TREE-RING BULLETIN, *Vol. 47, 1987*

THE DECOMPOSITION OF TREE-RING SERIES FOR ENVIRONMENTAL STUDIES

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ABSTRACT

Signal extraction in tree-ring research is considered as a general time series decomposition problem. A linear aggregate model for a hypothetical ring-width series is proposed, which allows the problem to be reduced to the estimation and extraction of five discrete classes of signals. These classes represent the signals due to trend, climate, endogenous disturbance, exogenous disturbance, and random error. For each class of signal, some mathematical/statistical techniques of estimation are described and reviewed. Except for the exogenous disturbance signal, the techniques only require information contained within the ring-width series, themselves. A unified mathematical framework for solving this decomposition problem has not yet been explicitly formulated. However, the general applicability of ARMA time series models to this problem and the power and flexibility of state space modelling suggest that these techniques will provide the closest thing to a unified framework in the future.

Die Gewinnung von Signalen aus einer Jahrringfolge wird als allgemeines Problem der Zeitreihenzerlegung betrachtet. Hierzu wird daher ein linear zusammengesetztes Modell einer hypothetischen Jahrringfolge vorgeschlagen, womit das Problem auf die Schätzung und Extraktion von fünf diskreten Klassen von Signalen reduziert werden kann. Diese Klassen repräsentieren die Signale, die durch einen Trend, durch das Klima, durch endogene sowie exogene Störfaktoren und durch einen Zufallsfehler hervorgerufen werden. Für jede Klasse werden einige mathematisch-statistische Schätzverfahren beschrieben und bewertet. Alle Verfahren benötigen nur solche Informationen, die in den Jahrringfolgen selbst enthalten sind, ausgenommen bei exogenen Störfaktoren. Bislang wurde noch kein einheitliches mathematisches Vorgehen zur Lösung dieses Zerlegungsproblems explizit formuliert. Jedoch könnte die allgemeine Anwendbarkeit von ARMA-Zeitreihenmodellen sowie die Leistungs- und Anpassungsfähigkeit von Zustandsraummodellen einem einheitlichen Vorgehen in der Zukunft sehr nahekommen.

L'extraction d'un signal dans la recherche dendrochronologique est considérée comme un problème général de désagrégation en des séries temporelles. Un modèle d'agrégation linéaire valable pour les épaisseurs des cernes est proposé, qui permet de réduire le problème à l'estimation et à l'extraction de cinq classes discontinues de signaux. Ces classes représentent les signaux dus à la tendance, au climat, à des perturbations endogènes et exogènes et à l'erreur aléatoire. Pour chaque classe de signal quelques techhniques mathématiques et statistiques d'estimation sont décrites et commises à critique. A l'exception du signal provenant de perturbations exogènes, les techniques n'exigent que les informations contenues dans les séries d'épaisseur des cernes elles-mêmes. Un cadre mathématique unifié pour résoudre ce problème de désagrégation n'a pas encore été formulé de façon explicite. Cependant la possibilité d'application des modèles ARMA à ce problème ainsi que la puissance et la flexibilité de la modélisation spatiale, suggère que ces techniques sont aptes à procurer le meilleur moyen pour utiliser un cadre unifié dans le futur.

INTRODUCTION

The information contained in annual tree rings is a valuable resource for studying environmental change. Past climate can be reconstructed from the year-to-year changes in annual ring-width and ring density (*e.g.* Fritts 1976; Schweingruber *et al.* 1978). The occurrence of previously unrecorded geomorphological events, such as earthquakes and landslides, can be inferred from anomalous changes in the ring-width pattern (*e.g.* Shroder 1980; Jacoby and Ulan 1983; Shroder and Butler 1987).

Forest stand disturbances and gap-phase dynamics can be inferred from suppression-release patterns in tree rings (*e.g.* Lorimer 1985; Brubaker 1987). And, anomalous changes in the forest environment, due perhaps to anthropogenic pollutants, can be examined based on the recent patterns of tree rings (*e.g.* Eckstein *et al.* 1983, 1984; Cook 1987; McLaughlin *et al.* 1987). This list of applications is not complete. It is only intended to show the wide range of application tree rings have for studying environmental change and disruption.

Although the use of tree rings for studying environmental change is widespread, the extraction of the desired signal from the unwanted noise can be difficult and uncertain. "Signal" is defined here, in a hypothesis testing sense, as that information in tree rings which is relevant to the study of a particular problem. In contrast, "noise" is defined as that information in tree rings which is irrelevant to the problem being studied. Quite clearly, one researcher's "signal" will frequently be another researcher's "noise". Given this reality, a tree-ring series is more appropriately thought of as being composed of several unobserved signals which become "signal" or "noise" only within the context of a specific hypothesis test or application. It is from this basis that the problem of signal extraction in tree-ring research is fundamentally related to the decomposition of the observed ring widths into a finite number of signals which represent the sum of the environmental influences on tree growth.

To provide a conceptual framework for this decomposition problem, a linear aggregate model for tree-ring series will be described. This model allows the problem to be broken down into a small number of discrete clases, each of which has some properties different from the others.

A LINEAR AGGREGATE MODEL FOR TREE RINGS

Consider a tree-ring series as a linear aggregate of several unobserved subseries. Let this aggregate series be expressed as:

$$R_t = A_t + C_t + \delta D1_t + \delta D2_t + E_t$$

where R_t is the observed ring-width series; A_t is the age-size related trend in ring-width; C_t is the climatically related environmental signal; $D1_t$ is the disturbance pulse caused by a local endogenous disturbance; $D2_t$ is the disturbance pulse caused by a standwide exogenous disturbance; and E_t is the largely unexplained year-to-year variability not related to the other signals. The terms "endogenous" and "exogenous" are used to differentiate forest disturbances that arise from processes dependent on the forest trees themselves (endogenous) from disturbances that arise from processes independent of the forest (exogenous). Thus, gap-phase stand dynamics is a dependent or endogenous process in the forest while insect attack is an independent or exogenous process. In this sense, these terms have the same "dependent" versus "independent" variable meanings used in econometrics (Granger and Newbold 1977; Koutsoyiannis 1977). The δ associated with $D1_t$ and $D2_t$ is a binary indicator of the presence ($\delta = 1$) or absence ($\delta = 0$) of either class of disturbance in the ring widths. Thus, A_t, C_t, and E_t are assumed to be continuously present in R_t while $D1_t$ and $D2_t$ may or may not be present depending on whether or not the intervention of a disturbance has occurred at some time t. Some general properties of these subseries will now be described which are pertinent to the problem of estimating each one as an discrete process.

