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A likelihood-based time series modeling approach for application in dendrochronology to examine the growth-climate relations and forest disturbance history

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Abstract

A time series intervention analysis (TSIA) of dendrochronological data to infer the tree growth-climate-disturbance relations and forest disturbance history is described. Maximum likelihood is used to estimate the parameters of a structural time series model with components for climate and forest disturbances (i.e., pests, diseases, fire). The statistical method is illustrated with a tree-ring width time series for a mature closed-canopy Douglas-fir stand on the west slopes of the Cascade Mountains of Oregon, USA that is impacted by Swiss needle cast disease caused by the foliar fungus, *Phaeocryptopus gaeumannii* (Rhode) Petrak. The likelihood-based TSIA method is proposed for the field of dendrochronology to understand the interaction of temperature, water, and forest disturbances that are important in forest ecology and climate change studies.

Keywords

Seasonal time series; intervention analysis; outlier detection; spline regression; maximum likelihood; dendrochronology

1. Introduction

Tree rings record growth in response to abiotic and biotic factors and can infer the timing and characteristics of past disturbance events including temporal and spatial variability. Tree-ring chronologies covering decades to several millennia are key data sources for dendrochronological studies investigating climatic effects on tree growth, reconstructing past climate patterns, dating natural disasters (e.g. eruptions of volcanoes, floods) and forest disturbance events (pests, diseases, fires), as well as tracking ecological processes (e.g., tree-line movement) (Cook and Kairiukstis, 1990). But growth-climate relations are difficult to infer because the effects of temperature and water on annual stem growth are nonlinear, seasonal, and interact with each other as well as with forest disturbances (Isebrands et al., 2000; Lloyd, Duffy, and Mann, 2013; Lee et al., 2013, 2016). Moreover, climate plays an

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important role in the population dynamics of forest pathogens and pests, which in turn affect tree growth (Alfaro et al., 1982, 2014; Black et al., 2010; Lee et al., 2013) and further complicate inferences of growth-climate relations.

Tree growth has been described conceptually by Cook (1985, 1987) as a structural time series (STS) model with components for age trend (A_t), climate (C_t), and disturbance (D_t), i.e., $E(Y_t) = A_t + C_t + D_t$ where $E(Y_t)$ is the mean response function for the tree-ring width chronology (Y_t). The correct specification of the mean function of tree growth is extremely difficult because growth is influenced by multiple climate factors and possibly latent disturbance factors that interact and are confounded. The form of A_t is typically an exponential-decay function such as a negative exponential or a simple linear function (Cook and Kairiukstis, 1990). Specification of the form of C_t and D_t is the focus of two important applications of dendrochronology, namely growth-climate relations and forest disturbance history. The climate component, C_t , represents the interactions of temperature, precipitation, soil moisture, and evapotranspiration demand on tree growth and applies for all trees within a stand (Fritts, 1976). Further, C_t may have a climate-related growth trend, particularly in the Pacific Northwest (PNW) where tree growth rates have changed in response to increasing temperature above the species' temperature optimum due to climate change (Barber et al., 2000; D'Arrigo et al., 2004; Beedlow et al., 2013; Lee et al., 2016). A multiple regression model is often used to describe the climate relations with tree growth (e.g., Fritts, 1971; Meko, 1981) but recent evidence suggests a more complex and nonlinear relationship between tree growth and climate (Briffa et al., 1998; Lloyd and Fastie, 2002; Wilmking et al., 2004, 2005; Ohse, Jansen, and Wilmking, 2012; Lloyd et al., 2013; Lee et al., 2016). D_t has been conceptually described as a pulse function for a discrete event (Cook, 1987; Mäkinen, 1997) but more recently, has been generalized to have other forms and possibly longer duration and is expressed as a combination of pulse, step and multi-year trend functions (Downing and McLaughlin, 1990; Druckenbrod et al., 2013; Lee et al., 2013, 2016). Depending upon the dendrochronological application of interest, the mean function is specified for either C_t or D_t but not both (Cook and Kairiukstis, 1990).

The reconstruction of a past species-specific forest disturbance does not require specification of C_t , assuming that the effects of climate and disturbance are additive. Past outbreaks of pests or disease can be identified through the comparison of the host chronology with a sympatric nonhost chronology, assuming that the host and nonhost time series share the same climate signal, C_t (Black et al., 2010; Alfaro et al., 2014). The control chronology may be either a coexisting but different species unaffected by the disturbance agent or the same species from other geographic areas not affected by the disturbance (Black et al., 2010). However, the growth-climate relation can vary by tree species and site conditions (Rozas, 2001; Friedrichs et al., 2009; Beedlow et al., 2013; Lee et al., 2016), raising concerns on the host-nonhost reconstructions of past disturbance regimes. Recent evidence suggests an interaction of temperature, water, and disturbance is responsible for tree pathogens (e.g., *Phaeocryptopus gaeumannii* (Rhode) Petrak) altering the climate relations of trees by impacting physiological processes and carbon assimilation (Lee et al., 2016). The interactions among climatic stressors (X) and forest disturbance agents (Z) are not the typical cross-product of X and Z because historical records of outbreaks of forest pests and diseases are generally not available nor quantifiable for input in a regression model. As an

alternative to the use of a control chronology as a climate proxy, time series intervention analysis (TSIA) has been used to isolate the disturbance signal (D_t) by explicitly characterizing the growth-climate relation (C_t) of the host species (Lee et al., 2016).

A tree-ring width chronology represents a stationary time series that can be approximated by a Box-Jenkins autoregressive moving average (ARMA) model (Fritts, 1976; Cook, 1985; Monserud, 1986; Guiot, 1986). Autocorrelation, age-related and climate trends, and the interactions of temperature, water, and disturbances pose problems in dendrochronology to understand these impacts on forested ecosystems. Numerous disturbance detection methods have been developed for inferring forest history events, but these methods do not allow for autocorrelation (Rubino and McCarthy, 2004) nor examine the growth-climate relations, and are difficult to apply in areas where field records of disturbance events are incomplete or not available.

Time series intervention analysis is well suited for both determining growth-climate relations and reconstructing forest history, but the modeling approach has been seldom applied in dendrochronology (Druckenbrod et al., 2013). This study builds on the TSIA approach for the detection of past disturbance events and the regression approach for climate-growth relations in dendrochronology to describe growth-climate-disturbance relations using a maximum likelihood framework for estimation. This statistical approach extends naturally to an intra-annual tree-ring series (i.e., earlywood and latewood width) that captures the seasonal patterns of climate including annual summer drought typical of a Mediterranean climate regime. The TSIA approach can detect suppression episodes, the years of the disturbance events, and quantify the magnitude and duration of the growth anomalies associated with one or multiple disturbance agents (Druckenbrod et al., 2013). Disturbance events are identified as outliers which can be detected based on a likelihood ratio or Wald test. Data requirements are fairly minimal but inferences of the growth-climate relations are limited to the time period when instrumental records for the region are available.

Key issues to be addressed include: (1) detecting of forest disturbance events (i.e., outbreaks of tree pathogens, forest pests, wildfires); (2) inferring radial stem growth response to the interacting effects of temperature, water, and forest diseases and pests; and (3) applying time series analysis to annual and intra-annual tree-ring width chronologies to understand the seasonal effects of multiple climate and latent disturbance factors.

2. Methods

2.1. Intervention Analysis of Dendrochronological Data

Tree-ring width data ($Y_1, Y_2, \dots, Y_n$) represent either an annual or intra-annual time series. We employ a regression model of the general form

$$y_t = f(\mathbf{X}, \mathbf{D}, t) + N_t$$

where $y_t = F(Y_t)$ is some appropriate power transformation of Y_t , $f(\mathbf{X}, \mathbf{D}, t)$ = deterministic effects of time, t , climate variables, $\mathbf{X}$, and interventions, $\mathbf{D}$, and N_t is a stationary time series

with absolutely summable covariance function V and zero mean. Power transformations are used to homogenize the variance in tree-ring width series but are difficult to apply in the presence of outliers. Estimation of the variance of the tree-ring time series to inform the power transformation requires specification of the mean response function which is difficult to infer for a tree-ring chronology having years with anomalously low growth (i.e., outliers). Alternatively, we prefer a log transformation to infer the multiplicative effects of climate and disturbances on growth and to stabilize the variance of ring widths (Cook, 1987).

In Section 2.2 we discuss the general linear model for representing the mean response function $f(\mathbf{X}, \mathbf{D}, t)$ that has components for climate and forest disturbances assuming N_t is normally and independently distributed. We use grafted polynomials to infer the climate-induced growth trend associated with climate stress that is not accounted for by the measured variables. In Section 2.5 we extend the statistical approaches for modeling growth-climate relations and forest disturbance history using TSIA assuming a regular or seasonal autoregressive model for representing the noise N_t . The associated parameter estimation procedures are given in each section using a likelihood framework (Figure 1). For the field of dendrochronology, we developed an alternative to a second-order or higher response surface model involving two or more variables and their cross-products to examine the interactions of temperature, water, and forest disturbance agents.

