School of Forestry, University of Canterbury, Christchurch, New Zealand.

TIME-SERIES ANALYSES APPLIED TO SEQUENCES OF *NOTHOFAGUS* GROWTH-RING MEASUREMENTS

Summary: Time-series analysis, a relatively uncommon technique in ecological studies, has been applied to annual tree growth-ring series. In agreement with earlier North American work, ARMA(1,1) models were found to be the predominant form for expressing stochastic growth processes, occurring in 58% of the 36 *Nothofagus menziesii* and *N. solandri* time-series examined. The remaining 42% conformed to an AR(1) process. The average parameter values of {0.79, 0.42} for the ARMA models are remarkably consistent with North American work.

Such derived stochastic models should be regarded as average processes; analyses of first-order autocorrelation coefficients indicate fluctuations in absolute value within series, including some short periods of independence. An apparent preference for a specific ARMA model with species is better explained by the lengths of the series; a shorter time-series is likely to have a simpler stochastic model over time, by virtue of lesser precision associated with model parameters. Thus, 81 % of the series longer than 200 years are modelled by an ARMA(1,1) process, while 78% of the series shorter than 200, are modelled by AR(1).

It is suggested that although fitting Box-Jenkins stochastic models to various genera represents an interesting area of research, the approximate equivalence of the various models, and their part-dependence on series length, negates the need to locate an optimal process in all circumstances. The principal advantage of utilising Box-Jenkins models in this application is to render data more suitable for analysis with environmental variables, and to enhance cross-correlation and mean sensitivity.

Keywords: Time-series; Box-Jenkins models; dendrochronology; *Nothofagus menziesii; Nothofagus solandri*.

Introduction

Time-series analysis is an area of statistics which departs a little from the mainstream of statistical theory and practice. The special feature of time-series data is that they are usually correlated in time, rather than being independent (as is assumed, for example, in regression analysis), which gives rise to more complicated underlying models. Nevertheless time-series analysis is an established statistical technique, and the current availability of suitable computer programs (e.g. SAS/ETS; Brocklebank and Dickey, 1986) has greatly facilitated practical application.

The use of time-series analysis in ecological literature is not common; time-series analyses are more commonly applied in the social sciences (e.g. McCleary and Hay, 1980), although they have also been used in applied biology. For example, Ferguson and Leech (1978) broached the subject to some extent by advocating generalised least squares as an analytical tool in growth and yield modelling in forestry. There is agreement that at least 50 data are required in order for most time-series techniques to be soundly applied (McCleary and Hay, 1980; Chatfield, 1985) and this prerequisite may exclude many ecological applications. One area of ecology where time-series techniques have been used is in conjunction with the study of tree growth-ring development (dendrochronology) and their relationships with climatic variables (dendroclimatology) (Fritts, 1976; Norton and Ogden, 1987). Objectives of such applications can be:

(1) to explore the resultant structure of time-series models, *per se,* and to categorise their type with different species and environmental conditions;

(2) to utilise time-series equations to remove serial (auto) correlation in growth-ring sequences, thus making such data more suitable for analysis with climatic variables.

In this contribution a brief overview of some time-series techniques relevant to the modelling of dendrochronological data is given and the techniques applied to several ring-width time-series obtained from two *Nothfagus* species (*N. menziesii* and *N. solandri*).

Time-series methodology

When applying time-series methods to sequences of data the measurement interval is assumed equidistant or evenly spaced in time; annual growth-rings from trees are a good example.

A time-series is assumed to be composed of four components (Kendall and Stuart, 1966):

(a) an overall trend, or long-term movement;

(b) oscillations about the trend, of greater or lesser regularity;

(c) a seasonal effect;

(d) a purely random or irregular component, often referred to as *'white noise'*, analogous to a residual effect postulated in regression models.

With dendrochronological series (based on annual ring-width measurements), component (c) is, by definition, non-applicable.

