THE USE AND LIMITATIONS OF DENDROCHRONOLOGY IN STUDYING EFFECTS OF AIR POLLUTION ON FORESTS

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ABSTRACT

The annual ringwidths of trees can be used to search for hypothesized air pollution effects on forests. This search is extremely complicated by the inherent statistical properties of ringwidth data and the high level of uncertainty regarding the sources of variance observed in the ringwidths. A linear aggregate model for ringwidths is described which highlights the general classes of variance which may be found in a tree-ring series. Dendrochronological principles and techniques are described which can be used to create a tree-ring chronology that is suitable for rigorous statistical analysis and hypothesis testing. The need to model climatic influences on tree growth prior to the search for pollution effects is necessary and a method for achieving this is described. Only after the variance due to age trends, stand dynamics effects and climatic influences has been accounted for can any confidence be placed on inferred pollution effects. An analysis of a red spruce tree-ring chronology indicates that a decline in ringwidths since 1968 cannot be explained by a linear temperature response model using monthly climatic variables. However, threshold responses to climate that could be responsible for the decline need to be considered before the anomalous decline can be attributed to non-climatic influences such as pollution.

INTRODUCTION

The recent decline of red spruce (*Picea rubens* Sarg.) in northern New York and New England (1, 2) has prompted considerable speculation and research concerning the possible impact of acid deposition on tree growth (3). Aside from the obvious visual symptoms of decline such as foliar dieback, a marked reduction in radial increment since the mid-1960's is apparent in many trees (4). Although this radial growth reduction appears to be anomalous compared to the radial growth of previous years or decades, numerous uncertainties must be addressed before this phenomenon can be interpreted as a pollution-caused event. As living organisms growing in an uncontrolled environment, trees respond to numerous natural growth modifying influences that are both beneficial and detrimental to annual ring formation. These influences represent the background variability of the trees' operational environment into which pollutants have been introduced. The presence of this potentially confounding background variability makes the identification of pollution effects very difficult and uncertain. This problem leads to the following proposition for tree ring/pollution research:

> The hypothesized existence of a pollution effect on radial growth cannot be ascertained with any confidence until the contributions of natural growth modifying influences have been taken into account.

This is a rather rigorous proposition given the considerable uncertainties regarding the nature and history of natural influences on tree growth. However, if tree ring/pollution studies are to achieve credibility and acceptance as a valid method of inquiry, a logical and objective scientific method must be developed that can satisfy this proposition.

The science of dendrochronology and the subdiscipline of dendroclimatology (5) have developed many principles and techniques for analyzing tree-ring data. Most of these principles and techniques have never been applied to tree ring/ pollution problems. Yet with minor modifications, all are applicable. The purpose of this paper is to describe a rational approach to tree ring/pollution or dendropollution research, given the limitations of the data and prior knowledge, based on dendrochronological principles. This approach will assume from the start that the tree-ring series being analyzed have been precisely dated using accepted cross-dating techniques (5, 6).

In order to clarify the problem of identifying pollution-related changes in ringwidths from other factors, a linear aggregate model will be described for a hypothetical ringwidth series.

A LINEAR AGGREGATE MODEL FOR RINGWIDTH SERIES

Consider a hypothetical annual ringwidth series as an aggregation of several unobserved subseries representing the sources of variance that may be found in the observed process. Let this aggregated time series be expressed as

$$R_t = G_t + C_t + \delta D1_t + \delta D2_t + \delta P_t + E_t$$

where:

R_t = the observed ringwidth series measured along a single radius

G_t = the growth trend associated with increasing age and size of the tree

C_t = the climatically-related growth variations common to a stand of trees including those produced through the interaction of climate with site factors

$D1_t$ = the variance due to endogenous disturbances, which only affect a small subset of trees in a stand at any one time

$D2_t$ = the variance due to natural exogenous disturbances, which have a standwide impact on radial growth

P_t = the variance due to anthropogenic pollutants which have a standwide impact on radial growth

E_t = the random variance representing growth influencing factors unique to each tree or radius

The δ associated with $D1_t$, $D2_t$ and P_t is a binary indicator of the presence ($\delta = 1$) or absence ($\delta = 0$) of a subseries in R_t for some year or group of years. Thus $D1_t$, $D2_t$ and P_t are not time invariant features of R_t and need not be present at all. The linearity of the components in the model is intended to simplify the exposition of this complex problem, not imply any structural interrelationships.

The growth trend, G_t, is a non-stationary process that typically arises, in part, from the geometrical constraint of adding a volume of wood each year to a stem of increasing radius. This constraint suggests that the trend in radial growth should possess an exponential decay as a function of time. Trees growing in open-canopy environments frequently have this form of ringwidth trend, which can be adequately modelled and removed by deterministic mathematical models such as the modified negative exponential curve (5). Unfortunately, the growth trends of trees growing in closed-canopy forests are much more complex and stochastic compared to those in open-canopy forests because of disturbances and competitive interactions within the forest. For this reason, the definition of G_t must be generalized to allow for the occurrence of a variety of linear and curvilinear growth trends of arbitrary slope and shape. As will be shown, G_t must be removed from the ringwidths before the modelling of C_t and search for P_t can proceed.

The climatically related subseries, C_t, reflects certain broad-scale meteorological variables that directly or indirectly limit the growth processes of trees in a stand. These variables are assumed to be uniformly important for all trees of a given species when the site characteristics of the stand, such as hydrology, elevation, exposure and soil, are more or less homogeneous. The response of the trees to this "climatic window" (5) of variables creates patterns of wide and narrow rings that agree among trees when matched correctly in time. This phenomenon, called cross-dating, allows the absolute dating of ringwidths, which is the cornerstone of dendrochronology. The input that produces C_t typically involves weakly-stationary stochastic processes such as temperature and precipitation. Thus, the mean and variance of C_t are independent of time, and the series evolves through time in a probabilistic fashion. As a common signal in the ringwidths of all trees, C_t could be mistakenly identified as a pollution signal if the recent behavior of C_t mimics the expected pollution effect on ringwidths. Thus, the effects of climate on ringwidth must be carefully modelled and removed before a pollution effect can be identified.

The variance accounted for by disturbances $D1_t$ and $D2_t$ can be split into two general classes of disturbance: endogenous and exogenous (7, 8). Conventionally, they are differentiated by the causal mechanisms involved, i.e. forces internal to the forest community versus forces external to it, although these differences become indistinct upon investigation (8).

Endogenous disturbances are caused by factors related to characteristics of the vegetation that are independent of the environment (8). Disturbances that are often described as such in closed-canopy forest communities occur when dominant overstory trees senesce, die and topple as a natural consequence of competition, aging and stand succession. Although the senescence and death of old-age trees from internally caused factors seems biologically reasonable, it rarely occurs without the impetus of external environmental factors such as insect attack, drought and windthrow (White 1979), hence, the difficulty in differentiating the causal mechanisms of endogenous and exogenous disturbances. In the context of searching for a pollution signal in tree rings, endogenous disturbances can be expected to occur randomly in space and time in forest communities. That is, the loss of a dominant tree in one section of a stand is not likely to be related temporally or spatially to similar losses at separate locations in the stand. This property immediately suggests that the resultant endogenous disturbance pulses in the tree rings will rarely be synchronous among separated trees in a stand except by chance alone. Thus, the lack of synchronicity in ringwidth fluctuations between trees during a hypothesized pollution effect period may be used as evidence for rejecting the presence of a pollution signal.

Exogenous disturbances are caused by natural environmental forces that lie external to and are independent of the vegetation (8). Unlike endogenous disturbances, these disturbances have many possible causal agents that can affect large areas of forest. Some of the important agents are fire, windstorm, ice storm, frost damage, disease and insect infestation. Because the areal extent of an exogenous disturbance can be great, the resultant disturbance pulse, $D2_t$, may occur contemporaneously in virtually all trees in a stand. This property presents obvious difficulties for differentiating a pollution caused ringwidth decline from that caused by a natural exogenous disturbance. Fortunately, the period of forest decline in many regions has only been in the past 15-20 years. Consequently, there should be adequate documentation of the more obvious exogenous disturbances in many forests to determine the presence or absence of this confounding source of variance.

The pollution signal, P_t, is the principal signal of interest in this paper. When present, it is assumed that the effect of the pollutant on radial growth will be similar for all sampled trees of the same species in a stand. Thus, P_t will be a common signal in the ringwidth series. This assumption could be criticized for being too restrictive in requiring a pollution effect on all sampled trees. It could be argued, for example, that the crowns of dominant and co-dominant trees "scrub out" wet and dry atmospheric pollutants before they reach understory trees. If this were the case, then the understory trees might not show a pollution effect. This possibility indicates the need for the stratified sampling of trees based on *a priori* criteria such as crown class or canopy position. In any case, the search for subsets of trees within the total sample that show a pollution effect should be based on an *a priori* experimental design, not on an *a posteriori* "fishing trip".

The last subseries, E_t, is the random variance in the ringwidth series due to such variables as localized responses to microenvironmental factors, variations in circuit uniformity, and measurement errors. E_t is assumed to be unrelated to the variance accounted for by C_t, A_t, $D1_t$ and $D2_t$, and P_t. In addition, it is assumed to be serially uncorrelated within each tree and spatially uncorrelated within the stand of trees. The standard way to reduce this random variance is through replicate sampling (5). That is, a number of trees (say, 20 to 40) are sampled from a forest stand. Then, after suitable standardization, the tree-ring series are averaged together to form a mean-value function for the site, which "averages out" the E_t.

The linear aggregate model has revealed the potentially very complex nature of annual ringwidth series. In the next section, some of the properties of this model will be validated and described in more detail using examples of actual ringwidth data. These examples will reveal the inherent non-stationarity of ringwidth series and the need to remove this property before the climate and putative pollution signals can be modelled.