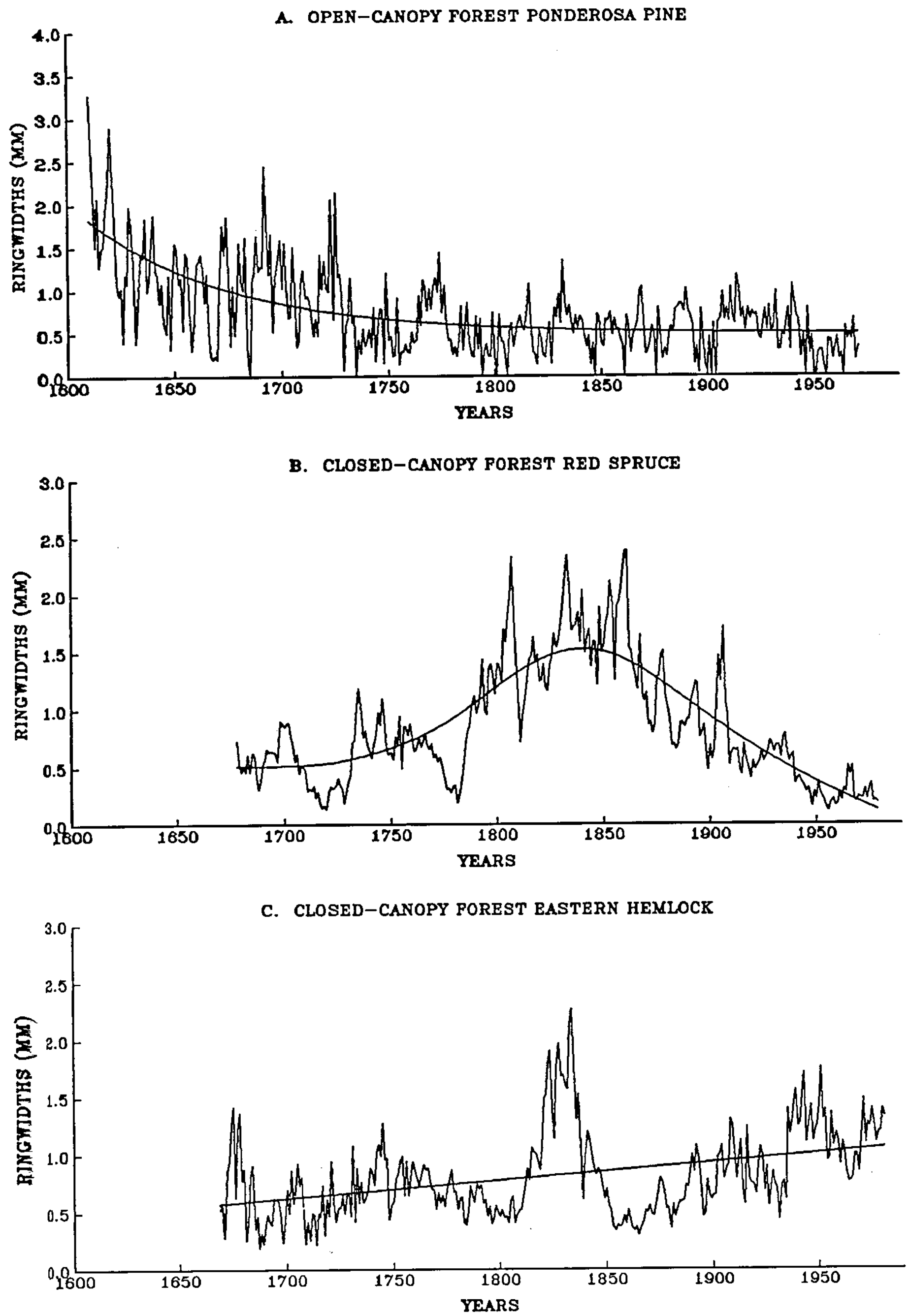

Figure 1. Three examples of the kinds of age-size trends that can be found in ring-width series of open-canopy and closed-canopy forest trees. The smooth curves are intended to highlight the general character of the trends, not model them explicitly.

A_t is a non-stationary process which reflects, in part, the geometrical constraint of adding a volume of wood to a stem of increasing radius. When this constraint is the principal source of the trend, A_t will exhibit an exponential-like decay as a function of time. This form of trend is most commonly found in trees growing in reasonably open environments where competition for light is minimal. Figure 1a shows one such ring-width series from an open-canopy, seminarid site ponderosa pine (*Pinus ponderosa* Laws.). More frequently, the behavior of A_t is strongly influenced and distorted by competition and disturbances in the forest. Figure 1 shows two typical examples of this problem. The ring-width series in figures 1b and 1c are from a red spruce (*Picea rubens* Sarg.) and an eastern hemlock (*Tsuga canadensis*)L.) Carr.), respectively. Each series shows the effects of suppression-release which are common in stands of shade-tolerant species such as spruce and hemlock. It is clear from Figure 1 that there is no expected shape for A_t in the most general sense. That is, A_t does not necessarily arise from any family of deterministic growth curve models such as the negative exponential curve. Rather, A_t should be thought of as a non-stationary, stochastic process which may, as a special case, be modelled as a deterministic process (*e.g.* Fritts *et al.* 1969).

C_t represents the combined influence on tree growth of all climatically related environmental variables save for those associated with stand disturbances. Typical variables composing C_t are precipitation, temperature, and heat sums as they affect available soil moisture supply, evapotranspiration demand, and phenology. These variables are assumed to be broadscale in that all the trees in a stand will be affected similarly by the same set of variables. Thus, C_t is a signal in common to all sampled trees in a stand. Some climatic variables that have been used to model C_t are monthly temperature and precipitation (Fritts 1976), and drought indices (Cook and Jacoby 1977). These variables can usually be regarded as stationary stochastic processes although they may be persistent in an autoregressive sense (Gilman *et al.* 1963). Methods for modelling the composition of C_t in tree-ring chronologies are many and well researched (*e.g.* Fritts *et al.* 1971; Meko 1981; Guiot 1982, 1985). A review of these methods is outside the aims of this paper. C_t will be regarded, here, simply as the common climatic signal among all sampled trees without regard to its makeup.

$D1_t$ represents the characteristic response of a tree to a local, or endogenous, disturbance in the forest. This response will be referred to as a *pulse* due to its expected transience and eventual disappearance in the ringwidths. Endogenous disturbances are frequently a consequence of gap-phase stand development in which individual trees are removed from the canopy by processes that do not affect the stand as a whole (White 1979). This pattern of stand development creates patterns of suppression and release in the ring widths of trees adjacent to the trees removed from the canopy. See Figure 1b for a typical pattern of ring-width variation caused by gap-phase stand dynamics.

An important property of endogenous disturbances, which is relevant to the decomposition of R_t, is the likelihood that truly endogenous disturbances will be random events both in space and time within a forest stand of sufficient size. This means that the endogenous disturbance pulse in the ring widths of a given tree will be largely uncorrelated with endogenous disturbance pulses in other trees, when those trees are sufficiently far from the disturbance influence. An example of this property is shown in Figure 2 for three red spruce trees from the same stand. Each series has divergent or out-of-phase ring-width fluctuations lasting 20 or more years in length, which are likely to be due to endogenous disturbance events.

