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BOX-JENKINS MODELS OF FOREST INTERIOR TREE-RING CHRONOLOGIES

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ABSTRACT

Time domain properties of 23 tree-ring chronologies derived from a large sample of Douglas-fir and ponderosa pine trees growing in closed-canopy forests of Colorado and New Mexico were analyzed using Box-Jenkins models. A variety of statistical criteria were employed during the identification and validation stages for evaluating the performance of different significant models, and the "best" Box-Jenkins model and its immediate "competitor" were reported for each tree-ring chronology.

All series were stationary, and only one was approximately a white noise series. Overall, the ARMA(1,1) model was judged the best for 11 series, and the second for 7 of the remaining 12 series. The AR(2) model was considered the best for 6 series, and the second for 4 of the remaining 17 series. No statistical evidence was found for moving average models, nor for models with more than three different parameters. However, both cyclical (or seasonal) models and third-order autoregressive models with a null second-order parameter were chosen for some series.

Fitted models explained from 7 to 51% of the variance of the original ring-index series, with an average of about 22%. All parameter estimates were positive, and they varied within a relatively small range. From a comparison of all employed criteria, Akaike's Information Criterion (AIC) was the one that performed best in identifying Box-Jenkins models for tree-ring chronologies.

Possible distinctions were recognized that would separate the selected models according to species and/or standardization option. Among the 12 chronologies from Colorado sites, all derived using the same standardization option, most Douglas-fir series were best fitted by the ARMA(1,1) model, while most ponderosa pine series were best fitted by the AR(2) model, suggesting a difference in the biological persistence of the two species. On the other hand, most of New Mexico chronologies, developed using various standardization options, were best fitted by the ARMA(1,1) model, and no difference was found between Douglas-fir and ponderosa pine series. Also, models fitted to Colorado chronologies explained a lower amount of variance than those for New Mexico chronologies (averages of 17 versus 29% respectively), and cyclical models were mainly selected for New Mexico series. Although periodicities in Douglas-fir series were probably caused by western spruce budworm outbreaks, similar periodic patterns in ponderosa pine series were more difficult to explain because pine trees in the study area had not been defoliated by that insect.

Compared to the original tree-ring chronologies, prewhitened series showed similar short-term growth patterns, reduced long-term growth fluctuations, lower standard deviations, and higher mean sensitivities. Also, cross-correlations between chronologies from the same area usually increased after prewhitening. Since the autocorrelation problem is crucial in analyzing the relationships between different time series, and in removing the biological persistence included in tree-ring chronologies, the Box-Jenkins approach should facilitate the analysis of the dynamic relationships between tree growth and environmental variables.

Die Zeitreihen—Eigenschaften von 23 Jahrringchronologien von Douglasie und Ponderosa-Kiefer aus Wäldern mit einem geschlossenen Kronendach in Colorado und New Mexico wurden mit Hilfe von Box-Jenkins-Modellen analysiert. Durch die Anwendung unterschiedlicher Kriterien während der Identifikation und Prüfung wurden das beste Box-Jenkins-Modell und sein unmittelbarer Konkurrent für jede Chronologie gefunden.

Alle Reihen waren stationär, und nur eine war annähernd eine 'White-noise'-Reihe. Insgesamt eignete sich das ARMA(1,1)-Modell am besten für 11 Reihen und am zweitbesten für 7 der verbliebenen 12 Reihen. Das AR(2)-Modell wurde als bestes für 6 Reihen und als zweitbestes für 4 der verbliebenen 17 Reihen bewertet. Für Modelle mit gleitenden Mitteln und für Modelle mit mehr als 3 verschiedenen Parametern ergaben sich keine statistischen Aussagen. Jedoch wurden für einige Reihen sowohl zyklische Modelle als auch autoregressive Modelle 3. Ordnung gewählt.

Die angepaß Modelle erklärten zwischen 8 und 56% der Varianz der originalen Index-Reihen, mit einem Mittel von etwa 30% für beide Modelle, das beste und seinen unmittelbaren Konkurrenten. Alle Parameterschätzungen waren positiv, und sowohl ihre Werte als auch die ausgewählten Modelltypen wurden innherhalb eines relativ engen Bereiches aufgenommen.

Von den 12 Chronologien in Colorado, die alle in gleicher Weise standardisiert worden waren, wurden die Douglasien-Chronologien zumeist von einem ARMA(1,1)-Modell und die Ponderosa-Chronologien zumeist von einem AR(2)-Modell am besten angepaßt. Möglicherweise ist die biologische Persistenz beider Baumarten unterschiedlich. Die New Mexico-Chronologien dagegen, die in verschiedener Weise standardisiert worden sind, wurden am besten durch ein ARMA(1,1)-Modell angepaßt, und es zeigte sich kein Unterschied zwischen Tanne und Kiefer. Zudem enthalten die New Mexico-Chronologien nahezu alle Reihen, für die ein zyklisches Modell gewählt worden ist. Während die Zyklen in den Douglasien-Reihen vermutlich durch einen periodischen Insektenbefall (western spruce budworm) verursacht werden, sind sie in den Ponderosa-Reihen schwieriger zu ereklären, da diese Kiefern normalerweise von diesen Insekten nicht entnadelt werden.

Die 'prewhitened' Reihen waren wie erwartet ähnlich den Originalreihen, aber zeigten eine viel höhere Sensitivität, besonders nach ihrer Normalisierung. Das 'prewhitening' ist ein kritischer Punkt beim Vergleich verschiedener Zeitreihen sowie bei der Eliminierung der biologischen Persistenz aus den Jahrringfolgen. Daher ist es sehr wahrscheinlich, daß die 'prewhitened' normalisierten Reihen nicht nur eine höhere Korrelation zwischen Chronologien, sondern auch mit Klimavariablen ergeben.

Les propriétés chronologiques de 23 séries de cernes de croissance provenant d'un large échantillonnage de sapin de Douglas et de pin ponderosa croissant dans des forêts denses du Colorado et du Nouveau Mexique, ont été analysées en utilisant les modèles de Box-Jenkins. L'emploi d'une variété de critères lors des étapes de vérifications de l'identification et du diagnostique, le meilleur modèle de Box-Jenkins et son plus proche compétiteur ont été trouvés pour chaque chronologie.

Toutes les séries étaient stationnaires et un seule était presque une série à bruit de fond blanc. Le modèle ARMA (1,1) a été considéré comme le meilleur pour 11 séries, tandis que le second l'était pour sept des 12 séries restantes. Le modèle AR (2) a été considéré comme le meilleur pour 6 séries et le second pour 4 des 17 autres séries. Il n'y avait pas d'évidence statistique incitant l'emploi des modèles à moyenne courante ni pour les modèles avec plus de 3 paramètres différents. Cependant, les modèles cycliques et ceux obtenus par auto-régression du 3e ordre avec un paramètre du second ordre nul ont été choisis pour quelques séries.

Les modèles ajutés expliquaient de 8 à 56% de la variance de la série originale des épaisseurs des cernes avec une moyenne de 30% à la fois pour le meilleur modèle et son plus proche compétiteur. Toutes les estimations de paramètre étaient positives et tant leurs valeurs que les modèles choisis étaient rassemblés dans un intervalle relativement étroit.

Parmi les 12 chronologies provenant du Colorado, toutes traitées par la même option de standardisation, la plupart des séries de Douglas étaient les mieux ajustées par le modèle ARMA (1,1), tandis que les séries de pins ponderosa l'étaient par le modèle AR (2), ce qui suggère une différence dans la persistance biologique des deux espèces. D'autre part, la plupart des chronologies du Nouveau Mexique, développées en utilisant des options de standardisation variables, étaient mieux ajustées par le modèle ARMA (1,1) et aucune différence n'était observée entre les Douglas et les pins. De plus, les chronologies du Nouveau Mexique comportaient presque toutes les séries pour lesquelles un modèle cyclique était choisi. Quoique les sapins de Douglas, les cycles sont probablement causés par des attaques périodiques de la larve parasite du bourgeon de l'épicéa occidental, les cycles des pins ponderosa sont plus difficiles à ex-

pliquer car ces arbres ne sont généralement pas défoliés par cet insecte. Comme attendu, les séries dépourvues du bruit de fond blanc étaient similaires aux originales mais elles montraient une plus grande sensitivité moyenne, particulièrement après avoir été normalisées. Puisque l'extraction du bruit blanc est crucial lors de l'analyse des relations entre différentes séries temporelles et lors de l'élimination de la persistance inclue dans les chronologies de cernes, il est très vraisemblable que les séries normalisées dépourvues du bruit blanc montrent non seulement une meilleure corrélation entre chronologies, mais aussi avec les variables climatiques.

INTRODUCTION

In the field of dendrochronology, a tree-ring series is any set of numbers (ring-widths, ring-indices, ring-densities, etc.) that measures the status of radial tree growth over time. In statistical terms, a tree-ring series is simply a discrete time series, *i.e.* a sequence of observations taken at equally spaced intervals of time. Statistical methods for investigating time series data vary greatly in degree of sophistication and application. However, since annual growth of trees is a complex phenomenon that cannot be described in terms of an exact mathematical model, it is useful to think of it as a stochastic process, *i.e.* a statistical phenomenon that evolves in time according to probabilistic laws.