SOME EXAMPLES AND PROPERTIES OF ACTUAL RINGWIDTH DATA

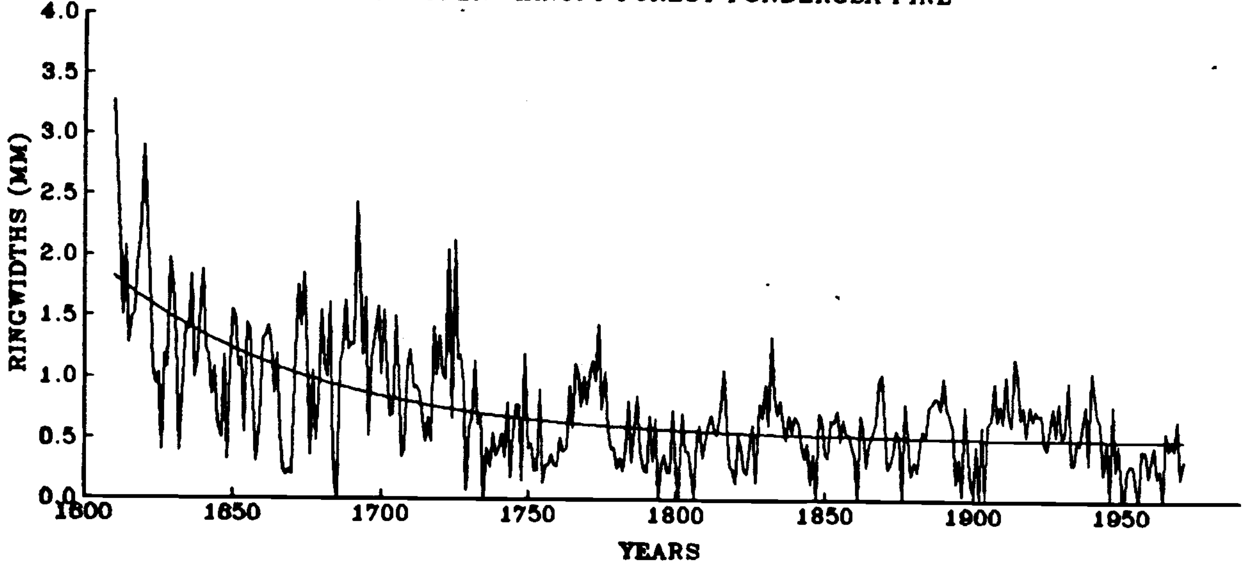
Figure 1 shows three examples of the kinds of stationarity frequently encountered in ringwidth series. The first series (Figure 1A) is from an open-canopy stand of ponderosa pine (Pinus ponderosa Laws.) from a lower forest border site in New Mexico. It shows the classic negative exponential trend in ringwidth, which is a function of increasing tree age and size. This type of growth function is also commonly found in Pinus species with low shade tolerance, such as shortleaf pine (P. echinata Mill.) and pitch pine (P. rigida Mill.), that frequently begin growing in low-shade environments.

The second series (Fig. 1B) is from a closed-canopy stand of red spruce in New Hampshire. It shows the effects of gap-phase dynamics that are typical in stands of shade tolerant species such as red spruce. This tree probably experienced a release from competition around 1790 through the creation of a gap in the canopy after the loss of an adjacent dominant tree. Note that after this tree exploited the gap, it entered a phase of exponential decay around 1870, which continues to the present time. The smooth function fitted to this series is only intended to highlight the overall shape of the non-stationarity, not to fit it well. But in general, the structure of the non-stationarity is comparatively simple, i.e. rather unimodal in shape.

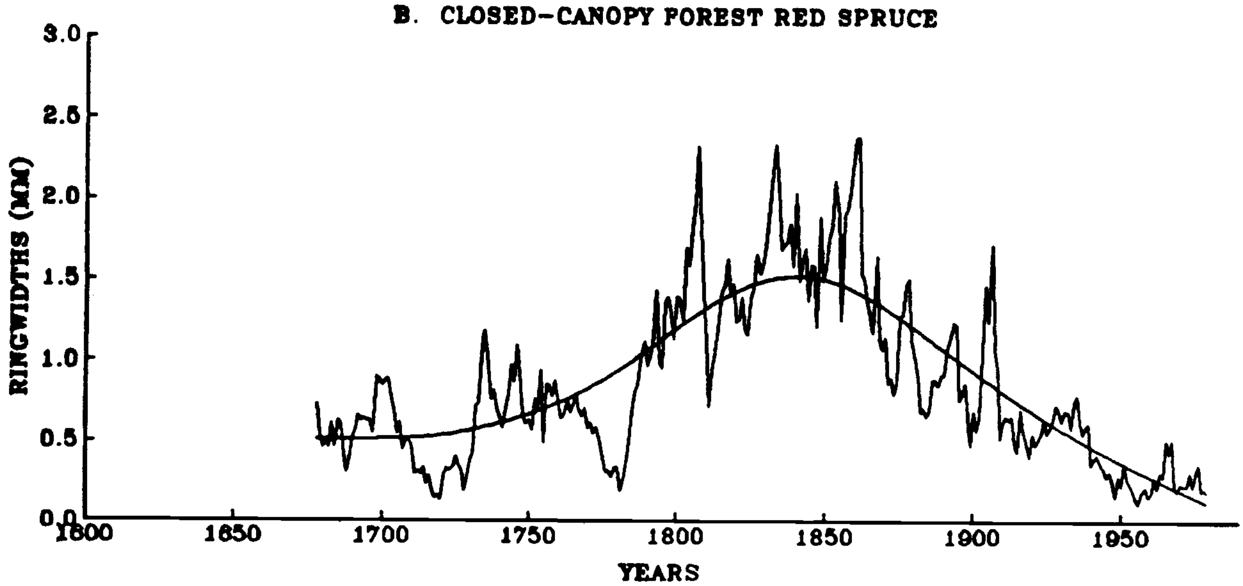
The third series (Fig. 1C) is from a closed-canopy stand of eastern hemlock (Tsuga canadensis Carr.) growing in Pennsylvania. Eastern hemlock is also a shade-tolerant species that is strongly influenced by gap-phase stand dynamics. The overall ringwidth trend is positive for the 312 years of record, but erratic, shorter-term fluctuations are present. There is very strong evidence for a competition release around 1810, but subsequent disturbances since 1850 have probably occurred to allow the

Figure 1. Three examples of the kinds of non-stationarity frequently found in ringwidth series. The smooth curves are intended to highlight the general forms of the non-stationarity, not model them closely.

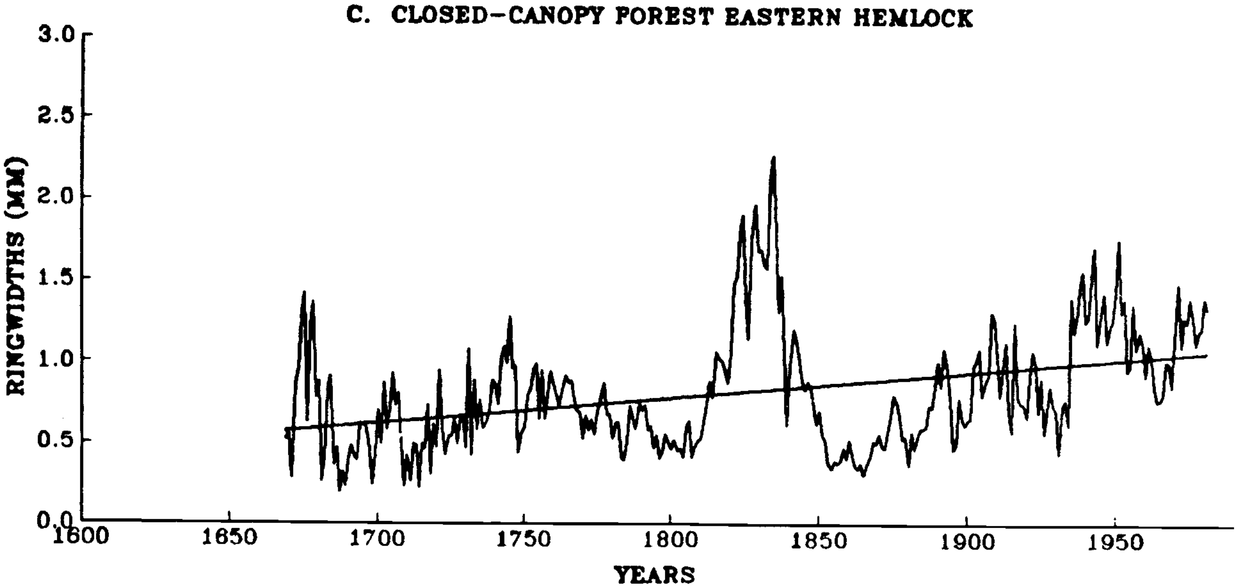
A. OPEN-CANOPY FOREST PONDEROSA PINE



B. CLOSED-CANOPY FOREST RED SPRUCE



C. CLOSED-CANOPY FOREST EASTERN HEMLOCK



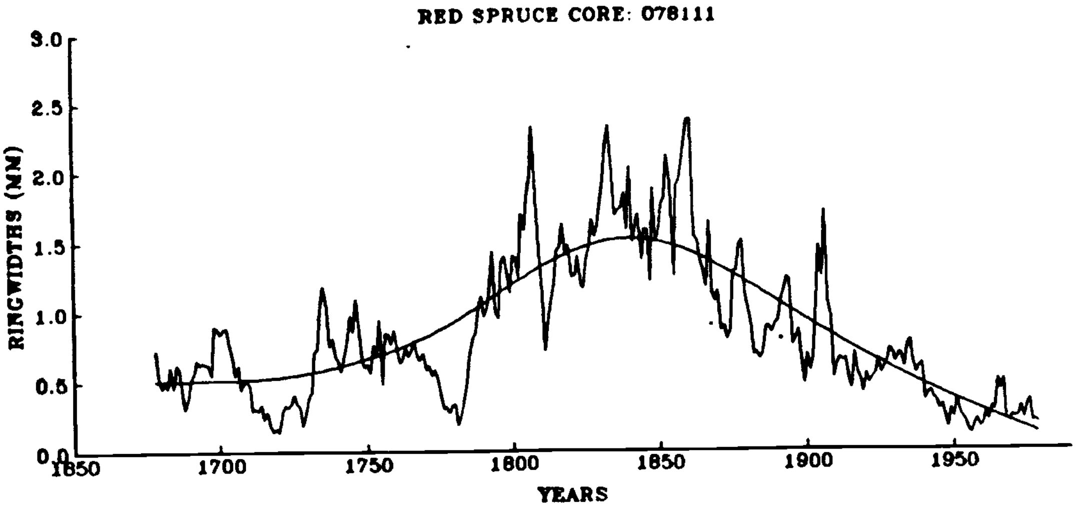
continuation of the general positive trend. The structure of the non-stationarity is more complicated than that for the other ringwidth series.

