

DENDROCLIM2002: A C++ program for statistical calibration of climate signals in tree-ring chronologies[☆]

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Abstract

Tree-ring chronologies are often calibrated against instrumental climate records using correlation and response functions. DENDROCLIM2002 uses bootstrapped confidence intervals to estimate the significance of both correlation and response function coefficients. Input and output file selection, as well as analytical options, are chosen from a user-friendly GUI. Final results are saved in ASCII format, and are plotted on screen using color-coded symbols. DENDROCLIM2002 is an extension of existing task-specific software, which is mostly MS-DOS based, and of available user-supplied code for statistical packages, such as SAS. In addition, DENDROCLIM2002 incorporates the ability to test for temporal changes of dendroclimatic relationships by means of evolutionary and moving intervals. This simple approach allows for a complete, dynamical representation of statistical relationships between climate and tree growth. An example using published dendroclimatic data is used to illustrate the analytical and graphical capabilities of the software.

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1. Introduction

Numerical calibration of proxy climate records with instrumental observations is an essential requirement of modern paleoscience (Alverson, 2002). Because of their annual to seasonal resolution, tree-ring chronologies are usually regressed against monthly climate variables, especially precipitation and temperature (e.g., Fritts, 1976). The most common statistical models used by dendrochronologists are called ‘correlation functions’ and ‘response functions’ (Blasing et al., 1984; Fritts et al.,

1971). The term ‘function’ indicates a sequence of coefficients computed between the tree-ring chronology and the monthly climatic variables, which are ordered in time from the previous-year growing season to the current-year one. In ‘correlation’ functions the coefficients are univariate estimates of Pearson’s product moment correlation (e.g., Morrison, 1983), while in ‘response’ functions the coefficients are multivariate estimates from a principal component regression model (Briffa and Cook, 1990; Morzুক and Ruark, 1991).

Interpretation of correlation and response functions is favored by an accurate assessment of statistical significance, so that appropriate ecophysiological hypotheses (e.g. Biondi, 1993; Biondi et al., 1997) and paleoclimatic reconstructions (e.g. Biondi, 2000; Biondi et al., 1999) can be generated. In response functions, normal significance levels of coefficients are misleading because error estimates are underestimated (Cropper, 1985; Morzুক and Ruark, 1991), hence some

[☆] Executable program for Windows 98, ME, NT, 2000, XP available from server at <http://woods.geography.unr.edu/dendrosite/software/dendroclim.html>.

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coefficients can erroneously pass the significance test. This usually causes a greater number of significant coefficients in response functions than in correlation functions (e.g. Villalba et al., 1994). As a solution, bootstrapped error estimates can be used to obtain more accurate results (Efron, 1979; Efron and Tibshirani, 1986; Guiot, 1990, 1991). Correlation functions can also be incorrectly tested for significance, as explained by Biondi (1997), and it is therefore desirable to compute bootstrapped confidence intervals for correlation functions as well.

Software programs currently available for dendroclimatic calibration are geared towards non-state-of-the-art operating systems, such as MS-DOS. Two such programs are RESPO (Holmes and Lough, 1999) and PRECON (Fritts, 1999). The former does not use bootstrapped confidence intervals, whereas the latter uses them for response functions only. Specific code for the SAS package (SAS Institute Inc., 2000) was recently provided by Fekedulegn et al. (2002), but without considering the fundamental issues studied by Cropper (1985). Furthermore, as climate-tree growth relationships may change over time, statistical calibration between a tree-ring chronology and monthly climate parameters needs to be tested for temporal changes. A simple, but effective way to explore the stability of calibration models is to compute them for multiple periods, or intervals, which ideally should be systematically selected to minimize bias.

We report here on the development of *DENDROCLIM2002*, a software package for 32-bit Windows operating systems that computes bootstrapped response and correlation functions for single and multiple intervals. The latter are defined using either a constant length progressively slid by one year (moving intervals) or a length that is incremented by one starting from the most recent year (backward evolutionary intervals) or from the least recent year (forward evolutionary intervals; Fig. 1; Biondi, 1997, 2000). Input and output file selection, as well as program options, are chosen from a user-friendly graphical user interface (GUI). Final results are saved in ASCII format, and are plotted on screen using color-coded symbols. The flowchart of the program is shown in Fig. 2, and the sequence of computational steps is detailed in Fig. 3.