Long-term trends in time-series data are frequently removed by differencing techniques (e.g. Chatfield, 1985; p.21), but more commonly with growth-ring data, suitable functions are fitted to the series and the residual values used in subsequent analyses. Fritts *et al.* (1969) proposed the use of the exponential function:

$$Y = \alpha\exp(\beta t) + \delta \qquad (1)$$

where in (1)

Y = tree growth-ring increase, at time (year), t

α,β,δ = equation parameters, from the tree ring sequence

exp = exponential function

as a candidate equation. Polynomials and straight-lines have also been suggested (Fritts, 1976). More recently Warren (1980) proposed the equation (in its simplest form):

$$Y = \alpha t^{\beta}\exp(\delta t) \qquad (2)$$

which has the advantage of increased flexibility, and is more descriptive of usual tree growth-rate development. An alternative approach using digital filters has been proposed (Briffa *et al.,* 1987) but as the underlying assumptions differ from the above methods, is not considered further here.

Assuming a dendrochronological series has been made stationary (that is, long-term trends removed) by one of the methods summarised above, the analyst requires appropriate models to depict the potential presence of component (b), namely short-term fluctuations. To achieve this, two stochastic models have been developed, so called *autoregressive* and *moving-average* processes.

An autoregressive (AR) process of order p is given by:

$$Z_t = \alpha_1 Z_{t-1} + \alpha_2 Z_{t-2} + \ldots \alpha_p Z_{t-p} + a_t \qquad (3)$$

where in (3)

$Z_t = (Y_t - \mu)$ the deviation of any observation Y_t from the series mean, μ, at time t

p = total number of preceding Z_t terms

α_i = parameters associated with an AR model $(I \leq p)$

a_t = an error term, distributed NID$(0,\sigma^2)$, commonly referred to as *'white noise'*

Equation (3) is analogous to a multiple regression model, except the predictor variables are past values of the dependent variable, Z_t.

Just as a sequence of past radial increments can be used as predictor variables, then likewise the preceding residual or error terms can be utilised. Thus, a moving average (MA) process of order q is given by:

$$Z_t = a_t - \beta_1 - a_{t-1} - \beta_2 - a_{t-2} - \ldots \beta_q - a_{t-q} \qquad (4)$$

where in (4)

β_i = parameters associated with a MA process $(i \leqslant q)$

q = total number of preceding a_i terms

Moving-average models can be difficult to visualise, since the a_i are never explicitly observed or measured. It is sometimes useful to regard each a_i as an input force or shock which causes perturbations to the (output) Z_t. Thus, in the case of tree ring growth series, it might be thought of as the many energy sources intercepted by a tree, which ultimately result in the laying down of cambial cells (radial growth).

Equations (3) and (4) can be combined to form a mixed series which is referred to as an ARMA (p,q) process:

$$Z_t - \alpha_1 Z_{t-1} - \alpha_2 A_{t-2} - \ldots - \alpha_p Z_{t-p} = \alpha_t - \beta_1 a_{t-1} - \beta_2 a_{t-2} - \ldots \beta_q a_{t-q} \qquad (5)$$

Such models have been developed and investigated at length by Box and Jenkins (1976) and form the foundation models of many time-series applications.

Equations such as (5) are purely empirical in the sense they are derived and estimated strictly for each time-series under scrutiny. To aid decision as to the correct order of p and q in (5) the autocorrelation coefficient, given by:

$$r_k = \sum_{t=k}^{n} (Z_t \times Z_{t-k}) / \sum_{t=1}^{n} Z_t^2 \qquad (6)$$

where in (6)

n = the length of the series

k = the chosen interval in time between observations, (referred to as the *lag)*

can be utilised as a diagnostic statistic. The sample autocorrelation function (ACF) is given by (6), for k = 1,2, ..., m, where m < n. Allied identification statistics are the partial and inverse autocorrelation functions (Box and Jenkins, 1976). Respective plottings of sample estimates against lag k are called correlograms. The theoretical correlogram structures of specific ARMA(p,q) processes have been documented (e.g. McCleary and Hay, 1980; pp. 68-80) and comparison to those obtained from actual time-series may allow the analyst to deduce the likely order of p and q.

The autoregressive parameters in (5) can be estimated explicitly by least-squares methodology, but moving average parameters need to be solved iteratively, analogous to non-linear regression estimation (Draper and Smith, 1981; Chapter 10). Once a candidate equation has been derived, there are a variety of criteria or test statistics available to test for residual goodness-of-fit. Among these is the Q-statistic of Ljung and Box (1978); the test criterion used here is distributed as chi-squared, and significant values indicate an inadequate model.

