estimated series.

# CHAPTER 5

## SUMMARY AND CONCLUSIONS

Response function and eigenvector analyses of tree growth in the northeastern United States have indicated that a relationship exists between tree-ring widths and climate of humid areas. Canonical correlations and regressions were therefore calculated between a set of New England tree-ring chronologies and a set of temperature and precipitation observations from meteorological stations in the northeast. Statistical results of the best calibrations compare favorably to the calibrations of H. C. Fritts and his co-workers (personal communication, 1979), using western, arid-site tree rings. In addition, many of those calibrations produced reconstructions which passed a high percentage of independent verification tests. The small number of chronologies and climatic stations used in the study permitted analysis of individual station reconstruction reliability. Two of the reconstructions were examined in light of inaccuracies that may occur because of characteristics of the original climatic data or tree-ring chronologies. Regional averages of the seasonal reconstructions of temperature and precipitation were prepared as preliminary interpretations of past conditions in New England, although the reader is encouraged to appreciate the possible inaccuracies therein and the potential for revision and refinement.

This first application of canonical analysis of ring widths and climate of the northeastern United States confirms that verifiable reconstructions of past climate in areas of adequate moisture are thereby obtainable. The best results in this study were obtained when original standardized chronologies and climatic data series were used as variables instead of selected eigenvector amplitudes of those series.

Of the three climatic variables finally selected for verifications, winter temperature overwhelmingly gave the best results. This may be hard to understand, as the trees are presumably dormant at this time. Table 3 (p. 27) showed, however, that there are several significant responses to winter (November through March) temperature and precipitation. Oak shows the least, as might be expected from its leafless condition. But the conifers retain their foliage, and although photosynthesis may not occur during the coldest months, especially at the more northerly sites (P. Marchand, personal communication, 1979), the needles may still be active in November and March. In addition, conditions of temperature or precipitation during dormancy can affect subsequent growth in terms of soil moisture from amounts of snowpack and rates of melting (Fritts 1976, p. 195-196).

Climatic data are subject to observational or local environmental changes which may enhance or obscure any macroclimatic trends that occur. When such changes take place during the calibration period, a break in the climatic relationship to the tree-ring data will occur, and the resulting calibration will be weakened. Artificial shifts in climatic data during the pre-calibration period will affect the apparent verification ability of the reconstructions. Knowledge of station histories of observational changes, and visual familiarity with the climatic time series themselves are important for identification of such problems when they occur.

The tree-ring data are also a potential source of reconstruction inaccuracy. Ring widths from humid areas are subject to non-climatic suppressions and releases of growth that at once incorporate and obscure the climatic signal. Standardization of the series with polynomial curves decreases the effects of such growth characteristics, but may simultaneously remove some of the important low-frequency climatic information. Increasing the number of cores per chronology may enhance the chronology's signal, as well as diminish the error due to sample size that is propagated throughout the reconstructions. The spatial coverage of chronologies in this study is poorly distributed, strongly weighted to the south. More chronologies, from a more evenly distributed grid and larger area, are needed. In this study, there were occasional strong correlations between one climatic station and one chronology, often the one deciduous chronology. Inclusion of a better balance of deciduous and coniferous trees might help to eliminate such disproportionate correlations.

Thus, increased collection of tree-ring chronologies in the eastern United States is recommended, to create a more complete and better distributed spatial coverage of sites. Such a balanced grid will improve the calibration potential of canonical analysis, and may produce reconstructions of past climate that more closely reflect past conditions.

# APPENDIX A

## RESPONSE FUNCTION RESULTS

Figures A-1, A-2, and A-3 are the plotted results of one regression step each from response functions for Camel's Hump, Nancy Brook, and Livingston (see text p. 12).

The Camel's Hump response function (Figure A-1) is the seventh regression step, with an F-level of 1.55, a total $r^2$ of .515, and variance due to climate of .499. Significant (at the 95% level) responses of tree growth to temperature occur in June through September previous to growth (inverse), November, January, and May (direct), and again in June concurrent with growth (inverse). Significant responses to precipitation occur only in June and July of the previous year. No prior growth values are significant.

The Nancy Brook response function (Figure A-2) is the thirteenth regression step, with an F-level of 1.16, a total $r^2$ of .704, and variance due to climate .447. The results here show greater response to precipitation and less to temperature than at Camel's Hump. Tree growth is inversely related to temperature in July and August of the previous year, and directly related in November and July of the current year. Growth responds inversely to precipitation in June of the previous year, directly in July and September of the previous year, inversely to October and January, and directly in December and in July concurrent with growth. The first year of prior growth is also directly related.

