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Standardization, Time Series and Response Function Analyses of Tree-Ring Chronologies from Southern Arizona Conifers*1

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南애리조나産 침엽수類 年輪年代記의 標準化, 時系列 및 反應函數 分析*1

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要 約

최근에 서로 다른 생장추세를 나타내고 있는 南애리조나産 침엽수 4樹種(*Pseudotsuga menziesii, Pinus ponderosa, Pinus strobiformis, Abies concolor*)의 연륜폭 年代記로 부터 반응함수를 구하기 위하여, 표준화 방법을 면밀히 검토하였으며 시계열모델에 의한 事前 濾過化(prewhitening)로 前生長量을 배제하는 것이 효과적인 것인지도 조사하였다. 전통적으로 사용되던 指數 또는 直線방정식에 의한 표준화가 대부분 성공적으로 적용되었으나 최근생장이 급격히 감소된 경우는 스플라인함수를 이용하는 것이 효과적이었다. 季節모델이 적용된 *Pinus ponderosa*의 경우를 제외하곤 사전여과화 前後의 반응함수間에 뚜렷한 차이를 발견할 수 없었다.

Keywords : tree ring, response function, dendrochronology, standardization, prewhitening, time series, Arizona

1. INTRODUCTION

Relationships between tree-ring and climatic data have been explored through a variety of multiple regression analyses.[6, 11] One of the limitations in these regressions results from the multicollinearity within climate data. The response function was developed to avoid this multicollinearity problem by converting original climatic variables into uncorrelated variables, called principal components or eigenvectors, and it also allows to reduce the number of climatic variables by choosing certain important principal components.[12] Response function analysis has been used in numerous studies[6, 10, 17], and has become the most commonly used method to identify relationships between tree-ring width and climate. In this

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study, ring-width chronologies of four conifers growing at a semiarid site of southeastern Arizona were analyzed to obtain response functions with emphasis on time-series modeling and standardizing.

Some studies claim that inclusion of the lagged tree-ring variables can alter some part of the response function which is supposedly determined by climatic relations alone.[2,17] Prewhitening the tree-ring data may eliminate persistence within the tree-ring data and may resolve the criticism about the inclusion of prior growth variables in the response function procedure. In this study, Box-Jenkins modeling was used to prewhiten the ring-width series and the performance of the prewhitening in the response function analysis was evaluated.

There are some basic assumptions for the Box-Jenkins time-series modeling. The observations of a series should be independent, and the series should be stationary ; i. e., common means and variances should be observed throughout the observation period.

Standardization is a procedure which transforms the nonstationary tree-ring series into a new stationary(weakly stationary, at least) time series with the removal of trend.[11], [14] However, it is controversial to derive stationary series by standardization without losing natural growth trends (for example, abnormal growth declines for certain species in this study). Furthermore, improper standardization of such series may produce totally different results due to the difficulty in identifying the biological growth trend and disturbances in the recent decades even though several models for predicting it have been suggested.[5, 6, 18, 26] For these reasons, several curve-fitting options for standardization were closely examined.

2. MATERIALS AND METHODS

2. 1. Sampling

The sampling site is located on the northwest-facing slope (about 2425~2450 meters above sea level, 32° 3′ 30″ N and 110° 3′ W) of Mica mountain, about 25 kms east of the metropolitan area of Tucson, Arizona, U. S.A.(Fig. 1).

The climate in the sample region is semiarid, characterized by dry and hot weather. Rainfall is concentrated in the periods of July to September (about 60% of total) and November to March. Tree growth in this region is known to be highly regulated by the rainfall and temperature regimes as they affect the water balance.[10] It is known that well-drained shallow subhumid soils at this site produce tree rings which are variable in width and correlated with yearly variation in rainfall and temperature, due to the enhanced limiting effects of soil moisture and air temperature on the tree-water balance.[10]

The species sampled were Douglas-fir (*Pseudotsuga menziesii*), ponderosa pine (*Pinus ponderosa*), southwestern white pine (*Pinus strobiformis*) and white fir (*Abies concolor*). The sampled trees were dominant trees (ca. 250~300 years old) in a mixed conifer community. A total of 31 trees (9 Douglas-fir, NSF ; 8 southwestern white pine, NSW ; 7 white fir, NSA ; and 7 ponderosa pine, NSP) were included in the ring-width analysis. Two cores (4mm in diameters) from each of sample trees were collected at breast heights in November 1987. The rings were crossdated and measured using the methods described in Stokes & Smiley[24] and Robinson & Evans[23].

2. 2. Standardization.

Ring-width plots of annual and 20 year-averages were produced using the PAGEPLOT (Lofgren, unpublished) and RWLIST(Graybill, unpub.) programs in order to determine standardization curves. To preserve growth trends, hopefully, not related to the biological growth trends, only negative exponential curves, negative-sloped straight line and stiff splines were considered among several options in the INDEX program. All standardization curves were laid over the ring-width series with Raster or Calcomp plotters using the TRPLOT program (Graybill, unpub.) in order to identify any unsatisfactory curves which could underestimate or overestimate the growth. This judgement was primarily based on the common climatic signals which have been already identified in the tree-ring chronologies of southern Arizona.