2. Numerical models

DENDROCLIM2002 was developed in Microsoft Foundation Classes with Visual C++, using the routines included in Press et al. (1997, 2002). Numerical accuracy has been verified by comparing the program output with results obtained using standard statistical procedures (SAS Institute Inc., 2000). In

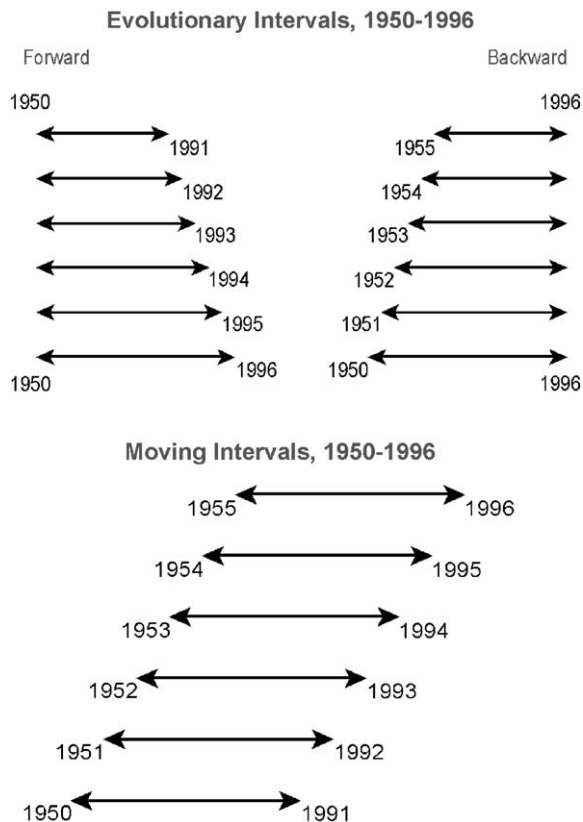


Fig. 1. Graphical representation of multiple intervals available in *DENDROCLIM2002* between 1950 and 1996 using a base length (or minimum interval) of 42 yr.

matrix notation

$$\mathbf{Y} = \mathbf{X}\mathbf{b} + \mathbf{e}$$

represents the statistical relationship between the $n \times 1$ vector \mathbf{Y} of tree-ring values, the $n \times q$ matrix \mathbf{X} of standardized monthly climate predictors, and the $q \times 1$ vector \mathbf{b} of regression parameters; \mathbf{e} is the $n \times 1$ vector of error terms, which are assumed to be independent and with the same variance σ^2 (Jolliffe, 1986). Because multicollinearity produces estimates of \mathbf{b} that are unstable, the original variables are orthogonalized into their principal components, and the model becomes

$$\mathbf{Y} = \mathbf{X}\mathbf{A}\mathbf{A}'\mathbf{b} + \mathbf{e} = \mathbf{Z}\mathbf{k} + \mathbf{e}$$

with \mathbf{A} being a $q \times q$ matrix whose columns are the eigenvectors of $\mathbf{X}'\mathbf{X}$ (the symbol $'$ indicates a transpose matrix); $\mathbf{Z} = \mathbf{X}\mathbf{A}$ is the $n \times q$ matrix of principal components; $\mathbf{k} = \mathbf{A}'\mathbf{b}$ is a $q \times 1$ vector of new regression parameters, and is also the linear transformation of the original parameters. Since \mathbf{A} is an orthogonal matrix, it follows that $\mathbf{b} = \mathbf{A}\mathbf{k}$, and this allows the computation of