These series illustrate several difficulties in interpreting ringwidths for pollution-related effects. There is a high probability that ringwidth series will show a trend in radial growth rate due to age and size related variables alone. Thus, a ringwidth decline cannot be used as *prima facie* evidence for abnormal decline in forest productivity or tree vigor due to pollution. Neither can a ringwidth increase be used as evidence for the lack of a pollution signal because the sampled tree may be in the middle of release from competition. For example, if the eastern hemlock in Fig. 1C were cored in 1830 or 1860 diametrically opposed interpretations of the ringwidths *vis-a-vis* pollution effects are possible. These series also illustrate the time dependence of the mean and variance, which is characteristic of all non-stationary ringwidth series. For example, the mean ringwidth of the red spruce series in the 1850-1860 period is about four times greater than that in the 1950-1960 period. The corresponding variances of these time periods differ by a similar magnitude.

Another problem arises in interpreting ringwidth series: the differentiation of tree-specific (endogenous) disturbance effects from effects due to common environmental influences such as climate, natural exogenous disturbances, and pollution. As described by the linear aggregate model, the characteristic of the endogenous disturbance pulse, which should allow its identification, is its unique placement in time in only a small subset of trees growing in the stand. The principal mechanism for creating this property is gap-phase dynamics. It is clearly impossible to differentiate endogenous disturbances from other sources of common (standwide) variance without the simultaneous scrutiny of all ringwidth series collected from the stand. For example, the red spruce series in Fig. 1B shows two pronounced periods of suppressed radial growth beginning around 1720 and 1775. Are these periods unique to this tree or common to the stand? No conclusion can be made until we examine Fig. 2, which shows this ringwidth series at the top and three others from the same stand. It is immediately apparent that neither of those suppression periods are common to the other series. Thus, they can be categorized as endogenous disturbance pulses. Ordinarily, many more series would be used in such a comparison, but this limited example illustrates the importance of using both within and between tree information when interpreting tree-ring series.

For the purpose of searching for hypothesized pollution effects in tree rings, the comparison of many series is useful but very cumbersome. A more efficient approach is the creation of a time series mean-value function, which concentrates the common signal among all series and simultaneously "averages out" the unique information or noise in the individual series. The creation of a statistically valid mean-value function requires that the individual ringwidth series are drawn from the same population of response variables. This criterion will usually be satisfied when the ringwidth series all come from trees growing in a stand with reasonably homogeneous physiographic, edaphic,

Figure 2. Four red spruce ringwidth series from the same stand. These series show the low-frequency lack of aggrement between series that is largely due to endogenous disturbances and tree histories.


RED SPRUCE CORE: 078111
RINGWIDTHS (MM)
YEARS
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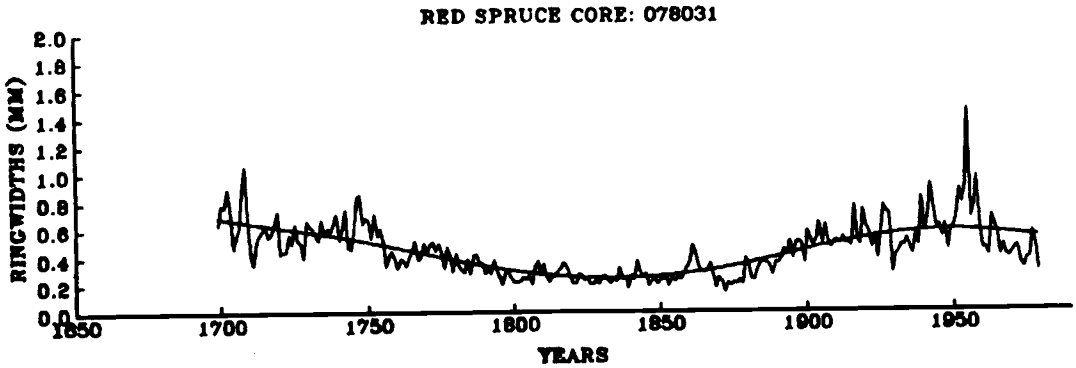
0.5
1.0
1.5
2.0
2.5
3.0
1650
1700
1750
1800
1850
1900
1950


RED SPRUCE CORE: 078031
RINGWIDTHS (MM)
YEARS
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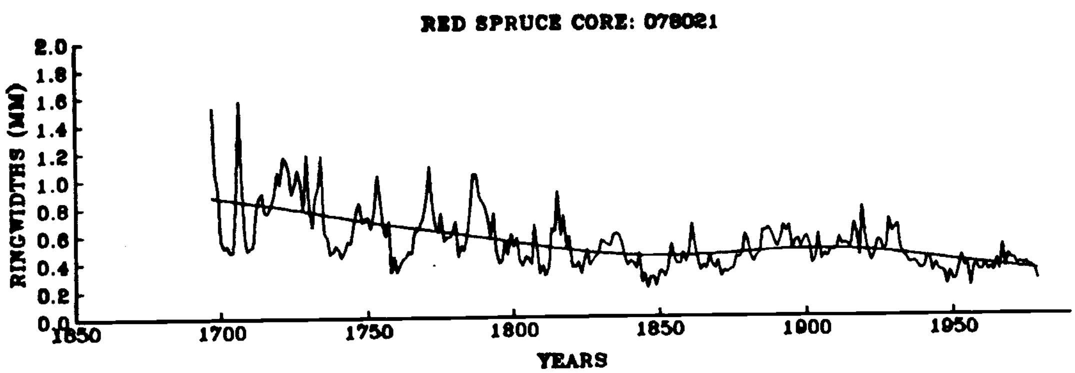
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1.6
1.8
2.0
1650
1700
1750
1800
1850
1900
1950


RED SPRUCE CORE: 078021
RINGWIDTHS (MM)
YEARS
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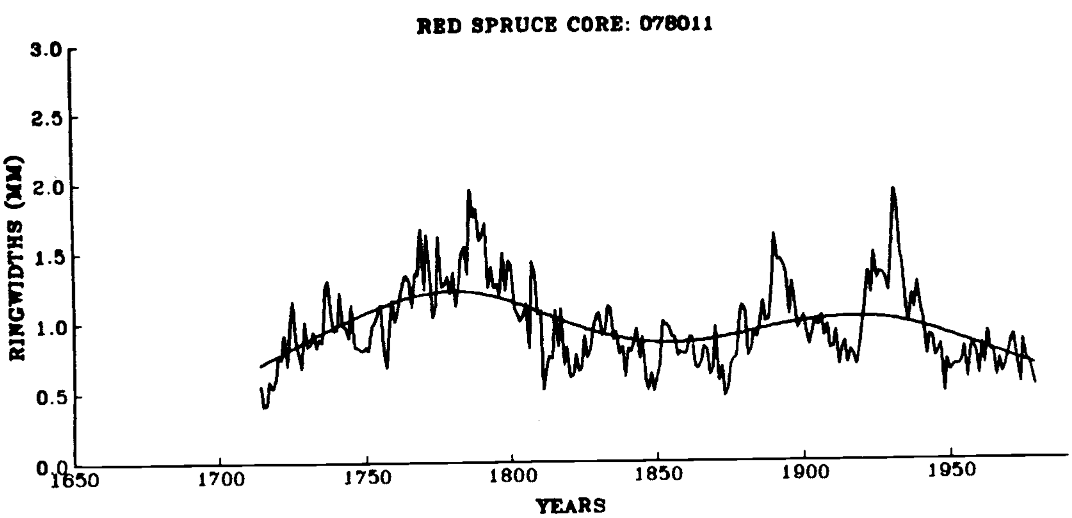
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1.6
1.8
2.0
1650
1700
1750
1800
1850
1900
1950


RED SPRUCE CORE: 078011
RINGWIDTHS (MM)
YEARS
0.0
0.5
1.0
1.5
2.0
2.5
3.0
1650
1700
1750
1800
1850
1900
1950

and hydrologic characteristics. In this case, the principal signal found in all trees may come from broad-scale environmental influences such as climate and, perhaps, natural exogenous disturbances and pollutants. As noted in the linear aggregate model, the presence of cross-dating between trees is an indication of a common environmental signal. Given the presence of a common environmental signal, the creation of the mean-value function can proceed.