2. 3 Statistical Quality

Site chronologies for each species were developed with the revised standardization curve options. The general characteristics (mean sensitivity, standard deviation, number of absent rings, first-order autocorrelation, etc.) of site chronologies were obtained.

Analysis of variance(ANOVA) and cross-correlation analysis (XCORA) were performed.[11, 14] The common period for and VA was 1850 to 1986 except for the white pine series where it was 1860~1986.

The sample depth in the early portion of the chronologies was shallow because the earlier sections were usually based on fewer cores than the later sections. It was necessary to determine the beginning year in each chronology as the point when the strength of the signal becomes strong enough for a subsample of cores to represent the complete chronology.[26] In this study, the beginning year for each chronology was the first year when a subset of cores constituted 90% of the popu-

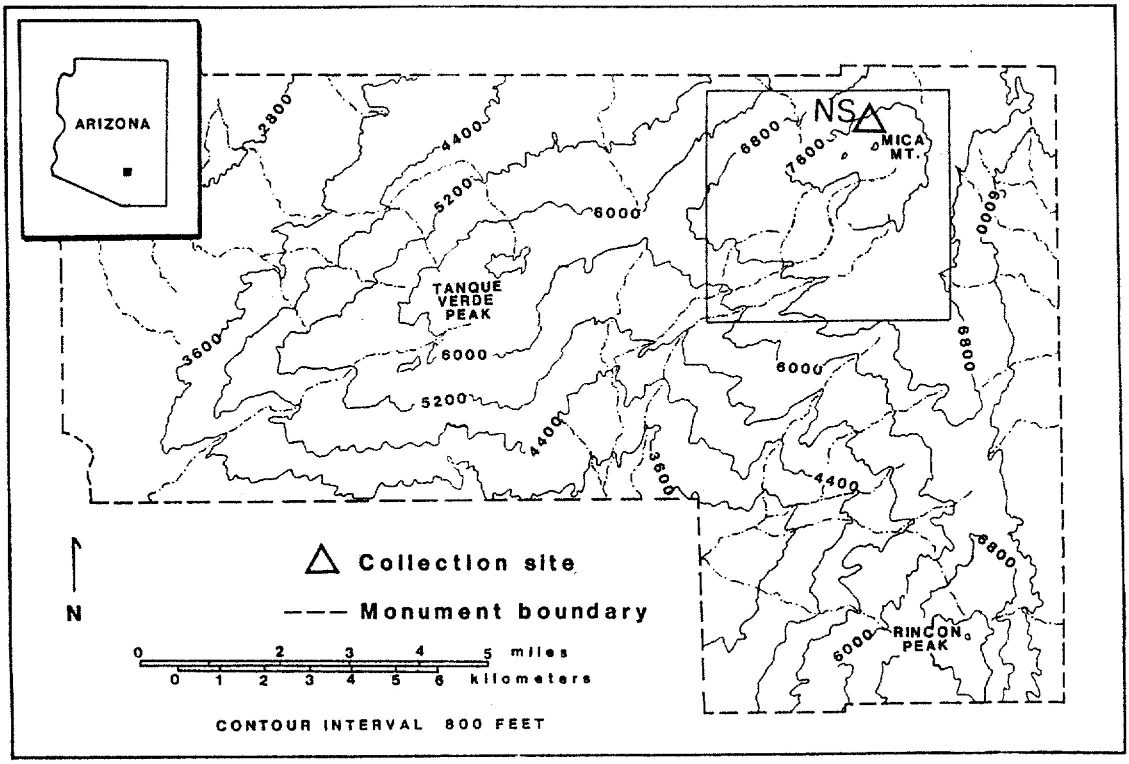

Fig 1. Location of the study site at the Saguaro National Monument East, Tucson, Arizona, U. S. A. (NS ; North Slope site).

lation signal.[15, 25] The remaining chronology values were used for the following ARMA modeling.

2. 4. Time-Series Modeling (Box-Jenkins)

The BMDP 2T program was used for all analysis of time series.[9] The candidates for the best model are identified by the shape and characteristics of the autocorrelation function (ACF) and partial autocorrelation function (PACF).[3, 21] Based on the ACF and PACF profiles, five to eight possible models which consisted of the combinations with low orders (less than 3) of the autoregression and /or the moving average terms were selected for the further estimation step. Parameters were estimated with the maximum likelihood functions using both conditional and unconditional least squares. The program performs conditional least-squares estimation first and then the unconditional least-squares (the backcasting method). A t-value for each parameter was calculated and its significance was tested at the 90% level. Any model which had insignificant parameters was eliminated in this step. Q-statistics[22] were used to check the smallness of the autocorrelations of the residuals which remained after filtering the original series using the selected models. A smaller Q-value indicates a better model in most cases. For those models with similar Q-values, Akaike Information Criteria (AIC) were used for the dignostic checking.