2.2. Growth-climate Relations and Disturbance Detection Model

The two important applications of dendrochronology, growth-climate relations and forest disturbance history, can be examined simultaneously in a likelihood framework. Initially, we assume that $(Y_1, Y_2, \dots, Y_n)$ are normally and independently distributed with mean $f(\mathbf{X}, \mathbf{D}, t)$ and variance σ^2 . Typically, the age-related growth trend, A_t , is removed from the tree-ring time series in the dendrochronological standardization process using a combination of detrending methods including a negative exponential function, a cubic spline smoother, or a regional growth trend. We assume that the tree-ring time series has been detrended to remove age-related trends while preserving the low frequency variability associated with a climate trend. We examine time series methods for growth-climate relations and disturbance detection by specification of a mean response function that separates the confounding effects of temperature, water, and disturbance on tree growth (Lee et al., 2016). We assume that growth response to temperature and water can be represented by a multiple regression equation, i.e., $C_t = \mathbf{X}_t' \boldsymbol{\beta}$ for $t=1, 2, \dots, n$ where $\mathbf{X}_t' = (X_{1t}, X_{2t}, \dots, X_{pt})$ is a vector of measured climate variables, and $\boldsymbol{\beta}' = (\beta_1, \beta_2, \dots, \beta_p)$ are the unknown model parameters. In dendrochronology, the mean function is highly complex and nonlinear, varies by tree species and site condition, involves multiple climate variables that interact with each other, and displays seasonality, and possibly, climate-mediated growth trend (Lee et al., 2016).

2.3. Pulse Intervention to Detect Disturbance Events

Time series intervention analysis is used to detect forest disturbances (Downing and McLaughlin, 1990; Druckenbrod, 2005; Druckenbrod et al., 2013; Lee et al. 2013). For illustration of the computations, we assume a single pulse disturbance for a known disturbance event at time $t=t_1$, i.e., $D_t = X_{p+1,t} \beta_{p+1}$ where $X_{p+1,t} = 0$ if $t \neq t_1$, and $=1$ if $t=t_1$ and β_{p+1} = magnitude of the disturbance effect on growth. The mean response function is

$$\mu_t = \sum_{i=1}^p \beta_i X_{it} + \beta_{p+1} X_{p+1t} \quad (\text{Equation 1})$$

which can be expressed in matrix notation for calculation of the least squares estimator for $\beta' = (\beta_1, \beta_2, \dots, \beta_{p+1})$. This model parametrization is a special case of the Type I outlier (Fox, 1972), additive outlier (Denby and Martin, 1979; Chang and Tiao, 1983) and the aberrant observation model (Abraham and Box, 1979). Let $y' = (y_1, y_2, \dots, y_n)$ and $X = [Z_c | Z_d]$ be the $n \times (p+1)$ matrix which we partition into a $n \times p$ data matrix, Z_c , whose t^{th} row is $X_t' = (X_{1t}, X_{2t}, \dots, X_{pt})$ and a $n \times 1$ vector, $Z_d = (X_{p+1,1}, X_{p+1,2}, \dots, X_{p+1,n})'$. We can organize the model parameters into the climate and disturbance components, i.e., $\beta' = (\beta_c' | \beta_d')$ where $\beta_c' = (\beta_1, \beta_2, \dots, \beta_p)$ and $\beta_d' = \beta_{p+1}$. Note $\mu = X\beta = Z_c\beta_c + Z_d\beta_d$ and the least squares solution for β is $(X'X)^{-1}X'y$. Computationally, the rows of X can be rearranged so that $t_1 = n$ such

that $X = \begin{bmatrix} X_c & | & 0 \\ X_d & | & 1 \end{bmatrix}$ where X_c is an $(n-1) \times p$ matrix whose t^{th} row is X_t' , $X_d = X_n'$ is an $1 \times p$ vector, and 0 is a $(n-1) \times 1$ vector of zeros. Similarly, $y' = (y_c' | y_d')$ where $y_c' = (y_1, y_2, \dots, y_{n-1})$ and $y_d' = y_n$. Then the least squares solution for β can be partitioned as follows

$$\hat{\beta}_c = (X_c'X_c)^{-1}X_c'y_c$$

$$\hat{\beta}_d = y_d - X_d\hat{\beta}_c. \quad (\text{Equation 2})$$

The growth-climate relation is calculated as $C_t = X_t'\hat{\beta}$ and the magnitude of the known disturbance event is equal to $\hat{\beta}_{p+1}$ which is the difference between the observed and the predicted growth response to climate at time $t=t_1$. The least squares estimator for σ^2 is

$$s^2 = \frac{1}{n-p-1} (y - X\hat{\beta})'(y - X\hat{\beta}) = \frac{1}{n-p-1} (y_c - X_c\hat{\beta}_c)'(y_c - X_c\hat{\beta}_c). \quad (\text{Equation 3})$$

The variance of $\hat{\beta}_{p+1}$ is estimated by $\widehat{\text{Var}}(\hat{\beta}_{p+1}) = (1 + X_d(X_c'X_c)^{-1}X_d')s^2$ assuming that $(y_1, y_2, \dots, y_n)$ are independently distributed with variance σ^2 unknown. Consequently, the Wald test statistic for disturbance detection is

$$t = \hat{\beta}_{p+1} / \sqrt{\widehat{\text{Var}}(\hat{\beta}_{p+1})} \quad (\text{Equation 4})$$

which has a Student's t -distribution with $n-p-1$ degrees of freedom. The least squares calculations extend naturally to allow for multiple pulse interventions (see Appendix A). When each potential outlier is represented by a dummy variable then the outlier's predicted

value will equal the observed value no matter what function is fit to the remaining data. Thus to minimize the error sum of squares, the regression on the nonsuspect points would give the appropriate estimates.

In general, the disturbance events $t^*=(t_1, t_2, \dots, t_r)$ are unknown and must be inferred by comparing y_t and C_t to detect growth divergences which cannot be attributed to the measured variables. The regression of y on $X_1, X_2, \dots, X_p, X_{p+1}, \dots, X_{p+r}$ where X_{p+j} is the 0–1 indicator variable = 1 if $t=t_j$ and =0 otherwise for $j=1, 2, \dots, r$ yields the least squares estimators and associated t-tests for the model parameters. Given specification of the growth-climate relation in Equation A.1, TSIA can detect one or more pulse disturbances using the Wald test statistic (Equation 4) for testing the null hypothesis that $\beta_{p+j}=0$ for $j=1, 2, \dots, r$. Some multiple testing adjustment like Bonferroni or Tukey and/or specification of a critical value M would be appropriate for outlier detection because every point is a potential outlier. Chang and Tiao (1983) suggest values of M between 3 and 4. In practice, the presence of anomalous growth values associated with endogenous or exogenous forest disturbances poses problems in understanding the growth-climate relations.

2.4. Trend Analysis

Tree-ring series contain information in tree-growth responses to different climate drivers and disturbances that vary on different time scales from several years to decades to centuries. Pulse intervention is useful to detect abrupt discontinuities in the tree-ring series associated with outbreaks of forest diseases and pests (Lee et al., 2013) whereas trend intervention is useful to detect a long-term change in growth due to canopy release following forest thinning (Druckenbrod et al., 2013) or due to multiple decades of warming temperatures (Beedlow et al., 2013, Lee et al., 2016). Tree-ring data may have both age-related and climatic growth trends (Figure 2). Age-related growth trends are most prominent in the earlier years but can continue throughout the life of a tree. Climatic growth trends due to gradually shifting environmental conditions can occur in distinct periods and are typically represented by a continuous trend function. Climate trends in the early part of the tree-ring series are difficult to detect because the age-related and climate trends are confounded. Consequently, climate trends pose a problem in the standardization process in dendrochronology to remove the age-related growth trends by detrending with a cubic spline smoother or negative exponential curve (Helama et al., 2004). A known weakness of detrending the whole tree-ring series is a failure to preserve the long-term climate trends (Briffa et al., 1992; Cook et al., 1995; Lloyd et al., 2013). For example, a cubic spline series applied to the master chronology of Douglas-fir removed the climate trend after 1990 (Figure 2). Because the climate trend in the Pacific Northwest occurs in the most recent part of the time series when the age-related trend no longer is present, we can preserve the climate trend by detrending the time series prior to ~1970 using a cubic spline smoother to remove the age-related trend. Esper et al. (2010) also considered piecewise detrending of tree-ring records from Siberia so as to preserve the low frequency variance in recent decades.