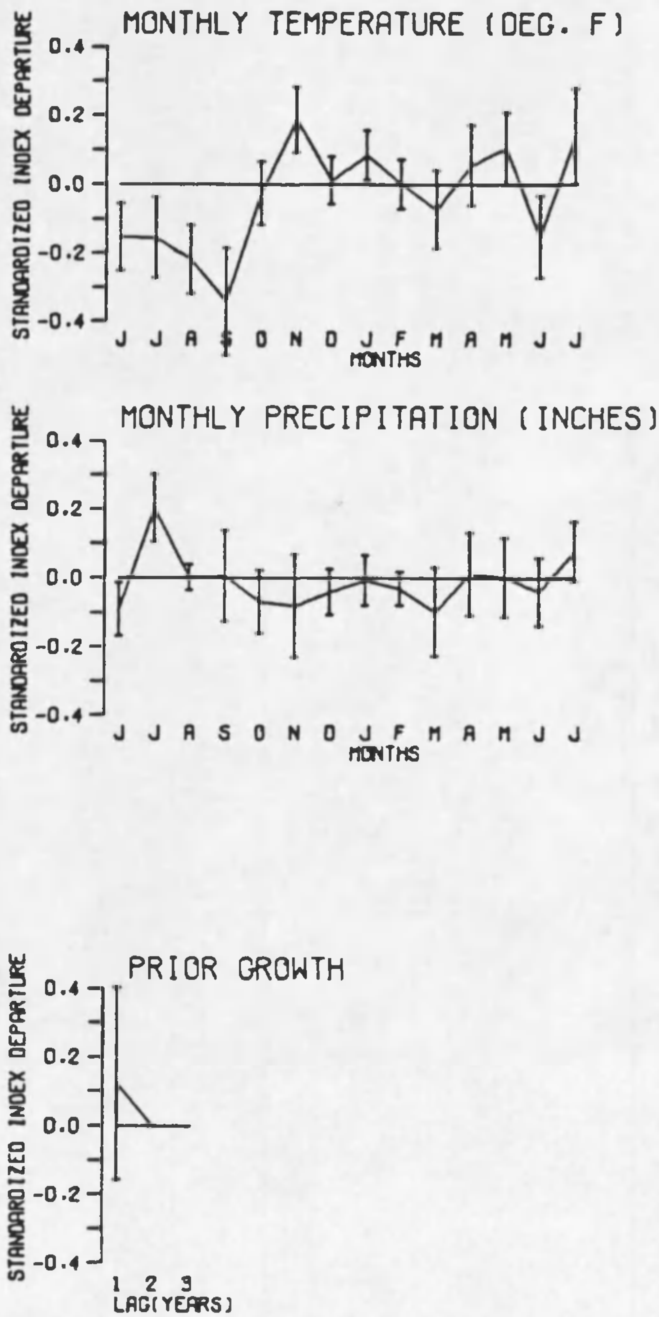


Figure A-1. Response function for Camel's Hump, VT. 1932-1971. -- Regression step no. 7, F-level = 1.55, total variance explained = 0.515, climatic variance = 0.499.