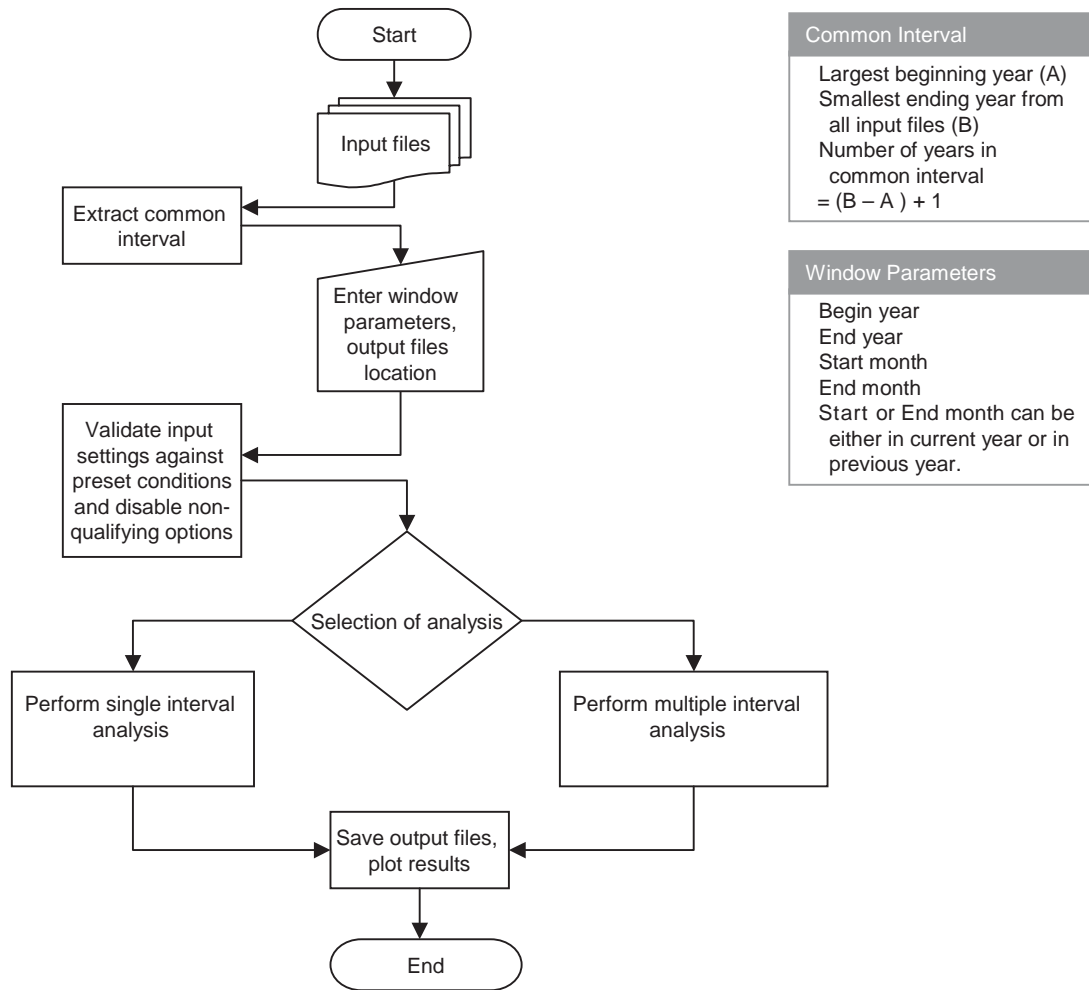


Fig. 2. Flowchart of application process.

regression parameters for the original predictors. In principal component regression, it is standard practice to discard the principal components with the smallest variances (eigenvalues). This ensures that the new design matrix is farther from being singular, thereby reducing the multicollinearity problem. In DENDROCLIM2002 principal components are selected according to the PVP criterion (Guiot, 1990; Fig. 3). The model then becomes

$$Y = Z_m k_m + \epsilon,$$

where Z_m is the $n \times m$ matrix obtained after discarding $(q - m)$ principal components, and ϵ incorporates both random disturbances and the discarded components. Linear least squares is used to estimate the $m \times 1$ vector k_m , and an estimate of b can be obtained after setting the last $(q - m)$ elements of k equal to zero. DENDROCLIM2002 uses 1000 bootstrapped samples to compute

response and correlation coefficients, and to test their significance at the 0.05 level. Bootstrap samples are drawn at random with replacement from the calibration interval. Median correlation and response coefficients are deemed significant if they exceed, in absolute value, half the difference between the 97.5th quantile and the 2.5th quantile of the 1000 estimates (Dixon, 2001).

3. Algorithmic complexity

In this section we discuss the algorithmic complexity of the software considering only the core computation and neglecting the user interface construction. We consider cases that lead to the maximum number of iterations, e.g. when single interval analysis uses the