Using this approach, a time series of N successive observations Z_t, $t = 1,2,\ldots,N$, is regarded as a sample from an infinite population of such time series that could have been generated by the stochastic process under study. A powerful way of extracting pertinent information on the underlying process solely on the basis of the past behavior of the time series itself is the univariate Box-Jenkins approach, named after the statisticians who proposed it during the 1960's and 70's.

Although originally developed for forecasting purposes (Box and Jenkins 1976, Nelson 1976), Box-Jenkins models are useful tools for describing the time dependent structure of stationary and nonstationary time series, where *stationary* indicates a series whose mean and variance are constant throughout time. Also, Box-Jenkins models can be used to transform autocorrelated time series data into serially uncorrelated data. The transformation of an autocorrelated series into a series of independent observations (or a *white noise* series, as it is called in engineering studies) is known as *prewhitening* (Box and Jenkins 1976, pp. 379-380). Since the prewhitening procedure removes the "pattern" (Hoff 1983, p. 17) included in a time series, the expression "random series" is often used in statistical works as a synonym of "white noise series", but it should not be confused with "random numbers" such as those artificially generated for simulation purposes.

Box-Jenkins models for stationary time series, or ARMA models, have been applied to tree-ring chronologies by Meko (1981), Rose (1983), Tessier (1984), and Monserud (1986). Although Meko identified the first-order autoregressive and moving average model, or ARMA (1,1), as the best fit for only one of 17 chronologies he studied, and Tessier for none of 29 series he reported, both Rose and Monserud found that the ARMA (1,1) model was the best for most tree-ring chronologies. The last two authors mainly examined tree-ring chronologies developed from sites at or near the lower or upper forest borders for reconstructing past climatic variations in western North America. Trees growing in such sites are more affected by climatic variables such as precipitation or temperature than by stand conditions, so that competition and density, for example, do not represent important limiting factors (Douglass 1914, Fritts 1976).

In closed-canopy stands of forest interiors, complex non-climatic factors such as disturbance and competition become prominent and the signal-to-noise ratio of tree-ring series from these sites is usually small, while autocorrelation is high (Cook 1985, Fritts and Swetnam 1986). Basic research is needed in order to test how Box-Jenkins models represent the behavior of tree-ring chronologies developed for forest interior sites. It is also important to identify and test various physiological and ecological explanations for the types of models that are found to be most appropriate.

This article describes the estimation of Box-Jenkins models for 23 tree-ring chronologies obtained from a large sample of trees growing in closed-canopy forests of Colorado and New Mexico. A first attempt to point out some of the ecological and physiological implications of the statistical results is then provided. The tree-ring data set was originally developed by the second author for his study of western spruce budworm (*Choristoneura occidentalis* Freeman) effects on tree growth (Swetnam 1985, 1987).

MATERIALS

The chronologies considered in the present study were developed from 11 sites, 6 situated within three National Forests of Colorado and 5 within one National Forest of New Mexico (Figure 1 and Table 1). The Colorado sites were distributed along a north-south transect of the state, while the New Mexico sites were concentrated in the northern part of the state. Elevation ranged from 2,400m to 3,048m. Detailed site conditions were reported by Swetnam (1987).

Two chronologies were developed for each site, one from increment cores of Douglas-fir (*Pseudotsuga menziesii* (Mirb.) Franco) and the other from ponderosa pine (*Pinus ponderosa* Dougl. ex Laws.) cores. One chronology was derived from pinyon pine (*Pinus edulis* Engelm.) cores (Figures 2A and 3A, Table 1). Cored trees were included in 0.5 ha plots that the U.S. Forest Service established throughout the natural stands. Following the usual practice in dendrochronology, these chronologies represented an average of dimensionless ring-index series, obtained from the original ring-width series by means of the standardization procedure described by Fritts (1976) and Swetnam *et al.* (1985). However, the number of samples averaged to build each of these chronologies was larger than usually reported for dendrochronological studies. On the average, Douglas-fir chronologies were computed from 81 cores corresponding to 41 different trees, and ponderosa pine chronologies were formed from 31 cores corresponding to 16 different trees (Swetnam 1987).

Colorado chronologies were developed using the same growth curve for standardizing each ring-width series, *i.e.* a cubic spline of 50% frequency response at a period of 100 years (Cook and Peters 1981). New Mexico chronologies were built using various growth curves, including cubic spline, negative exponential, and straight line with zero or negative slope (Graybill 1979; Table 1).

Two series, DVG and DVG50, were obtained by standardizing the same set of individual ring-width series with a cubic spline of 50% frequency response at a period of 100 years (DVG) and 50 years (DVG50). The overall shape (Figure 3A) and the mean sensitivity of these two series were similar, but the variance of series DVG was 23% higher than that of series DVG50. Since the sample autocorrelations of series DVG were higher than those of series DVG50, this different amount of variation is related to the different amount of autocorrelation removed from the original ring-width series by the growth curve used in the standardization stage. In fact, the "flex-

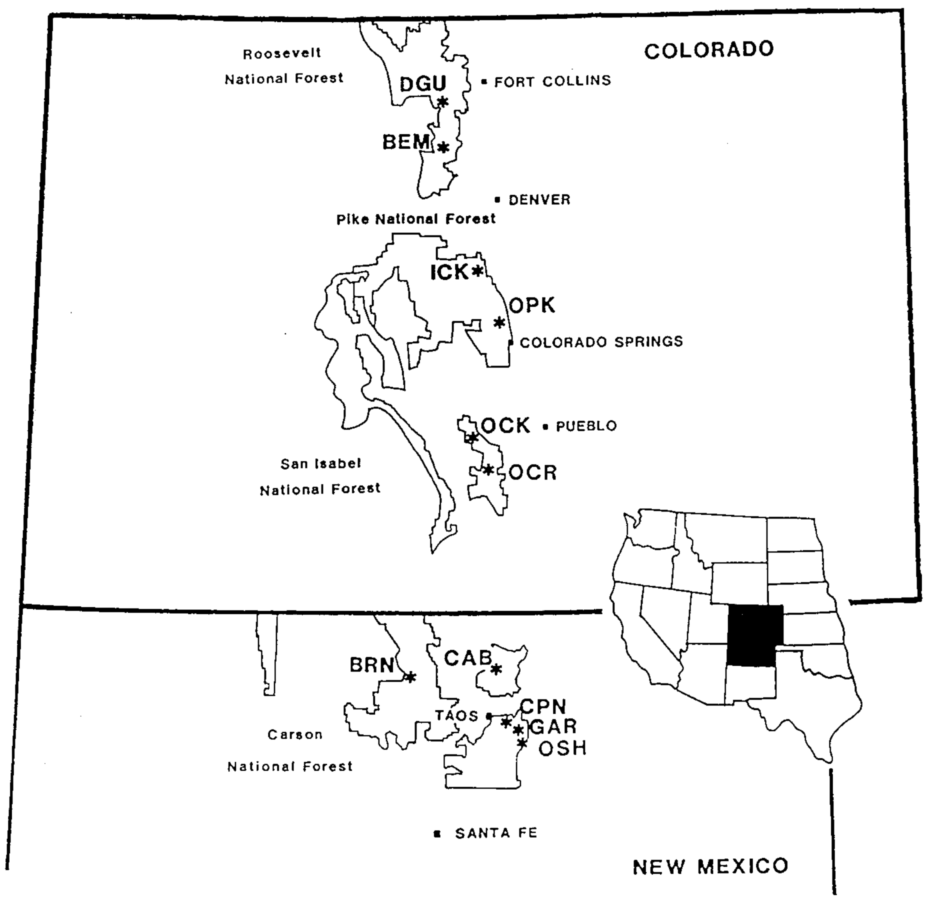

Figure 1. Site locations: each collection site is indicated by the Douglas-fir series code (see Table 1 for full site name).

ibility" of a cubic spline is inversely proportional to its period (Cook and Peters 1981, Holmes 1986).

The use of different standardization options for building New Mexico and Colorado chronologies might be one of the reasons for differences in mean sensitivity (averages of 0.242 versus 0.295 respectively) and first-order autocorrelation (averages of 0.450 versus 0.363 respectively). The average mean sensitivities (0.261 for ponderosa pine, 0.272 for Douglas-fir) of these 23 chronologies were smaller than those reported by Fritts and Shatz (1975) for 65 chronologies they selected for dendroclimatic analysis, but the first-order autocorrelations (0.436 for ponderosa pine, 0.395 for Douglas-fir) were very similar to Fritts and Shatz' values. As found in previous works (Drew 1976), the pinyon pine chronology had a higher mean sensitivity and a lower autocorrelation than Douglas-fir and ponderosa pine chronologies.

Series length ranged from 91 to 291 years for Douglas-fir, and from 122 to 401 years for ponderosa pine (Table 1). The average length was higher for the 12 pine chronologies (263 years) than for the 11 Douglas-fir chronologies (214 years).