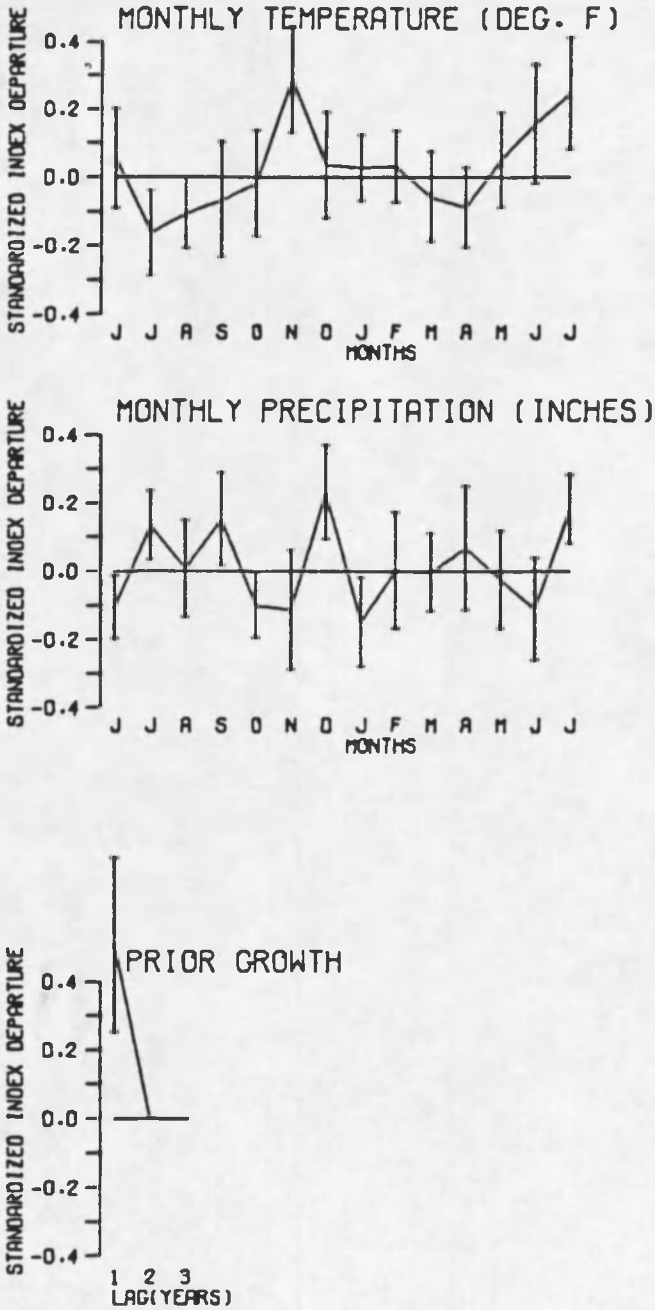


Figure A-2. Response function for Nancy Brook, NH. 1932-1971. -- Regression step no. 13, F-level = 1.16, total variance explained = 0.704, climatic variance = 0.447.

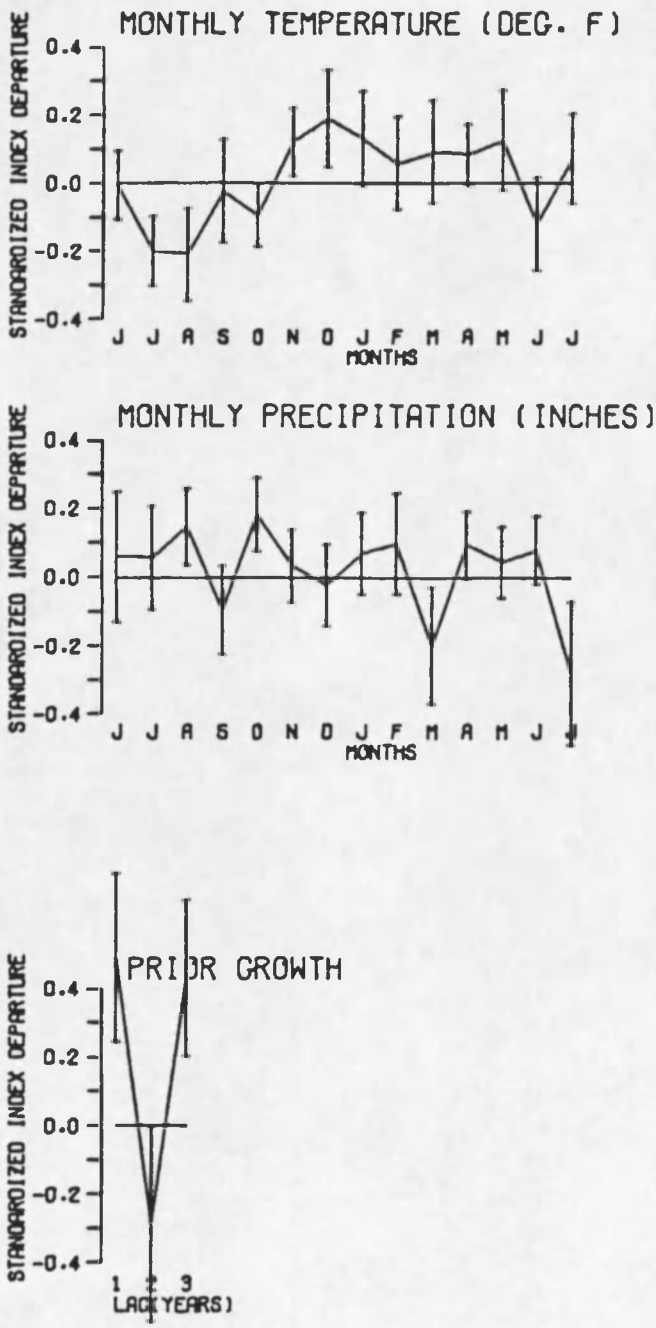


Figure A-3. Response function for Livingston, MA. 1932-1971. -- Regression step no. 14, F-level = 2.35, total variance explained = 0.757, climatic variance = 0.395.

The Livingston chronology response function (Figure A-3) is the fourteenth regression step, with an F-level of 2.35, a total $r^2$ of .757, and variance due to climate .395. Tree growth is inversely related to temperature of July, August, and October of the previous year, and directly related in November and December. There are direct responses to precipitation in August and October prior to growth, and inverse responses to March and July precipitation concurrent with growth. Prior growth at one and three lags are directly related, and prior growth at two lags is inversely related.

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