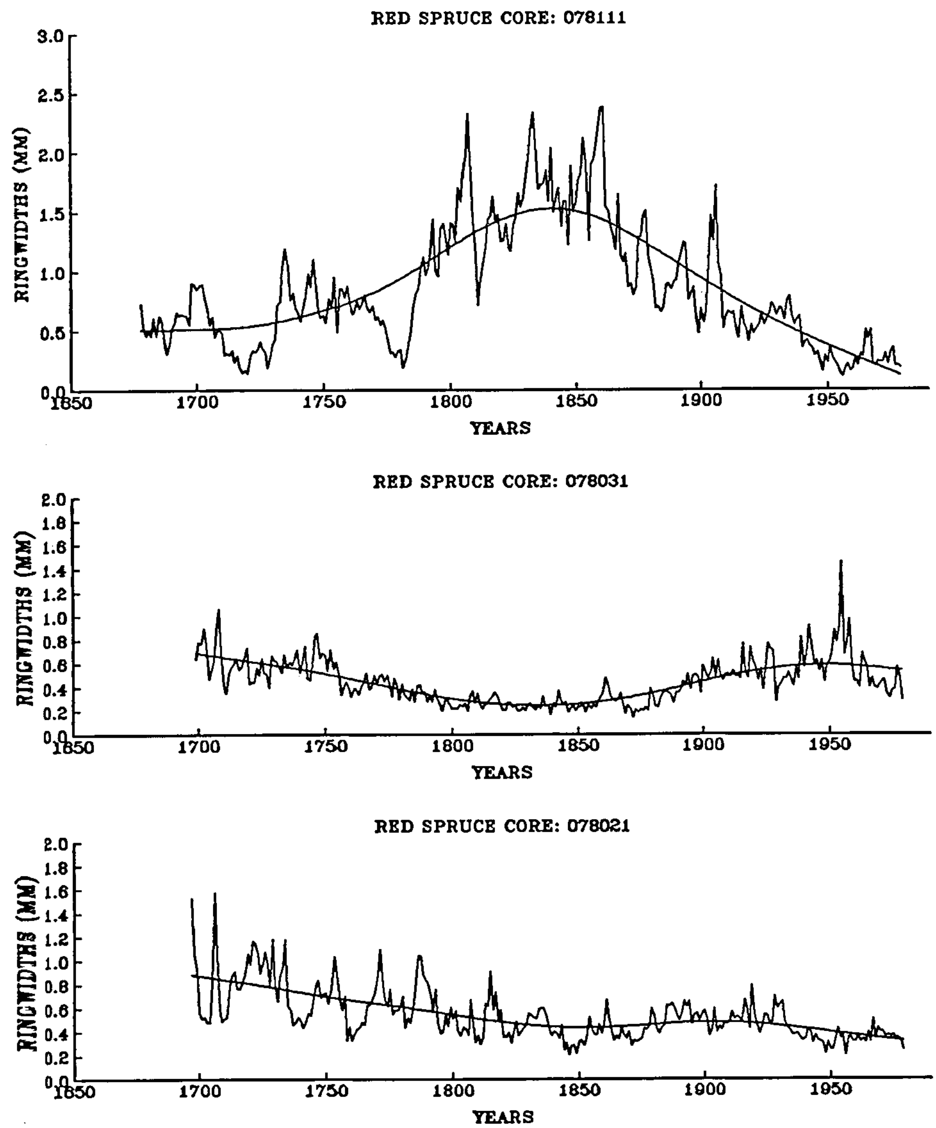

Figure 2. Three ring-width series, from the same stand of red spruce, showing endogenous disturbance effects. Note the large out-of-phase fluctuations between series due to competition effects and gap-phase stand dynamics.

$D2_t$ represents the characteristic response of a tree to a standwide disturbance. Agents capable of producing a standwide disturbance are fire, wind, insects, disease, logging, and pollution, to name just a few. The pertinent feature of the resultant exogenous disturbance pulse, which can differentiate it from that caused by an endogenous disturbance, is the synchrony in time of this event in all sampled trees from a stand. This indicates that $D2_t$ will be a common feature among all trees, unlike $D1_t$. Figure 3 shows some examples of an exogenous disturbance pulse in the ring-

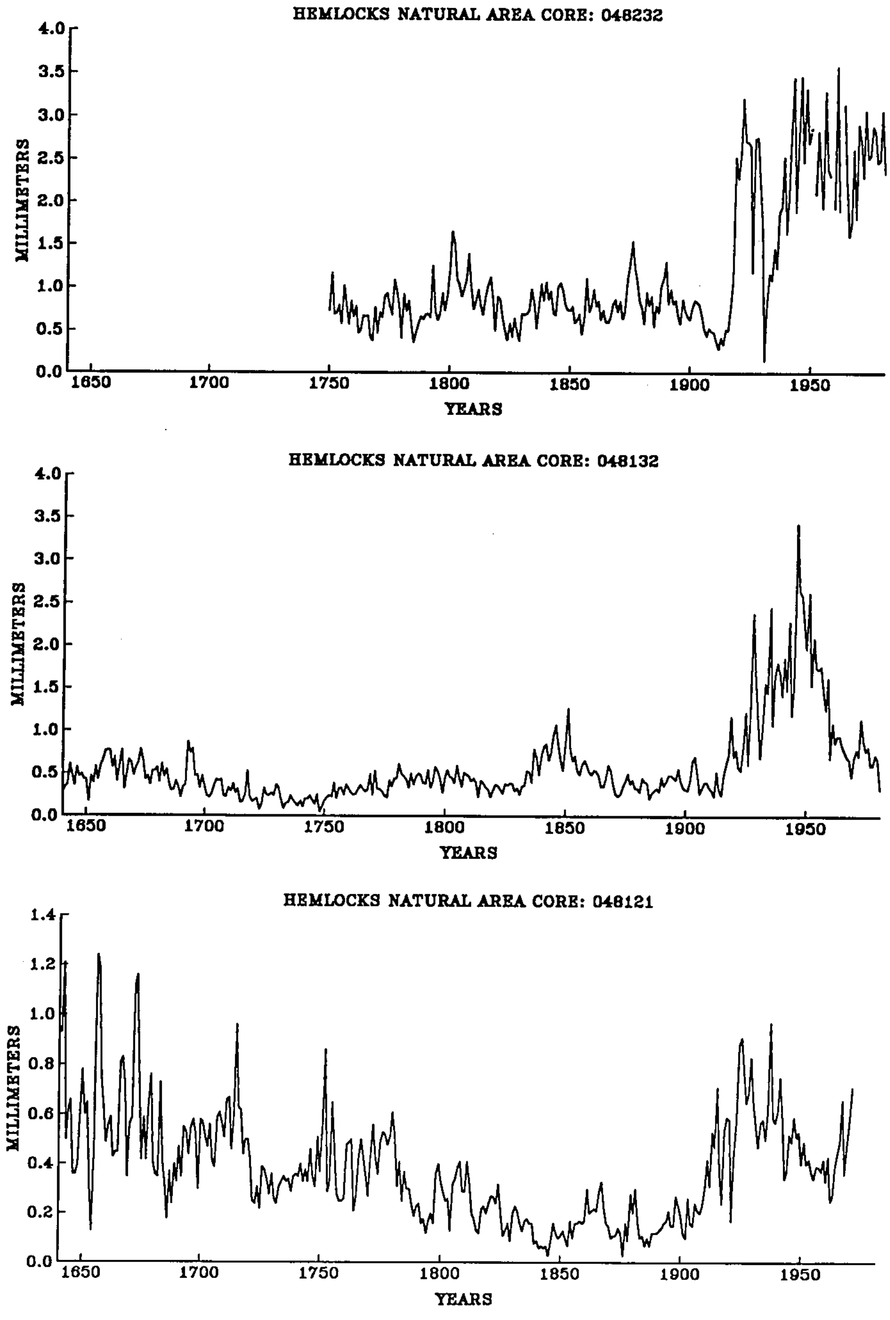

Figure 3. Three ring-width series, from the same stand of eastern hemlock, showing an example of an exogenous disturbance effect. Note the large release in all 3 series in the early 1900's following documented logging of the surrounding forest.

widths of three trees, which were all influenced by logging activity in the early 1900's. Note the sudden and synchronous increase in ring-width after about 1910 in all three series.

E_t represents the unexplained variance in the ring-width series after the contributions of A_t, C_t, $D1_t$, and $D2_t$ have been taken into account. Some likely sources of E_t are microsite differences within the stand, gradients in soil characteristics and hydrology, and measurement error. E_t is assumed to be serially uncorrelated within and spatially uncorrelated between trees in the stand.

The conceptual model for ring widths, based on the linear aggregate model, indicates that a ring-width series may be broadly decomposed into a trend component (A_t), two common signal components (C_t and $D2_t$), and two unique signal components ($D1_t$ and E_t). This breakdown into discrete classes assumes that there is no covariance between any of the components. That this assumption will not always hold is apparent by considering the problem of separating the trend component, A_t, from either of the disturbance pulses, $D1_t$ and $D2_t$. If the response time of a tree to either kind of disturbance is short relative to the length of the ring-width series, than A_t may be differentiated from $D1_t$ and $D2_t$ within the limits of the method used to estimate A_t. However, if the ring-width series is short relative to the transient response to either kind of disturbance, than the trend component may, in fact, be largely composed of $D1_t$ and/or $D2_t$. In this case, it may be impossible to factor out either disturbance pulse unless *a priori* assumptions are made about the expected shape of A_t.