Returning, now, to Fig. 2, it is readily apparent that averaging ringwidths together to produce a mean-value function cannot be recommended. The non-stationarity of the series coupled with large differences in absolute ringwidth between series could produce a response variable mean-value function that is dominated and confounded by stand dynamics effects. The average correlation between these series for the common period 1716-1979 is -0.028, which is clearly not statistically significant. The corresponding signal-to-noise ratio (SNR) (9) is also negative, indicating the complete lack of common signal in the mean-value function. This result seemingly violates the underlying assumption that these series were sampled from the same population of response variables. Yet, each series does contain a common environmental signal. This can be demonstrated by modelling and prewhitening the ringwidth series using autoregressive time series modelling (10, 11) to reduce the effects of non-stationarity and endogenous disturbances on the correlation structure between series. When this is done, the average correlation between series rises to 0.27, which is statistically significant at the 99% confidence level, and the SNR is 1.4:1. From this example, it is clear that non-stationarity due to age-size effects and stand dynamics must be removed before the tree-ring series can be used to search for pollution impact on radial growth or other common growth influences such as climate. This is the principal purpose of tree-ring standardization (5, 11).

TREE-RING STANDARDIZATION AND ITS LIMITATIONS

Tree-ring standardization is, perhaps, the most poorly understood procedure used in dendrochronological studies. The principal goal of tree-ring standardization is the reduction of the non-stationary ringwidths to a sequence of relative tree-ring indices that are stationary through time. This is accomplished by removing age-size and stand dynamics effects using smooth mathematical curves such as those seen in Fig. 1 and 2.

The relative tree-ring indices are computed as

$$I_t = R_t / G_t$$

where I_t is the tree-ring index, R_t is the measured ringwidth, and G_t is the fitted growth curve value, all for year t. Tree-ring indices produced by this procedure have a long-term mean of 1.0 and a variance that is largely stabilized by the division process. In the usual dendrochronological interpretation, the growth curve (G_t) is a sequence of expected ringwidth values that would be produced by the tree if shorter-term fluctuations such as those attributable to climate (I_t) were unchanging through time. Conversely, the I_t can be thought of as fractional departures from the expected growth curve, G_t, which are related to variations in climate. For the purpose of this paper, the I_t also contain any common signal due to pollution stress. Once the tree-ring series have been standardized, they can be averaged together into a mean-value function.

As should be readily apparent, the principal difficulty in standardizing ringwidths is the estimation of a satisfactory growth curve. For trees growing in open-canopy environments, simple monotonic functions, such as the negative exponential curve (5), are often satisfactory (see Fig. 1A). Unfortunately, such idealized models cannot be applied to closed-canopy forest trees, as Fig. 1 and 2 clearly show. Orthogonal polynomials (5) and cubic smoothing splines (12) can be used as data-adaptive methods for estimating the more complex and stochastic growth curves found in closed-canopy tree-ring series. These curves have little theoretical basis and implicitly admit the ignorance of tree histories in most, if not all, unmanaged or natural forest stands. However, there is the very real danger that these more flexible curves will inadvertently remove some or all of the pollution signal being sought for study.

The primary reason for potential loss of the pollution signal during standardization is its probable beginning and continued presence in the last 15-20 years of the ringwidth series. For example, the current red spruce decline in New England probably began in the early to mid-1960's as evidenced by a sudden reduction in ringwidth in many trees (4). This reduction with no recovery has continued to the present time in surviving trees. The occurrence of this hypothesized pollution signal at the series end makes it susceptible to "end-effect" problems during the curve-fitting procedure. If a pollution-related ringwidth reduction coincides with a longer downward trend in ringwidth due to natural factors, the curve may track some fraction of the pollution signal. The end-effect problem also occurs because there is no information about the expected behavior of the time series off the ends, which can be used to constrain the end-fitting behavior of the growth curve. Thus, there will always be more uncertainty regarding the proper curve fit at the ends of a ringwidth series than for its interior portion. The end-effect problem will be examined in more detail later in this paper.

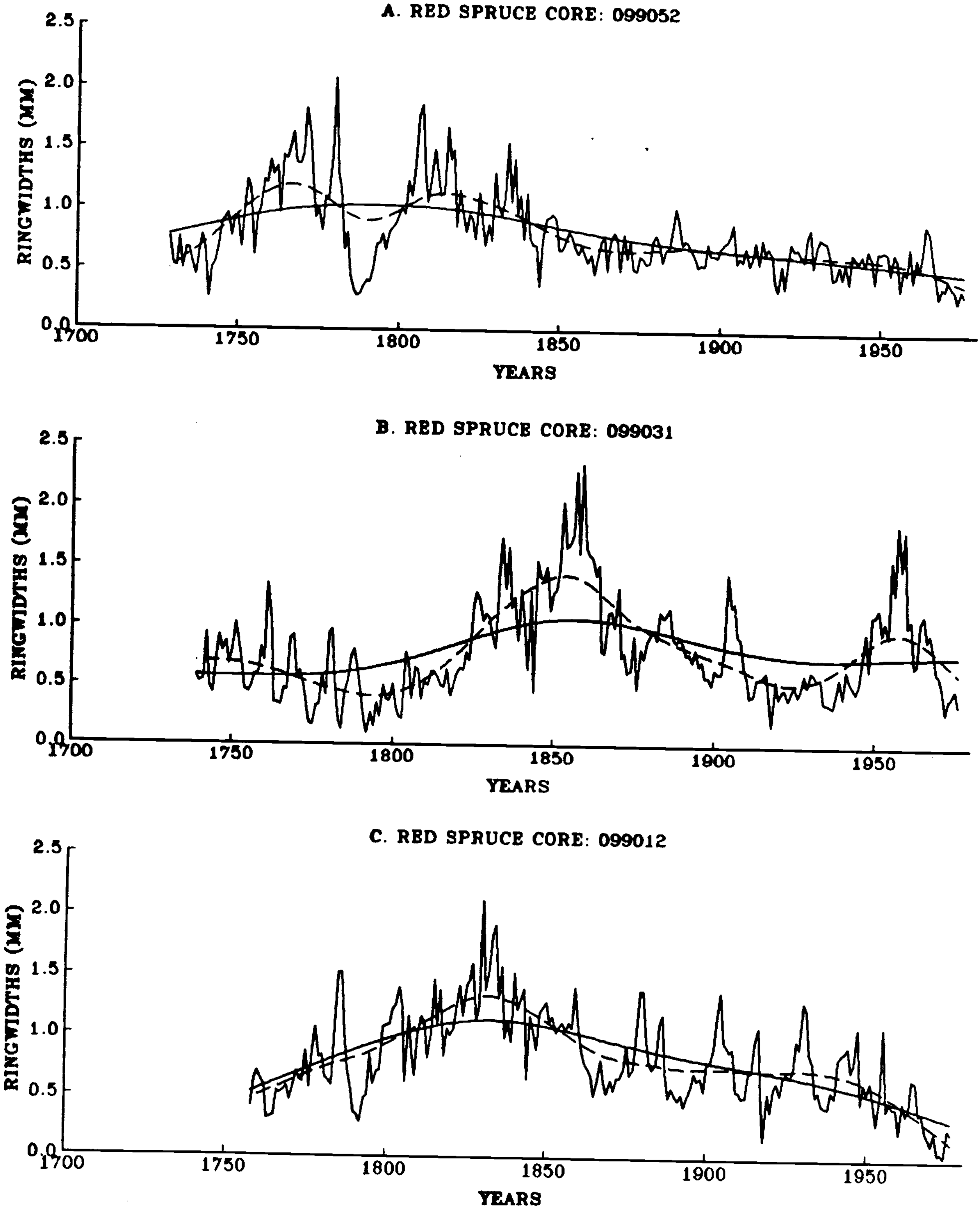
For detrending closed-canopy forest ringwidth series, the cubic smoothing spline (12) has been used with considerable success. It is more data adaptive than orthogonal polynomials and has less severe end-effect problems. In addition, the smoothing properties of this spline function can be expressed in terms of a low-pass digital filter with precisely defined frequency response characteristics. This allows the ringwidth detrending process to be based on frequency domain considerations.

A simple and objective guideline to use for spline detrending is the "trend-in-mean" concept (13). From time series theory, the lowest frequency harmonic that is resolvable in an annual ringwidth series has one complete period or cycle equal to the series length. From this definition of the resolvability limit, trend in ringwidths is defined as all variance with periods longer than the series length. Thus, the trend-in-mean concept states that time series detrending should only remove long-term variance in the mean that cannot be resolved given the length of the series being detrended. This definition of trend places no restrictions on the kind of mathematical model used for detrending as long as it adheres to the above concept. The easiest way to use the spline for stochastic detrending is to tie its frequency response characteristics directly to the series length. The 50% frequency response cutoff of the spline (12) can be set at some large fraction of the number of observations. Several different cutoff points, ranging from 50%N (half the series length) to 100%N (total series length) were investigated in (11). The best results fell in the 67N% to 75%N range based on spectral analysis of the tree-ring chronologies developed after the %N spline detrending experiments.

Figure 3 shows examples of spline detrending of three red spruce ringwidth series from the Adirondack Mountains in New York. These trees are from an area where abnormal dieback related to acid deposition is suspected. The ringwidth declines after 1960 are thought to be a manifestation of the dieback syndrome. The solid line curves are splines having a 50% frequency response cutoff of 67%N. They conform closely to the trend-in-mean concept. For comparison, a spline having a 50% frequency response cutoff of 60 years was computed for each series (the dashed-line curve). These tighter fitting splines are in the frequency response range originally advocated (12) based on "eyeball" splining experiments.