Besides the above criteria, all ACF and PACF of the residuals were examined visually to check the randomness of residuals. The residuals should have independent and identical normal distributions, therefore, none of the sample autocorrelations and sample partial autocorrelations should be significant. Three time series among four chronologies were successfully fit with the non-seasonal models except for the ponderosa pine series, so a seasonal model was tried for this series.

2. 5 Response Function

The residuals from the best Box-Jenkins models were applied to the RESPONS program.[12] The climatic data (monthly total precipitations and monthly average temperatures) were taken from regional average data for southeast Arizona (Climate Division 7 of Arizona, National Climatic Data Center, Asheville, North Carolina). The period of the climatic variables was 14 months beginning in June of the prior growth year and ending in July of the growth year. This period has been commonly used for the response function analyses of southern Arizona conifers.[11] The period of the response function analysis was from 1900 to 1950 (51 years). The period after 1950 was not included since an abnormal growth decline was visible in some species during the last few decades which could alter the response functions. The lags of prior growth were not considered because the ARMA model is believed to remove any serial correlation terms. In addition to the residual chronologies, the raw index chronologies (except for the ponderosa pine chronology) were also applied to the response function analysis. Three lag variables were included at this time. The response functions obtained from the prewhitened chronologies and index chronologies were compared to examine the performance of prewhitening on the response functions.[13]

3. RESULTS AND DISCUSION

3. 1. Standardization

Of the total 63 cores, representing four species, about half (52%, 33 cores) were successfully standardized with the negative exponential curves. Twenty five cores(40% of total) and five cores (8% of total) were standardized with the negative sloped straight lines and with the stiff cubic splines, respectively.

Several kinds of problems were discovered in determining the option of curve fit. Exponential curves could not be fit successfully for some cores in which the growth for the period (1910~1940) increased in response to wet conditions following the fast, early growth period (from the juvenile stage to about 70~90 year old ages). These cores were fit with straight lines. However, a straight line fit for one NSF core turned out to be unreasonable because the estimates of the last few decades were exaggerated (Fig. 2, Plot C). A stiff spline curve was also unsuccessful at fitting this series. A flexible spline with 80year length of 50%response period was fit, but it also produced an abrupt rise in the last decade. This series was deleted.

More frequently, this underfit was observed in the exponential curve fits. As shown in Fig. 2. (Plot B), exponential curves estimate ring-widths of the last few decades as extremely small values (less than 0.1mm). In ordinary ring index series, it is uncommon for the indices to exceed 2.0for more than two decades. A lack of steady increases in the raw ring-width data during this period makes it clear that the abruptly rising values of the indices are too artificial to be considered a growth trend. Stiff splines with 130~139 years of 50%response-frequency period were adopted to remedy this kind of problem (three