Once detrending is used to remove the age-related trend, the tree-ring series is assumed to be a smooth function of time but the functional form may have different trends in growth rate in

different periods. Polynomials have been used previously for detrending tree-ring width time series, but are no longer recommended because polynomials are not monotonic and have multiple changes in sign of the derivative which have no biological meaning (Cook and Kairiukstis, 1990). An alternative regression approach that overcomes these undesirable mathematical properties is to partition the time series by its trend and fit a low order polynomial to each section (Fuller 1976). This piecewise polynomial approach is called grafted polynomials, spline regression, or segmented regression.

To illustrate the use of grafted polynomials, let $(Y_1, Y_2, \dots, Y_n)$ satisfy a structural time series model with components for climate (C_t) and disturbance (D_t), i.e., $\mu_t = C_t + D_t$ given in Equation 4. We assume that C_t can be further decomposed into a climate trend, T_t , and a growth response function of the measured variables. Suppose that the time series can be divided into two periods such that the mean function displays a quadratic in time in each period. Furthermore the mean response function is continuous in the first derivative. The form of the spline regression model for T_t is

$$T_t = \begin{cases} \beta_1 + \beta_2 t + \beta_3 t^2, & \text{if } t \leq t_0 \\ \beta_4 + \beta_5 t + \beta_6 t^2, & \text{if } t \geq t_0 \end{cases}$$

where t_0 is the join year and $(t_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6)$ are unknown model parameters. The parameters are constrained by the continuity of T_t at t_0 so that

$\beta_1 + \beta_2 t_0 + \beta_3 t_0^2 = \beta_4 + \beta_5 t_0 + \beta_6 t_0^2$. A second parameter constraint is imposed by the continuity in the first derivative, i.e., $\beta_2 + 2\beta_3 t_0 = \beta_5 + 2\beta_6 t_0$. The data are used to estimate the join point $t_0 = -(\beta_5 - \beta_2) / (2(\beta_6 - \beta_3))$ and the other parameters (Gallant and Fuller, 1973; Fuller, 1976). While the climate trend, T_t , can be modeled as a series of discrete pulse interventions as in Section 2.3, trend intervention is preferred for its parsimony and continuous properties and for its ability to determine the onset of a change in growth rate associated with a gradual shift in environmental conditions due to climate change.

2.5. Autocorrelation

Autocorrelation in tree-ring width series is widely known in the field of dendrochronology (Fritts, 1976). The autocorrelation structure represents the stochastic processes in which the effect of past climate on tree growth and physiology is propagated forward in time (Fritts, 1976). A low order autoregressive model is typically used to describe the stochasticity in tree-ring series associated with carbon and water relations. Inferences of the growth-climate relation and forest disturbance history are developed using a likelihood framework. The model development begins with the assumption of a constant mean which we will modify in later sections to allow for the growth-climate relation and pulse disturbance events. For a first-order autoregressive moving average model, denoted ARMA (1,0), with constant mean μ , the model is

$$(Y_t - \mu) = \rho(Y_{t-1} - \mu) + e_t \text{ where } e_t \sim \text{NID}(0, \sigma^2). \quad (\text{Equation 5})$$

The variance of an ARMA (1,0) time series is $\sigma^2/(1-\rho^2)$ and the stationarity condition requires $-1 < \rho < 1$. The logarithm of the likelihood of a sample of n observations from an ARMA (1,0) model is

$$\log L(\mu, \rho, \sigma^2 | Y_1, Y_2, \dots, Y_n) = \log L(\mu, \rho, \sigma^2 | Y_1) + \log L(\mu, \rho, \sigma^2 | Y_2, Y_3, \dots, Y_n; Y_1)$$

$$\text{where } \log L(\mu, \rho, \sigma^2 | Y_1) = -\frac{\log(2\pi)}{2} - \frac{\log(\sigma^2)}{2} + \frac{\log(1-\rho^2)}{2} - \frac{(Y_1 - \mu)^2(1-\rho^2)}{2\sigma^2}$$

$$\log L(\mu, \rho, \sigma^2 | Y_2, Y_3, \dots, Y_n; Y_1) = -\frac{(n-1)\log(2\pi)}{2} - \frac{(n-1)\log(\sigma^2)}{2} - \sum_{t=2}^n \frac{\{(Y_t - \mu) - \rho(Y_{t-1} - \mu)\}^2}{2\sigma^2}$$

(Equation 6)

The computation of the maximum likelihood (ML) estimators is closely related to that of ordinary least squares regression if we consider Y_1 as fixed and maximize the conditional likelihood (Fuller, 1976). Let $\lambda = \mu(1-\rho)$, then the ML estimators of λ and ρ are the least squares solution obtained by conditioning on Y_1 and

$$\hat{\sigma}^2 = \frac{1}{n-1} \sum_{t=2}^n (Y_t - \hat{\lambda} - \hat{\rho}Y_{t-1})^2. \quad (\text{Equation 7})$$

The least squares estimator of σ^2 divides the numerator in Equation 7 by $n-3$ and is typically used in place of $\hat{\sigma}^2$

2.6. ARMA (1,0) with Non-constant Mean

Given the mean response function with r known pulse interventions at times $\mathbf{t}^* = (t_1, t_2, \dots, t_r)$ in Equation A.1, a first-order autoregressive model with non-constant mean is

$$(Y_t - \mu_t) = \rho(Y_{t-1} - \mu_{t-1}) + e_t \text{ where } e_t \sim \text{NID}(0, \sigma^2). \quad (\text{Equation 8})$$

The logarithm of the likelihood of a sample of n observations from an ARMA (1,0) model is

$$\begin{aligned} \log L(\beta_c, \beta_d, \rho, \sigma^2 | Y_1, Y_2, \dots, Y_n; \mathbf{Z}_c, \mathbf{Z}_d) &= \log L(\beta_c, \beta_d, \rho, \sigma^2 | Y_1; \mathbf{Z}_c, \mathbf{Z}_d) \\ &+ \log L(\beta_c, \beta_d, \rho, \sigma^2 | Y_2, Y_3, \dots, Y_n; Y_1, \mathbf{Z}_c, \mathbf{Z}_d) \end{aligned} \quad (\text{Equation 9})$$

where $\log L(\beta_c, \beta_d, \rho, \sigma^2 | Y_1; \mathbf{Z}_c, \mathbf{Z}_d) = -\frac{\log(2\pi)}{2} - \frac{\log(\sigma^2)}{2} + \frac{\log(1-\rho^2)}{2} - \frac{(Y_1 - \mathbf{Z}'_{c1}\beta_c - \mathbf{Z}'_{d1}\beta_d)^2(1-\rho^2)}{2\sigma^2}$

$$\log L(\beta_c, \beta_d, \rho, \sigma^2 | Y_2, Y_3, \dots, Y_n; Y_1, \mathbf{Z}_c, \mathbf{Z}_d) = -\frac{(n-1)\log(2\pi)}{2} - \frac{(n-1)\log(\sigma^2)}{2} - \sum_{t=2}^n \frac{\{(Y_t - \mathbf{Z}'_{ct}\beta_c - \mathbf{Z}'_{dt}\beta_d) - \rho(Y_{t-1} - \mathbf{Z}'_{ct-1}\beta_c - \mathbf{Z}'_{dt-1}\beta_d)\}^2}{2\sigma^2}$$

(Equation 10)

and $\mathbf{Z}'_{ct}$ is the t^{th} row of $\mathbf{Z}_c$ and $\mathbf{Z}'_{dt}$ is the t^{th} row of $\mathbf{Z}_d$. The conditional ML estimators of β_c , β_d and ρ are computed by fixing Y_1 and optimizing the conditional likelihood function in Equation 10. With the advent of computing software, the unconditional ML estimators are generally computed. The conditional ML estimator for σ^2 is

$$\hat{\sigma}^2 = \frac{1}{n-1} \sum_{t=2}^n \{(Y_t - \mathbf{Z}'_{ct}\hat{\beta}_c - \mathbf{Z}'_{dt}\hat{\beta}_d) - \hat{\rho}(Y_{t-1} - \mathbf{Z}'_{ct-1}\hat{\beta}_c - \mathbf{Z}'_{dt-1}\hat{\beta}_d)\}^2 \quad (\text{Equation 11})$$

where $\hat{\rho}$, $\hat{\beta}_c$ and $\hat{\beta}_d$ are the ML estimators. The least squares estimator of σ^2 divides the numerator in Equation 11 by $n-2-p-r$ and is typically used in place of $\hat{\sigma}^2$. Because the ML estimators are closely related to that of multiple regression, the ML estimators of β_c , σ^2 and ρ are strongly influenced by $\mathbf{y}_c$ and marginally influenced by $\mathbf{y}_d$, particularly when ρ is near zero.