The estimation and removal of A_t from a ring-width series has been a procedure of dendrochronology since its modern day development by A. E. Douglass (1914, 1919). This procedure is known as *standardization* (Douglass 1919; Fritts 1976). Standardization transforms the non-stationary ring-widths in a new series of stationary, relative tree-ring indices that have a defined mean of 1.0 and a constant variance. This is accomplished by dividing each measured ring-width by its expected value, as estimated by A_t. That is,

$$I_t = R_t / A_t$$

where I_t is the relative tree-ring index. Division is used instead of differencing to produce indices because ring-width series are heteroscedastic. That is, the variance of ring-widths in a given time period is proportional to the mean of those ring-widths. Monserud (1986) shows, by letting $I_t = A_t + \epsilon_t$, that tree-ring indices are simply weighted residuals from the growth trend having the form

$$I_t = 1.0 + \epsilon_t / A_t$$

This weighted form of residual serves to stabilize the variance. It is also clear from this derivation, that the expected value of tree-ring indices is 1.0.

The relationship between the mean and variance in ring widths is linear when the mean and its standard deviation is compared over time. Figure 4a shows a plot of decade-mean ring widths versus their standard deviations for a collection of lodgepole pine ring-width series. The positive correlation (r = .67) between the two is quite apparent. Figure 4b shows the same data after the ring-width series have been standardized using negative exponential and linear regression curves. The correlation between mean and standard deviation (r = .08) is now largely gone. The existence of a few remaining large standard deviations in figure 4b probably reflects poor goodness-

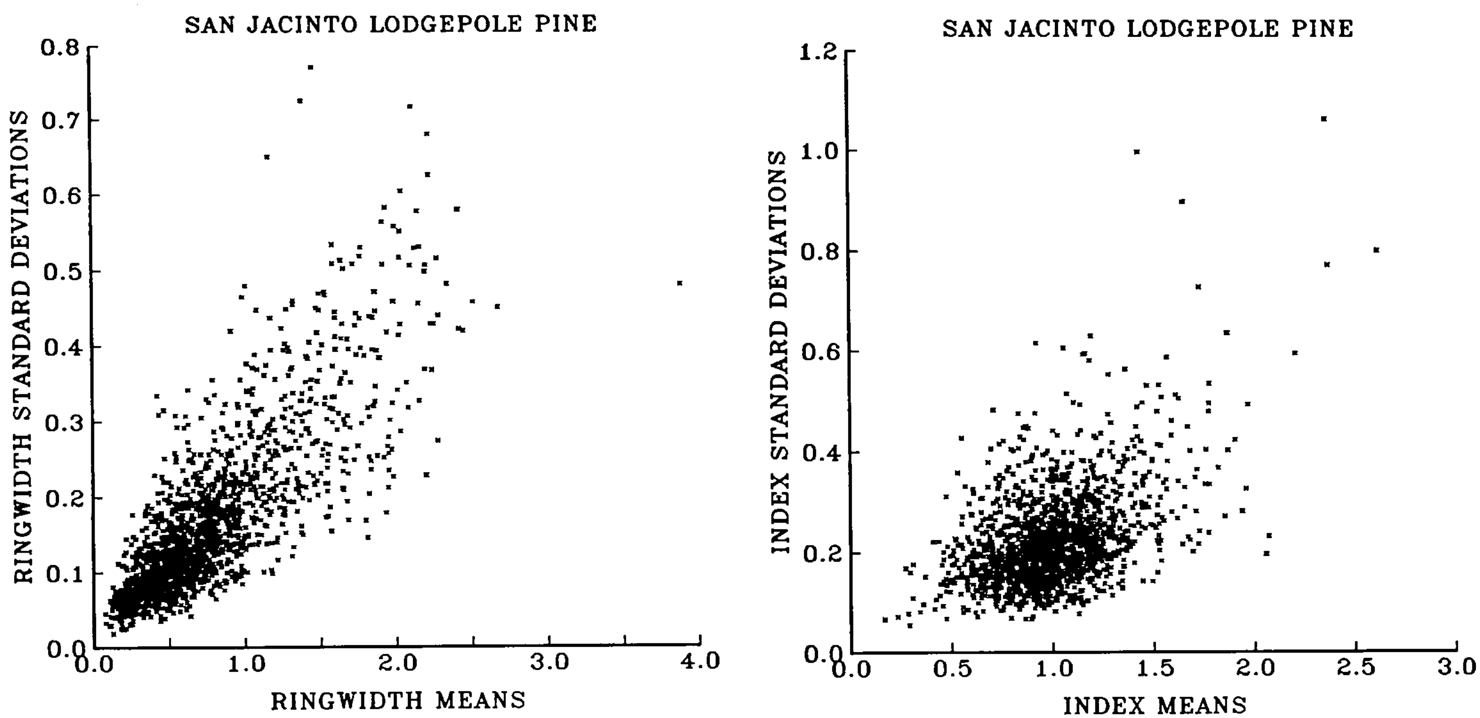

Figure 4. The relationship between the mean and the standard deviation of ring widths (A) and standardized indices (B) for a lodgepole pine (*Pinus contorta* Dougl.) tree-ring site. Each point represents the mean and standard deviation for a non-overlapping 10-year period. The correlation of mean versus standard deviation in scatterplot A is r=.67, while that is scatterplot B is r=.08.

of-fit of the growth curve in some time periods. Cook (1985) pointed out that the degree to which the variance of tree-rings is stabilized by standardization is dependent on how close the growth curve passes through the local mean of the ring widths. Another way of stabilizing the variance is by transforming the ring widths to logarithms. In this case, the resultant indices are computed by subtracting A_t from R_t, not by dividing as above. This follows from the mathematical equality between dividing two numbers or subtracting their logarithms.

Because tree-ring indices are stationary processes, the index series of many trees from a site can be averaged together to form a mean-value function. The mean-value function of tree-ring indices is frequently used to study past climate (Fritts 1976). When climate (i.e. C_t in the linear aggregate model) is the signal of interest, all other information in the ring-widths (*i.e.* A_t, $D1_t$, $D2_t$, and E_t) is considered as noise and either discarded in the estimation of A_t or minimized through averaging into the mean-value function. However, the method chosen to standardize tree-ring series for climate studies may not be appropriate for other environmental studies. For example, Cook and Peters (1981) and Blasing *et al.* (1983) advocated using a cubic smoothing spline with a 50% frequency response cutoff of 50-80 years as a method for standardizing ring-widths for climatic studies. Using this method of standardization would effectively lump A_t, $D1_t$, and $D2_t$ into the general trend component due to the rather flexible nature of this smoothing spline. It would be difficult to decompose this composite component into its constituent elements.

As noted earlier, the salient feature of endogenous disturbance component $D1_t$, which ultimately can allow its decomposition from R_t, is its random occurrence in space and time in forest stands. This property suggests that $D1_t$ can be modelled as a persistent or autocorrelated form of E_t in the sense that both are caused by random effects in the forest. This concept will be exploited later as part of an estimation procedure for $D1_t$. Unfortunately, the same cannot be said for exogenous disturbance component $D2_t$ because, by definition, it is a common feature among all sampled trees. Because of this property, the decomposition of $D2_t$ from R_t cannot be guaranteed unless prior information is available about the occurrence of an exogenous disturbance; or additional tree-ring data from unaffected, adjacent stands are available for comparison (*e.g.* Nash *et al.* 1975; Jacoby and Ulan 1983; Swetnam 1987).

Given this lengthy introduction of the tree-ring decomposition problem, some methods of estimating the signals will be briefly described. The approach taken will be a stepwise process starting with the estimation and removal of A_t followed by the estimation of the common signal, C_t, the joint estimation of $D1_t$ and E_t, and, finally, the estimation of $D2_t$.