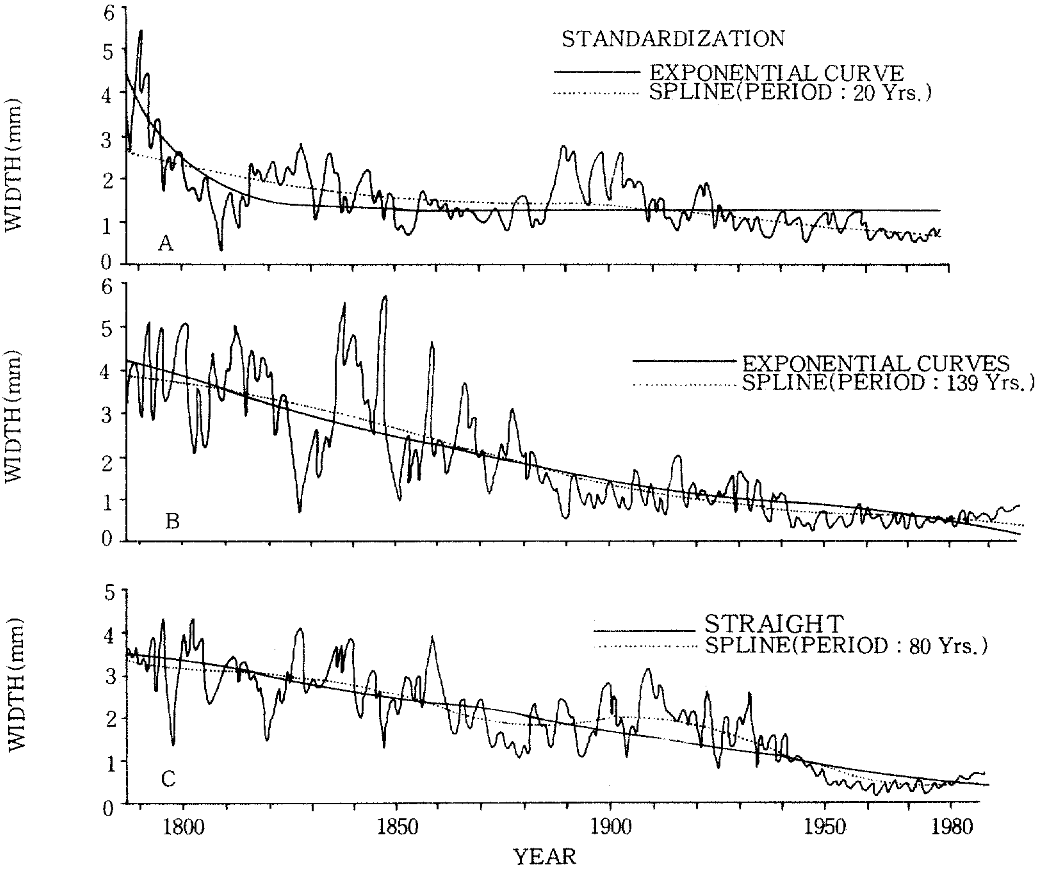

Fig 2. Standardization curve options for Douglas fir (PlotA and B) and white fir (Plot B) core series.

cases ; one in the NSW series and two in the NSA series). Stiff splines were also used for two other cases in the NSA series. For these series, splines were preferred to both exponential curves and straight lines because the growth trends were very constant throughout the entire period.

Four series of Douglas-fir seemed to be overfit by exponential curves in the period 1940 to 1987 (e. g., Fig. 2, Plot A). These are the cases which Holmes *et al.*[19] described. They found that exponential curves usually fit well over the highly variable, steeply descending juvenile portion, but then often either overfit or underfit systematically for many consecutive decades associated with maturity and old ages. Stiff spline could fit successfully these four series, but it was unclear that the underfitted portions in these series represented real growth decline. The exponential curves for these cases were kept.

The standardization options, except for the cubic splines, in the INDEX program represent a deterministic method. They apply least square fitting techniques to the entire length of the chronology. In some cases, the fitting of the curve can be dominated by portions of the chronology that have high variance such as in the juvenile phase of growth.[6, 19] However, the spline option is a stochastic method which can fit the curve in a piecewise fashion. It was first applied in dendrochronology for detrending ring-width series from mesic forests where stand disturbances, e.g., competition among trees, are greatest[7] It can effectively remove the effects of those disturbances. However, too flexible a spline can remove important climatic signals or other common signals of interest.[5]

In this study, most ring-width series were successfully standardized with negative exponential curve and straight lines.

However, a few exponential curves seemed to underfit or overfit later portions of the series due to the predominant high variances in earlier portions. Stiff splines were effective for detrending these series. But stiff splines could not bend sharply enough to fit the steep early portion of the series. To correct problems associated with both exponential curve and spline fitting, Cook[5] and Holmes et al.[19] proposed a 'double detrending' procedure which employs a two-step standardization with both an exponential curve and a stiff spline. First, a negative exponential curve is fit to the ring-width series, then a stiff spline is fit to the indexed chronology produced by the first fit. In this study, the double detrending method was not used because of possible loss of information at low frequencies, which were the most important part of the chronology for detecting growth trends. More work on the double detrending method would be necessary to apply it to the research associated with forest decline since the fit of the last portion is more critical.

Nevertheless, there were no clear cut methods for determining the best standardization. Standardization attempts to reduce the low-frequency noise which was not associated with the signal of interest. However, it was difficult to identify what was "signal" and what was "noise" in this study. So it was inevitable to make some assumptions in order to determine what the signal of interest was.[4]

3. 2. Statistical Quality.

In Table 1, the results for the ANOVA and XCORA for four species are given. The common variance component was greatest (50.2 %) in the NSF series and least (36.7%) in the NSP series. The NSW and NSA series contain 47.7% and 48.1% common variance components. These figures are a little smaller than average(approximately 60%) for arid-site trees in western North America.[8] In an extensive analysis from various sites in Southwest U. S.[10], trees from lower forest border or tim-

Table 1. Results from analysis of variance and cross-correlation analysis (XCORA)for four chronologies.

Series	VARIANCE COMPONENTS(%)				Core NO.	r_{bw}[*2]	S/N	90%	Start
ID[*1]	Sides	Trees	Common	Cores	in XCORA		Ratio	Core#[*3]	Year[*4]
NSF	0.0	24.7	50.2	25.1	16	.549	19.4	5	1710
NSW	0.0	33.5	47.7	18.8	12	.546	14.4	5	1711
NSP	0.8	31.2	36.7	31.3	12	.441	9.4	6	1777
NSA	0.0	20.4	48.1	31.4	14	.553	17.2	5	1792

[*1] NSF : Doulas-fir, NSW : southwestern white pine, NSA : white fir, NSP : ponderosa pine chronologies.