To detect a disturbance event, $H_0: \beta_{p+j} = 0$, several test statistics can be used including the Wald test which is approximately distributed as a Student's t with $n-2-p-r$ degrees of freedom. Let $S(\beta) = \sum_{t=2}^n \{(Y_t - \mathbf{X}'_t\beta) - \rho(Y_{t-1} - \mathbf{X}'_{t-1}\beta)\}^2$, then for moderately large n , $\hat{\beta}$ is approximately distributed as a multivariate normal with mean β and covariance matrix $\text{Var}(\hat{\beta}) = \sigma^2 \{S_{ij}\}^{-1}$ where

$$S_{ij} = \frac{1}{2} \partial^2 \{S(\beta)\} / \partial \beta_i \partial \beta_j |_{\beta=\hat{\beta}} \quad (\text{Equation 12})$$

For σ^2 unknown, $\widehat{\text{Var}}(\hat{\beta}) = s^2 \{S_{ij}\}^{-1}$ where $s^2 = S(\hat{\beta}) / (n-2-p-r)$ (Box and Tiao, 1975). The limiting distribution of the standardized estimators is normal for a wide class of time series (Fuller, 1976). If ρ is known, then the best linear unbiased estimator of β is given by $\hat{\beta}_G = (\mathbf{X}'\mathbf{V}^{-1}\mathbf{X})^{-1}\mathbf{X}'\mathbf{V}^{-1}\mathbf{y}$ and $\text{Var}(\hat{\beta}_G) = (\mathbf{X}'\mathbf{V}^{-1}\mathbf{X})^{-1}$ where $\mathbf{V} = \text{Var}(\mathbf{y})$. Alternatively, the maximum likelihood ratio test for outliers has been derived for an autoregressive process (Fox, 1972) and for ARIMA models (Chang and Tiao, 1983).

2.7. Seasonal Autoregressive Time Series

Stem growth in trees is the result of cell division and occurs in a discrete annual or seasonal pattern that is captured by total annual ring width or partitioned as earlywood (EW) and latewood (LW) ring widths. The EW and LW ring widths reflect seasonal climate conditions during cell formation, which allows intra-annual resolution of climate factors affecting growth (Meko and Baisan, 2001; Watson and Luckman, 2002; Griffin et al., 2011). Partitioning the annual total ring width into EW and LW is applicable for capturing the seasonal climate patterns with an annual summer drought typical of the PNW. The EW and LW width series can be viewed as a seasonal time series with two measurements per year that display both regular and seasonal autocorrelation. For a first-order seasonal and regular ARMA, denoted SARMA $(1,0)_2 \times (1,0)$, with a non-constant mean μ_t , the model is

$$(Y_t - \mu_t) = \rho_1(Y_{t-1} - \mu_{t-1}) + \theta_1(Y_{t-2} - \mu_{t-2}) - \rho_1\theta_1(Y_{t-3} - \mu_{t-3}) + e_t \quad (\text{Equation 13})$$

where $e_t \sim \text{NID}(0, \sigma^2)$, ρ_1 and θ_1 are less than one in absolute value. The variance of a stationary SARMA $(1,0)_2 \times (1,0)$ model and the first three autocovariances are:

$$\gamma_0 = \frac{(1 + \rho_1^2\theta_1)}{(1 - \rho_1^2)(1 - \theta_1^2)(1 - \rho_1^2\theta_1)} \sigma^2$$

$$\gamma_1 = \frac{\rho_1(1 + \theta_1)}{(1 + \rho_1^2\theta_1)} \gamma_0$$

$$\gamma_2 = \frac{(\rho_1^2 + \theta_1)}{(1 + \rho_1^2\theta_1)} \gamma_0$$

$$\gamma_3 = \frac{\rho_1(1 + \theta_1)(\rho_1^2(1 - \theta_1) + \theta_1)}{(1 + \rho_1^2\theta_1)} \gamma_0 \quad (\text{Equation 14})$$

where $-1 < \rho_1, \theta_1 < 1$. The logarithm of the likelihood of a sample of n observations from a SARMA $(1,0)_2 \times (1,0)$ model is

$$\begin{aligned} \log L(\beta_c, \beta_d, \rho_1, \theta_1, \sigma^2 | Y_1, Y_2, \dots, Y_n; \mathbf{Z}_c, \mathbf{Z}_d) = & \log L(\beta_c, \beta_d, \rho_1, \theta_1, \sigma^2 | Y_1, Y_2, Y_3; \mathbf{Z}_c, \mathbf{Z}_d) \\ & + \log L(\beta_c, \beta_d, \rho_1, \theta_1, \sigma^2 | Y_4, Y_5, \dots, Y_n; Y_1, Y_2, Y_3, \mathbf{Z}_c, \mathbf{Z}_d) \end{aligned}$$

where

$$\begin{aligned} \log L(\boldsymbol{\beta}_c, \boldsymbol{\beta}_d, \rho_1, \theta_1, \sigma^2 | Y_1, Y_2, Y_3; \mathbf{Z}_c, \mathbf{Z}_d) \\ = -\frac{3 \log(2\pi)}{2} - \frac{\log(|V|)}{2} \\ - (Y_1 - \mathbf{Z}'_{c1}\boldsymbol{\beta}_c - \mathbf{Z}'_{d1}\boldsymbol{\beta}_d, Y_2 - \mathbf{Z}'_{c2}\boldsymbol{\beta}_c - \mathbf{Z}'_{d2}\boldsymbol{\beta}_d, Y_3 - \mathbf{Z}'_{c3}\boldsymbol{\beta}_c - \mathbf{Z}'_{d3}\boldsymbol{\beta}_d) V^{-1} \begin{pmatrix} Y_1 - \mathbf{Z}'_{c1}\boldsymbol{\beta}_c - \mathbf{Z}'_{d1}\boldsymbol{\beta}_d \\ Y_2 - \mathbf{Z}'_{c2}\boldsymbol{\beta}_c - \mathbf{Z}'_{d2}\boldsymbol{\beta}_d \\ Y_3 - \mathbf{Z}'_{c3}\boldsymbol{\beta}_c - \mathbf{Z}'_{d3}\boldsymbol{\beta}_d \end{pmatrix}, \end{aligned}$$

$$\begin{aligned} \log L(\boldsymbol{\beta}_c, \boldsymbol{\beta}_d, \rho_1, \theta_1, \sigma^2 | Y_4, Y_5, \dots, Y_n; Y_1, Y_2, Y_3, \mathbf{Z}_c, \mathbf{Z}_d) \\ = -\frac{(n-3) \log(2\pi)}{2} - \frac{(n-3) \log(\sigma^2)}{2} \\ - \sum_{t=4}^n \frac{\{(Y_t - \mu_t) - \rho_1(Y_{t-1} - \mu_{t-1}) - \theta_1(Y_{t-2} - \mu_{t-2}) + \rho_1\theta_1(Y_{t-3} - \mu_{t-3})\}^2}{2\sigma^2} \end{aligned}$$

$$\text{and } \mathbf{V} = \begin{bmatrix} \gamma_0 & \gamma_1 & \gamma_2 \\ \gamma_1 & \gamma_0 & \gamma_1 \\ \gamma_2 & \gamma_1 & \gamma_0 \end{bmatrix}, \mu_t = \mathbf{Z}'_{ct}\boldsymbol{\beta}_c + \mathbf{Z}'_{dt}\boldsymbol{\beta}_d. \quad (\text{Equation 15})$$

The computation of the conditional ML estimators is easier than full ML and is obtained by regarding Y_1 , Y_2 and Y_3 as fixed. The difference between the full and conditional ML estimators depends primarily on Y_1 , Y_2 and Y_3 and is small for large n because the log likelihood is dominated by the second quadratic form in Equation 15. Assuming that the time series is regular with absolutely summable covariance function, then the distribution of the standardized estimators of $\boldsymbol{\beta}$ is approximately normal (Fuller, 1976). Let $\boldsymbol{\rho} = (\rho_1, \theta_1)$ and $S(\boldsymbol{\beta}, \boldsymbol{\rho}) = \sum_{t=4}^n \{(Y_t - \mathbf{X}'_t\boldsymbol{\beta}) - \rho_1(Y_{t-1} - \mathbf{X}'_{t-1}\boldsymbol{\beta}) - \theta_1(Y_{t-2} - \mathbf{X}'_{t-2}\boldsymbol{\beta}) + \rho_1\theta_1(Y_{t-3} - \mathbf{X}'_{t-3}\boldsymbol{\beta})\}^2$, then for moderately large n , $\hat{\boldsymbol{\beta}}$ is approximately distributed as a multivariate normal with mean $\boldsymbol{\beta}$ and covariance matrix $\text{Var}(\hat{\boldsymbol{\beta}}) = \sigma^2 \{S_{ij}\}^{-1}$ where S_{ij} is given in Equation 12. Because the ML computations are approximately equal to those of least squares estimation, the usual general linear model theory holds, approximately, for the seasonal autoregressive model particularly when the roots of the autoregressive equation are near zero (Fuller, 1976).