In general, within the same site, both fir and pine chronologies showed a similar

Table 1. Chronology statistics of the original tree-ring series (compare with Table 7). (PSME = Pseudotsuga menziesii; PIPO = Pinus ponderosa; PIED = Pinus edulis)

Site and Series	Species Code	Number of yrs.	Stand. Dev.	Mean Sens.	% Abs. Rings	Max. Lag	1st AC 1st PAC	2nd AC	2nd PAC	X-Corr. P-value < 0.05
Capulin Canyon										
CPN(1)	PSME	194	0.253	0.224	0.083	45	0.436	0.264	0.091(*)	0.665
CPL(1)	PIPO	192	0.225	0.193	0.000	45	0.427	0.196	0.017(*)	(1790-1981)
Burned Mountain										
BMT(1)	PIPO	194	0.226	0.182	0.194	45	0.553	0.438	0.191	0.640
BRN(1)	PSME	194	0.259	0.168	0.218	45	0.689	0.519	0.086(*)	(1790-1983)
Garcia Park										
GAR(2)	PSME	282	0.309	0.281	0.364	70	0.423	0.321	0.174	0.701
GPK(2)	PIPO	361	0.361	0.331	0.902	90	0.481	0.318	0.113	(1700-1981)
Osha Mountain										
OSM(2)	PIPO	401	0.275	0.197	0.000	100	0.615	0.466	0.140	0.537
OSH(2)	PSME	289	0.210	0.153	0.115	70	0.582	0.429	0.136	(1700-1981)
Cabresto Canyon										
CAB(1)	PSME	111	0.278	0.303	0.060	25	0.214	0.055(*)	0.010(*)	0.726
CCN(1)	PIED	390	0.329	0.385	1.899	95	0.082(*)	0.062(*)	0.056(*)	(1880-1981)
Devils Gulch										
DVG50	PIPO	331	0.347	0.339	0.429	80	0.403	0.341	0.213	0.649
DVG(3)	PIPO	331	0.396	0.337	0.429	80	0.555	0.489	0.261	0.625
DGU(3)	PSME	248	0.403	0.411	0.912	60	0.300	0.279	0.207	(1740-1980)
Big Elk Meadows										
BIG(3)	PIPO	184	0.259	0.226	0.594	45	0.477	0.334	0.137(*)	0.646
BEM(3)	PSME	172	0.304	0.311	0.629	40	0.351	0.238	0.130(*)	(1820-1983)
Indian Creek										
ICR(3)	PIPO	125	0.194	0.176	0.001	30	0.316	0.206	0.118(*)	0.474
ICK(3)	PSME	291	0.245	0.195	0.000	70	0.511	0.339	0.105(*)	(1860-1983)
Ormes Peak										
ORP(3)	PIPO	271	0.270	0.286	0.234	65	0.274	0.305	0.249	0.630
OPK(3)	PSME	265	0.278	0.278	0.173	65	0.285	0.204	0.133	(1720-1984)
Oak Creek										
OAK(3)	PIPO	122	0.269	0.292	1.450	30	0.287	0.268	0.202	0.759
OCK(3)	PSME	91	0.358	0.412	0.119	20	0.197(*)	0.164(*)	0.130(*)	(1900-1982)
Ophir Creek										
OPH(3)	PIPO	259	0.326	0.311	0.803	60	0.405	0.219	0.065(*)	0.640
OCR(3)	PSME	214	0.275	0.257	0.053	50	0.359	0.167	0.044(*)	(1780-1984)

(1) Standardized using negative exponential or straight line of non-positive slope.
(2) Standardized using cubic spline of 50% frequency response at period equivalent to 66% of the total number of years in each ring-width series, and with minimum period of 100 years.
(3) Standardized using cubic spline of 50% frequency response at period of 100 years.
AC = sample autocorrelation PAC = sample partial autocorrelation.
X-Corr. = Cross-correlation between the chronologies for each site (time interval in parenthesis.)
(*) Smaller than twice its standard error, i.e. not significant at the 0.045 level.

The average length was higher for the 12 pine chronologies (263 years) than for the 11 Douglas-fir chronologies (214 years).

In general, within the same site, both fir and pine chronologies showed a similar response to climatic variation. Differences in growth trends and patterns were mainly caused by periodic spruce budworm outbreaks (Swetnam 1987). Past occurrence, duration and severity of insect outbreaks were reconstructed and quantified by means of statistical and graphical comparisons between the host species (Douglas-fir) and the non-host species (ponderosa pine) (Swetnam *et al.* 1985, Fritts and Swetnam 1986).

METHODS

The analysis was conducted in the time domain, assuming that each time series could be described by a particular version of the general multiplicative model ARMA(p,q) x ARMA(P,Q)$_s$ (Box and Jenkins 1976, SPSS Inc. 1986a,b), that for a series with null mean can be written as follows (see Table 2 for the meaning of all symbols and abbreviations included in this article):

$$\phi_p(B)\Phi_P(B^s)\,Z_t = \Theta_q(B)\Theta_Q(B^s)a_t \qquad (1)$$

This general model parsimoniously describes stationary time series that exhibit periodic behavior with period *s*, *i.e.* that present similarities between observations *s* time intervals apart (Box and Jenkins 1976, chapter 9). Although periodic time series models are usually called "seasonal" models in the Box-Jenkins approach, the term "cyclical" is adopted in this article because tree-ring data are yearly rather than monthly data.

All autoregressive parameters are on the left-hand side of equation (1), and all moving average parameters are on the right-hand side. "Moving average" parameters relate what happens in year *t* only to previous error components, whereas "autoregressive" parameters relate what happens in year *t* only to previous series values (Box and Jenkins 1976, p. 10; Hoff 1983, p. 51). Therefore, for a tree-ring series, equation (1) measures the dependence of each year's radial growth on previous radial growth, the left-hand side representing the link with previous ring-values and the right-hand side with previous error components. The "error component" is also called "random error", "random shock", "innovation" or "white noise", depending on the author. It is assumed to be independent and normally distributed, with null mean and constant variance σ_a^2, and it represents what is left of a single ring-value after accounting for the "pattern" of the entire tree-ring series (Hoff 1983, p. 17). Since in the real world we cannot observe such errors, we only deal with their estimates, called "residuals" or "prewhitened values".

Model fitting consisted of a trial-and-error procedure based on three equally important steps, which might overlap and interact: 1) identification of a possible model; 2) estimation of the parameters of the model; 3) validation (or diagnostic checking) of the estimated model.

Model Identification

Preliminary models were identified by studying graphical and statistical characteristics of each tree-ring chronology, including a) plot of the series values, b) plot of the autocorrelation function (ACF), c) plot of the partial autocorrelation func-

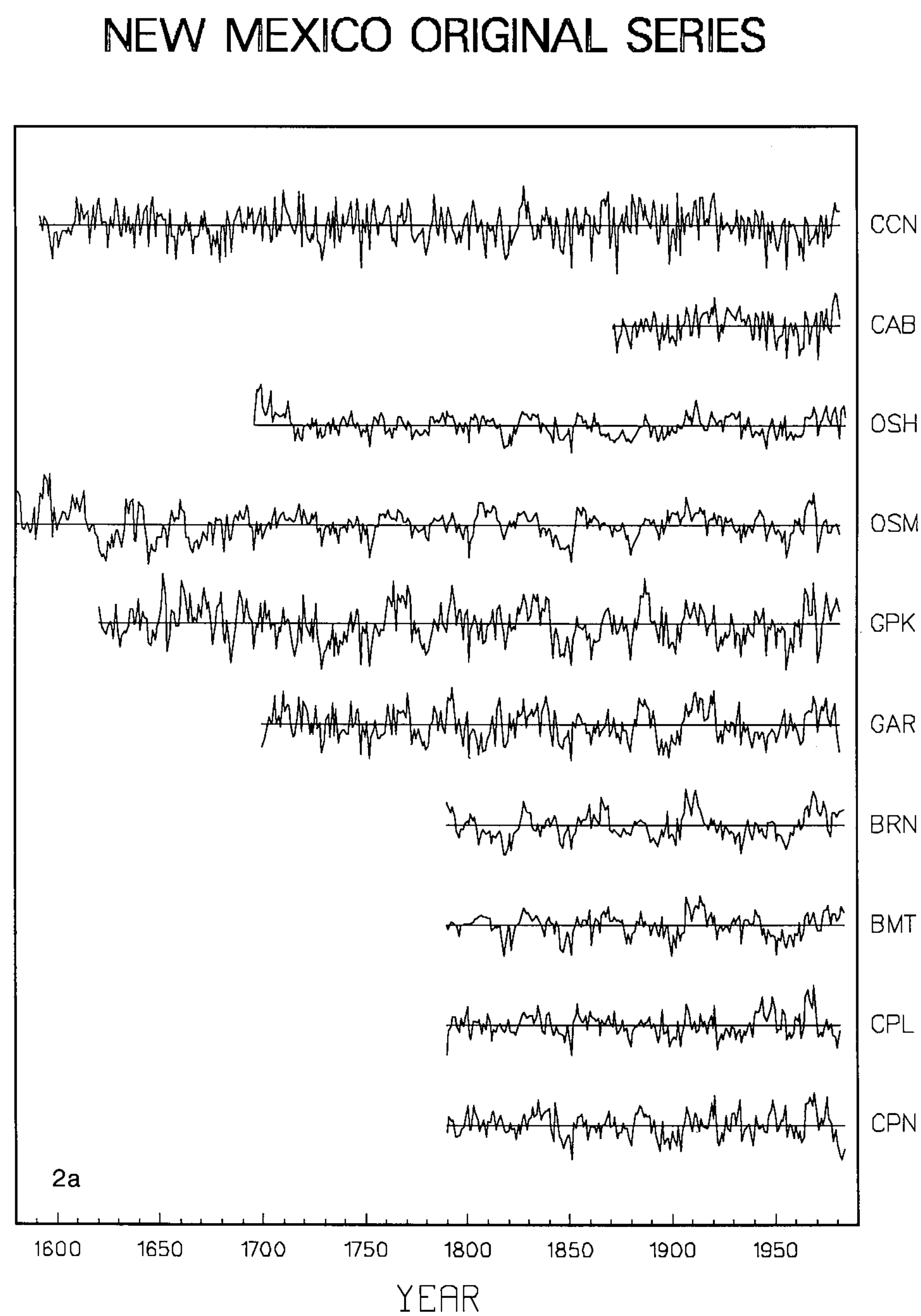

Figure 2. Plots of New Mexico chronologies. It is possible to compare graphically each original chronology (Figure 2a) with its prewhitened version (Figure 2b).