[*2] Mean of between-tree correlation coefficients.

[*3] Numbers of cores needed to represent 90% of the population signal.

[*4] The first year of chronology which includes 90% core#.

Table 2. Characteristics of standardized chronologies.

ID	No. of yrs. [Periods]	Mean width(mm)	Mean sensitivity	S.D.	Absent rings(%)	lst Order autocorrelation
NSF	350 [1638~1987]	.92	.252	.320	.28	.491
NSW	295 [1693~1987]	1.34	.258	.309	.18	.450
NSP	278 [1710~1987]	1.52	.239	.276	1.35	.475
NSA	209 [1779~1987]	2.17	.248	.279	–	.450

ber line show approximately 60 65% variance in common for the entire chronology. It was an expected result that a higher S/N ratio was obtained from the series whose percent common variance is higher.[11] The NSP series has the lowest S/N ratio (9.4). Others range from 14.4 to 19.4 (Tab. 1). Other statistical characteristics of the standardized chronologies are given in Table 2.

3. 3. Time-Series Modeling.

Table3 presents the results of time series analyses including the estimated parameters and several statistical criteria of the best and competing models for four species chronologies. ARMA(1, 1) was the best model for the NSF and NSW series. For the NSA series, the first-order autoregressive model (AR(1)) was best. A complicated mixed model (AR(1, 4) MA(1)) was best for the NSP series. Other possible models were AR(2), AR(3), AR(2) and MA(2) for the NSF, NSW, NSP and NSA series, respectively. In the NSW and NSP analysis, the chosen best models had lower Q-values and smaller AIC values than the competing models. However, the Q-value for the best fit model of NSF was almost the same as that of the competing model (AR(2)), so AIC became the next criterion to select the model. The AR(2) model was chosen as the best model for the NSF series in the former study.[15] For NSA series, the competing model (MA(2)) had a slightly smaller AIC value (0.709), but the difference in the Q-values was large enough to make the decision to choose the AR(1) model. The models explained 22.0 to 35.4 percent of the variances of original index series (Tab. 3). The AR(1) model for the NSA series explained the least variance (22.0%) and the others explained more than 30.0% of the variance, which is above the average (20~22%) values obtained from closed-canopy stands[1] or America.[21] The final chronologies of standard and prew hitened series are presented in Fig. 3.

The ARMA(1, 1) model is often overall best model in past tree-ring studies.[1, 20, 21] The sites for these studies vary widely from lower or upper forest borders to closed-canopy stands,

Table 3. Statistics for the Box-Jenkins models.

ID.	Best models	Estimated parameters	LBQ^{*1}	AIC^{*2}	Competing models	LBQ	AIC
NSF	ARMA(1,1) [35.4%]^{*3}	Θ_1=.501(6.17)^{*4} Φ_1 =.865(18.27)	27(.048)	−731.13	AR(2)	26(.099)	−725.20
NSW	ARMA(1,1) [34.1%]	Θ_1=.769(14.55) Φ_1 =.964(42.20)	22(.232)	−749.03	AR(3)	26(.099)	−729.39
NSP	AR(1,4) MA(1) [30.3%]	Θ_1=.416(3.11) Φ_1 =.834(8.67)	17(.523)	−585.61	AR(2)	21(.279)	−577.73
NSA	AR(1) [22.0%]	Θ_4=−.153(−2.97) Φ_1 =.466(7.28)	19(.392)	−530.30	MR(2)	23(.190)	−531.01

^{*1} Q−statistics.[22]

^{*2} Akaike Information Criteria.

^{*3} Percent variances explained by ARMA models.

^{*4} t−values of mean(against zero).

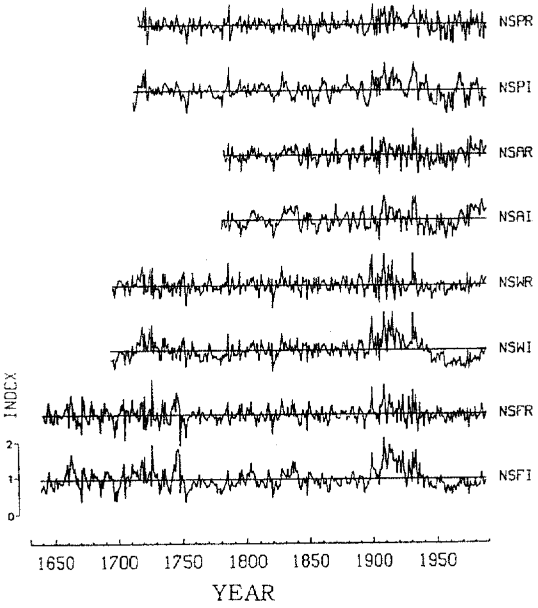

Fig 3. Final summary chronologies of four species (See Table. 1 for the series abbreviations. The last letters I and R represent indexed and residual series, respectively).

however, parameter estimates for this mixed model were tightly clustered. The estimates of two ARMA(1, 1) models selected for the NSF and NSW series in this study also belong to this cluster.