For σ^2 and $\boldsymbol{\rho}$ unknown, $\widehat{\text{Var}}(\hat{\boldsymbol{\beta}}) = s^2 \{S_{ij}\}^{-1}$ where $s^2 = S(\hat{\boldsymbol{\beta}}, \hat{\boldsymbol{\rho}})/(n-5-p-r)$ (Box and Tiao, 1975). To detect a disturbance event, we use the Wald test statistic (Equation 4), which is approximately distributed as a Student's t with $n-5-p-r$ degrees of freedom. The conditional ML estimation of $\boldsymbol{\beta}$ and $\boldsymbol{\rho}$ can be obtained using a standard nonlinear least squares program for the numerical minimization of $S(\boldsymbol{\beta}, \boldsymbol{\rho})$. The maximum likelihood procedure for outlier detection and parameter estimation has been developed for autoregressive processes by Fox (1972) and the general class of ARIMA (p,d,q) models by Chang and Tiao (1983). The unconditional ML estimation can be performed using the Cochrane-Orcutt procedure (Cochrane and Orcutt, 1949), or using a Gauss-Marquardt algorithm as implemented in the AUTOREG procedure in SAS/ETS® software, Version 9.4 of the SAS System for

autoregressive models, and SAS/ETS's ARIMA procedure, the ARIMA function or the GLS function in the NLME package in R 3.1.2 (available at <http://www.r-project.org>) for ARMA models. See Peña (1990) for a review of outlier detection methods in time series.

3. Material - Dendrochronological Example

We demonstrate the novel application of the likelihood-based TSIA method in dendrochronology to develop the growth-climate relations and forest disturbance history for a mature (115–125 years old), closed-canopy Douglas-fir stand, Falls Creek (N44°25', W122°24'), at 530 m elevation on the west slopes of the Cascade Mountains of Oregon; see Beedlow et al. (2013) and Lee et al. (2007) for a complete description of the site. The size of Douglas-fir trees ranged from 0.6 to 1.1 m in diameter at 1.4 m height and 48 to 63 m in height. This region experiences a Mediterranean climate regime characterized by an annual summer drought and moist-cool winters with little snowfall. The mean annual air temperature is 9.2°C, with winter and summer temperatures averaging 3.2 and 16.0°C, respectively. Total annual precipitation is 1708 mm on average, 89% of which falls between October and May. At this site, Douglas-fir growth is impacted by Swiss needle cast (SNC) disease caused by the foliar fungus, *Phaeocryptopus gaeumannii* (Rhode) Petrak which impairs physiological processes by stomatal occlusion and early needle abscission (Lee et al., 2016).

Tree core samples from 26 dominant and co-dominant Douglas-fir trees were taken at approximately breast height (1.4 m) using 5-mm diameter increment borers (Haglöf, Sweden) in 2011, collecting one or two cores per tree (Lee et al., 2016). The cores were air-dried, mounted, sanded, and digitized using a color flatbed scanner. EW and LW ring widths were measured to the nearest 0.01 mm using WinDENDRO 2008g software (Regent Instruments Inc., Quebec, Canada). The ring width time series were visually cross-dated and verified using the program COFECHA (Holmes, 1983) to ensure the correct calendar year was assigned to each ring (Table 1). Prior to analysis, the EW and LW time series were log transformed and detrended individually to remove the age-related growth trend but preserve the climate-related growth trend (Figure 1). A cubic spline smoother with a 50% frequency response of 32 years was used to remove the age-related trend prior to 1967 and a horizontal trend line after 1967 so as to be continuous in the join year. A master chronology for EW and LW ring width was calculated as the median of the standardized time series for individual trees.

The time series for Douglas-fir at this site has been studied by Lee et al. (2016) to infer the seasonal effects of temperature, water, and disturbances on intra-annual tree growth using climate data from several sources. Monthly mean maximum, minimum, and dewpoint temperatures and total precipitation data for the period 1895–2012 were obtained from the PRISM Climate Group at Oregon State University at <http://prism.oregonstate.edu>. The divisional monthly Palmer Drought Severity Index (PDSI) for the period 1895–2012 were obtained from the National Oceanic and Atmospheric Administration's National Climate Data Center at <http://www.ncdc.noaa.gov>. Dewpoint deficit (DPD) was calculated from monthly PRISM data as the difference between mean air temperature and the dewpoint temperature and is a measure of evaporative demand. The climate variables used in the

regression model for C_t were daily maximum air temperature, total precipitation, DPD, and PDSI which were summarized as seasonal averages that corresponded best with intra-annual growth.

Earlywood forms in May, June, and July while soil moisture is available and air temperature is below or at the growth optimum. Latewood forms in mid-July, August, and September, during the summer drought when air temperature is at or above the optimum and soil moisture is minimal. Consequently, the mean response function that separates the confounding effects of temperature, water, and SNC on tree growth varies by growth period (Lee et al., 2016). The EW and LW width series represent a seasonal time series having both regular and seasonal autocorrelation. The autocorrelation structure also varies by growth period because the current-year EW is more highly correlated with current-year LW than previous-year LW. Because the model parameters vary by growth period, the ML estimation of β^1 and ρ^1 for EW and β^2 and ρ^2 for LW are calculated iteratively by alternating between updating β^1 and ρ^1 on the odd iterations and β^2 and ρ^2 on the even iterations.

4. Results

Identification of the mean response function and autocorrelation structure is problematic due to potential outliers, notably the anomalously low growth in the period 1984–1986 (Figures 3 A&B). In particular, record low growth occurred in 1984 when summer PDSI was near a record high (i.e., abnormally wet summer), indicating a divergence between growth and climate (Figure 3C). Consequently, TSIA with pulse interventions was used to detect outliers which represent latent forest disturbance events (i.e., SNC outbreaks) in the past. The pulse intervention coefficients have negative signs for disturbance years but can be positive for years having above-average tree growth which cannot be attributed to the measured climatic variables.

To illustrate the use of grafted polynomials in dendrochronology, we assume a linear change in growth rate due to climate change. The tree-ring series is divided into two periods, the first period is assumed to have a slope of zero and the second period is assumed to have a non-zero slope. The onset of the climate trend is assumed to be unknown but occurs in response to warming temperatures that increased linearly at an accelerated rate of $\sim 0.2^\circ\text{C}$ per decade in the 1980–2012 period in the PNW (Abatzoglou et al., 2014). The tree-ring data have been centered about zero during the standardization process to remove the age-related growth trend. A linear grafted polynomial has the form

$$f_1^s(t) = \begin{cases} 0, & \text{if } t \leq t_0 \\ \beta_1^s(t - t_0), & \text{if } t \geq t_0 \end{cases} \quad (\text{Equation 16})$$

for $t=1, 2, \dots, n/2$ years and $s=1$ for EW and 2 for LW. Based on the ML estimates of t_0 and β , the onset of forest decline due to climate change occurred in 1989, after which growth declined steadily at a rate of -0.0062 (s.e.=0.0008) for EW and -0.0077 (s.e.=0.0010) for LW on a log scale (Figure 2).

The growth response to previous-year DPD ($pDPD_t^s$), winter temperature (WT_t^s), summer DPD (DPD_t^s), summer temperature (ST_t^s), and summer precipitation (P_t^s) was modeled by a first-order response surface. Because cell formation changes from EW to LW in mid- to late-July, the current-year climate variables were calculated using different averaging periods for the two growth periods and were selected based on statistical fit. The growth-climate relation was modeled as follows

$$f_2^s(pDPD_t^s, WT_t^s, DPD_t^s, ST_t^s, P_t^s) = \beta_0^s + \beta_2^s pDPD_t^s + \beta_3^s WT_t^s + \beta_4^s DPD_t^s + \beta_5^s ST_t^s + \beta_6^s P_t^s.$$

(Equation 17)

The mean response function $\mu_t^s = C_t^s + D_t^s$ where $C_t^s = f_1^s(t) + f_2^s(pDPD_t^s, WT_t^s, DPD_t^s, ST_t^s, P_t^s)$ and $D_t^s = \sum_{j=1}^r \beta_{6+j}^s X_{j,t}^s$ where $X_{j,t}^s = 1$ if $t = t_j^s$ and $= 0$ otherwise.

The TSIA model explained 75% of the variation in the EW and LW time series and inspection of the residuals and their autocorrelations revealed no model inadequacies. The ML estimates and the associated standard errors of the climate and disturbance components of the mean response functions of EW and LW are given in Table 2. Current-year summer DPD, summer and winter temperature, and previous-year DPD ($pDPD$) were the principal seasonal climatic variables affecting radial stem growth. Growth was reduced by increasing DPD in the previous summer/fall when evaporative demand was high and after LW growth had peaked. Time series intervention analysis of Douglas-fir radial stem growth identified 9 and 7 anomalously low growth years for EW and LW series, respectively, associated with SNC that could not be attributed to climate (Figures 2 A&B). These episodic patterns of low growth anomalies were likely due to a ubiquitous forest disturbance agent specific to Douglas-fir (i.e., SNC), notably in 1984–1986 (Figures 2 A&B). Furthermore, the anomalously high growth for LW in 1931 could not be attributed to climate and was identified as an outlier.