The 67%N splines show the very conservative nature of the trend-in-mean concept. Only the grossest trends are removed. Consequently, little, if any, variance in the post-1960 putative decline period is lost. In contrast, the 60-year splines fit the series more closely and, in some respects, better than the 67%N

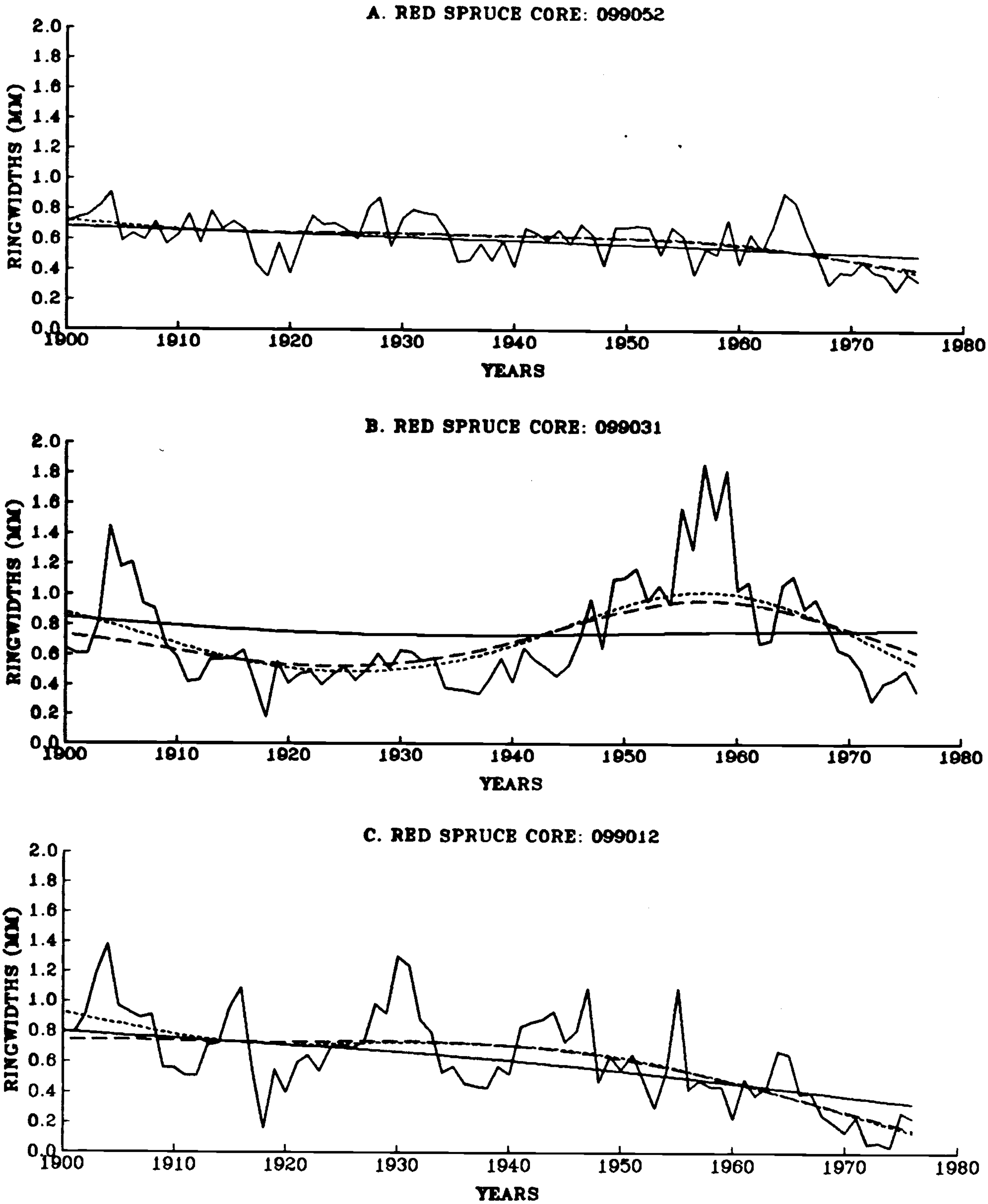
Figure 3. Examples of detrending ringwidth series using the cubic smoothing spline. The solid-line curves are splines computed using the trend-in-mean concept, in this case, 67%N where N is the series length. The dash-line curves are splines with a 50% frequency response cutoff of 60 years.


A. RED SPRUCE CORE: 099052
RINGWIDTHS (MM)
2.5
2.0
1.5
1.0
0.5
0.0
1700
1750
1800
1850
1900
1950
YEARS
B. RED SPRUCE CORE: 099031
RINGWIDTHS (MM)
2.5
2.0
1.5
1.0
0.5
0.0
1700
1750
1800
1850
1900
1950
YEARS
C. RED SPRUCE CORE: 099012
RINGWIDTHS (MM)
2.5
2.0
1.5
1.0
0.5
0.0
1700
1750
1800
1850
1900
1950
YEARS

splines. However, there is a noticeable tracking of the post-1960 data by the 60-year splines, which would result in a loss of a possible pollution signal in the standardized tree-ring indices. There is an obvious conflict between goodness-of-fit and the conservation of the suspected decline signal. On a core-by-core basis, this conflict is virtually insoluble. However, providing that a large number of ringwidth series are utilized in creating the index mean-value function and, more importantly, that the lack of fit is largely non-synchronous between series, the spline detrending method advocated here is very satisfactory. The excess error variance in the detrended tree-ring indices, which comes from non-synchronous endogenous disturbances and spline lack-of-fit, can be greatly reduced by autoregressive time series modelling without affecting the common signal (11).

The principal drawback of the spline detrending method is the way that it is tied directly to the length of each series being detrended. This means that the filtering characteristics of the spline will be more severe for shorter series than longer series using a %N criterion. To illustrate this point, the three series in Fig. 3 were cut off in 1899 leaving three ringwidth series of 77 years beginning in 1900. Each series was then detrended using a 67%N spline, which results in a 50% frequency response cutoff of 51 years. Figure 4 shows these spline curve fits along with those estimated for the longer series in Fig. 3. The short-series splines (dotted line curves) are very similar to the 60-year splines (dashed line curves) due to the closeness of their respective frequency response functions. Consequently, there is similar tracking of the hypothesized decline signal.

Figure 4. The problem of detrending short ringwidth series using the smoothing spline. The ringwidth series in fig. 3 were truncated at 1900 in this example. The solid-line and dash-line curves are identical to those in fig. 3. The dotted-line curves computed for the truncated series series used the identical 67%N criterion as the solid-line curves computed for the long series.



A. RED SPRUCE CORE: 099052
RINGWIDTHS (MM)
YEARS
B. RED SPRUCE CORE: 099031
RINGWIDTHS (MM)
YEARS
C. RED SPRUCE CORE: 099012
RINGWIDTHS (MM)
YEARS

This illustrates the need for longer series if the %N criterion is used as described.

For second-growth forests on the order of 50 to 100 years old, the conservation of the suspected decline signal will be more difficult because the length of the decline period (15-20 years) may be a significant fraction of the total series length. In addition, trees from second-growth stands often exhibit very dynamic ringwidth trends as the stand develops towards a fully stocked equilibrium state characteristic of a mature forest.

For these reasons, the search for pollution effects in old second-growth and old-growth stands (i.e. >150 years old) is likely to be easier than in young to moderately aged second-growth forests. Considerable research is still needed to determine the best way to process short ringwidth series for dendropollution studies.

MODELLING THE CLIMATIC SIGNAL IN TREE-RING SERIES FOR DENDRO-POLLUTION STUDIES

Once a mean-value function of precisely dated and standardized tree-ring indices has been created, the modelling of the climatic signal within those indices can proceed. The purpose of this exercise is to create a prediction model for tree rings from climate, which can be used to test for the intervention of a non-climatic influence on growth such as pollution. This procedure is necessary because the climatic influences on tree growth may either obscure a pollution signal or mimic its expected behavior. By predicting tree-ring indices from climate and comparing these predictions to the actual indices, the presence or absence of a possible pollution signal can be determined.

Modelling the climatic signal in tree rings is complicated by the lack of any theoretical climatic response model for trees. Inferences can be made regarding the likely set of climatic variables based upon the forest site characteristics and the species being studied. However, the "correct" climatic model is never known *a priori* for any tree-ring chronology. This lack of prior information necessitates the use of variable screening techniques for selecting a subset of predictors from a larger pool to build the climatic response model.

The construction of the climatic response model is usually based on multiple regression techniques. One technique, which has found wide application, is response function analysis (5). It utilizes a principal components regression approach to eliminate the effects of multicollinearity among the climate predictor variables and reduce the number of candidate predictors. Alternately, when multicollinearity is low, a regression screening procedure such as stepwise regression (14) is suitable. In any case, the selection of variables is inevitably based on *a posteriori* criteria such as a minimum F-level for entering variables into the model. Because such model building criteria "look at" all of the candidate variables before the final model is created, a highly significant regression model can be created by chance alone. This problem of spurious regression, which arises in part from *a posteriori* screening procedures, is discussed in detail in (15). Monte Carlo experiments (16) also indicate that the problem of spurious regression increases dramatically as the number of *candidate* predictors becomes a large fraction of the number of observations. Thus, a climatic response model that is largely spurious may be developed for a tree-ring chronology. If this is the case, then incorrect conclusions may be drawn regarding the presence or absence of a pollution signal.

The problem of spurious regression principally manifests itself through the lack of time stability in the final regression model. That is, if the spurious regression model is used to predict new values of the dependent variable, the resultant predictions will be very poor estimates of true values. In dendroclimatology, the time stability of regression equations used to reconstruct climate from tree rings is routinely tested. This procedure, known as verification (5), is based on withholding actual climatic data from the estimation of the regression model. Once the parameters of the model have been estimated, the withheld climatic data are predicted by tree rings. If the predictions are sufficiently similar to the actual data, then the time stability of the regression model has been verified. In this case, the model can be used to reconstruct past climate.

The techniques of statistical model construction and verification used in dendroclimatology can also be used in dendropollution studies. Providing that the climatic signal in the tree-ring chronology is sufficiently time stable, a climatic response model can be developed to predict tree rings from climate through the recent forest decline period. This procedure can test the hypothesis that natural environmental variables related to climate are responsible for an observed decline in radial increments.