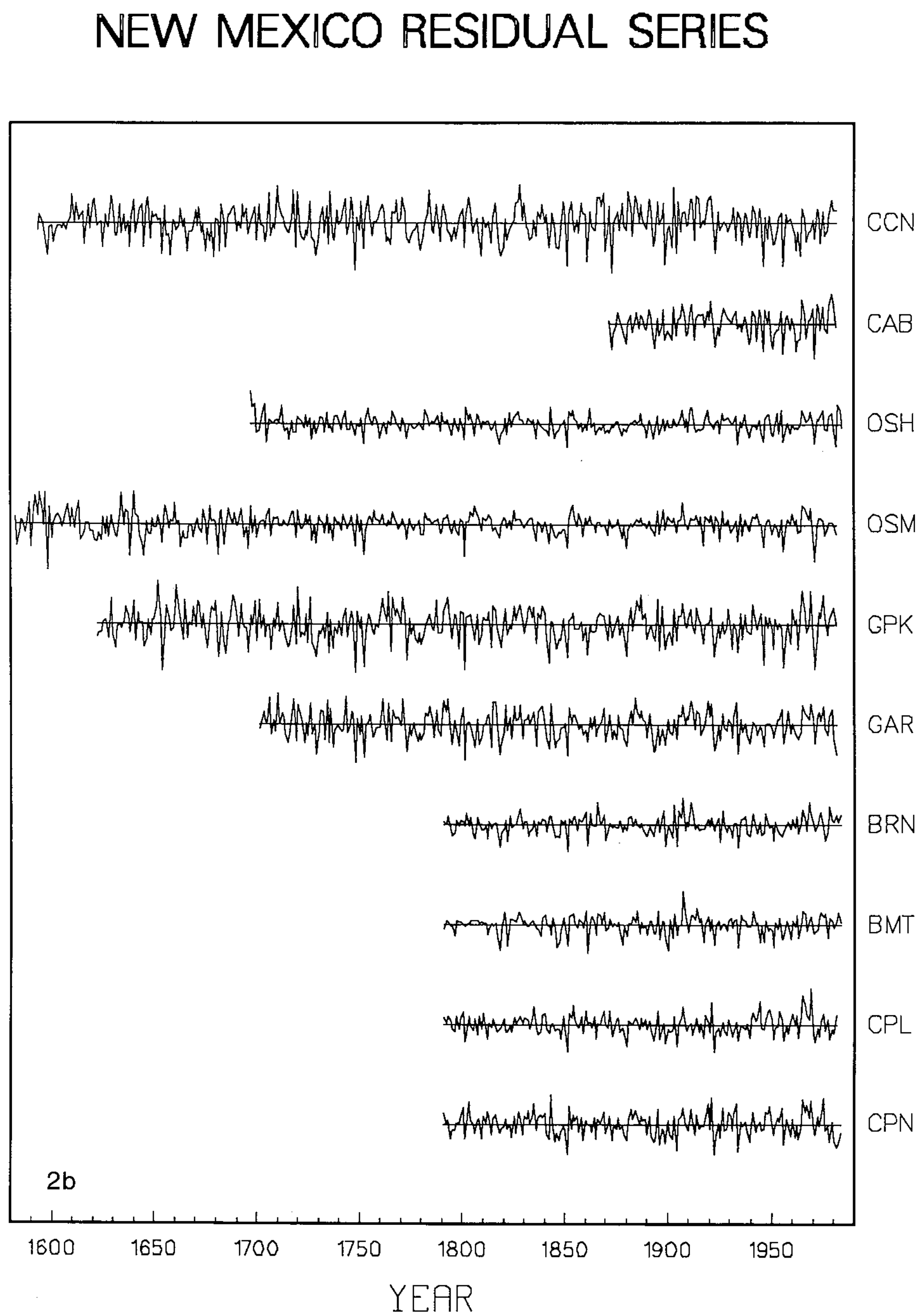

Figure 2, *continued*

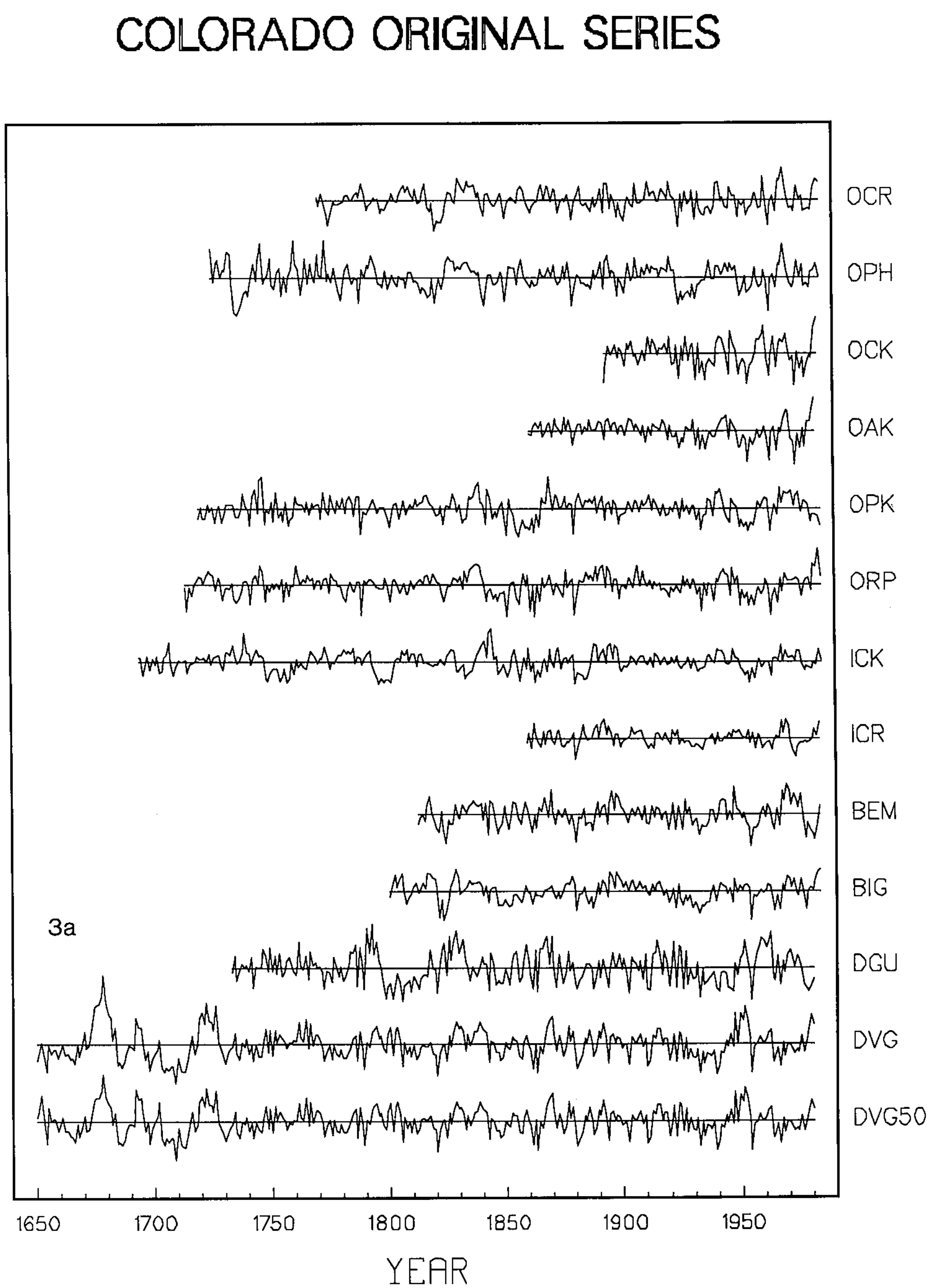

Figure 3. Plots of Colorado chronologies. It is possible to compare graphically each original chronology (Figure 3a) with its prewhitened version (Figure 3b).