Examination of the negative outlier years indicated that increasing DPD reduced growth more in years when disturbance was present than in years when disturbance was absent (Figures 4 A&B). This interaction of $pDPD$ and disturbance was modeled as a change in slope of $pDPD$ for the years identified as outliers as follows

$$f_3^s(pDPD_t^s) = \begin{cases} \beta_2^s pDPD_t^s, & \text{if no disturbance} \\ (\beta_2^s + \delta^s) pDPD_t^s, & \text{if disturbance} \end{cases}$$

This modification to the mean response function resulted in a more parsimonious model having fewer pulse intervention terms (Table 3) and a better statistical fit based on a lower Akaike Information Criterion (AIC) (Table 4). Pulse intervention terms for 1984–1985 were still required because these growth anomalies could not be fully explained by the interaction of climate and disturbance. Pulse intervention terms and trend explained more of the variability in EW and LW series than any of the seasonal climatic factors based on a lower

Akaike Information Criterion (Table 4). Several outliers were not statistically significant at the 0.05 level using a Bonferroni correction but were verified as outliers based on residual analysis of the more parsimonious model.

Air temperature and/or DPD affected growth in all seasons whereas only latewood growth was limited by precipitation during the annual summer drought. Earlywood growth rate decreased with spring/summer DPD and LW growth rate decreased with summer temperature. Warming temperatures due to climate change had a more pronounced effect on LW than EW growth as indicated by a greater downward trend in the LW time series (Figures 2 A&B). The negative growth trends represent a multi-decadal decline in tree growth due to chronic temperature and water stress that is not explained by annual and seasonal changes in the climate variables.

SNC impact on Douglas-fir growth is inferred based on the original time series model with pulse interventions, back-transformed to the original scale. It is possible to infer the SNC impact as the sum of pDPD multiplied by the change in its slope for the disease suppression years and the pulse interventions, but this approach may not be generalizable to other forest disturbance agents. The reconstruction of the history of SNC impact on stem growth based on TSIA indicates a sinusoidal disease cycle with primary and secondary periodicities of ~20–24 and 10–11 years, respectively (Figure 5). Based on the EW chronology, estimated SNC outbreak events peaked in 1918 and 1984–1986 and reduced stem growth by >25% in these years. TSIA is a useful statistical method to detect outliers in dendrochronological data when the effects of latent forest disturbance events on radial stem growth exceeds that of temperature and water stress (typically <25% in absolute value).

A SARMA (1,0)₂ model was identified for EW and a SARMA (1,0)₂ × (1,0) model was indicated for LW. The ML estimates of the autoregressive parameters are

$$(1 - 0.16B^2)(Y_t - \mu_t^1) = e_t \text{ for } t \text{ odd,}$$

$$(1 - 0.38B)(1 - 0.15B^2)(Y_t - \mu_t^2) = e_t \text{ for } t \text{ even,}$$

where μ_t^1 and μ_t^2 are the mean response functions for EW and LW, respectively, B is the backshift operator (e.g., $B(Y_t - \mu_t^2) = Y_{t-1} - \mu_{t-1}^2$).

5. Discussion

The interaction of climate and forest disturbances are key processes in forest ecosystem dynamics which are host to many diseases and pests. Identifying the key climatic factors influencing tree growth is difficult because multiple climate factors interact and are highly seasonal and are confounded with forest disturbances. Autocorrelation, seasonality, confounding of age-related and climate growth trends, and the confounding effects of climate and disturbance on growth pose problems in the dendrochronological study of growth-climate relations and forest disturbance history.

Time series intervention analysis is a general approach for growth-climate relations and the reconstruction of the history of forest disturbances and is applicable for sites where records of disturbance are incomplete. Data requirements for TSIA are modest in comparison to other disturbance detection methods such as the boundary-line release criteria and do not require a climate-sympatric, non-host chronology to adjust the host chronology. However, a non-host chronology provides useful auxiliary information for TSIA to better understand the growth-climate relations in the presence of outliers and reconstruct the history of host-specific forest disturbance agents at sites where disturbance history is unknown.

The TSIA approach provides a unified solution to a number of problems encountered in dendrochronological research including: (1) the ability to simultaneously infer the growth-climate relations and forest disturbance history across time and space using a likelihood framework for model development; (2) the ability to separate age-related and climatic growth trends to determine the onset, duration, and magnitude of changes in forest condition and productivity in a changing climate; (3) the ability to reconstruct the magnitude of past disturbance effects on tree growth and infer the climate relations with forest pests and pathogens; (4) a unified statistical modeling approach for total annual tree-ring width time series that extends naturally to a seasonal time series approach for earlywood/latewood width time series to understand the seasonal effects of temperature and water on tree growth; (5) the dendrochronological process of standardization of annual and seasonal tree-ring chronologies to account for age-related growth trends (i.e., detrending process) and autocorrelation (i.e., prewhitening process); and (6) the ability to examine the interaction of temperature, water, and forest pests and pathogens (e.g., *P. gaummannii*) that alter the climate relations by impacting physiological processes of gas exchange. In particular, dendrochronological data for Douglas-fir in the PNW and elsewhere almost always have multiple growth anomalies associated with ubiquitous climate-mediated forest disturbance agents such as *P. gaummannii* (Lee et al., 2016).

Our TSIA approach to simultaneously account for deterministic and stochastic variability is widely used to analyze business and economic data (Fuller, 1976) but differs from the time series approach commonly used to analyze dendrochronological data at an annual (Cook and Kairiukstis, 1990) or seasonal time step (Meko and Baisan, 2001) in the presence of outliers (Downing and McLaughlin, 1990; Druckenbrod, 2005; Druckenbrod et al., 2013). Our approach uses the conceptual structural component model of Cook (1985, 1987) which specifies a mean response function comprised of deterministic components for climatic growth trend, climatic variability, and forest disturbances and a Box-Jenkins model for the stochastic component, then estimate the parameters by maximum likelihood method. In contrast to the simultaneous estimation of the deterministic and stochastic components using maximum likelihood, an alternative approach often used in dendrochronology uses a multiple-step procedure to first standardize the tree-ring data using low-frequency filters to remove nonclimatic growth trends, followed by an autoregressive filter to remove autocorrelation, then analyze the prewhitened residuals to either infer the growth-climate relations C_t (e.g., Fritts, 1976) or reconstruct the history of forest disturbance D_t (e.g., Druckenbrod, 2005; Druckenbrod et al., 2013), but not both. When outliers are detected, the autoregressive filter is recalculated by setting the residuals in question to zero (Downing and McLaughlin, 1990; Druckenbrod et al., 2013).

While the multi-step methods are designed to preserve the climate signal during standardization (Briffa et al., 1992; Cook et al., 1995; Briffa and Melvin, 2011), multi-decadal or longer climate trends and higher-frequency patterns may be removed by the detrending (Briffa et al., 1992; Cook et al., 1995; Lloyd et al., 2013) and/or autoregressive filters. The preservation of the climate signal in tree-ring data has focused on different detrending methods in the standardization process (Helama et al., 2004) or combining the steps to model the climatic and nonclimatic signals simultaneously in a Bayesian framework (Schofield et al., 2016), with minor consideration of the autoregressive model. The Yule-Walker (YW) calculations for an AR model in the standardization process, as implemented in ARSTAN (Cook and Holmes, 1986) and the R package dplR (Bunn, 2008), center the tree-ring data about its mean which is assumed to be constant. However, the assumption of a constant mean is not valid for a tree-ring width time series because annual stem growth is influenced by climatic factors and possibly forest disturbances. Correct specification of the mean response function is critical to the correct identification of the autoregressive filter and to retain the climate signal in the prewhitened series.

To understand the differences in modeling the deterministic and stochastic components either jointly using a maximum likelihood framework or separately using the multi-step approach, consider the time series, $Y_t = \beta \sin(\omega t)$ which can be modeled either as a purely deterministic or stochastic process. The joint approach assumes a time series with a non-constant mean and assigns correctly the variation in Y_t to the deterministic component having a sinusoidal pattern with periodicity $2\pi/\omega$. In comparison, the standardization process in the dendrochronological approach prewhitens the time series using an AR(2) filter in this example, i.e., $(1 - \rho_1 B - \rho_2 B^2)(Y_t - \mu) = (1 - \alpha_1 B)(1 - \alpha_2 B)(Y_t - \mu) = 0$ where $\mu = E(Y_t)$ and α_1 and α_2 are a pair of complex conjugate roots of the form $\eta \exp(\pm i \omega)$ for some modulus η (Figure 6A). Unlike the maximum likelihood approach, the dendrochronological approach assigns the total variation of Y_t to the stochastic component. Note that both solutions result in the same statistical fit, which is problematic in a Bayesian framework that is prone to under-identification of the model parameters. Consequently, the Bayesian alternative to the multi-step approach generally does not converge to a solution when an ARMA model and non-constant mean response function are both specified (Schofield et al., 2016).