Unlike dendroclimatic studies, the choice of the verification period in dendropollution studies must be based on prior information regarding the known or suspected beginning of the pollution effect period. For the red spruce decline in New England, this hypothesized intervention date is probably sometime after 1960. Having specified an intervention date, the verification period should begin several years _before_ that date. For example, if the pollution effect period is suspected to have begun in 1965, then the verification period should begin in, say, 1950. The reason for this extended verification period is two-fold. First, the verification period is necessary to test the time stability of the regression model as described earlier. Second, the verification period can also be used to reveal significant changes in the relationships between the climate and tree-ring variables that _may be_ reflecting the intervention of a non-climatic agent. However, it may be very difficult to separate the effects of spurious regression from non-climatic (e.g. pollution) effects if the verification period only includes the suspected pollution period. By including earlier tree-ring data in the verification period, which are believed to predate the onset of forest decline, the stability of the regression model can be tested up to the intervention date without the possibly confounding influence of the decline signal. If the regression model verifies up to the intervention date, then it is reasonable to expect the model to verify in the post-intervention period. This assumes that no other agents have intervened to disrupt the time invariance of the model. If both periods verify well, then there is no reason to pursue the pollution intervention hypothesis any farther. It has been repudiated. Conversely, a lack of model verification in the post-intervention period will provide evidence for a change in some aspect of the growth environment of the tree that may be related to pollution effects.

A lack of model verification in the pre-pollution verification period is more difficult to assess because there are many possible causes. Among these are:

1. The *a priori* chosen pool of candidate climatic predictors does not contain the correct variables to predict tree rings.

2. The *a posteriori* screening of predictors is flawed by any of a number of possible problems such as multicollinearity and insufficient degrees of freedom.

3. The tree-ring series does not contain a time stable or stationary climatic signal.

4. The impact of pollution on tree growth actually began before or during the "pre-pollution" verification period.

5. Other non-climatic influences such as natural exogenous disturbances have occurred in the pre-pollution verification period.

Remedial measures are possible for some of the above problems, but the lack of a time stable climatic signal may doom the development of a meaningful climatic response model for predictive purposes. Unfortunately, this will be the case for some (possibly many) tree-ring chronologies. In such cases, an anomalous decline in ringwidth during the hypothesized pollution impact period cannot necessarily be interpreted as being non-climatic because the trees may still be responding to climate in a non-stationary or threshold sense. That is, some climatic variable such as drought may not have any signficant impact on radial growth until it exceeds a critical threshold of severity. For example, the severe 1960's drought over the northeastern United States has been cited as a possible inducing stress mechanism of red spruce decline in New England (4).

The problem of threshold responses to climate brings in the possibility that climatic change could be responsible for red spruce decline. The concept that climatic change could be directly or indirectly responsible for forest declines was first discussed by George Hepting (17). He proposed that climatic change could create the necessary conditions for major outbreaks of decline-inducing forest pathogens. In addition, he suggested that climatic change could also induce physiogenic forest declines which are not associated with any primary pathogens. The 1960's and 1970's have been notable for anomalous climatic patterns throughout the Northern Hemisphere (18). In the United States, a series of extreme winters has occurred since 1975 that has a return time probability of more than 1000 years (19). Thus, a greater frequency of extremes in climate that cross some critical threshold for red spruce could explain the decline syndrome of that species. Wintertime damage to red spruce needles, which is associated with anomalously warm temperatures for several days in mid-winter, has been reported (20) as part of the decline syndrome. This is a clear temperature threshold phenomenon, which needs to be investigated in the context of climatic change.

The possiblity of threshold responses to climate, which may be frequency modulated by climatic change, makes the interpretation of the climatic response model verification tests more difficult. While model verification prior to the intervention date followed by non-verification after the intervention date is a good indicator of a change in the forest growth environment, it may still be difficult to infer a pollution effect. If a climate-induced forest decline is suggested by observational evidence (i.e. with foliar damage) or by association (i.e. following extreme drought), then such hypothesized threshold climatic variables need to be examined within the framework of a climatic change. If climatic change can be ruled out as a likely cause of forest decline, then pollution can be considered a strong contender, either alone or in consort with normal climatic variability, as an agent affecting tree decline and mortality.

AN EXAMPLE OF MODELLING THE DECLINE SIGNAL FOR RED SPRUCE

The principles and techniques just described for examining dendropollution hypotheses will now be utilized in an example. The tree-ring series in this example were obtained from a stand of red spruce growing at an elevation of 1150 meters in the Adirondack Mountains of northern New York. This stand, which is near Lake Arnold high up on the northeastern flanks of Mount Colden, is very near the upper elevational limit of full-sized red spruce. It is only 27.5 kilometers from Whiteface Mountain where symptoms of red spruce decline have been documented (2, 4).

The trees were cored in July 1977 for the purpose of developing a tree-ring chronology for dendroclimatic studies. The sampled trees are from a highly stratified population of dominant and co-dominant trees. Two increment cores were extracted at DBH from each of 20 trees. Of the 40 total cores, three were eliminated because of reaction wood problems that distorted the ringwidth patterns. The remaining 37 cores were cross-dated and measured following standard dendrochronological techniques (5). Due to severe ringwidth decline in the outermost years of three trees, the ringwidths of five increment cores could not be dated out to the last complete ring (1976). Those ringwidth series were truncated after 1964, 1966, 1967, 1971 and 1975, respectively. The ringwidth series range from 142 years to 297 years long with the majority lying within the 200-250 year class.

The ringwidth series (three of which are shown in Fig. 3) were standardized using spline detrending and autoregressive modelling as described earlier and in (11). For the common interval between all series of 1837-1964, the average correlation between series is 0.475 which equates to a signal-to-noise ratio of 21.7:1. Thus, there is a substantial common signal among all series of unknown composition. The tree-ring chronology mean-value function is shown in Fig. 5 for the time period 1750-1976. Prior to 1750, the chronology quickly loses statistical precision due to a rapid decline in sample size. The chronology reveals an abrupt and prolonged decrease in the tree-ring indices which appears to have begun in 1968. The pattern and timing of tree-ring index decline with no recovery is consistent with the ringwidth patterns seen in other red spruce stands exhibiting the decline syndrome (4).

As discussed earlier, there is an end-effect problem associated with detrending ringwidth series, which is due to the unknown behavior of a series off its ends. Given the problem, is it possible that the post-1967 decline pattern seen in Fig. 5 is an artifact of the end-fitting behavior of the smoothing spline? To investigate this hypothesis, the ringwidth series were successively truncated backwards on decade years and, then, detrended using the identical smoothing parameters of the splines used to detrend the full length series. The mean of the last ten years of the truncated mean-value function was compared to the mean of the same ten years of the complete series (Fig. 3) to see how much end-effect bias exists in the spline detrending method. This comparison assumes that any end-effect bias in the complete series is mainly restricted to the last 5-10 years of that series. Consequently, mean indices prior to about 1970 are assumed to be free of end-effect biuas. These pre-1970 indices will be used as controls in the search for end-effect bias in the truncated series.

Table IA shows the results of the search. Twelve truncation years beginning in 1860 and ending in 1970 were examined. The sample depth of each ten-year end period is 37 except for a portion of the 1960-69 period where it drops to 34. The end-effect bias ranges from an underestimate of -0.05 to an overestimate of +0.05 index units. The maximum underestimate is insufficient to explain the magnitude of the post-1967 decline period in the complete series. More importantly, the direction of the bias

Table 1. The end-effect bias tests of the splines used in detrending the Lake Arnold red spruce ringwidth series. The direction of bias is noted. as being either towards the long-term mean (T) or away from the long-term mean (A) where the long-term mean for tree-ring indices is equal to 1.0.

A. Spline end-effect tests of decade means having the same sample depth.

TRUNCTION YEAR	END PERIOD	COMPLETE SERIES MEAN	TRUNCATED SERIES MEAN	END-EFFECT BIAS	DIRECTION OF BIAS
1860	1850-1859	1.04	1.02	-.02	T
1870	1860-1869	0.94	0.97	+.03	T
1880	1870-1879	0.97	1.02	+.05	T
1890	1880-1889	1.02	1.06	+.04	A
1900	1890-1899	0.98	1.03	+.05	A
1910	1900-1909	1.13	1.12	-.01	T
1920	1910-1919	1.01	1.00	-.01	T
1930	1920-1929	1.03	1.00	-.03	T
1940	1930-1939	0.99	0.97	-.02	A
1950	1940-1949	0.98	0.98	.00	-
1960	1950-1959	1.07	1.04	-.03	T
1970	1960-1969	1.05	1.00	-.05	T
mean	1850-1969	1.02	1.02	.00	8/3

B. Spline end-effect tests of two high and low 10-year mean periods.

TRUNCTION YEAR	END PERIOD	COMPLETE SERIES MEAN	TRUNCATED SERIES MEAN	END-EFFECT BIAS	DIRECTION OF BIAS
1835	1825-1834	1.16	1.10	-.06	T
1845	1835-1844	0.91	0.91	.00	-