(A) Single interval analysis	(B) Evolutionary and moving interval analysis
<ol style="list-style-type: none"> 1. Assemble data matrix from the input files using the entered start and end months for the selected interval 2. Repeat Steps 3 to 11 for 1000 times 3. Bootstrap sample: select randomly with replacement a row of the data matrix obtained in Step 1; repeat until the number of rows in the bootstrap sample is equal to the number of rows in the original data matrix 4. Standardize the matrix X of climatic predictors and the tree-ring vector Y using column-wise means and standard deviations 5. Compute eigenvalues and matrix of normalized eigenvectors ($A_{q \times q}$) of correlation matrix $X'X$, then sort the normalized eigenvectors according to descending eigenvalues 6. Apply PVP criterion, i.e. compute cumulative product of eigenvalues until it falls below 1. Get the index of last eigenvalue in product, and use it as cutoff value (m) 7. Compute principal component scores $Z_{n \times m} = X_{n \times q} A_{q \times m}$ where X = Matrix of standardized climatic predictors from Step 4 A = Reduced matrix of eigenvectors obtained after discarding $q-m$ components in Step 6 8. Solve the system of equations $Z_{n \times m} K_{m \times 1} = Y_{n \times 1}$ using singular value decomposition; note that Y = Vector of standardized tree-ring values from Step 4 K = Reduced vector of principal regression coefficients 9. Pad $K_{m \times 1}$ with $q-m$ zeros to obtain $K_{q \times 1}$, then compute $B_{q \times 1} = A_{q \times q} K_{q \times 1}$ 10. B is the vector of response function coefficients 11. Compute Pearson's correlation coefficients between Y and X 12. Use the 1000 vectors of response and correlation coefficients to obtain response (R) and correlation (C) matrices of size $1000 \times q$ 13. Find the column-wise medians of R and C and test their significance using the 95% Percentile Range method 14. The results are vectors of size $1 \times q$ with bootstrapped response and correlation functions 	<ol style="list-style-type: none"> 1. The data matrix includes all available years 2. The analysis shown in Figure 2 is repeated on multiple intervals. The user specifies the way in which the intervals are defined by entering their type (forward evolutionary, backward evolutionary, or moving intervals) and their base length. 3. The base length (L) must satisfy two conditions: <ol style="list-style-type: none"> I. $L < 80\%$ of all available years (so that a large enough number of intervals can be generated) II. $L \geq$ twice the number of predictors (so that a large enough number of degrees of freedom is available for the analysis) 4. Evolutionary intervals are generated by adding 1 year to the base length at each iteration. Moving intervals are generated by shifting the base length 1 year at each iteration. The process stops when all available years have been used. 5. Forward evolutionary intervals begin with the oldest year in common to all variables, and increase progressively forward in time up to the most recent year in common to all variables. 6. Backward evolutionary intervals end with the most recent year in common to all variables, and increase progressively backward in time, until they reach the oldest year in common to all variables. 7. Moving intervals begin with the oldest year in common to all variables, and they are shifted progressively forward in time up to the most recent year in common to all variables. 8. Response and correlation functions from each iteration (or interval) are stored in an $r \times q$ matrix, with r = number of intervals, and q = number of climatic variables (or predictors)

Fig. 3. Detailed list of computational steps in (A) single interval analysis, and (B) multiple interval analysis.

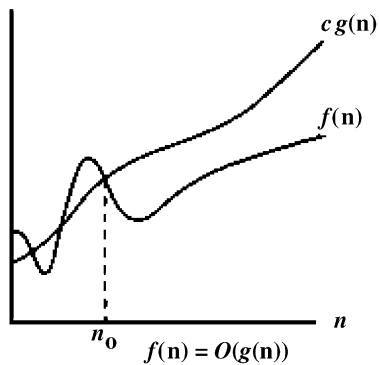
entire common interval or when multiple interval analysis uses the minimum base length. We employ 'Big-Oh' (O) notation, which gives the asymptotic upper bound on execution time but is not necessarily related to running time for every input combination (Cormen et al., 2001). Mathematically it is represented as

$$O(g(n)) = f(n) \quad 0 \leq f(n) \leq cg(n) \quad \forall n \geq n_0,$$

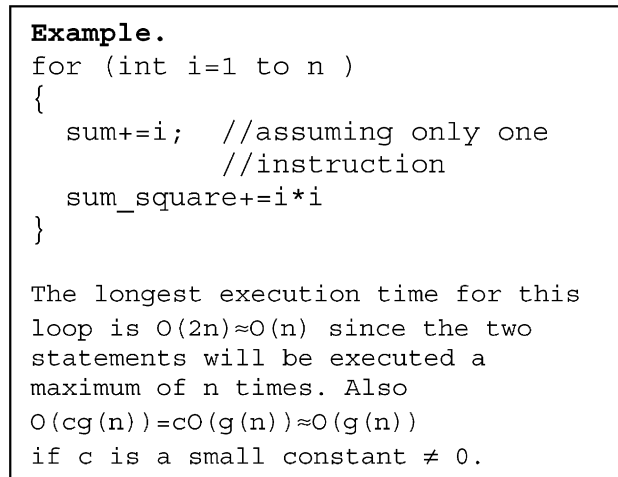
where c and n_0 are non-zero constants (Fig. 4).