Abnormal growth patterns seem to demand more complicated models to explain their time domains. The NSP series required a seasonal model (AR(1, 4)MA(1)).

The NSP series has the highest percentage of missing rings of the four series and half of the sampled trees were not included in its site chronology because of many undatable rings in the recent few decades when growth has been extremely suppressed. Such an abnormal growth decline may change the characteristics of biological persistence and randomness in time series.

The discrepancy between the models for the NSA series selected by the Graybill & Rose's study[15] and this study may be explained by two aspects. They used the same data but the period of modeling was limited up to 1960 or 1950 (prepollution period). The biological response of trees to the environment may change over their life span. Guiot[16] found different time-series models were required to explain youth, maturity and awakening (explosive growth) phases of tree growth. A site chronology can include all combinations of growth phases, therefore, the best model may vary with the tested period. Further research is needed to explain fully the time-dependent characteristic of ARMA modeling in tree-ring series.

The different models can also result from growth decline of some species. Abnormally low growth may cause a violation of an assumption of stationarity required for Box-Jenkins modeling. The modeling assumes the time series to be stationary, which means that 'the process remains in equilibrium about a constant mean level'.[3] However, growth of some species during the last few decades were far below average. Exclusion of this period, as Graybill & Rose[15] did, may mitigate this problem.

3. 4 Response Functions.

A summary of the response function statistics is given in Tab. 4. The stepwise regressions for the four series were terminated after entering 10 to 12 eigenvectors. The climatic variables explained 41.8 to 67% of the total variances. In the NSA prewhitened series, the explained climatic variance was highest (67.0%). The response functions, which are transformed into the normalized unit relevant to ring-width indices, are given in Fig. 4. Except for the NSP series, previous fall precipitation had a direct effect on tree growth. An inverse effect of fall precipitation was found for the NSP series. Precipitation during the growing season had a direct effect on tree growth, while temperature generally had an inverse effect during the growing season.

Strong directeffects of precipitation for previous and current growing season found in the three species (NSF, NSW and NSA) response functions suggest that increasing precipitation primarily increases radial growth for these species. However, the temperature regime also plays a role. Inverse effect of the temperature for the growing season suggests that increasing evapotranspiration due to high temperature for this period decreases growth. On the other hand, highly significant direct-effect of the previous late growing season suggests that warm temperature during the late growing season prolongs photosynthesis, and photosynthates produced during this period carry over to the following year's growth.

The NSP precipitation response function was very different from the others. An inverse effect of prior fall precipitation was found. This has also been observed in response functions of the same species from Mt. Bigelow in the Catalina Mountains which is only 30 km far away from the Rincon Mountains (Fritts, unpub.). Further studies are necessary to examine whether this intrinsic relationship is real or the result of improper manipulations in standardization or statistical analysis. If it is real, calibration and verification using yearly total precipitation can not be justified for this species in this area as applied by Graybill & Rose[15].

No distinct differences were observed in the response weight profiles for the prewhitened and unprewhitened chronologies except for ponderosa pine ones (Fig. 4). Large discrepancies in the ponderosa pine ones were found in previous October, current March and April precipitation weights and previous August, December, current April and May temperature weights. These discrepancies may result from the complicated model applied for prewhitening. Further study is needed to test whether other chronologies prewhitened by seasonal models, such as AR(1, 4)MA(1) applied to NSP, make different response functions compared with raw chronologies. The regression statistics of response function analyses were summarized in Table 4.

4. CONCLUSIONS

Standardization options should be carefully examined for the ring-width series. The negative exponential curve fit, which was known to represent an ideal biological growth trend, should be carefully selected if it produces un-