We extend this discussion to a time series with disturbance to compare the differences in the decomposition of the deterministic and stochastic components between TSIA using the multi-step approach proposed by Downing and McLaughlin (1990), Druckenbrod (2005), and Druckenbrod et al. (2013) and our joint maximum likelihood-based approach. Consider the time series, $Y_t = C_t + D_t$, where $C_t = \beta \sin(\omega t)$, $D_t = \delta X_t$, and $X_t = 1$ if $t=t_0$ and $=0$ otherwise. While the two TSIA approaches model the single anomaly in the time series using the disturbance component $D_t = \delta X_t$, there are marked differences in the statistical inferences of C_t and the stochastic component. The ML solution assigns correctly the total variation in Y_t to the deterministic component which consists of C_t and D_t and the ML estimate of the magnitude of the disturbance is equal to δ . In contrast, the multi-step approach applies an AR(2) filter to Y_t , detects the outlier at $t=t_0$ using pulse intervention analysis, then refits the AR(2) model by setting the residual for $t=t_0$ equal to 0. Prior to outlier detection and removal, the AR(2) filter partially removes the sinusoidal function C_t

so that the prewhitened residuals are no longer equal to 0 and the disturbance is propagated moving forward (Figure 6B). Unlike the ML approach that infers C_t and D_t and no stochastic component, the multi-step TSIA approach infers D_t and an AR(2) stochastic process without specification of C_t . In general, greater violation of the assumption of a constant mean can result in more serious errors in the AR residuals moving forward in the process.

The sensitivity of the YW calculations to a non-constant mean is further examined based on the differences in the AR models for the EW and LW ring width series for Falls Creek between the likelihood and the multi-step dendrochronological approaches. The detrended ring width series centered about the sample mean display greater autocorrelation than the series detrended to remove the age-related trend and adjusted for disturbance, climate trend, and/or climate (Table 5). That is, the sample autocorrelation function is biased high by a quadratic, non-centrality term associated with a climate trend and a growth response to climate. The biases in the YW calculations can be computed as a function of the noncentrality parameters associated with a noncentral chi-squared distribution and the sample autocovariances but these calculations are outside the scope of this paper.

An alternative approach is to modify the YW estimators for the AR parameters by centering the tree-ring width series about a non-constant mean equal to the sum of C_t and D_t rather than about a constant mean (and D_t). The modified YW estimators for the AR model will closely approximate the ML estimators, but now, an expectation-maximization algorithm is required to iterate the calculations by updating the estimators of the first- and second-moments at odd and even steps, respectively. This is more efficiently done using the joint ML-based TSIA approach than the multi-step TSIA approach proposed by Downing and McLaughlin (1990).

Separating the annual total ring width chronology into its EW and LW constituents can allow a better relation of the annual and seasonal variability in stem growth to changes in temperature and water, particularly in western U.S. forests that experience an annual summer drought. Several dendrochronological studies have shown that the LW ring width chronology is a better climate proxy than the EW chronology (Meko and Baisan, 2001; Griffin et al., 2011), consistent with our findings that LW growth is limited primarily by summer temperature and water in the current year (Lee et al., 2016). The multi-step approach in common use in dendrochronology treats the EW and LW chronologies as two univariate time series with constant means in the standardization process, then the EW residuals are used as a covariate in a linear regression model to isolate the climate signal in the LW residuals (Meko and Baisan, 2001; Stahle et al., 2009). This multi-step approach assumes that the seasonal and regular autocorrelation structures are separable whereas the maximum likelihood-based approach that we propose extends naturally to a multiplicative SARMA $(P,Q)_2 \times (p,q)$ model. The YW and least squares estimators of the seasonal and regular autoregressive parameters, respectively, can be markedly different than the maximum likelihood estimators when the mean is non-constant, as is the case for dendrochronological data.

Unlike outlier detection methods in time series that consider the suspect points as nuisance parameters (Cook and Weisberg, 1982; Belsley et al., 1980; Peña, 1990), all model

parameters for a dendrochronological time series are used to infer the growth-climate relations and forest disturbance history. A unified statistical approach such as TSIA can be very useful because the presence of additive outliers can have a strong influence on the estimates of model parameters for the seasonal climatic factors (Peña, 1990). The TSIA method using a likelihood framework proposed in this paper allows improved resolution in the field of dendrochronology to simultaneously model the growth-climate relation, forest disturbance history, and autocorrelation structure and should have broad application to a wide range of forest types, climate and disturbance regimes. The TSIA method is also applicable in the field of dendroecology to analyze stable carbon and oxygen isotope time series in tree rings which correlate with climate variables (e.g., Barnard et al., 2012; Johnstone et al., 2013), discriminate for forest disturbances (Saffell et al., 2014), and display autocorrelation (Monserud and Marshall, 2001). The statistical analysis of a regular or seasonal dendrochronological time series in the presence of outliers using the maximum likelihood-based TSIA approach can be performed using commercial SAS/ETS® software or the freely available R software environment.

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Appendix A

Generalization of time series intervention analysis having multiple pulse interventions

We generalize the mean response function to allow for r known pulse disturbances at times $t^*=(t_1, t_2, \dots, t_r)$ where $1 \leq t_1 < t_2 < \dots < t_r \leq n$. The form of the mean response model is

$$\mu_t = \sum_{i=1}^p \beta_i X_{it} + \sum_{j=1}^r \beta_{p+j} X_{p+j, t} \quad (\text{Equation A.1})$$

where $X_{p+j, t} = 1$ if $t=t_j$, and $=0$ if $t \neq t_j$ for $j=1, 2, \dots, r$. Let $\boldsymbol{\mu}' = (\mu_1, \mu_2, \dots, \mu_n)$ and $\boldsymbol{\beta}' = (\boldsymbol{\beta}_c' \mid \boldsymbol{\beta}_d')$ where $\boldsymbol{\beta}_c' = (\beta_1, \beta_2, \dots, \beta_p)$ and $\boldsymbol{\beta}_d' = (\beta_{p+1}, \beta_{p+2}, \dots, \beta_{p+r})$, then $\boldsymbol{\mu} = \mathbf{X}\boldsymbol{\beta} = \mathbf{Z}_c\boldsymbol{\beta}_c + \mathbf{Z}_d\boldsymbol{\beta}_d$ where $\mathbf{X} = [\mathbf{Z}_c \mid \mathbf{Z}_d]$, $\mathbf{Z}_c$ is a $n \times p$ matrix whose elements are the measured variables and $\mathbf{Z}_d$ is a $n \times r$ matrix consisting of 0s and 1s. Computationally, the rows of $\mathbf{X}$ can be rearranged so that $(t_1, t_2, \dots, t_r) = (n-r+1, n-r+2, \dots, n)$. We partition the model parameters and data matrix as before: $\mathbf{y}' = (\mathbf{y}_c' \mid \mathbf{y}_d')$ where $\mathbf{y}_c' = (y_1, y_2, \dots, y_{n-r})$ and $\mathbf{y}_d' = (y_{n-r+1}, y_{n-r+2}, \dots, y_n)$;

and $\mathbf{X} = \begin{bmatrix} \mathbf{X}_c & \mathbf{0} \\ \mathbf{X}_d & \mathbf{I}_r \end{bmatrix}$ where $\mathbf{X}_c$ is $(n-r) \times p$, $\mathbf{0}$ is an $(n-r) \times r$ matrix of zeros, $\mathbf{X}_d$ is $r \times p$, and $\mathbf{I}_r$ is a $r \times r$ identity matrix. The least squares estimator for $\boldsymbol{\beta}$ is given in Equation 2 and the least squares estimator for σ^2 is

$$s^2 = \frac{1}{n-p-r} (\mathbf{y} - \mathbf{X}\hat{\boldsymbol{\beta}})'(\mathbf{y} - \mathbf{X}\hat{\boldsymbol{\beta}}) = \frac{1}{n-p-r} (\mathbf{y}_c - \mathbf{X}_c\hat{\boldsymbol{\beta}}_c)'(\mathbf{y}_c - \mathbf{X}_c\hat{\boldsymbol{\beta}}_c). \quad (\text{Equation A.2})$$

Note that the least squares estimators of $\boldsymbol{\beta}_c$ and σ^2 given in Equations 2 and A.2, respectively, are calibrated using the undisturbed values $\mathbf{y}_c$ and exclude the outliers associated with forest disturbances, $\mathbf{y}_d$.

Figure 1.

Flowchart for development of a time series intervention model of tree-ring width chronology having a mean response function with components for climate (C_t) and disturbance (D_t) and an autocorrelation structure associated with an ARMA (p, q) model. The tree-ring width time series is standardized by detrending to remove the age-related trend while preserving the climate trend if present. Unlike the multi-step dendrochronological approach, the data are not prewhitened to remove autocorrelation. As an alternative approach, the model parameters for C_t , D_t , and autocorrelation are estimated simultaneously in a likelihood framework.