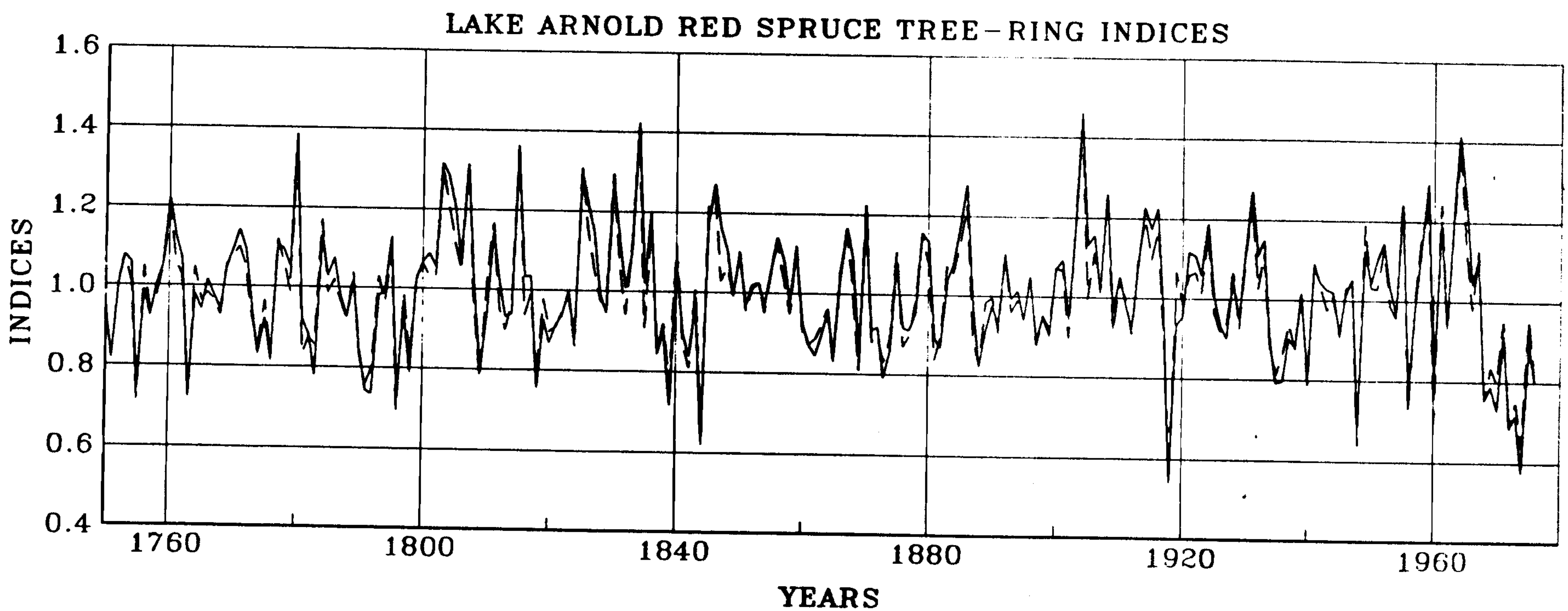
either towards (T) or away (A) from the long-term mean is most commonly towards the mean. This means that the smoothing spline is more likely to track the behavior of the data at the ends than diverge from it. This property makes it even less likely that the post-1967 decline period is an artifact. If anything, the magnitude of decline has been slightly underestimated.

One final end-effect bias test was run on two adjacent ten-year periods covering the interval 1825-1844. The mean indices in this interval most closely mimic the behavior of the 1957-1976 period. That is, the first ten years are largely above the mean and the following ten years are largely below the mean. The results of this test in Table 1B are entirely consistent with the earlier resuts. There is no evidence for an end-effect bias which could have created the post-1967 decline pattern.

Monthly mean daily temperature data were used for modelling the climatic signal in the chronology. The choice of monthly temperatures as candidate predictors of red spruce growth was based on previous dendroclimatic studies of the species in New England (21, 22). The monthly temperature data used here are divisional averages of all available single-station records for the Northern Plateau Climatic Division of New York. This divisional average record covers the period 1889-1976. Because of well documented lag reponses of tree growth to climate through physiological preconditioning (5), the monthly temperatures were adjusted into a dendroclimatic year which begins in the previous March and ends in the current September of annual ring formation. This time window spans two complete growing seasons. This resulted in a pool of 19 candidate predictors of tree growth and the loss of one year of data after developing the lagged dendro-climatic year.

Two regression and verification analyses will be described: one with existent autocorrelation left in the chronology and one with autocorrelation removed. These will be referred to as the unwhitened and prewhitened chronologies, respectively. The pre-whitened chronology was developed by modelling the chronology as an order-3 autoregressive (AR) process for the time period 1750-1960 using the minimum AIC selection criterion (23). The coefficients of the AR process were then used to prewhiten the entire series up through 1976. This method of prewhitening is based on the premise that the AR model for the 1750-1960 pre-decline period is a time invariant representation of the chronology autocorrelation structure in the absense of any anomalous decline signal. Any residual persistence in the post-1960 period may be due to the decline signal. The coefficients of the fitted AR model are: $\phi_1 = .232$, $\phi_2 = .062$ and $\phi_3 = -.138$. Prewhitening also reduces any autocorrelation in the regression residuals due to differences in persistence between the tree-ring indices and monthly temperature. The temperature data have very little, if any, autocorrelation. The prewhitened chronology is shown superimposed on the unwhitened chronology in Fig. 5. There is little difference between the two even in the anomalous post-1967 deline period. It is clear that the persistently below average 1968-1976 period is not consistent with the long-term persistence structure of the chronology. Stepwise regression analysis was used to select a subset of predictors of tree growth. The time

Figure 5. The Lake Arnold red spruce chronology used in the climatic modelling example. The solid-line plot is the chronology with existent autocorrelation left in. The dash-line plot is the same chronology after the autocorrelation has been removed by autoregressive time series modelling.


LAKE ARNOLD RED SPRUCE TREE-RING INDICES
INDICES
1.6
1.4
1.2
1.0
0.8
0.6
0.4
1760
1800
1840
1880
1920
1960
YEARS

period used in the regression analysis was 1890-1950. This allowed data in the 1951-1976 period to be used for verification tests. The minimum F-level for entering variables into the regression equation was set at 2.0.

The regression results are given in Table 2. Seven and six temperature variables were entered into the unwhitened and pre-whitened regression models, respectively. Each model explains at least half of the tree-ring chronology variance and is highly significant statistically. The prewhitened chronology model performs somewhat better in terms of R^2, R^2_a and model parsimony. However, except for an extra variable in the unwhitened model, the models are extremely similar. Note the very important contribution of antecedent temperature to radial growth. Such lagged variables do not have a strong intuitive "feel" and probably would have been ignored in a pure *a priori* model. Yet they consistently show up in *a posteriori* dendroclimatic models of red spruce growth (21, 22). Thus, there is probably a physiological basis for these relationships.

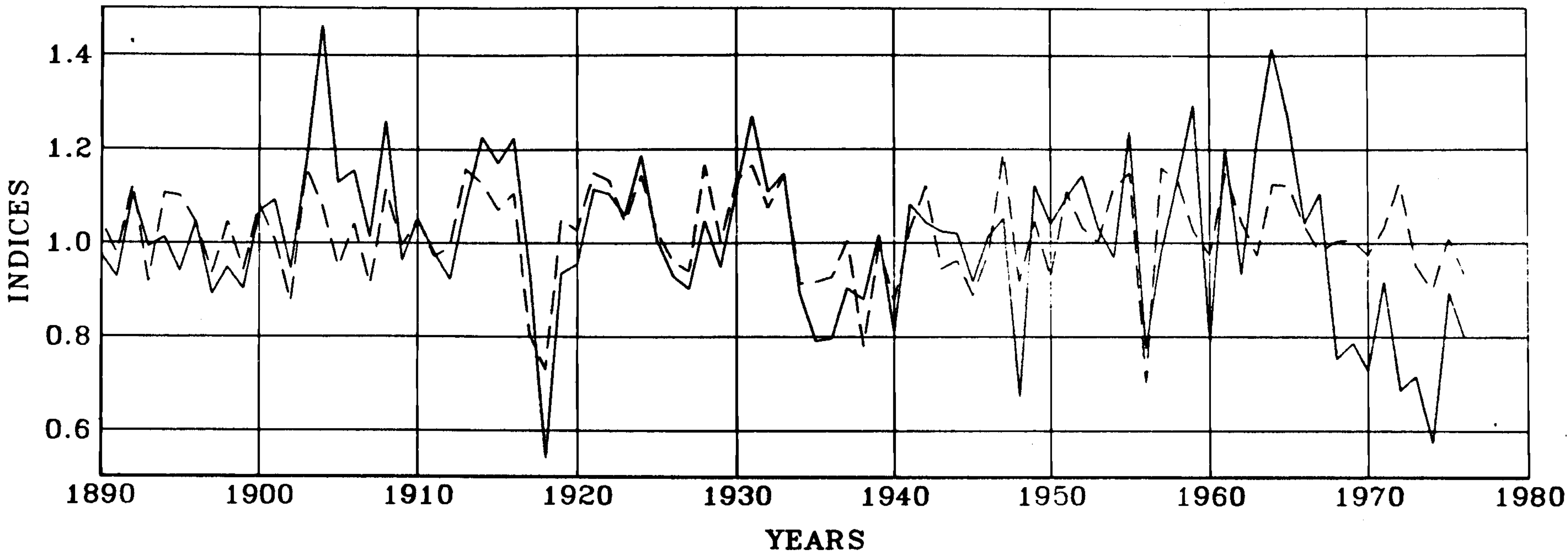
The actual and estimated tree-ring indices are shown for each model in Fig. 6, including the model predictors in the 1951-1976 verification period. The models appear to do a reasonably good job in predicting the indices up to 1967. After 1967, the predictions are noticeably inferior especially in estimating the mean level of the actual indices. These observations are confirmed by the verification test statistics in Table 3. In both the 1951-1960 and 1951-1967 periods, the difference between means ($\Delta\bar{x}$) is very small and well within the limits of chance. In addition, the product-moment correlations (r) are statistically

TABLE 2. The stepwise regression results for the unwhitened and prewhitened chronologies. The standardized regression coefficients (b) and their standard errors (se) are given for the temperature variables entered into the model. The fractional variance explained by the regression equation (R^2), the R^2 adjusted for lost degrees of freedom (R^2_a), and the residual degrees of freedom (DF) are also given below.