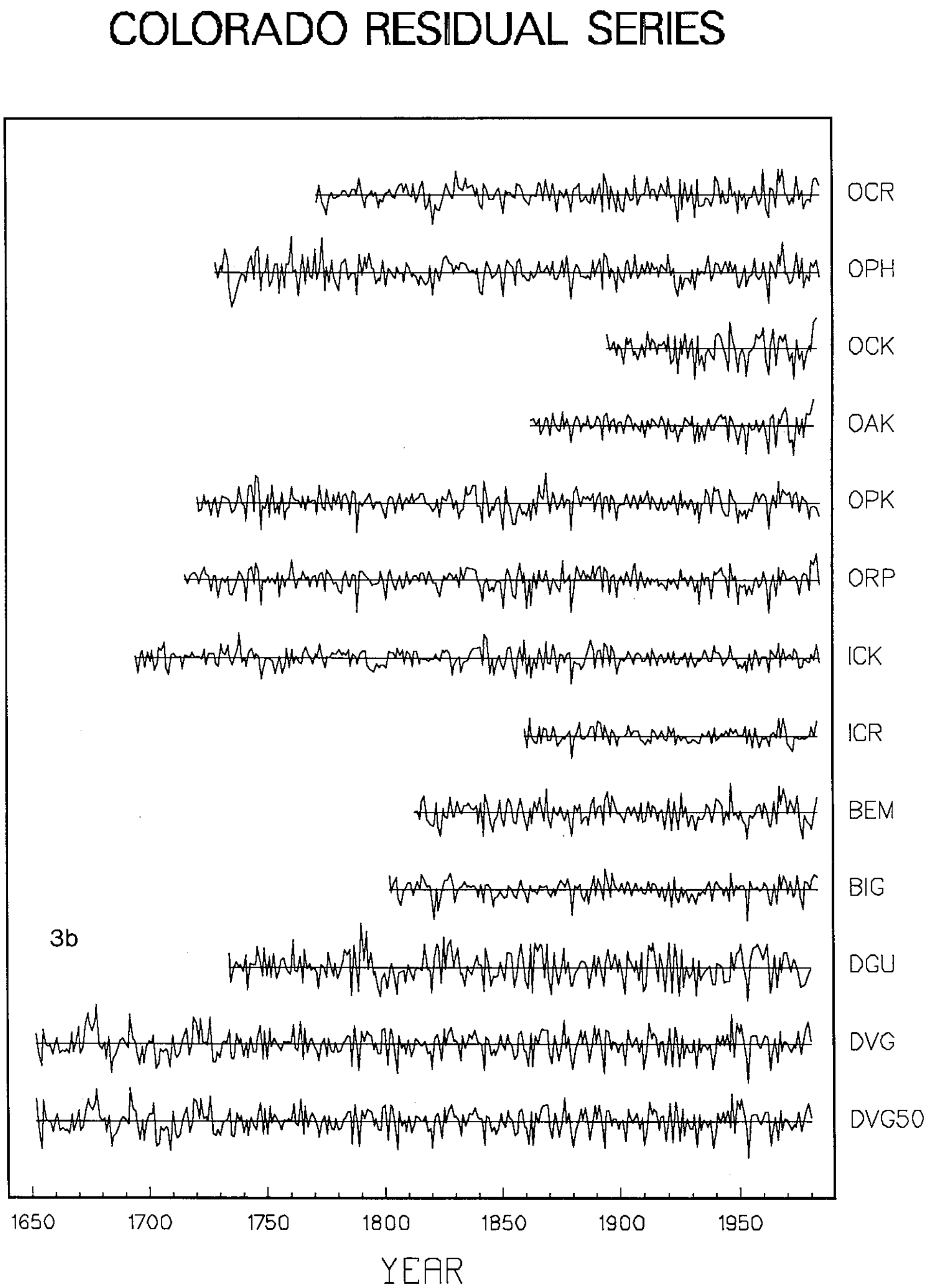

Figure 3, *continued*

Table 2. Explanation of symbols and abbreviations used in the text.

$\phi_p(B)$	$= 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p$ = AutoRegressive operator of order p within each period of the cycle = AR(p);
$\Phi_P(B^s)$	$= 1 - \Phi_1 B^s - \Phi_2 B^{2s} - \ldots - \Phi_P B^{Ps}$ = AutoRegressive operator of order P between different periods of the cycle = AR(P);
s	= period of the cycle;
z_t	= series value at year t, centered around the mean of the series = departure at year t from the mean of the series (all other z's listed below are "series values" are actually "departures");
$\theta_q(B)$	$= 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q$ = Moving Average operator of order q within each period of the cycle = MA(q);
$\Theta_Q(B^s)$	$= 1 - \Theta_1 B^s - \Theta_2 B^{2s} \ldots - \Theta_Q B^{Qs}$ = Moving Average operator of order Q between different periods of the cycle = MA(Q);
a_t	= error component at year t;
ϕ_1	= autoregressive parameter of 1st order;
z_{t-1}	= series value at year t-1;
ϕ_2	= autoregressive parameter of 2nd order;
z_{t-2}	= series value at year t-2;
ϕ_3	= autoregressive parameter of 3rd order;
z_{t-3}	= series value at year t-3;
θ_1	= moving average parameter of 1st order;
a_{t-1}	= error component at year t-1.
Θ_1	= periodic moving average parameter of 1st order;
a_{t-15}	= error component at year t-15.

Note: In Tables 4, 5, and 6 the autoregressive parameter "ϕ" is estimated by "p", the moving average parameter "θ" is estimated by "q", and the cyclical moving average parameter "Θ" is estimated by "Q".

tion (PACF), d) residual variance criterion, e) Schwarz's order criterion and f) Akaike Information Criterion.

Characteristic a) was employed to detect any anomalies of the series, especially nonstationarity and outliers. Criteria b) through f) served in the actual identification of a preliminary model (Table 3).

ACF and PACF Plots

Both the sample autocorrelations and partial autocorrelations were computed and plotted against their two-standard error limits up to a maximum lag obtained by rounding N/4 to the near smaller multiple of 5, with N = number of years in the time series under study (Table 1). Assuming that both sample autocorrelations and partial autocorrelations have a Z distribution (Box and Jenkins 1976, p. 178), then only values outside the interval (−2s.e.; +2s.e.) were considered significantly different from zero at the 0.045 level. The large-lag standard error of the sample autocorrelations and partial autocorrelations were computed from the formulas given by Ling and Roberts (1982, p. 8-3) and Box and Jenkins (1976, p. 178) respectively.

If too many (as a rule of thumb, more than the first 10) low-lags sample autocorrelations exceed twice their standard error, then the series may be nonstationary. Other important features of the ACF and PACF plots are the presence or absence of a cut-off point, and their overall shape while approaching zero: the interaction between these features and their meaning are described by Box and Jenkins (1976, p. 176).

AIC, Schwarz's, and Residual Variance Order Criteria

The Akaike Information Criterion (AIC: Akaike 1974) and Schwarz's order criterion (S: Schwarz, 1978) were computed according to the formulas given by Priestley (1981, pp.373 and 376 respectively). Their values, and the residual variance as well (Priestley 1981, pp. 370-371), were found for different models, including at least the MA(1), MA(2), AR(1), AR(2), AR(3), AR(4), AR([1,3]), ARMA(1,1), ARMA(2,1), ARMA(3,1), and ARMA([1,3],1). Theoretically, these three order criteria should attain a minimum value in correspondence of the best model for the time series under study.

Akaike's and Schwarz's order criteria were proposed as objective ways of selecting a Box-Jenkins model. Unlike the residual variance criterion, they both include a penalty term for models of increasing order. Although they have been recognized as very useful tools (Priestley 1981, pp. 372-376), their value is usually not computed for all possible models, so that the investigator still makes a subjective choice in deciding what models to consider. Therefore, they were used together with the criteria originally proposed by Box and Jenkins for the identification, estimation, and validation stages.

Model Estimation and Validation

Final estimation of paramater values was based on a maximum likelihood procedure, closely approximated by a complex iterative computation starting from the preliminary estimates of the parameter values. Parameter estimates were not influenced by the mean of the original series because they were computed after centering the series around its mean.

Table 3. Summary of the model identification stage. (s = period of cyclical model)

Site and Series	Akaike's AIC	Schwarz's S	Residual Variance	ACF, PACF
Capulin Canyon				
CPN	AR(1)	AR(1)	ARMA(1,1)	AR(1)
CPL	AR(1)xMA(1);s=15	AR(1)xMA(1);s=15	AR(1)xMA(1);s=15	AR(1)
Burned Mountain				
BMT	ARMA(1,1)xMA(1);s=15	ARMA(1,1)	ARMA(1,1)xMA(1);s=15	ARMA(1,1);s=15
BRN	AR(1)xMA(1);s=15	AR(1)xMA(1);s=15	AR(1)xMA(1);s=15	AR(1);s=15
Garcia Park				
GAR	ARMA(1,1)	ARMA(1,1)	ARMA(1,1)	AR(2)
GPK	ARMA(1,1)xMA(1);s=7	AR(1)	ARMA(1,1)xMA(1);s=7	ARMA(1,1)
Osha Mountain				
OSM	ARMA(1,1)	ARMA(1,1)	AR(2)	AR(2)
OSH	ARMA(1,1)	ARMA(1,1)	ARMA(1,1)	AR(2)
Cabresto Canyon				
CAB	ARMA(1,1)	AR(1)	ARMA(1,1)	ARMA(1,1)
CCN	ARMA(1,1)	AR(1)	ARMA(1,1)	White Noise
Devils Gulch				
DVG50	AR(2)	AR(2)	AR(2)	AR(2)
DVG	AR(2)	AR(2)	AR(2)	AR(2)
DGU	ARMA(1,1)	ARMA(1,1)	ARMA(2,1)	AR(2)
Big Elk Meadows				
BIG	ARMA(1,1)	AR(1)	AR(2)	ARMA(1,1)
BEM	ARMA(1,1)	AR(1)	AR(3)	AR(1)
Indian Creek				
ICR	AR(1)	AR(1)	AR(2)	AR(1)
ICK	ARMA(1,1)	AR(1)	ARMA(1,1)	AR(1)
Ormes Peak				
ORP	AR(2)	AR(2)	AR(2)	AR(2)
OPK	ARMA(1,1)	ARMA(1,1)	AR(3)	ARMA(1,1)
Oak Creek				
OAK	ARMA(1,1)	AR(1)	AR(2)	ARMA(1,1)
OCK	AR(1)	AR(1)	AR(2)	White Noise
Ophir Creek				
OPH	AR(1)xMA(1);s= 7	AR(1)	AR(1)xMA(1);s=7	ARMA(1,1)
OCR	AR(1)xMA(1);s=13	AR(1)	ARMA(2,1)	AR(1)

Obviously, real data are never generated by one theoretical statistical model, so that it is only possible to decide which model best describes the real series among a set of a few plausible models. However, the statistical properties of estimators used in time series analysis are not always completely satisfactory. For instance, the estimators of the autocorrelations are autocorrelated themselves (Box and Jenkins 1976, p. 35). Although no criterion provides a definite answer by itself to the problem of model selection, the Box-Jenkins approach includes a set of validation criteria whose overall response allows the researcher to compare the performance of different models for a given time series. Such criteria are usually grouped into 3 categories: a) parameter analysis; b) residual analysis; c) overfitting.

a) Parameter Analysis

Since stationarity conditions are required for autoregresive (AR) models, and invertibility conditions for moving average (MA) models (Box and Jenkins 1976, pp. 49-51), parameter estimates were first checked for such conditions to be satisified.