In single interval analysis, the first step of reading data files requires $O(4n)$, where n is the number of years (rows) in each input file, for a maximum of 4 files. Therefore, execution time for this step is directly proportional to the size of the data sets. Computing the boundaries of the common interval involves $O(1)$. The following step of reading the input data into the array that will be used for bootstrapping samples requires $O(nq)$, where n is number of years (rows) and q is number of predictors (columns). The initialization

process for result storage matrices takes up to $O(2q^2)$, where q is number of predictors and the factor 2 refers to the computation of both correlation and response functions. The generation of each one of the 1000 bootstrap samples requires $O(nq + n)$, with the additional n factor due to the tree-ring index data vector (predictand). Both predictand and predictors are then standardized, which involves $O(cnq)$ computations, c being a small constant. Principal component regression requires initialization of new matrices, so that $O(Cnq)$ will be performed, C being a large constant. The first step is to compute $X'X$, where X is the predictor matrix; this involves $O(nq^2)$. Computing eigenvalues requires $O(nq)$ to reduce the diagonal elements of the symmetric matrix to 1, and $O(Cq^3)$ to apply Jacobian estimation (Press et al., 1997, 2002). Eigenvectors are sorted in descending order according to their eigenvalues, a process which takes another $O(q^2)$. Applying the PVP criterion and multiplying the original matrix X by the



(A)



(B)

Fig. 4. (A) Plot of mathematical expression of “Big-Oh” notation. (B) Example of C code and of its execution time in “Big-Oh” notation.

selected principle components involves a total runtime of $O(nq^2)$. The solution vector is obtained by Singular Value Decomposition (SVD; Press et al., 1997, 2002), which takes $O(Cq^4)$ steps, with C being a very large constant (in the order of 10^4). Obtaining correlation coefficients requires $O(q^2)$ computations. Significance tests of median coefficients based on the 0.975 and 0.025 quantiles are done in $O(q^2)$. In summary, most of the running time is dedicated to the calculation of response functions, especially because of the SVD included there.

In multiple interval analysis, response and correlation coefficients are computed a number of times. Hence the complexity of this analysis is $\approx O(nq^4)$, where n is the number of years in the common interval. This can be approximated as $\approx O(q^5)$, since the value of n is comparable to q in most cases. Such computational intensity gives rise to an important user interface issue. Execution time was often 20–25 min or longer on Intel Celeron and Intel Pentium III processors with 256 MB of RAM. In addition, the computer became practically unusable while the application was running. Therefore, a worker thread was created to handle all CPU-intensive computations. This allows the operating system to respond to user requests while the program executes as a background process.

4. Comparison with other programs

Results obtained using DENDROCLIM2002 were compared to those derived using other software

programs. Data used by Fekedulegn et al. (2002), were retrieved from the world wide web, and re-analyzed using SAS, RESPO, PRECON, and DENDROCLIM2002. However, we found that RESPO v.6.06P incorrectly read the input data sets, hence no reliable results could be obtained. That program has since been removed from distribution until further notice (Richard Holmes,¹ Tucson, AZ, pers. comm.). Sample linear correlations were calculated using SAS, and their t -values, computed according to Press et al. (2002), were used to plot the correlation function (Fig. 5). No monthly climatic correlation stands out; coefficients for current July precipitation (positive) and February temperature (negative) are barely significant. In addition, current February (negative) and May (positive) precipitation are almost significant, together with previous-year August temperature (negative).

In their analysis of the same data set, Fekedulegn et al. (2002), used response functions whose significance was tested without considering the issues raised by Cropper (1985). Because of that, a large number of predictors were deemed significant: 9 precipitation variables (all positive), and 7 temperature variables (4 positive and 3 negative). Of those, 5 predictors were from the previous year, even though autocorrelation had been removed from the tree-ring indices. Climate-tree growth relationships are clarified using bootstrapped response functions, as shown by the PRECON output (Fig. 6). Winter signals no longer appear, and summer

¹Deceased.