Q-statistics can be computed for any lag, and it is normal practice to examine a sequence of values, calculated at equidistant ascending lags.

Methods

The tree-ring time-series used here were developed from *Nothofagus menziesii* (silver beech) and *N. solandri* (mountain beech) trees in Fiordland, South Island, New Zealand. Trees were sampled using an increment borer at two sites [lower Takahe Valley (OBL, TKV) and upper Takahe Valley (UTV, TST)- see Norton (1983a, 1983b) for more details]. The ring-width patterns were crossdated (Fritts, 1976) between all ring-width series within each species and at each site, thus ensuring that the dating of individual growth rings was accurate. Ring-width was then measured to 0.01 mm and where two cores were available from the same tree, averaged arithmetically to give tree time-series. Data from 19 silver beech and 17 mountain beech trees are used here.

It became quickly apparent that the removal of long-term growth trends by either equation (1) or (2) would not be feasible. For a large majority of the trees, graphical plottings of annual radial growth against time revealed complicated and contrasting periods of suppression and release. Accordingly, each tree series was modelled by:

$$r = f(t) + R \tag{7}$$

where in (7)

r = annual radial increment

f(t) = a polynomial expression of time (t), expressed in years

R = residual value

To obtain the best available polynomial model for each dataset, the SAS statistical subroutine RSQUARE (SAS Institute, 1985; p. 711) was utilised. This program is superior to most step-wise regression methods, insofar as all combinations of predictor variables are evaluated, as opposed to the addition or deletion of a single variable. The R^2 statistic is used as the criterion of best fit, which can be supported by the calculation of Mallows Cp statistic (Mallows, 1973) and its subsequent plotting against the number of predictors, to secure a measure of unbiased estimation (Daniels and Wood, 1971:p. 71).

In addition, graphical plottings were obtained for each candidate model, depicting residual values against time, so to verify that no systematic patterns or grouping of data were present, symptomatic of an ill-fitting equation [Draper and Smith, 1981: Chapter 4]. In general, the silver beech series were satisfactorily modelled with polynomials using permutations of power terms (in time) up to the sixth degree, but the mountain beech series (particularly TKV) proved more intractable, sometimes requiring powers up to the ninth degree to acquire an adequate fit. All series data were then transformed to ring-width indices by:

$$I=1+R/P \tag{8}$$

where in (8)

I = a ring-width index

R = residual value for a specific datum in a series, obtained from (7)

P = the corresponding predicted value

to give a scaled, homogeneous and stationary series for each growth-ring sequence (Fritts, 1976; p. 266).

Box-Jenkins stochastic models of form (5) were then fitted to each tree index-series using the ARIMA procedure of the SAS/ETS statistical package (SAS Institute, 1984), a subroutine written expressly for the fitting of time-series equations. First, the likely order of α and β in (5) were identified by close inspection of the respective correlograms (produced by ARIMA). Second these parameters were confirmed or rejected if they failed to be significant at least at the 5% level (analogous to regression model building, t-statistics are available for the α_i , β_i coefficients, testing the null hypotheses $H_o : \alpha_i = o$ or $\beta_i = o$). Third, entire models were discarded if autocorrelation checks of the residuals showed a majority to be significant at the

5% level, as evaluated through the Q-statistic of Ljung and Box (1978). [Both the t and Q statistics are calculated automatically by the subroutine].

Four ring-width index chronologies were then formed as follows:

(a) Silver beech data, from 1660-1979, at location 1 (cf OBL of Norton, 1983b);
(b) Silver beech data, from 1740-1979, at location 2 (cf UTV of Norton, 1983b);
(c) Mountain beech data from 1680-1979, at location 1 (cf TKV of Norton, 1983a);
(d) Mountain beech data, from 1840-1979, at location 2 (cf TST of Norton, 1983a).

Each index chronology was calculated by the arithmetic average of the respective tree time-series indices. The time constraints shown above were imposed to ensure that all periods of a specific chronology were represented by at least four trees. Box-Jenkins models were fitted to the four chronologies, the preferred fits to which were again provided by either ARMA(1,1) or AR(1) processes.