Variable	b	(se)	b	(se)
Previous July	-.261	(.106)	-.232	(.100)
Previous August	-.300	(.107)	-.271	(.099)
Previous October	.180	(.103)	-	
Previous November	.202	(.107)	.293	(.101)
Previous December	.291	(.099)	.337	(.094)
Current May	.155	(.103)	.214	(.098)
Current September	.209	(.105)	.213	(.097)
R^2	.502		.538	
R^2_a	.436		.487	
DF	53		54	

Figure 6. The actual and estimated red spruce indices based on a temperature response model. The model was developed using the 1890-1950 data. Model predictions run from 1951 through 1976. Solid lines are actual, dashed lines are temperature estimates.

A. ACTUAL AND ESTIMATED UNWHITENED RED SPRUCE INDICES



B. ACTUAL AND ESTIMATED PREWHITENED RED SPRUCE INDICES

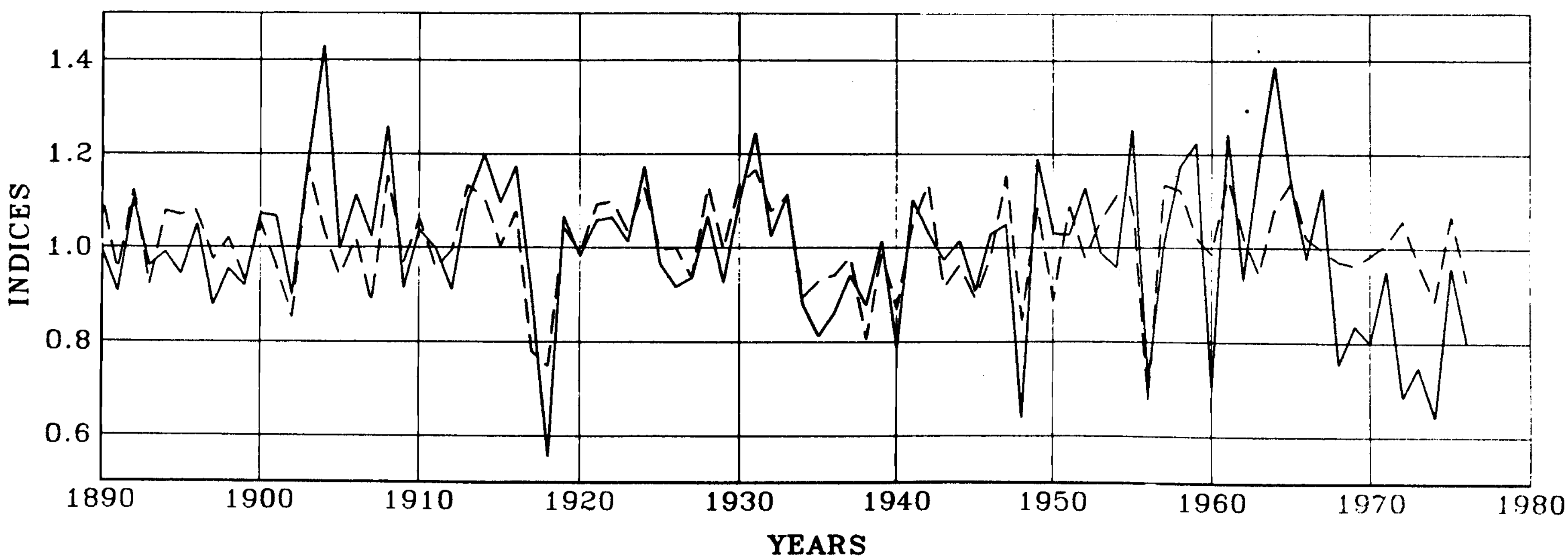


TABLE 3. The verification test results of the two regression models. The difference between the means of the actual and predicted indices ($\Delta\bar{x}$), the product-moment correlation coefficient (r), and the reduction of error (RE) are estimated for three verification periods. The asterisks indicate those statistics which are significantly different from zero ($p = .05$) using a one-tailed test. The RE has no significance test, but an $RE > 0$ is an indication of some prediction skill when coupled with a significant r.

		Unwhitened			Prewhitened		
Verification Period	N	$\Delta\bar{x}$	r	RE	$\Delta\bar{x}$	r	RE
1951-1960	10	.005	.585*	.322	-.011	.600*	.346
1951-1967	17	.046	.539*	.347	.032	.533*	.328
1968-1976	9	-.232*	.290	.148	-.184*	.490	.228

significant ($p = .05$) and the reduction of error statistics (RE) (5) are positive indicating some predictive skill for each model (24). The 1968-1976 period shows a virtual reversal of verification results. The $\Delta\bar{x}$ for each model is significantly different from zero indicating a substantial bias in the predictions of tree-ring index. The direction of bias is consistent with an abnormal decline in ringwidth as part of the red spruce decline syndrome. The r and RE also show degradation in both models. These results indicate that the observed ringwidth decline of red spruce in this stand cannot be explained by the verified climatic response models developed here. As a result, a change in the growth environment of these trees has probably occurred which had a standwide impact on the sampled trees by 1968.

This conclusion indicates that pollution is still a viable hypothesis for explaining red spruce decline. However, climatic change and threshold response to climate cannot be ruled out at this point. In this regard, the wintertime foliar damage hypothesis (20) needs to be tested within the context of climatic change. This test must examine both the recent behavior of wintertime climate in creating the conditions necessary to cause freeze damage and the long-term pattern of occurrence of this phenomenon. It should determine if climatic change has led to a higher frequency of probable freeze damage events since 1967 which can explain a substantial portion of the unexplained variance in the post-1967 tree-ring decline period. This analysis may also reveal that red spruce have developed an apparent sensitivity to wintertime freeze damage which could be related to a predisposing stress such as acid deposition or excessive nitrogen (20). Either conclusion could represent a significant advance in the understanding of red spruce decline in eastern North America.

CONCLUSIONS

A general methodology has been presented for examining dendropollution hypotheses based on dendrochronological principles and techniques. In presenting this methodology, some inherent limitations of ringwidth data have been described which require careful treatment before the tree-ring data can be interpreted. The interpretation of tree-ring variations is complex and difficult because of the high level of ignorance regarding causal mechanisms. A correlative approach such as regression analysis can be used to model natural environmental influences on ringwidth such as climate providing that the model is verified. By carefully modelling the effects of natural environmental influences on ringwidth, a much more rigorous assessment of the impact of pollution on tree growth is possible. Hopefully, these principles will provide a framework for the continuing development of dendropollution research techniques.

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REFERENCES

(1) Siccama, T.G.; Bliss, M.; Vogelmann, H.W. Bull. Torrey Bot. Club 1982, 109, 162-8.

(2) Scott, J.T.; Siccama, T.G.; Johnson, A.H.; Briesch, A.R. Bull. Torrey Bot. Club 1984, 111, 438-44.

(3) Johnson, A.H. J. Air Pollut. Control Assoc. 1983, 33, 1049-54.

(4) Johnson, A.H.; Siccama, T.G. Environ. Sci. Tech. 1983, 17, 294-306.

(5) Fritts, H.C. "Tree Rings and Climate"; Academic Press: New York, 1976.

(6) Stokes, M.A.; Smiley, T.L. "An Introduction to Tree-Ring Dating"; University of Chicago Press; Chicago, 1968.

(7) Bormann, F.H.; Likens, G.E. Amer. Scientist 1979, 67, 660-9.

(8) White, P.S. Bot. Rev. 1979, 45, 229-99.

(9) Wigley, T.M.L.; Briffa, K.R.; Jones, P.D. J. Cli. Appl. Meteor. 1984, 23, 201-13.

(10) Box, G.E.P.; Jenkins, G.M. "Time Series Analysis: Forecasting and Control"; Holden-Day: San Francisco, 1970.

(11) Cook, E.R. "A Time Series Analysis Approach to Tree Ring Standardization"; Ph.D. thesis, University of Arizona, Tucson, 1985.

(12) Cook, E.R.; Peters, K. Tree-Ring Bull. 1981, 41, 45-54.

(13) Granger, C.W. Econometrics 1966, 34, 150-61.

(14) Draper, N.R.; Smith, H. "Applied Regression Analysis"; John Wiley: New York, 1981.

(15) Barnett, T.P.; Hasselmann, K. Rev. Geophys. Space Phys. 1979, 17, 949-68.

(16) Rencher, A.C.; Pun, F.C. Technometrics 1980, 22, 49-53.

(17) Hepting, G.H. Ann. Rev. Phytopathy, 1963, 1, 31-50.

(18) Lamb, H.H. "Climate: Past, Present and Future, Vol. 2, Climatic History and the Future"; Methuen & Co.: London, 1977.

(19) Karl, T.R.; Livezey, R.E.; Epstein, E.S. Bull. Am. Meteor. Soc. 1984, 65, 1302.

(20) Friedland, A.J.; Gregory, R.A.; Karenlampi, L.; Johnson, A.H. Can. J. For. Res. 1984, 14, 963-5.
(21) Conkey, L.E. Tree-Ring Bull. 1979, 39, 29-38.

(22) Cook, E.R. In "Climate from Tree Rings"; Hughes, M.K.; Kelly, P.M.; Pilcher, J.R.; LaMarche, V.C. Jr., Eds.; Cambridge University Press, Cambridge, 1982.

(23) Akaike, H. IEEE Trans. Automatic Control 1974, 19, 716-23.

(24) Gordon, G.A.; LeDuc, S.K. In "Conference on Probability and Statistics in Atmospheric Science"; Monterey, Calif.; 1981.