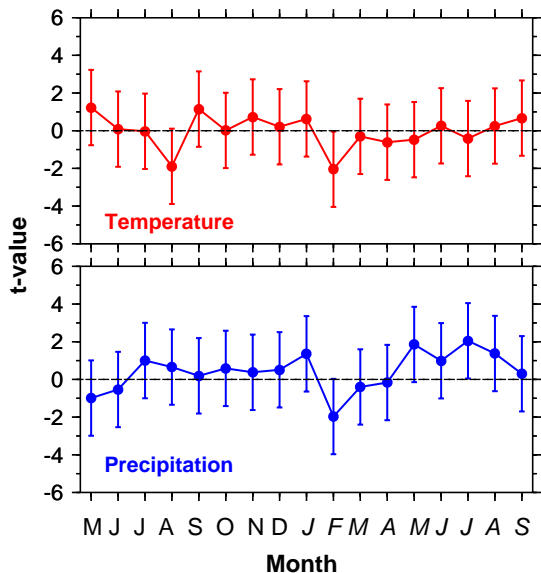


Fig. 5. Plot of correlation function for example data set. Sample linear correlation coefficients computed using SAS were transformed in *t*-values to facilitate graphical representation of their 95% confidence limits.

moisture stress dominates the response, with a significant current July precipitation (positive). Current August precipitation (positive) and previous-year August temperature (negative) are, respectively, close to and barely significant.

In DENDROCLIM2002 significant coefficients are plotted with color-coded symbols (Fig. 7). Although output files can be used to display correlation and response functions in the style of Fig. 6, which was originally used by Fritts et al. (1971), we found that identifying the main climate signals ‘at a glance’ was facilitated by making all non-significant coefficients equal to zero. This is especially the case when showing results of multiple-interval analysis (Biondi, 1997, 2000). In the particular example used here, summer precipitation (mainly July) has a positive relationship with tree growth. Minor differences between PRECON and DENDROCLIM2002 results are related to computational procedures, such as the way in which final coefficients are estimated (mean in PRECON, median in DENDROCLIM2002) and tested for significance (2 standard deviation interval in PRECON, difference between the 97.5 and the 2.5 percentile in DENDROCLIM2002).

Analysis of temporal stability requires a large enough number of intervals and of degrees of freedom within each interval (Fig. 3). In the example data set, the number of predictors (34 variables total, 17 for temperature and 17 for precipitation) is too large when compared to the overlap between tree-ring and climate

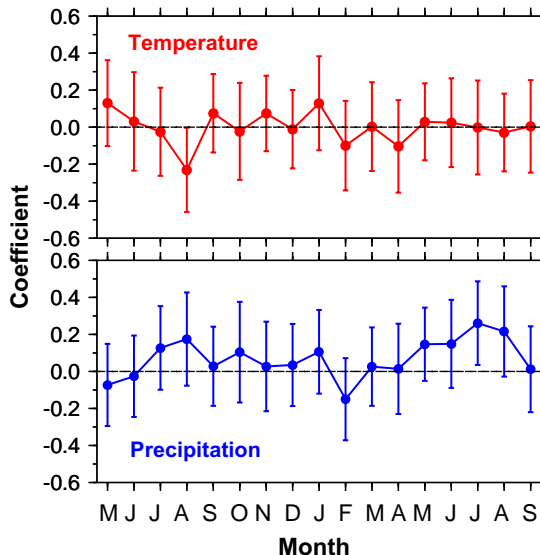


Fig. 6. Plot of response function generated by PRECON for example data set. A total of 1000 bootstrap samples were used to compute mean coefficients and their 2 standard deviation intervals.

records (62 yr total, from 1935 to 1996). However, considering that previous-year coefficients are not significant, it would be possible to reduce the number of predictors by studying current-year relationships alone. As an example, moving interval correlation and response functions are shown in Fig. 8 for January through October precipitation and temperature, using a base length (or minimum number of years) equal to 45. The positive relationship with June–July precipitation is the main climate signal in the tree-ring chronology, although it is not particularly stable over time. Backward and forward evolutionary interval analyses (not shown) also point to growing season precipitation as the dominant relationship, with a tendency to become more significant in recent decades.

5. Conclusions

The temporal stability of climate-proxy connections is an extremely important issue in any type of paleoclimatic reconstruction. In dendroclimatology the investigator has the opportunity to actually investigate such issue because of the exact calendar dates assigned to the proxy records. Considering that software for dendroclimatic analysis is in dire need of updating, DENDROCLIM2002 is expected to facilitate the identification of climatic signals, and their potential changes over time, embedded in tree-ring records.