The stability of the estimated first-order autocorrelation coefficients (r,) for the four chronologies was tested by computing l00-year running average values through equation (6).

Results and discussion

The producton of valid growth-ring index chronologies from cores obtained from *Nothofagus* species growing in a closed canopy environment was not without some difficulty. The periods of suppression and release through competition cannot always be readily removed; careful use of polynomial time models as was assayed here, provides a partial answer, but it is not ideal. Least-squares estimation of the polynomial coefficients is well-known to exert an undesirable weight on extreme index-values (Fritts, 1976; Warren, 1980), while there is always some risk that some competition effects are inadequately removed, or alternatively true climatic effects may be partially modelled out.

The results of modelling the thirty-six tree index series by Box-Jenkins stochastic models are summarised in Tables 1 and 2. For brevity the Q-statistics are given at lags 12 and 24 [it is normal practice to calculate values at 5 or 6 intervals].

These results confirm that all the tree-ring series can be satisfactorily modelled by either ARMA(1,1) or AR(1) processes; higher order or alternative models do not enhance precision or give equivalent goodness-of-

Table 1: *Time-series analyses from* Nothofagus menziesii *data*.

Tree	Length of series (years)	Parameter estimates and t-values α	β	Q-statistic level at lag 12 and 24	R^2 value for model
Location 1					
1	314	0.80 (13.4)	0.41 (4.6)	0.86, 0.79	0.283
2	279	0.73 (9.4)	0.31 (2.9)	0.51, 0.19	0.257
3	265	0.79 (10.0)	0.49 (4.4)	0.73, 0.59	0.176
4	220	0.87 (17.3)	0.46 (5.2)	0.33, 0.84	0.387
5	200	0.81 (10.2)	0.48 (4.1)	0.30, 0.33	0.221
6	228	0.82 (13.7)	0.39 (4.0)	0.14, 0.19	0.355
7	190	0.82 (11.4)	0.46 (4.1)	0.14, 0.08*	0.273
8	370	0.73 (10.1)	0.38 (3.8)	0.71, 0.82	0.209
9	220	0.73 (8.5)	0.32 (2.7)	0.18, 0.28	0.252
10	208	0.56 (9.7)	-	0.72, 0.84	0.307
11	396	0.84 (17.3)	0.49 (6.6)	0.20, 0.19	0.269
12	220	0.83 (12.4)	0.48 (4.6)	0.15, 0.06*	0.267
Location 2					
1	170	0.71 (4.0)	0.52 (2.4)	0.41, 0.15	0.052
2	130	0.26 (3.1)	-	0.58, 0.23	0.057
3	140	0.84 (11.8)	0.43 (3.6)	0.14, 0.19	0.357
4	222	0.81 (11.3)	0.44 (4.1)	0.17, 0.61	0.253
5	257	0.73 (7.8)	0.39 (3.2)	0.71, 0.57	0.278
6	358	0.81 (17.6)	0.29 (3.9)	0.03, 0.09	0.431
7	220	0.78 (10.7)	0.32 (3.0)	0.47, 0.87	0.316

*contains a significant autocorrelation at lags 12-24, but this is considered spurious.

Table 2: *Time-series analyses from* Nothofagus solandri *data.*

Tree	Length of series	Parameter estimates and t-values		Q-statistic level at lag 12 and 24	R^2 value for model
	(years)	α	β		
Location 1					
1	170	0.48 (5.7)	-	0.54, 0.59	0.153
2	140	0.41 (5.2)	-	0.53, 0.56	0.152
3	230	0.83 (11.4)	0.50 (4.6)	0.56, 0.06*	0.220
4	220	0.72 (7.8)	0.61 (2.5)	0.74, 0.05*	0.237
5	220	0.53 (9.1)	-	0.17, 0.16	0.270
6	300	0.76 (11.9)	0.29 (3.1)	0.91, 0.53	0.328
7	350	0.78 (12.0)	0.43 (4.3)	0.27, 0.19	0.545
8	200	0.53 (8.8)	-	0.88, 0.83	0.233
9	300	0.60 (12.1)	-	0.29, 0.66	0.354
Location 2					
1	140	0.48 (6.3)	-	0.49, 0.20	0.210
2	140	0.54 (7.5)	-	0.35, 0.34	0.284
3	140	0.48 (6.5)	-	0.08, 0.07*	0.223
4	140	0.43 (5.5)	-	0.03, 0.11	0.167
5	140	0.29 (3.6)	-	0.38, 0.14	0.073
6	140	0.49 (6.5)	-	0.23, 0.15	0.223
7	140	0.61 (9.0)	-	0.47, 0.62	0.362
8	140	0.52 (7.2)	-	0.26, 0.66	0.264