Parameter estimates were then tested for significance using a t-test with degrees of freedom given by the difference between the number of observations in the series, and the number of estimated parameters in the model (Nelson 1976, p. 114).

b) Residual Analysis

The Residual AutoCorrelation Function (RACF) was plotted against its two-standard error limits, as the ACF and PACF. If the model is correct, the residuals should form an uncorrelated series, that is their autocorrelations should be not significantly different from zero. When a significant amount of residual autocorrelations exceed twice their standard error, the plot of the RACF may also give some indication of how the fitted model should be modified.

Two main problems had to be considered at this point. First, we considered residuals derived from real data, while their properties were referred to errors from a theoretical model (Nelson 1976, p. 115). Second, the standard error of sample autocorrelations was computed with a formula that might underestimate, for low lags, the statistical significance of values different from zero (Box and Jenkins 1976, p. 290). Therefore, in order to test the significance of the sample residual autocorrelations as a whole, the Ljung-Box Q-test was employed (Ljung and Box 1978, SPSS Inc. 1986b). LBQ values for 20, 25 and 30 degrees of freedom are listed in Tables 5 and 6, together with their approximate P-values. Unlike most hypothesis tests, larger P-values indicate stronger evidence of model adequacy because the null hypothesis of this test is "model is correct".

c) Overfitting

This criterion is based on adding one parameter at a time to the model, and then testing the hypothesis that the new model fits the series better. This was done using a t-test on the added parameter and by comparing the new residual variance, RACF and LBQ values to those of the simpler model. However, when a significant higher order model performs as well as a lower order one, the latter should be preferred because of its parsimony (Ledolter and Abraham 1981).

A particular problem may arise because of *model redundancy*, which consists in choosing a model that could be simplified to an equivalent, simpler one. A classic case of model redundancy is fitting an ARMA(1,1) model to a white noise series. An example reported by Cryer (1986, p. 158) shows that model redundancy is possible even when parameter values are not identical. In that example, an ARMA(1,1) model was fitted to a simulated white noise series. Although the model was obviously redundant, the maximum likelihood estimates of the two parameters were not equal: p_1 was -0.407 and q_1 was -0.582.

RESULTS

None of the series considered in the present study showed any evidence of nonstationarity, since their sample autocorrelations were not significant after 3 to 6 lags. This is not surprising because they were obtained as an average of standardized series all having a mean close to 1.0 and a scaled variance (Fritts 1976, p. 266).

Identified models were all AR or ARMA (Table 3), and no evidence for MA models was found. Also, series OCK and CCN showed no significant sample autocorrelations at low lags. For series OCK (the shortest series analyzed), this might depend on the small value of N, together with the low reliability of the estimated standard error for small-lag autocorrelations. In fact, fitted models accounted for about 9% of its total variance. For series CCN (the only pinyon pine series analyzed), this was probably caused by a real lack of autocorrelation within the series, as suggested by the low amount of variance explained by fitted models (about 2%, the smallest one among all series). Since series CCN was best fitted by an ARMA(1,1) model with fairly similar parameter estimates ($p_1 = 0.818$ and $q_1 = 0.736$), there is also a possibility of model redundancy, even if both parameter estimates were highly significant (Table 5).

Overall, no more than three different parameters were included in the selected models, and about 84% of the 46 reported models consisted of only two parameters (Tables 5 and 6). The ARMA(1,1) model was selected as the best for 11 series (48% of the cases) and as the closest competitor for 7 of the remaining 12 series. The AR(2) model was considered best for 6 series (26% of the cases) and the closest competitor for 4 of the remaining 17 series. These two models can be written as follows:

ARMA(1,1) $$Z_t = \phi_1 Z_{t-1} + a_t - \Theta_1 a_{t-1}$$
AR(2) $$Z_t = \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + a_t$$

For tree-ring series, we may say that an ARMA(1,1) model considers the ring-value at year t as a function of three elements: the ring-value for the previous year, an error component for year t, and an error component for the previous year. In the same way, an AR(2) model indicates that the ring-value at year t is related to a combination of the ring-values for the two immediately preceding years plus an error component for year t (Hoff 1983, p. 50).

The AR(1) model, chosen by Meko (1981, p. 82) and Tessier (1984, p. 108) for most of the tree-ring series they examined, was considered the best for only three series in our data set, and the closest competitor for 4 of the remaining 20 series.

The presence of significant residual autocorrelations after modeling series CPL, BRN, BMT, GPK, OPH and OCR suggested that cyclical models with periods of 7 (GPK, OPH), 13 (OCR), or 15 years (CPL, BRN, BMT) could be more appropriate for those chronologies. Also, a third-order autoregressive model in which the second-order parameter was not significantly different from zero, or AR([1,3]), was fitted to some series (Tables 5 and 6). Both of these results have no counterpart in the results of Meko (1981) and Rose (1983). Monserud (1986) reported an AR(3) model with a non-

Table 4. Variation in parameter estimates for 11 ARMA(1,1) models, 6 AR(2) models, and 5 AR(1) models reported in Tables 5 and 6. Monserud's (1986) results are reported in parenthesis for comparison.

Model	Parameter(*)	Range	Mean
ARMA(1,1)	p_1	0.674-0.915	0.77
		(0.52-0.93)	(0.74)
	q_1	0.218-0.780	0.44
		(0.26-0.68)	(0.42)
AR(2)	p_1	0.201-0.422	0.30
		(0.10-0.42)	(0.30)
	p_2	0.149-0.272	0.22
		(0.08-0.24)	(0.15)
AR(1)	p	0.329-0.702	0.45
		(0.35-0.57)	(0.43)

(*)See footnote of Table 2.

significant second-order coefficient for a spruce chronology, and 6 AR(4) models with a non-significant third-order coefficient for three ponderosa pine, two Douglas-fir, and one spruce chronologies. Tessier (1984, p. 108) fitted cyclical models to 4 of the 29 series he reported, three with a 7-year period and one with a 9-year period.

All parameter estimates were positive and varied within a relatively small range, showing excellent agreement with Monserud's (1986) results (Table 4). All t-ratios ranged from 1.79 to 16.50, and their approximate P-value ranged from less than 0.05 to less than 0.0001 (Tables 5 and 6).

The average amount of variance explained by the best models was about 22%, with a maximum of 51.2% and a minimum of 7.1% (Tables 5 and 6). The amount of variance explained by Monserud's (1986) and Rose's (1983) models was almost the same, ranging approximately from 5 to 46% with an average of 20% in both studies. This finding was quite unexpected because sampled stands in Colorado and New Mexico had relatively closed canopies and were more mesic than sites studied by Rose and Monserud. Also, sampled stands had a history of at least three known spruce budworm outbreaks during the twentieth century, and possibly as many as 6 additional outbreaks from 1700 to 1900 (Swetnam 1987). Trees growing in forest interior stands, with a history of standwide disturbances, often exhibit persistent radial growth depressions and fluctuations that tend to increase the amount of autocorrelation in the ring-width series (Fritts 1976, Cook 1985).

The average explained variance for Colorado chronologies (about 17%) was significantly lower than that for New Mexico chronologies (about 26%, that increased to 29% by excluding series CCN), probably because of the different amount of autocorrelation removed by the different growth curves used in the standardization stage. As pointed out in the following paragraphs, the systematic use of two different standardization options in building New Mexico and Colorado chronologies was reflected by several other time dependent properties of these two sets of tree-ring series.

Table 5. Summary of the estimated Box-Jenkins models for New Mexico tree-ring chronologies.