SOME ESTIMATION PROCEDURES FOR THE DECOMPOSITION PROBLEM

1. Estimation of the non-stationary age-size trend: A_t

There are many methods available for estimating A_t. They fall into two general classes: deterministic and stochastic. The simplest deterministic model is the linear trend model, viz.

$$A_t = b_0 + b_1X_t \qquad 1.0$$

where b_0 and b_1 are the y-intercept and slope of the fitted linear regression line, and X_t is time in years from 1 to n. The slope coefficient, b_1, may be constrained to be negative or zero if the *a priori* expectation of A_t requires it. However, as noted earlier, A_t may also be negative exponential in form because of the "geometrical constraint" argument. Therefore, Fritts *et al.* (1969) suggest fitting the modified negative exponential curve of the form

$$A_t = \alpha \exp^{-\beta t} + k \qquad 1.1$$

where α, $-\beta$, and k are coefficients of this non-linear regression function, all a function of time, t. Other functions have been used for estimating A_t, such as the power function (Kuusela and Kilkki 1963)

$$A_t = \alpha t^{-\beta} \qquad 1.2$$

the generalized exponential function (Warren 1980)

$$A_t = \alpha t^{\beta} \exp^{-ct} \qquad 1.3$$

and the Weibull probability density function (Yang 1979)

$$A_t = \alpha t^{\alpha-1} \beta^{-\alpha} \exp[-(t/\beta)^{\alpha}] \qquad 1.4$$

All of these deterministic models produce monotonic or unimodal curves, which clearly require that the underlying age trend is simple in form. Thus, they are most appropriate for open-canopy stands of undisturbed trees and for young trees with strong juvenile age trends. And it is also clear that these models only depend on time, t, for predictive purposes. Hence, they are deterministic. The latter functions (equations 1.2-1.4) have not been used much in dendrochronology, although their use in forest mensuration to estimate growth increment functions is more common (Federer and Hornbeck 1987).

Another family of deterministic age trend models is found in polynomial detrending (Jonsson and Matern 1974; Fritts 1976). This model for A_t has the form

$$A_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \ldots + \beta_p t^p \qquad 1.5$$

This method is not based on any *a priori* age trend model. Rather, a best-fit, order-p polynomial, which is initially unknown, is fit to a ring-width series based on the behavior of the ring-width series alone. In this sense it is far more data-adaptive than the previous models, although it still maintains its dependence on time alone for predictive purposes. Polynomial detrending of the form above suffers from potentially severe end-fitting problems and poor local goodness-of-fit (Cook and Peters 1981; Cook 1985). For these reasons, it is not recommended as a general method for detrending ring-width series.

Another method of removing age trends is the "corridor" method (Shiyatov and Mazepa 1987), which is based on generating smooth curves of the maximal and minimal possible ring widths for each series as a function of time. It replaces a time-dependent mean (i.e. the normal growth curve) with a time-dependent range. This is seen in the formula for "corridor" indices as

$$I_t = (R_t - A_t)/(B_t - A_t) \qquad 1.6$$

where A_t and B_t are the minimal and maximal possible ring widths, respectively, and I_t and R_t are as previously defined. Whereas tree-ring indices computed from a single growth curve are (effectively) percentage departures from expected ring width, the "corridor" indices are (effectively) percentages of the expected range in ring width.

Alternately, stochastic methods of detrending may be used. Low-pass digital filtering (Briffa *et al.*, 1983; 1987) and the cubic smoothing spline (Cook and Peters 1981) are two such methods. Digital filtering typically involves passing an odd-numbered set of symmetrical, low-pass filter weights over a ring-width series to produce a smoothed estimate of the actual series. This is accomplished as:

$$A_t = \sum_{i=-n}^{+n} w_i R_{t+i} \Big/ \sum_{i=-n}^{+n} w_i \qquad 1.7$$

where there are $2n+1$ filter weights. From eq. 1.7, it is clear that this digital filter is a centrally weighted moving average of the actual data. The symmetry of the filter preserves the original phase information in the time series. See Mitchell *et al.* (1966) and Fritts (1976) for more detail on the use of digital filters in time series analysis.

The degree of smoothness of the filter estimates of A_t depends on the frequency response of the filter weights. Because there is often little theoretical basis for selecting the "proper" degree of curve flexibility or data smoothing, any chosen digital filter can be rather difficult to justify. Briffa *et al.* (1983) used *a priori* information about stand management practices in Europe to select the frequency response for their low-pass filter used in estimating A_t. Their selection criterion is based on the concept that the unwanted "noise" in the ring-widths is "frequency dependent" (Briffa *et al.* 1987). In this case, it was felt that the "noise" was largely restricted to wavelengths longer than about 50 years. A similar determination was made by Cook and Peters (1981) and Blasing et al. (1983), based on using the cubic smoothing spline as a digital filter on ring-widths from North American trees. However, the filters advocated by these studies may be too flexible for disaggregating A_t from the $D1_t$ and $D2_t$.

A quite different stochastic estimate of A_t is possible by using exponential smoothing (Barefoot *et al.* 1974). This smoothing function consists of two components: an average $\bar{R}_t$, and a lag correction for trend $\bar{\bar{R}}_t$. This is expressed as

$$A_t = \alpha\bar{R}_t + (1-\alpha)\alpha\bar{\bar{R}}_t \qquad 1.8a$$

where A_t is the smoothed estimate for year t,

$$\bar{R}_t = \alpha(R_{t-1}) + (1-\alpha)\,(\bar{R}_{t-1}) \qquad 1.8b$$

and

$$\bar{\bar{R}}_t = \alpha(R_t - R_{t-1}) + (1-\alpha)/\alpha \bullet (\bar{\bar{R}}_{t-1}) \qquad 1.8c$$

The quantity α is a weighting factor that determines the degree of smoothing. Barefoot *et al.* (1974) selected $\alpha = 0.2$ to smooth their ring widths, which allows the previous 10-15 years of data to influence the current estimate of A_t.

In contrast to the symmetrical digital filter, the exponential smoother is a one-sided, causal filter (Robinson and Treital 1980) that only relies on current and prior values in its estimation. Unlike weighted symmetrical filters, which do not distort the phase information in the indices, exponential smoothing affects the phase because of its one-sided form. Although this may seem undesirable, trees also have the capacity to distort phase information because of the one-sided way that they grow through time. Thus, the exponential smoothing filter is actually more biologically realistic then symmetrical filters and has the capacity to correct for phase shifts caused by tree growth. However, the selection of a α may be series dependent and difficult to select. In this sense, it has the same problem as digital filtering.

Recently, Visser and Molenaar (unpubl. man.) have tested a promising new stochastic trend estimation method based on a time-dependent linear trend model. This method uses equation 1.1 as the trend model, but allows both the slope (b_1) and intercept (b_0) terms to vary through time as random walks. This is accomplished by casting the problem into "state-space" form and using the Kalman filter recursion to solve for the best fit stochastic trend, in a prediction mean-square error sense. This model has the form

$$b_{0,t} = b_{0,t-1} + b_{1,t-1} + \eta_t \qquad 1.9a$$

$$b_{1,t} = b_{1,t-1} + \zeta_t \qquad 1.9b$$

when η_t and ζ_t represent the noise processes associated with the estimates of $b_{0,t}$ and $b_{1,t}$ (Visser and Molenaar, unpubl. man.). In adapting this model to tree rings, the ring widths are usually transformed to logarithms to achieve a linear model. Then, the ring width can be expressed as the sum of the stochastic trend plus noise as

$$R_t = b_{0,t} + \epsilon_t \qquad 1.10$$

In this case, $\epsilon_t = I_t$, the tree-ring indices. The noise terms η_t, ζ_t, and ϵ_t are assumed to be independent of each other. Although the slope and intercept noise variances are assumed known in the Kalman filter recursion, they can be objectively estimated by the method of maximum likelihood. If the variances of η_t and ζ_t equal zero, then model 1.9 defaults to a simple deterministic linear trend model (equation 1.1). Examples provided by Visser and Molenaar (unpubl. man.) indicate that the method can work very well in some cases and has the capacity to respond quickly to sudden changes in ring width possibly caused by disturbances.