*contains a significant autocorrelation at lags 12-24, but this is considered spurious.

fit, and not one tree-series reduces to a white-noise model.

$$Z_t = a_t \qquad (9)$$

Overall, 58% of the series subscribed to an ARMA(l,l) process. These results can be compared to recent work by Rose (1983), Monserud (1986), and Biondi and Swetnam (1987) who examined large numbers of north-west and western American chronologies using similar methods. While the scope of these studies are far more extensive than attempted here, some including the modelling of chronologies (as opposed to individual trees) sometimes over 1000 years long, and embracing species from three genera *(Pinus, Pseudotsuga,* and *Picea),* comparison of results is quite revealing (Table 3). In all four studies, a majority of series have subscribed to an ARMA(1,1) process and have given virtually identical average parameter values.

The summary statistics (Tables 1 and 2) confirm that the large majority of the tree-series are satisfactorily modelled by the processes shown. The R^2 values may seem very low by traditional regression application criteria but as emphasised by Monserud (1986), R^2 reflects here the degree by which the series cannot be regarded as independent in time. Estimated values range from 0.05 to 0.43 suggesting that some

Table 3*: Overall results of Rose (1983), Monserud (1986), Biondi and Swetnam (1987), and Woollons and Norton (this paper).*

Study	% modelled by ARMA(1,1) process	Av. parameter values		correlation
		a	β	(α and β)
Rose	740,10	0.77	0.46	0.76
Monserud	850,10	0.74	0.42	0.79
Biondi and Swetnam	480,10	0.77	0.44	(not given)
Woollons and Norton	580,10	0.79	0.42	0.36

series are quite heavily serially-correlated, despite the removal of age and competition effects.

The four chronologies rationally separate into ARMA(1,1) or AR(1) processes, despite some presence of conflicting individual (tree) processes (Table 4). The averaging procedures result in some dilution in the degree of dependence, as shown by the overall R^2 values, but the analyses of the autocorrelation coefficients warn that the Box-Jenkins models must be regarded as overall trends. It may be that the chronologies modelled by Rose (1983) and Monserud (1986) also conceal more variable stochastic processes amongst the individual trees they are derived from. However, as our results show, the chronology model reflects the dominant model of its constituent trees.

Table 4: *Results from analysing chronologies (a) to (d) by Box-Jenkins models.*

Chronology	Parameter estimates and t-values* α	β	Q-statistic level at lags 12 and 24	R^2	r_1	s_y
Silver beech (1)	0.84 (13.0)	0.61 (6.5)	0.65, 0.36	0.15	0.33	±0.29
Silver beech (2)	0.64 (5.1)	0.34 (3.3)	0.34, 0.89	0.08	0.30	±0.28
Mountain beech (1)	0.47 (9.1)	—	0.48, 0.18	0.21	0.47	±2.8
Mountain beech (2)	0.41 (5.5)	—	0.16, 0.12	0.17	0.41	±0.34

*in parenthesis

There is clear evidence that the autocorrelation coefficients fluctuate with time (Table 5, Fig. 1), with periods when some chronologies are essentially independent. Recently, Briffa *et al.* (1987) have produced evidence that a chronology of *Pinus sylvestris* fluctuated in r, between -0.5 to 0.7 as opposed to an overall value of 0.39. However, the authors used 30-year running values to calculate r_1, which may be an overly-harsh indictment of time-series modelling of tree chronologies, since no serious advocate of Box-Jenkins models would attempt such methods on so short time periods. Conversely, the results of Briffa *et al.* (1987) and those presented here confirm that ARMA(p,q) processes must be regarded as average phenomena, and there may well be periods in specific chronologies where a fitted time-series model does not reflect the true degree of dependence.