Site and Series	Best Model	Estimated Parameters(1) p_1	q_1	Q_1(s=15)	Corr.(2)	Expl. Var.(%)	LBQ Test (3) df=20	df=25	df=30	Competitor Model
Capulin Canyon										
CPN	AR(1)	0.445 (7.34*)				19.5	23.4 (0.25)	24.3 (0.40)	26.5 (0.60)	ARMA(1,1)
CPL	AR(1)xMA(1);s=15	0.423 (7.08*)		0.298 (4.45*)	−0.008	24.9	17.1 (0.60)	18.0 (0.70)	24.4 (0.70)	AR(1)
Burned Mountain										
BMT	ARMA(1,1)	0.817 (12.84*)	0.393 (3.93*)		0.787	33.7	21.4 (0.30)	23.7 (0.50)	36.3 (0.10)	ARMA(1,1)xMA(1);s=15
BRN	AR(1)xMA(1);s=15	0.702 (14.65*)		0.202 (3.01^)	0.071	51.2	17.6 (0.50)	20.9 (0.60)	29.7 (0.40)	ARMA(1,1)
Garcia Park										
GAR	ARMA(1,1)	0.753 (10.03*)	0.408 (3.89*)		0.868	21.4	19.0 (0.50)	27.6 (0.30)	33.1 (0.30)	AR(2)
GPK	ARMA(1,1)	0.687 (9.46*)	0.272 (2.84^)		0.861	24.3	25.4 (0.10)	34.3 (0.10)	38.1 (0.10)	ARMA(1,1)xMA(1);s=7
Osha Mountain										
OSM	ARMA(1,1)	0.757 (15.74*)	0.218 (3.02^)		0.763	40.0	19.1 (0.50)	20.0 (0.70)	24.6 (0.70)	AR(2)
OSH	ARMA(1,1)	0.813 (16.50*)	0.367 (4.66*)		0.751	36.0	15.6 (0.70)	20.8 (0.60)	22.1 (0.80)	AR(2)
Cabresto Canyon										
CAB	ARMA(1,1)	0.915 (11.62*)	0.780 (6.57*)		0.885	7.1	21.7 (0.30)			AR([1,3])
CCN(4)	ARMA(1,1)	0.818 (5.92*)	0.736 (4.54*)		0.979	1.8	20.4 (0.40)	23.0 (0.50)	30.8 (0.40)	AR(1)

(1) Parameter estimates are given only for the best models. T-ratios are given in parenthesis, below the estimate. See note Table 2.
(2) Correlation between parameter estimates.
(3) Approximate P-values are given in parenthesis, below the LBQ value.
(4) This chronology should probably be considered as a white noise series (see text for details).
* = P-value < 0.0001 ** = P-value < 0.001 ^ = P-value < 0.01 " = P-value < 0.05
s = period of cyclical model

Table 6. Summary of the estimated Box-Jenkins models for Colorado tree-ring chronologies.

Site and Series	Best Model	Parameter Estimates (1) p_1	p_2	p_3	q_1	Corr.(2)	Expl. Var.(%)	LBQ Test (3) df=20	df=25	df=30	Competitor Model
Devils Gulch											
DVG50	AR(2)	0.318 (6.17*)	0.216 (4.19*)			−0.402	19.7	33.8 (0.03)	38.9 (0.03)	45.9 (0.03)	ARMA(1,1)
DVG	AR(2)	0.412 (8.12*)	0.269 (5.27*)			−0.559	35.9	28.4 (0.05)	36.4 (0.05)	42.1 (0.05)	ARMA(1,1)
DGU	ARMA(1,1)	0.777 (8.47*)			0.528 (4.30*)	0.909	12.9	29.6 (0.05)	35.7 (0.05)	38.1 (0.10)	AR(3)
Big Elk Meadows											
BIG	AR(2)	0.422 (6.18*)	0.149 (2.17")			−0.469	24.5	24.1 (0.20)	28.1 (0.25)	32.7 (0.30)	ARMA(1,1)
BEM	ARMA(1,1)	0.674 (5.15*)			0.371 (2.24")	0.918	14.6	33.6 (0.03)	36.9 (0.05)	41.8 (0.05)	AR([1,3])
Indian Creek											
ICR	AR(1)	0.329 (4.24*)					10.0	23.7 (0.20)	28.5 (0.25)		AR(2)
ICK	ARMA(1,1)	0.679 (8.77*)			0.230 (2.24")	0.848	27.2	27.7 (0.10)	33.9 (0.10)	43.9 (0.03)	AR([1,3])
Ormes Peak											
ORP	AR(2)	0.205 (3.68**)	0.272 (4.82*)			−0.271	15.6	16.2 (0.60)	24.6 (0.40)	27.7 (0.50)	ARMA(1,1)
OPK	ARMA(1,1)	0.745 (7.29*)			0.505 (3.83**)	0.924	11.2	16.4 (0.60)	19.8 (0.70)	26.3 (0.60)	AR([1,3])
Oak Creek											
OAK	AR(2)	0.254 (3.08^)	0.235 (2.81^)			−0.268	12.2	22.0 (0.30)	23.7 (0.50)		ARMA(1,1)
OCK	AR(2)	0.201 (2.21")	0.166 (1.79")			−0.198	9.3	22.5 (0.30)			AR(1)
Ophir Creek											
OPH	AR([1,3])	0.391 (7.20*)		0.105 (1.93")		−0.229	19.8	19.8 (0.40)	22.2 (0.60)	27.1 (0.60)	AR(1)
OCR	AR(1)	0.364 (6.05*)					12.7	19.9 (0.40)	30.4 (0.20)	35.2 (0.20)	AR(1)xMA(1);s=13

(1) Parameter estimates are given only for the best models. T-ratios are given in parenthesis, below the estimate. See note Table 2.
(2) Correlation between parameter estimates.
(3) Approximate P-values are given in parenthesis, below the LBQ value.
* = P-value < 0.0001 ** = P-value < 0.001 ^ = P-value < 0.01 " = P-value < 0.05

Series DVG and DVG50 were both best described by an AR(2) model. However, the amount of autocorrelation removed during standardization was different (see "Materials" section, this article), and this determined the large difference in the amount of variance explained by the same model for the two series (36% for series DVG versus 20% for series DVG50).

Among the 12 chronologies from Colorado sites, all derived using the same standardization option, the ARMA(1,1) model was the best for most Douglas fir series, but it was never the best for ponderosa pine series, while the AR(2) model was the best for most ponderosa pine series, and for only one Douglas-fir series (Table 6). Thus, Douglas-fir series were best represented by the ARMA(1,1) model, while ponderosa pine series were best represented by the AR(2) model. It is possible that certain phenological characteristics of needle development and retention of these tree species may account for differences in the observed autocorrelation structure of the ring series. For example, ponderosa pine needles elongate and mature progressively throughout the growing season (spring and summer), while Douglas-fir needles emerge rapidly from the buds and are relatively mature early in the growing season (Fritts *et al.* 1965). Also, Douglas-fir retains its needles for 5 to 8 years while ponderosa pine needles persist for about three years (Vines 1960, Preston 1976). It might be that the rapidly maturing and longer persisting Douglas-fir needles somehow introduce a different component in the time dependent structure of radial growth. The slower developing needles of ponderosa pine may not substantially contribute to ring growth until the following growing season. However, the nature of possible physiological effects of these phenological differences remains unclear.

Different reproductive strategies, including periodic cone production, might be another factor related to different time dependent properties of tree-ring series. An inverse relationship between cone production and radial growth was reported by Eklund (1957) for spruce, and by Eis, Garman, and Ebel (1965) for Douglas-fir, whereas Daubenmire (1960) was unable to prove any such relationship for ponderosa pine.

Species differences in the selected models were not found among the 10 New Mexico chronologies, developed using various standardization options (Table 1). The ARMA(1,1) model was the best in most cases, without distinction between Douglas-fir and ponderosa pine series, and the AR(2) model was never the best (Table 5). Also, the New Mexico chronologies included the two series for which a cyclical model represented the best selection, and two of the three series for which a cyclical model was the closest competitor to the best one. If the standardization options had been the same, we could infer that a periodic phenomenon was more influencial in New Mexico sites than in Colorado sites. However, since 6 New Mexico chronologies were built using a negative exponential or a straight line, it is possible that such growth curves left unaltered the periodic patterns which the cubic spline removed from the ring-width series. Further investigation, involving the standardization of all Colorado ring-width series using a negative exponential or a straight line, will be needed to test any systematic effect of the standardization option on the periodic behavior of tree-ring chronologies.

Model AR([1,3]), chosen as the best for one ponderosa pine series and as the closest competitor for 4 Douglas-fir series, might either reflect species, site or standardization distinctions, since most of these series were from Colorado sites (Tables 5 and 6). This model can be written as follows:

AR([1,3]) $$Z_t = \phi_1 Z_{t-1} + \phi_3 Z_{t-3} + a_t$$

It is interesting to note that Fritts, Smith and Stokes (1965) found a highly significant direct relationship between current year's growth and the growth of three years earlier for Douglas-fir and pinyon pine series from Mesa Verde, Colorado. Also, Fritts *et al.* (1965) reported that Douglas-fir, ponderosa pine, and pinyon pine from northern Arizona exhibited a high third-order autocorrelation, especially at the lower altitudinal limit for each species. However, in both studies no physiological or ecological explanation was suggested for this relationship. Eis, Garman and Ebell (1965) found that abundant cone production following a three-year periodic pattern reduced radial growth of Douglas-fir only in the year when cones were produced.

The cyclical models that were chosen for two Douglas-fir series (BRN, with a 15-year period, and OCR, with a 13-year period) were formed by a first-order autoregressive model within each period, and by a first-order moving average model between adjacent periods. Cyclical models were also found adequate for three ponderosa pine chronologies (CPL and BMT, with a 15-year period, and GPK, with a 7-year period). These models still include a first-order moving average component between adjacent periods, but the within-period component is either an AR(1) model (series CPL) or an ARMA(1,1) model (series BMT and GPK) (Table 5). An example of the procedure used for fitting and then evaluating cyclical models is outlined in the Appendix.