Another method of stochastic detrending is based on differencing (Box and Jenkins 1976). In this approach, a ring-width series is considered as a random walk with deterministic drift. This process has the form

$$R_t = R_{t-1} + e_t + \delta \qquad 1.11$$

where R_t is the observed ring-width, e_t is a serially uncorrelated random shock, and δ is the deterministic drift of the process. By taking 1st-differences of R_t (usually after logarithmic transformation) as

$$\nabla R_t = R_t - R_{t-1} \qquad 1.12$$

the deterministic drift, which imparts linear trend to the R_t, is nothing more than the arithmetic mean of ∇R_t. The advantage of differencing lies in its simplicity and total objectivity, while its disadvantage lies in the lack of an explicit estimate of A_t. Differencing has only recently been applied to the problem of tree-ring detrending and standardization (Van Deusen 1987; Guiot 1987). Because of this and its importance in autoregressive-integrated moving average (ARIMA) time series modeling (Box and Jenkins 1976), it deserves additional research and testing.

The estimation of A_t or, equivalently, the removal of trend clearly remains somewhat arbitrary in the sense that there are many possible ways of removing time series non-stationarity. Whatever method is chosen should be based on as much initial insight as possible into the characteristics of the ring-width series and the eventual goal of the decomposition (*i.e.* the definitions of signal and noise).

2. Estimation of the stationary common signal: Ct

Once a collection of ring-width series has been detrended and indexed into a new ensemble of tree-ring indices, the estimation of the common signal, C_t, can proceed. As mentioned earlier, tree-ring indices can be treated as stationary, stochastic processes which allows them to be treated as a collective ensemble of realizations containing both a common signal in the form of C_t (and perhaps $D2_t$) and signals unique to the individual series ($D1_t$ and E_t).

The classical method of estimating C_t is by averaging the ensemble of detrended tree-ring indices across series for each year using the arithmetic mean (Fritts 1976). This produces a time series mean-value function that concentrates the common signals (C_t and $D2_t$) and averages out the noise ($D1_t$ and E_t). A measure of the strength of the resultant estimate of the common signal is the signal-to-noise ratio (SNR) and related statistics (Fritts 1976; Wigley *et al.* 1984).

Other more involved methods are available for computing the mean-value function. If there are suspected outliers, or extreme values, in the tree-ring indices, then a robust mean such as the biweight mean (Mosteller and Tukey 1977) can be used in place of the arithmetic mean. When outliers are present, the arithmetic mean is no longer a minimum variance estimate of the population mean nor is it guaranteed to be unbiased. In contrast, robust means automatically discount the influence of outliers in the computation of the mean and, thus, reduce the variance and bias caused by the outliers. The use of a robust mean tacitly admits the likelihood of endogenous disturbance effects in the tree-ring indices. Such effects are likely to act as outliers because, as defined earlier, endogenous disturbances are random events in space and time. Extensive use of the biweight robust mean on closed-canopy forest tree-ring data (Cook 1985) revealed that approximately 45% of the yearly means of 66 tree-ring chronologies showed some reduction in error variance using the biweight robust mean. This resulted in an average error variance reduction of about 20% in the robust mean-value functions compared to those based on the arithmetic mean. These results indicate the high level of outlier contamination in closed-canopy forest tree-ring data that can corrupt the common signal due to climate if unattended.

Shiyatov and Mazepa (1987) and Mazepa (1982) describe another method of computing the mean-value function, which is based on examining the frequency distribution of the individual indices for each year. If the distribution is symmetrical and unimodal, the arithmetic mean is computed. However, if the distribution appears to be bimodal or multimodal, then the distribution is tested for a mixture of two or more normal distributions. If this hypothesis is accepted, the mean value of the maximal grouping is used for that year.

The computation of the mean-value function, whether by arithmetic or robust means, is easily done with the tree-ring indices. However, if the autocorrelation within each series is high, than a more statistically efficient estimate of the mean-value function (*i.e.* one with a higher SNR) is possible, in many cases, through the use of time series modelling and prewhitening techniques. Tree-ring series have an autocorrelation structure that allows the estimation of common signal to be broken down into a two-stage procedure (Cook 1985; Guiot 1987), based on autoregressive- moving average (ARMA) time series modelling (Box and Jenkins 1976).

Tree-ring indices can be expressed, in difference equation form, as an autoregressive-moving average (ARMA) process of order p and q, *viz.*

$$I_t = \phi_p I_{t-p} + \ldots + \phi_1 I_{t-1} + e_t - \Theta_1 e_{t-1} - \ldots - \Theta_q e_{t-q} \qquad 2.1$$

where the e_t are serially random inputs or shocks that drive the tree growth system as reflected in the tree rings, the ϕ_i are the p autoregressive (AR) coefficients, the Θ_i are the q moving average (MA) coefficients that produce the characteristic persistence or memory seen in the I_t. Equation 2.1 can be simply re-expressed in polynomial form using the backshift operator, B, as

$$I_t = [\Theta(B) / \phi(B)] e_t \qquad 2.2$$

where: $\phi(B) = 1 - \phi_1 B - \ldots - \phi_p B^p$ and $\Theta(B) = 1 - \Theta_1 B - \ldots - \Theta_q B^q$ (Box and Jenkins 1976). On an individual series basis, the e_t are assumed to be composed of inputs due to climate (the C_t) and those due to disturbances and random variability (the $D1_t$ and E_t). Component A_t is assumed to be either non-existent in the raw ring-width series in total or for certain periods (Guiot 1987) (*i.e.* $I_t = R_t$), or to have been removed by detrending or differencing. Extensive ARMA modelling of chronologies by Rose (1983) and Monserud (1986) indicate that western North American conifers are most commonly ARMA (1,1) processes, with the best competing models falling in the AR(1)−AR(3) classes. Cook (1985) restricted his analyses of eastern North American conifer and hardwood tree-ring chronologies to the AR process and found that AR(1)−AR(3) models were satisfactory in most cases.

ARMA processes are examples of casual feedback-feedforward filters (Robinson and Treital 1980) that are used extensively in geophysical signal analysis. The AR part of the process operates as a *feedback* filter while the MA part operates as a *feedforward* filter (Robinson and Treital 1980). That is, the current I_t is a product of the current e_t, plus past I_{t-1} which were fed back into the process, and past e_{t-i} which are fed forward upon the arrival of the current e_t. In this way, the potential for current growth is largely affected by previous radial growth (the I_{t-i}) and by reflections of antecedent environmental inputs (the e_{t-i}). Thus, the ARMA process is an elegant mathematical expression of "physiological preconditioning" (Fritts 1976).

An important concept of ARMA processes is the way in which they can operate as signal amplifiers. The amplifier mechanism can be seen in the variance formula of AR(p) processes, *viz.*

$$\sigma_y^2 = \frac{\sigma_e^2}{1 - \rho_1\phi_1 - \rho_2\phi_2 - \ldots - \rho_p\phi_p} \qquad 2.3$$

where σ_y^2 is the variance of the observed AR process, σ_e^2 is the variance of the unobserved random shocks, and the ρ_i and ϕ_i are the theoretical autocorrelation and autoregression coefficients of the process. If both the ρ_i and ϕ_i are positive, which is usually the case for tree-ring indices, then σ_y^2 will always be greater than σ_e^2. A reflection of this amplifier mechanism is *transience*. That is, the effect of a given e_t in a tree-ring series, whether climatic or from disturbance, will last for several years, or in extreme cases, decades before it disappears (Cook 1985). The consequence of transience, when endogenous disturbance shocks are present in the e_t, is a degradation of the SNR of the common signal in the mean-value function of tree-ring indices.