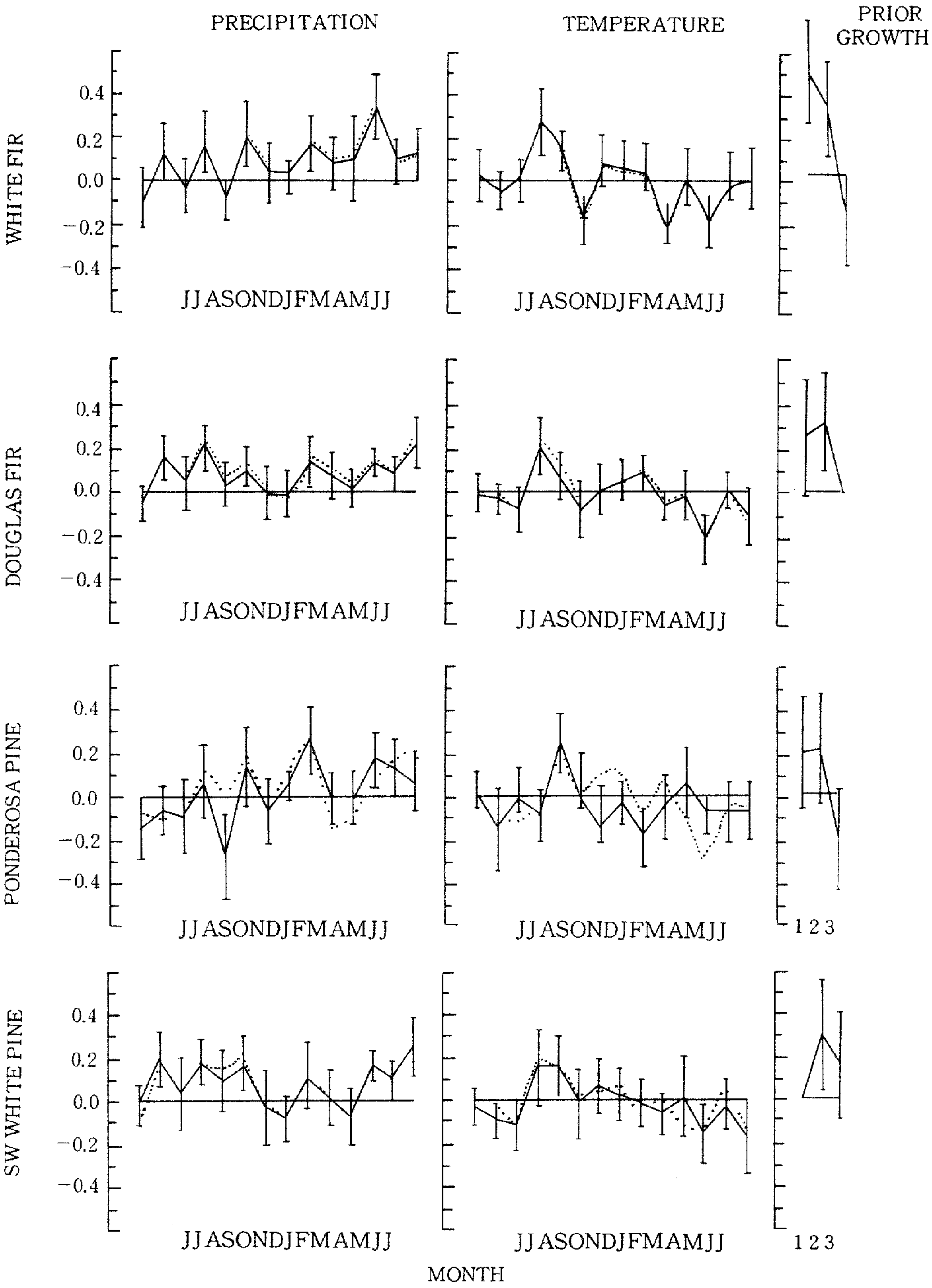

Fig 4. Response functions for four conifers. Y-axis : Normalized indices. The vertical bars are the computed 95% confidence limits. The dashed lines are the response functions obtained from standard chronologies (Prior growth values are shown on the right). The solid lines are the response functions obtained from prewhitened chronologies (without prior growth).

Table 4. Summary of response function analysis.

I.D.	No. EV[*1]	Explained climatic var(%)	R^2_{adj}	Significant elements[*3] TEM	PPT
NSF	10	57.1 (50.1)[*2]	.464	3	6
NSW	10	41.8 (47.7)	.272	1	5
NSP	11	49.4 (61.0)	.351	3	4
NSA	12	67.0 (40.4)	.565	5	5

[*1] Eigen vectors entered into regression.

[*2] Climatic variances explained by the response functions for the standard chronology are given in the parentheses.

[*3] TEM : Temperature, PPT : Precipitation.

usual underfit or overfit at the end of series. Stiff spline fits were more successful for these cases. Twenty-year average plots of the actual and estimated series produced by the present INDEX program were not sufficient to examine the performance of .the curve fitting. An option for higher resolution plots of ring widths (at least 5 year average plot) is recommended to be included in the INDEX program.

The statistical qualities of the width chronologies in this study were similar to those for the other chronologies from the semiarid Southwest region. Response function analysis confirmed that the precipitation and temperature regimes highly influence the radial growths of conifers from the semiarid Arizona region.

Time series modeling does not appear to be necessary to obtain reliable response function results. The inclusion of the lagged ring series in the RESPONS program appears to be sufficient to obtain general climate-growth relationship.