Figure 2.

Raw total ring width data (black line with closed circles) for mature Douglas-fir for Falls Creek display an age-related trend prior to ~1956 and a climate trend after 1990. The site is located at 530 m elevation on the west slope of the Cascade Mountains of Oregon. The cubic spline smoother (black line) removed the climate trend after 1990 which is an undesirable end effect. The detrended series (black line with open circles) is the difference between the raw series and the cubic spline smoother. Spline regression was used to model the age-related trend in the first segment using a cubic spline smoother and the climate trend in the last segment using a first-order polynomial. Note the growth anomalies in 1984–1986 represent an intervention event. The growth data for the first several years were excluded from the analysis because of end effects indicated by a divergence between the raw data and the cubic spline smoother.

Figure 3.

Observed and predicted A) earlywood and B) latewood width chronologies of Douglas-fir for Falls Creek based on time series intervention model. Vertical red bars represent anomalously low growth associated with Swiss needle cast and not accounted for by the effects of climatic factors. The vertical blue bar in 1931 represents a high growth anomaly that was not accounted for by the climatic factors. These anomalous growth years are identified as statistically significant divergences between the host chronology (black line) and the predicted growth response to seasonal climatic factors (gray line) at the 0.05 level of significance. The climate-induced decline in growth rate after 1989 is indicated by a blue line.

Figure 4.

The interaction of previous-year dewpoint deficit (pDPD) and Swiss needle cast (SNC) on (A) earlywood (EW) and (B) latewood (LW) growth of Douglas-fir for Falls Creek. Growth response to pDPD is more negative in disturbed years than in years having no forest disturbance. EW and LW ring widths were adjusted for the other climatic variables in the regression model to isolate the growth response to pDPD.

Figure 5.

Dendrochronological reconstruction of the history of Swiss Needle Cast (SNC) impact on Douglas-fir growth based on time series intervention analysis. A) The SNC index is equal to the pulse interventions in Figures 3 A&B, back-transformed to the original scale. B) The SNC index displays a sinusoidal disease cycle having primary and secondary periodicities of ~20–24 and 10–11 years, respectively.

Figure 6.

Illustration of the loss of a sinusoidal signal (black line) by a second-order autoregressive filter applied to a time series with A) a non-constant mean (●) and B) in the presence of a single outlier. B) The autoregressive residuals (▲) are no longer equal to zero and are distorted by the single anomaly moving forward.

Table 1

Dendrochronology summary statistics for Douglas-fir at Falls Creek.

Species	Pith date	No. trees cored	Interseries correlation ¹	Mean sensitivity ²
Douglas-fir	1890	26	0.53	0.16

¹The average correlation between each detrended time series and the mean of all other detrended time series.

²The mean absolute first difference of each detrended time series relative to its running mean value. The index ranges from 0 (i.e., no variability) to 2 (i.e., high variability with periodicity of 2 years).

Table 2

Growth response of Douglas-fir to seasonal climatic variables based on time series intervention model of earlywood and latewood ring width series for Falls Creek. Maximum likelihood estimates and the associated standard errors of the slopes for the measured climate variables are reported. Coefficients in bold are significantly different from 0 at the 0.05 level of significance.

Variable	Parameter	Earlywood			Latewood		
		Season	Estimate	Standard error	Season	Estimate	Standard error
Intercept	β_0^s		0.086	0.049		0.298	0.077
Trend	β_1^s		-0.0062	0.0008		-0.0077	0.0010
Prior-year DPD	β_2^s	Jul-Sep	-0.0073	0.0042	Oct-Nov	-0.0149	0.0045
Winter Temp	β_3^s	Nov-Feb	0.0089	0.0028	Jan-Mar	0.0117	0.0028
Summer DPD	β_4^s	May-Jun	-0.013	0.004			
Summer Temp	β_5^s				Jul-Aug	-0.0135	0.0029
Precip	β_6^s				Jun-Jul	0.0015	0.0008
Pulse 1900	β_7^s					-0.1123	0.0405
Pulse 1917	β_8^s					-0.0826	0.0414
Pulse 1918	β_9^s		-0.1280	0.0336			
Pulse 1931	β_{10}^s					0.2024	0.0409
Pulse 1956	β_{11}^s		-0.0742	0.0329			
Pulse 1962	β_{12}^s		-0.0683	0.0333			
Pulse 1963	β_{13}^s		-0.0937	0.0340			

Variable	Parameter	Earlywood			Latewood		
		Season	Estimate	Standard error	Season	Estimate	Standard error
Pulse 1984	β_{14}^s		-0.2500	0.0342		-0.3112	0.0417
Pulse 1985	β_{15}^s		-0.2165	0.0340		-0.2912	0.0415
Pulse 1986	β_{16}^s		-0.1581	0.0336		-0.1676	0.0406
Pulse 2004	β_{17}^s		-0.0884	0.0343		-0.0751	0.0407
Pulse 2005	β_{18}^s		-0.0768	0.0353			
Pulse 2009	β_{19}^s					-0.1056	0.0427
Seasonal AR	θ_1		0.16			0.15	
Regular AR	ρ_1					0.38	
	σ		0.0291			0.0375	

Table 3

Alternative growth response of Douglas-fir to seasonal climatic variables based on time series intervention model of earlywood and latewood ring width series for Falls Creek. The negative pulse intervention terms in Table 2 were modeled by a change in slope of the previous-year DPD. Maximum likelihood estimates and the associated standard errors of the slopes for the measured climate variables are reported.

Variable	Parameter	Earlywood			Latewood		
		Season	Estimate	Standard error	Season	Estimate	Standard error
Intercept	β_0^s		0.097	0.047		0.277	0.074
Trend	β_1^s		-0.0062	0.0008		-0.0077	0.0010
Prior-year DPD	β_2^s	Jul-Sep	-0.0077	0.0040	Oct-Nov	-0.0147	0.0045
Winter Temp	β_3^s	Nov-Feb	0.0088	0.0027	Jan-Mar	0.0106	0.0027
Summer DPD	β_4^s	May-Jun	-0.0134	0.0038			
Summer Temp	β_5^s				Jul-Aug	-0.0123	0.0028
Precip	β_6^s				Jun-Jul	0.0017	0.0008
Prior-year DPD for disturbance years	δ^s	Jul-Sep	-0.0106	0.0014	Oct-Nov	-0.0227	0.0039
Pulse 1931	β_7^s					0.2004	0.0407
Pulse 1984	β_8^s		-0.1727	0.0353		-0.2186	0.0440
Pulse 1985	β_9^s		-0.1077	0.0348		-0.1908	0.0427
Seasonal AR	θ_1		0.16			0.15	
Regular AR	ρ_1					0.36	
	σ		0.0320			0.0382	

Table 4

Comparison of full and reduced models for earlywood and latewood ring width series based on Akaike Information Criterion.

Model	Earlywood		Latewood	
	Model 1 ¹	Model 2 ²	Model 1 ¹	Model 2 ²
Full model	−428.8	−436.0	−386.3	−390.4
Excluding Trend	−394.3	−401.8	−349.0	−354.0
Excluding Prior-year DPD	−427.5	−386.0	−376.6	−354.7
Excluding Winter Temp	−419.7	−427.0	−369.8	−376.4
Excluding Summer DPD	−419.5	−425.4		
Excluding Summer Temp			−365.9	−372.6
Excluding Precipitation			−384.3	−387.5
Excluding Pulses	−356.1	−413.5	−306.3	−342.5
Excluding AR	−428.0	−435.3	−378.1	−382.9

¹Time series intervention model with pulse interventions for the growth anomalies.

²Time series intervention model with a change in slope of previous-year Dewpoint Deficit for disturbance years.

Table 5

Comparison of the autoregressive model parameters (ρ_1 , ρ_2) for the fully detrended and partially detrended earlywood and latewood ring width chronologies for Falls Creek. The age-related and climate trends were removed using a cubic spline smoother for the whole series. Alternatively, the climate trend for the period 1989–2010 was preserved by applying the cubic spline smoother to the period 1890–1967 and modeled using grafted polynomials. Each ring width series was either adjusted or not adjusted for outliers associated with Swiss needle cast disease.

Time series	Earlywood		Latewood	
	ρ_1	ρ_2	ρ_1	ρ_2
Fully detrended	0.45	−0.19	0.25	−0.20
Fully detrended adjusted for disturbance	0.18		0.15	−0.22
Partially detrended	0.74	−0.27	0.41	
Partially detrended adjusted for disturbance	0.40	0.23	0.39	
Partially detrended adjusted for climate trend	0.42	−0.16	0.31	−0.18
Partially detrended adjusted for disturbance and climate trend	0.19		0.21	−0.18
Partially detrended adjusted for disturbance, climate and climate trend ^I	0.16		0.15	

^I Seasonal autoregressive model parameters from time series intervention model (Table 3)