In order to remove the effects of unwanted, disturbance-related transience on the common signal among trees, the tree-ring indices can be modelled and prewhitened as AR(p) (Cook 1985) or ARMA(p,q) (Guiot 1987) processes before the mean-value function is computed. The order of the process can be determined at the time of estimation using the Akaike Information Criterion (AIC) (Akaike 1974).

Once the ARMA(p,q) coefficients are estimated, the prewhitening is carried out as

$$e_t = I_t - \phi_1 I_{t-1} - \ldots - \phi_p I_{t-p} + \Theta_1 e_{t-1} + \ldots + \Theta_q e_{t-q} \qquad 2.4$$

in difference equation form, or

$$e_t = [\phi(B) / \Theta(B)]\, I_t \qquad 2.5$$

in backshift operator form. The tree-ring series are now "white noise".

The resulting e_t represent the contributions of C_t, $D1_t$, and E_t, with $D2_t$ assumed to be absent at this stage. The reduction of the transient effects of endogenous disturbance pulses results in an increase in fractional common variance (Wigley et al. 1984) or %Y (Fritts 1976), and an improved SNR in the mean-value function of the e_t, $\mathbf{e_t}$. This results in an improved estimate of C_t, especially if the robust mean is used in computing $\mathbf{e_t}$. Cook (1985) found that the average absolute increase in fractional common variance between sampled trees was about 7% for 66 tree-ring chronologies developed from closed-canopy forest stands. The average relative increase in fractional common variance, compared to that of a mean-value function developed without using AR modelling, was about 25%. There are not any comparable figures for ARMA-based models.

The estimate of the common signal, in the form of $\mathbf{e_t}$, is incomplete because it is missing the natural persistence due to climate and tree physiology. In order to have a complete model of the common signal within the ensemble, an estimate of the common persistence structure among all detrended tree-ring series is necessary. For the pure AR model, a pooled estimate of autoregression, denoted $\Phi(B)$, can be computed directly from lag-product sum matrices of the ensemble that include information on persistence *both* within and between series (Cook 1985). The method appears to be quite robust in the face of high levels of out-of-phase fluctuations between series that are caused by endogenous disturbances. Unfortunately, this pooling procedure is difficult to generalize to the ARMA case because of the highly non-linear MA coefficients. Guiot (1987) has addressed the estimation of the common ARMA model by first creating a mean-value function of raw ring-width series, which were selected by principal components and cluster analysis of the corresponding white noise series. The common ARMA(p,q) model, denoted $\Theta(B)/\Phi(B)$, is than estimated for a stationary sub-period in the mean ring-width series. This method requires the existence of stationary sub-periods for the series. This was possible for the very old, open-canopy trees analyzed by Guiot (1987). However, this approach may be difficult to apply to closed-canopy forest ring widths, where stationary sub-periods rarely exist for any length of time (*e.g.* Figures 1 and 2). As an alternative, the ring-width series could be detrended first, a robust mean-value function created, and the mean series modelled as an ARMA process to produce $\Theta(B)/\Phi(B)$. This method would depend on sufficient replication to dampen-out the effects of endogenous disturbance effects. Experiments in detrending ring-width series (Cook 1985) indicate that the choice of the detrending method will have little effect on the order and coefficients of the mean ARMA process as long as the variance removed by the trend line is effectively all trend, as defined by Granger (1966).

The estimation of the common signal components is now complete. A final tree-ring chronology, I_t, containing both common signal components can be easily created by simply adding back the pooled AR, $\Phi(B)$, or the ARMA, $\Theta(B)/\Phi(B)$ persistence to the $\mathbf{e}_t$ (Cook 1985; Guiot 1987) once suitable starting values are obtained. The q starting values for the MA component will ordinarily be set to zero, the unconditional expected value of $\mathbf{e}_t$. The p starting values for the AR component may be obtained from the I_t lost through prewhitening (Cook 1985), by back-forecasting of the I_t past the beginning of the I_t (Box and Jenkins 1976), or by using the unconditional expected value of the I_t (= 1.0 for indices). If the characteristic transience of the AR component decays rapidly, then the choice of starting values will have little effect on the final series.

For the full ARMA case, the final estimate of C_t is

$$I_t = [\Theta(B)/\Phi(B)]\,\mathbf{e}_t \qquad 2.6$$

Aside from producing an efficient estimate of C_t, knowledge of $\Theta(B)/\Phi(B)$ and $\mathbf{e}_t$ are also useful for decomposing $D1_t$ and E_t from the individual tree-ring series.

3. Estimation of the unique signals: $D1_t$ and E_t

Knowledge of the common components in C_t provides information for estimating the unique signals, $D1_t$ and E_t, in individual tree-ring series. A disturbance pulse $D1_t$ can be thought of as an autocorrelated form of E_t in the sense that $D1_t$ represents a persistent departure from the common signal. However, $D1_t$ differs from E_t in that, while E_t is always present to some degree in the ring-width series, the random shock leading to the creation of $D1_t$ has a defined arrival time and an impact on radial growth that eventually disappears from the record. These properties of $D1_t$ suggest that an endogenous disturbance pulse may be modelled using intervention analysis (Box and Tiao 1975). Unfortunately, this method assumes that the arrival time of the intervention is known. Such information is rarely available for forest stands.

If the dates of disturbances are not known *a priori*, then the characteristics of the tree-ring series can be used in an *a posteriori* search for probable past disturbances. This search can be done using intervention detection (Reilly 1984), which is based on a time series outlier detection method of Chang (1982) and intervention analysis. A pulse or spike intervention of the form [. . 0 0 1 0 0 . .] and a step intervention of the form [. . 0 0 1 1 1 . .] are fit at successive points in a time series from $t = 1$ to n and tested for statistical significance.

For the simple case of one intervention occurring in a time series at year T, the intervention model is expressed as

$$X_t = Z_t + [\Theta(B)/\phi(B)]\omega\zeta_t(T) \qquad 3.1$$

where X_t is the observed series, Z_t is the unobserved outlier-free series, $\Theta(B)/\phi(B)$ is the ARMA model of the process, ω is the magnitude of the intervention, and $\zeta_t(T)$ is the time indicator of the intervention which $= 1$ if $t = T$, and $= 0$ otherwise. Z_t follows the same ARMA process as the intervention model because the same system dynamics are assumed to be operating with or without the occurrence of an intervention. By letting $Z_t = [\Theta(B)/\phi(B)]e_t$, equation 3.1 can be re-expressed as

$$X_t = [\Theta(B)/\phi(B)]e_t + [\Theta(B)/\phi(B)]\omega\zeta_r(T) \qquad 3.2$$

or

$$X_t = [\Theta(B)/\phi(B)]\,[e_t + \omega\zeta_t(T)] \qquad 3.3$$

From eq. 3.3, it is readily apparent that the intervention detection method is based on searching the residual series, e_t, for outliers in the form of spikes or changes in mean level in the form of step functions. Model 3.1 is easily generalized to the multiple intervention case. A more computationally efficient method of detecting outliers in time series is described by Tsay (1986). The method of intervention detection has been used to document the timing of the anomalous decline in radial growth of red spruce (*Picea rubens* Sarg.) in the Appalachian Mountains of North America (McLaughlin *et al.* 1987; Downing and McLaughlin 1987).

Although the probable occurrence of an intervention can be detected, endogenous and exogenous disturbances, and the effects of anomalous climatic extremes, cannot necessarily be differentiated if the measured ring-width series are analyzed in their raw form. For this reason, any method used to search for endogenous disturbances in tree rings should be applied to tree-ring series *after* the potentially confounding influence of the common signal has been removed.