Monserud (1986) suggested that an ARMA(1,1) process might be a universal stochastic model describing tree growth, but further commented that "such a conjecture will doubtless prove false". Our results certainly substantiate that there is a strong tendency for such an outcome, with predictably close parameter values. Monserud emphasised the need to study further trees growing in contrasting stand densities, pointing out that the majority of the American chronologies were constructed from open-grown, "sensitive" trees *(sensu* Fritts, 1976). In this, and other respects, the results presented here provide useful adjunct information, since the sampled trees in the present study represent totally different genera, are angiosperms as opposed to gymnosperms, reside on a different continent, and grow in a strictly closed canopy situation.

Table 5: *Estimated lag-1 autocorrelation coefficients for each chronology based on 100-year running averages.*

Chronology	Mean	S.D.	Mode	Max	Min	% of data within ±0.1 from mean
Silver beech (1)	0.29	±.29	0.33	0.44	0.09	71
Silver beech (2)	0.27	±.16	0.12	0.53	0.04	32
Mountain beech (1)	0.49	±0.11	0.52	0.64	0.26	61
Mountain beech (2)	0.40	±0.01	0.41	0.42	0.38	100

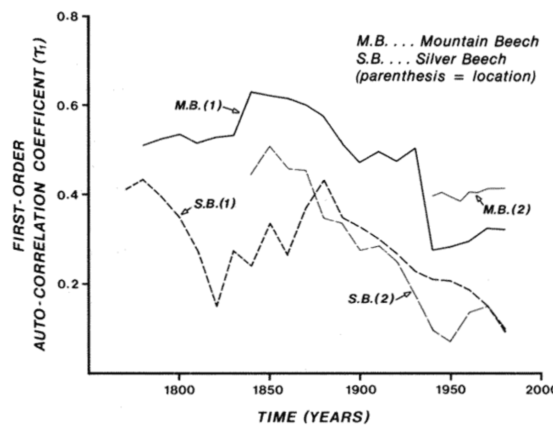

Figure 1: *Running-average lag-1 autocorrelations for the four average ring-width index chronologies.*

Further perusal of Tables 1 and 2 may suggest that the division of AR(1) and ARMA(1,1) models is a function of species; 89% of the *N. menziesii* conform to an ARMA(1,1) process, while 76% of the *N. solandri* prefer an AR(1) model. Unfortunately, the situation is totally confounded; the silver beech ring-series are considerably longer than the mountain beech [average lengths are 242 and 178 years, respectively]. Further analyses show that 81 % of series longer than 200 years subscribe to an ARMA(1,1) process, but 78% of shorter series are adequately depicted by an AR(1) model. On the premise that fewer observations are likely to be modelled by a simpler stochastic process, (by virtue of less precision associated with parameters), division caused by length of series is a more salient interpretation. Monserud (1986) preferred an AR(1) model for only three of 33 chronologies studied, but where chosen the lengths of the former were 199, 255, and 196 years [overall average, 739 years]. Furthermore, Biondi and Swetnam (1987) found 3 chronologies out of 23 to be best fitted by an AR(l) model, and here the series lengths were 194, 125, and 214, so the trend is clearly established.

Conclusions

Combining results obtained here with the American studies suggest two general conclusions. First, there is undoubtedly a strong preference for tree genera to be modelled by an ARMA(1,1) stochastic process, irrespective of canopy state. Nevertheless, the length of the radial series has an influence on the applicable Box-Jenkins model, so searching for "best" equations in all situations, may not be justified or necessary, particularly as the processes are in fact mathematically related [Box and Jenkins (1976)].

Conversely, irrespective of the methods used to eliminate long-term fluctuations, use of Box-Jenkins equations highlight that serial correlations remain in growth-ring series, but can be largely removed by such methods. Thus, not only does data become more tractable for use with environmental variables, but chronologies exhibit better cross-correlation and sensitivity (Biondi and Swetnam, 1986). Processing tree-ring chronologies by time-series equations is therefore recommended; if time does not allow the deduction of an optimal model, then the assumption of either an ARMA(1,1) or AR(l) process, dependent on the series length, will probably suffice.

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