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REFERENCES

1. Biondi, F. and T. W. Swetnam. 1987. Box-Jenkins models of forest interior tree-ring chronologies. *Tree-Ring Bull.* 47 : 71−96
2. Blasing, T. J., A. M. Solomon and D. N. Duvick. 1984. Response function revisited. *Tree-Ring Bull.* 44 : 1−15
3. Box, G. E. P. and G. M. Jenkins. 1976. Time Series Analysis : Forecasting and Control. Revised ed. Holden-Day Inc., San Francisco. : 575
4. Briffa, K. R., T. M. L. Wigley and P. D. Jones. 1987. Towards an objective approach to standardization. In proceedings of the task force meeting on methodology of dendrochronology : East /West approaches. 2−6 June 1986, Krakow, Poland : 69−86
5. Cook, E. R. 1985. A time series analysis approach to tree ring standardization. Ph. D. Dissertation, Univ. of Ariz., Tucson, Arizona. : 175
6. Cook, E. and L. Kairiukstis. 1990. Methods of dendrochronology : applications in the environmental sciences. Kluwer Acad. Pub., Dordrecht, The Netherlands. : 394 lands. : 394
7. Cook, E. R. and K. Peters. 1981. The smoothing spline: A new approach to standardizing forest interior tree-ring width series for dendroclimatic studies. *Tree-Ring Bull.* 41 : 45−55
8. DeWitt, E. and M. Ames. 1978. Tree-ring

chronologies of eastern North America. Chronology series VI, vol. 1. Lab. of Tree-Ring Res., Univ. of Arizona, Tucson, Arizona. 42

9. Dixon, W. J., M. B. Brown, L. Engelman, M. A. Hill and R. I. Jennrich. 1988. BMDP software manual. Univ. of California Press, Berkeley. : 1234
10. Fritts, H. C. 1974. Relationships of ring widths in arid-site conifers to variations in monthly temperature and precipitation. *Ecological Monographs* 44(4) : 411－440
11. Fritts, H. C. 1976. Tree rings and climate. Academic Press Inc, New York. : 565
12. Fritts, H. C., T. J. Blasing, B. P. Hayden and J. E. Kutzbach. 1971. Multivariate techniques for specifying tree-growth and climate relationships and for reconstructing anomalies in paleoclimate. *J. Applied Meteorology* 10 : 845－864
13. Fritts, H. C. and X. Wu. 1986. A comparison between response-function analysis and other regression techniques. *Tree-Ring Bulletin* 46 : 31－46
14. Graybill, D. A. 1982. Chronology development and a nalysis. *In* Climate from Tree Rings, eds. by Hughes, M. K., P. M. Kelly, J. R. Pilcher and V. C. LaMarche, Jr. Cambridge Univ. Press, Cambridge : 21－31.
15. Graybill, D. A. and M. Rose. 1989. gon. Lab. of Tree-Ring Res., Univ. of Arizona, Tucson. : 110
16. Guiot, J. 1987. Standardization and selection of the chronologies by the ARMA analysis. In method of dendrochronology I. proceedings of the task force meeting : East / West approaches, eds. by Kairiukstis L., Z. Bendnarzand E. Feiksik. Warsaw, Poland : 97－105
17. Guiot, J., A. L. Berger and A. V. Munaut. 1982. Response functions. In Climate from Tree Rings, eds. by Hughes, M. K., P. M. Kelly, J. R. Pilcher and V. C. LaMarche Jr., Cambridge Univ. Press, Cambridge : 38－45
18. Hari, P., H. Arovaara, T. Raunemaa and A. Hautojarvi. 1984. Forest growth and the effects of energy production : A method for detecting trends in the growth potential of trees. *Can. J. For. Res.* 14 : 437－440
19. Holmes, R. L., R. K. Adams and H. C. Fritts. 1986. Tree-ring chronologies of western north America. Chronology Series VI, Lab. of Tree-Ring Research. Univ. of Ariz., Tucson. : 182
20. Meko, D. M. 1981. Application of Box-Jenkins methods of time-series analysis to the reconstruction of drought from tree-rings. Ph. D. dissertation. Univ. of Ariz., Tucson, Arizona. : 148
21. Monserud, R. A. 1986. Time-series analysis of tree-ring chronologies. *Forest Sci.* 32 (2) : 349－372
22. Nelson, C. R. 1976. Applied time series analysis for managerial forecasting. Holden-Day Inc., San Francisco. : 231
23. Robinson, W. J. and R. Evans. 1980. A microcomputer-based tree-ring measuring system. *Tree-Ring Bull.* 40 : 59－64
24. Stokes, M. A. and T. L. Smiley. 1968. An introduction to tree-ring dating. Univ. of Chicago Press, Chicago. : 73
25. Wigley, T. M. L., K. R. Briffa and P. D. Jones. 1984. On the average value of correlated time series, with applications in dendroclimatology and hydrometeology. *J. Climate and Applied Meteorology* 23 : 201－213
26. Zahner, R. 1988. A model for tree-ring time series to detect regional growth changes in young, evenaged forest stands. *Tree-Ring Bull.* 48 : 13－20