An estimate of $D1_t$ and E_t, together, is possible simply by subtracting the index mean-value function, I_t, from the indices derived from each ring-width series, *viz.*,

$$[D1_t + E_t] = I_t - I_t \qquad 3.4$$

$[D1_t + E_t]$ could then be scanned for outliers as described above to identify probable endogenous disturbances. Alternatively, if the two-step estimation of C_t has been employed, $[D1_t + E_t]$ may be estimated as

$$[D1_t + E_t] = [\Phi(B)/\Theta(B)]\, I_t - e_t \qquad 3.5$$

From equation 3.5, $[D1_t + E_t] = E_t$ only if the ARMA model for the individual series is the same as that of the common model and there are no endogenous disturbance effects. Otherwise, $[D1_t + E_t]$ will have residual persistence due to the possible existence of endogenous disturbance effects and/or a difference in ARMA models.

The modelling and decomposition of $[D1_t + E_t]$ into $D1_t$ and E_t could proceed, as before, using intervention detection (Reilly 1984) or the outlier detection method of Tsay (1986) to identify the timing of probable disturbances in $[D1_t + E_t]$. Each of these methods can also produce an estimate of the disturbance pulse in the series as

$$D1_t = [\Theta(B)/\phi(B)]\omega\zeta_t^{(T)} \qquad 3.6$$

once the timing T and the magnitude ω of the disturbance are estimated.

4. The estimation of the common disturbance signal: $D2_t$

If the impact of an exogenous disturbance on radial growth is sufficiently strong, it should be possible to identify its presence in the estimate of C_t through the use of intervention detection. However, when an exogenous disturbance effect does not clearly exceed the background variance of C_t, the decomposition of $D2_t$ from the other signals will require more information than is contained within the tree-ring data from one site alone. When this is the case, other tree-ring chronologies from (hopefully) unaffected sites in the region can be used to factor out the $D2_t$ from the common C_t signal among all sites. This concept was applied by Nash *et al.* (1975) in a search for possible pollution on tree growth in Arizona.

Nash *et al.* (1975) sampled trees downwind from a copper smelter and on several other unaffected, or control, sites in the region. The standardized tree-ring indices of the control sites were averaged into a regional master. In so doing, any site-specific tree-ring anomalies were averaged out, and the regional dendroclimatic signal emphasized. This regional tree-ring index series was then subtracted from the indices of the affected site and rescaled. The result was a series of "predicted residual indices," or PRI, which were calculated as

$$PRI = S_{TRI}/S_{RCI}\,(TRI - \overline{X}_{RCI}) \qquad 4.1$$

where TRI is the affected tree-ring chronology, RCI is the regional control chronology, $\overline{X}_{RCI}$ is the mean of the regional chronology, and S_{TRI} and S_{RCI} are the standard deviations of the chronologies (Nash *et al.* 1975). The ratio of the standard deviations is used to rescale the PRI, but does not affect their interpretation. The PRI calulated by Nash *et al.* (1975) indicated the possibility of reduced radial growth during years of copper smelter operation near the affected site. This same technique has been used by Swetnam (1987) in developing a history of spruce budworm attack on Douglas-fir in New Mexico. Jacoby and Ulan (1983) used a similar method to define the extent of a poorly documented earthquake in Alaska.

None of the above studies utilized any sort of intervention detection techniques on the residuals. However, any of the methods described for factoring out endogenous disturbance pulses should work equally well for factoring out exogenous disturbance pulses, once the regional climatic signal has been removed.

The Nash *et al.* (1975) technique is dependent on the availability of control site trees having sufficiently similar dendroclimatic responses as the affected site trees. Ideally, the structure and time history of the dendroclimatic signal will be similar enough between sites to produce a sequence of departures that strongly reflect the standwide disturbance event(s), but not other signals. If the control and affected site tree-ring chronologies differ much in their respective persistence structures, then the technique could produce a series of persistent residuals that reflect the differences in the response of each chronology to the same input. Such departures could be erroneously interpreted as evidence for a standwide disturbance on the affected site. For this reason, it is recommended that the tree-ring chronologies be modeled for persistence before the differences are computed. If the persistence structures differ very much, then the series can be prewhitened to minimize this potentially confounding influence.

Another promising approach to the detection of interventions is the method of "parameter mapping" (Bennett 1979). Parameter mapping explicitly models the parameters of a system that are thought to have varied through time due to the intervention of some external force into the system. The modelling is accomplished by casting the problem into state-space form and using the Kalman filter recursion to solve for the time-varying system parameters in a recursive fashion (Bennett 1979). This approach has been used to model the time-dependence of the climatic response in tree-ring chronologies for the purpose of detecting possible pollution effects on tree growth (Van Deusen 1987; Visser and Molenaar 1986, 1987). The state-space form of the linear regression model is composed of a system equation

$$Y_t = X_t T\alpha_t + \epsilon_t \qquad 4.2$$

and a parameter equation

$$\alpha_t = T\alpha_{t-1} + \eta_t \qquad 4.3$$

where the Y_t is the dependent variable, the X_t are the independent variables used to predict Y_t, T is the state transition matrix, α_t is a vector of regression coefficients that are usually allowed to vary as random walks, and the ϵ_t and η_t are noise terms. Equations 4.1 and 4.2 are solved recursively using the Kalman filter algorithm (Bennett 1979) for each time step, $t = 1,n$. Van Deusen (in press) has used this time-dependent regression model to estimate low-elevation, second-growth red spruce ring widths from nearby old-growth red spruce ring widths in an effort to determine the effect of canopy closure on the recent ring-width decline in the second-growth forests. He found that much of the decrease in the second-growth ring widths since 1960 could be explained by internal stand evolution and canopy closure. This innovative approach could also be applied to pollution studies, such as Nash *et al.* (1975), when there are affected and control populations of trees to sample.

The state space model is much more general than is indicated above. In fact, most of the techniques described thus far can be reformulated in state space form and solved using the Kalman filter (Harvey 1984). Mettes and Visser (1987) have recently produced a computer program that implements much of the structural model approach to the decomposition of time series that Harvey (1984) describes. It allows for the decomposition of time series into trend, cycles, and explanatory variables, all of which can be estimated separately or simultaneously. For this reason, it is probably the most general method available for analyzing tree-ring series. See Bennett (1979), Harvey (1984), Visser and Molenaar (1986, 1987), and Van Deusen (1987) for more complete descriptions and examples of state space modelling and the Kalman filter.

DISCUSSION

In this paper, I have proposed a conceptual model for the decomposition of tree-ring series into four discrete classes of signals for environmental studies. This model allows the decomposition problem to be broken down into a stepwise process of signal estimation and extraction. For each step, some mathematical/statistical estimation techniques are described, which show promise in extracting the signal of interest from the tree-ring series. Except for exogenous disturbance signals, the proposed methods of analysis do not require any information other than that which is contained within the ring-width series, themselves.

As presented here, there is not a unified mathematical framework to the decomposition problem. This is not necessarily a detriment since it allows for great flexibility and control over the methods used for signal estimation and extraction. However, given the plethora of techniques for detrending, for example, it is desirable that the methods of analysis be limited, as much as possible, to a reasonably unified family of techniques. In this regard, the general applicability of ARMA models (Box and Jenkins 1976) and state space modelling (Bennett 1979; Harvey 1984) to many of the statistical techniques described here suggests that they will produce the closest thing to a unified mathematical framework in the future for decomposing tree-ring time series.

ACKNOWLEDGMENTS

This research has been made possible, in part, by several grants (ATM 83-13789 and ATM 85-15290) from the National Science Foundation Division of Climate Dynamics. Many of the concepts and much of the research leading up to this paper derived from my Ph.D. dissertation research under the expert guidance of Professor Harold C. Fritts. Lamont-Doherty Geological Observatory Publication Number 4238.

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