Although cyclical Box-Jenkins models were selected because of statistical evidence, their application to tree-ring research is relatively new, and their biological meaning was not completely clear. The cyclical model fitted to series BRN and CPL, for example, can be written as follows:

$AR(1)xMA(1)_{15}$ $$Z_t = \phi_1 Z_{t-1} + a_t - \Theta_1 a_{t-15}$$

This model relates the ring-value at year t to a linear combination of the previous ring-value, the current error component, and the error component at year $t-15$. It is important to remember that not every significant model was reported, but only those that performed best according to the previously discussed criteria. As mentioned in the Appendix, the periodic behavior of tree-ring chronologies could sometimes be expressed by more than one cyclical model, but only one among various significant models was selected.

Cyclical models for Douglas-fir chronologies might be related to periodic western spruce budworm outbreaks, which in the New Mexico sites induced low growth periods with an average duration of approximately 14 years (Swetnam 1987). Duration of the actual period of tree defoliation was estimated at 7-10 years by adjusting the reduced growth periods for possible years of recovery. However, periodic patterns in ponderosa pine series were more difficult to explain because pine trees in the study area had not been defoliated by the budworm. Since tree-ring chronologies for Capulin Canyon and Garcia Park were derived from cores of Douglas-fir and ponderosa pine trees growing in the same stand, it is possible to conjecture an indirect effect of budworm outbreaks on pine growth in such stands, mainly by reducing number and vigor of competing Douglas-fir trees. However, this was not the case for Burned Mountain, where pine trees were growing in a separate, nearby stand

(Swetnam 1987). It might also be possible that both species were responding to some climatic factor that induced a periodic behavior in the tree-ring chronologies by itself and/or by interacting with budworm effects.

From a comparison between Table 3 on one hand, and Tables 5 and 6 on the other hand, it is evident that the AIC criterion was the one that best agreed with the chosen models. In fact, the model associated with the minimum AIC value was considered the best for 16 series, and the closest competitor for 6 of the remaining 7 series. Therefore, Akaike's Information Criterion, if properly computed for a variety of models, might represent a reasonably good short-cut way of identifying the best Box-Jenkins model for a given time series.

The prewhitened series were graphically similar to the original ones, especially with respect to short-term growth patterns (Figures 2 and 3). However, the long-term growth fluctuations visible in the original series were less evident in the residual series. Periods of growth reduction caused by known and inferred spruce budworm outbreaks were usually still present in the prewhitened Douglas-fir series, but their duration was shorter. Cross-correlations between chronologies from the same area increased after prewhitening, except for Burned Mountain (Table 7). Thus, the prewhitening procedure appears to have increased the similarity between ponderosa pine and Douglas-fir chronologies by partially removing differences related to biological persistance and growth response to spruce budworm outbreaks.

The prewhitened chronologies showed null serial correlations, lower standard deviations, and higher mean sensitivities than the original series. According to Fritts and Shatz (1975), low autocorrelation and high mean sensitivity are typical of tree-ring series that contain the highest amount of climatic information. Although "high mean sensitivity is a sufficient, but not necessary, indicator of climatic responsiveness" (LaMarche *et al.* 1982, p. 5), the usual guidelines followed in developing tree-ring chronologies for dendroclimatic analysis should probably be modified considering the utility of the prewhitening procedure. In fact, it has already been found that prewhitening is a crucial point in analyzing the relationships between tree growth and environmental variables when they are measured sequentially through time (Ford and Milne 1980, Ford *et al.* in press).

CONCLUSIONS

The time dependent structure of tree-ring chronologies analyzed in this study presented some unique characteristics, as could be expected from real data reflecting ing the complexity of the physical world. The mixed autoregressive and moving average model of first order, or ARMA(1,1) model, was judged the best for most series, but its superiority was not as striking as in Monserud's (1986) and Rose's (1983) studies. No statistical evidence was found for moving average models, nor for models with more than three different parameters.

Cyclical models for Douglas-fir chronologies may be related to western spruce budworm outbreaks, whose periodicity agreed fairly well to the periods of the selected models. Cycles were found significant also for ponderosa pine chronologies, even though pine trees in the study area had usually not been defoliated by the budworm. For sites where the two species grow together, it is possible to conjencture an indirect effect of budworm outbreaks on pine growth, probably by reducing number and vigor of competing Douglas-fir trees. However, additional tests of this hypothesis are needed, especially for those sites where sampled pines are not growing in the same

Table 7. Chronology statistics of the residual tree-ring series (compare with Table 1).

Site and Series Names	Species Code	Model	No. of yrs.(*)	Stand. Dev.	Mean Sens.	1st AC (**)	X-Corr. (P-value < 0.05)
Capulin Canyon							
CPN	PSME	AR(1)	193	0.227	0.272	−0.043	0.696
CPL	PIPO	AR(1)xMA(1);s=15	191	0.195	0.226	−0.004	(1791-1981)
Burned Mountain							
BMT	PIPO	ARMA(1,1)	193	0.184	0.210	0.000	0.635
BRN	PSME	AR(1)xMA(1);s=15	193	0.181	0.207	−0.056	(1791-1983)
Garcia Park							
GAR	PSME	ARMA(1,1)	281	0.274	0.326	−0.009	0.758
GPK	PIPO	ARMA(1,1)	360	0.314	0.390	0.005	(1701-1981)
Osha Mountain							
OSM	PIPO	ARMA(1,1)	400	0.213	0.241	−0.017	0.624
OSH	PSME	ARMA(1,1)	288	0.168	0.184	0.027	(1700-1981)
Cabresto Canyon							
CAB	PSME	ARMA(1,1)	110	0.268	0.315	0.024	0.757
CCN	PIED	ARMA(1,1)	389	0.326	0.397	−0.014	(1880-1981)
Devils Gulch							
DVG50	PIPO	AR(2)	329	0.311	0.378	−0.005	0.774
DVG	PIPO	AR(2)	329	0.317	0.386	−0.004	0.769
DGU	PSME	ARMA(1,1)	247	0.376	0.455	−0.029	(1740-1980)
Big Elk Meadows							
BIG	PIPO	AR(2)	182	0.225	0.270	−0.014	0.738
BEM	PSME	ARMA(1,1)	171	0.281	0.337	−0.011	(1820-1983)
Indian Creek							
ICR	PIPO	AR(1)	124	0.184	0.204	−0.036	0.616
ICK	PSME	ARMA(1,1)	290	0.209	0.240	0.002	(1860-1983)
Ormes Peak							
ORP	PIPO	AR(2)	269	0.248	0.302	−0.010	0.720
OPK	PSME	ARMA(1,1)	264	0.262	0.308	−0.011	(1721-1984)
Oak Creek							
OAK	PIPO	AR(2)	120	0.252	0.314	0.003	0.799
OCK	PSME	AR(2)	89	0.341	0.428	−0.006	(1900-1982)
Ophir Creek							
OPH	PIPO	AR([1,3])	256	0.292	0.347	0.004	0.667
OCR	PSME	AR(1)	213	0.257	0.289	−0.017	(1780-1984)

(*) Each residual series begins "p" years after the original series, with "p" = order of the last autoregressive parameter included in the fitted model.
(**) = All reported values are not significantly different from zero at the 0.045 level. s = period of cyclical model.

stand of sampled Douglas-firs.

It is likely that standardization techniques, disturbance factors, and species characteristics such as climatic response, reproductive strategy, needle growth and retention influence the time dependent structure of forest interior tree-ring chronologies. Improved understanding of these relationships will require ecophysiological studies in combination with time series analysis of tree-ring series, which should lead to better estimation and reconstruction of past environmental variations that have affected tree growth.

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APPENDIX

Fitting a Cyclical Model to Series CPL

The ACF and PACF plots did not agree in their indication of a preliminary model for series CPL. The PACF pointed towards an AR(1) model because it dropped after the first lag, but the ACF showed a pseudo-periodic behavior suggesting either an AR(2) or an ARMA(1,1) model. As usual in this situation, preference was first given to the indication of the PACF (see Table 3).

The AIC and S order criteria confirmed the preliminary choice of an AR(1) model, while the residual variance criterion pointed towards an AR([1,3]) model.

The overfitting procedure strongly suggested the highly significant AR(1) model (t-ratio for p_1 of 7.54), since the added parameter in the AR(2) model (t-ratio for p_2 of 0.22), in the ARMA(1,1) model (t-ratio for q_1 of 0.33), and in the AR([1,3]) model (t ratio for p_3 of 1.18) was never statistically significant.

After fitting the AR(1) model to the original series, the RACF showed values exceeding the two-standard error limit only at lags 15, 29, and 44, *i.e.* about 7% of the considered lags. Since this percentage was higher than what might be expected by chance alone, the AR(1) model could not be considered the "best" choice for series CPL. Also, its RACF suggested that an MA(1) model could link observations 14 or 15 time intervals apart, and in fact the model $AR(1)xMA(1)_{15}$ removed all significant autocorrelations from the original series.

The LBQ test held P-values that were much higher (about twice as much) for the cyclical model than for the AR(1) model. Also, the estimate of the cyclical moving average parameter was highly significant (Table 3) and the AIC, S, and residual variance criteria were all confirming the superiority of the cyclical model (see Table 3).

Although the $AR(1)xAR(1)_{15}$ model was also significant, its performance was not so good as the selected models because of the higher AIC, S, residual variance and LBQ values, and smaller t-ratios of the parameter estimates.

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