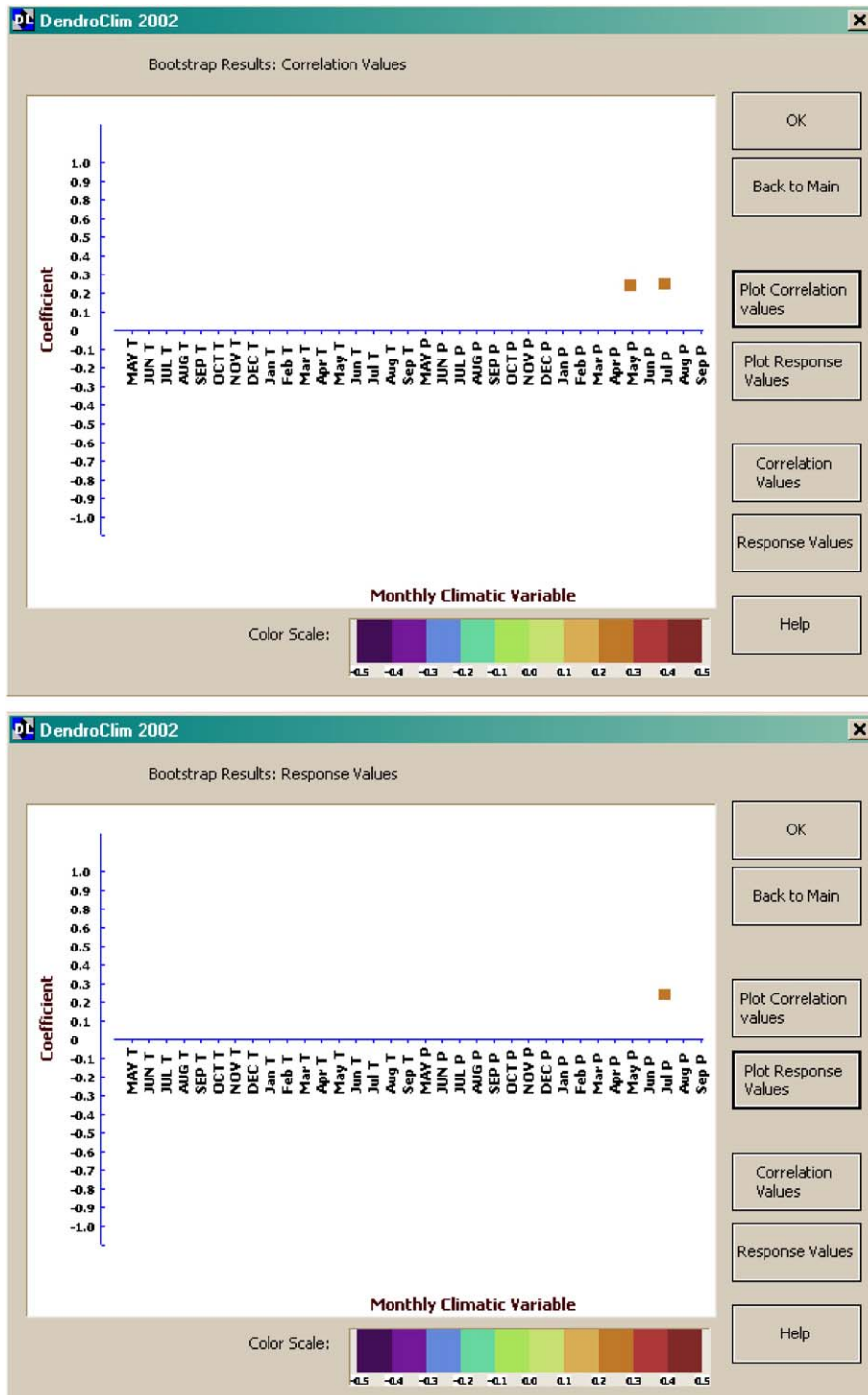


Fig. 7. Correlation and response functions computed using DENDROCLIM2002 for example data set.



Fig. 8. Moving interval correlation and response functions computed using DENDROCLIM2002 for example data set. A base length of 45 years was progressively slid through the total number of available years (without missing values), i.e. from 1935 to 1995.

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References

- Alverson, K., 2002. Forward to the past: the future of PAGES. *Global Change Newsletter* 50 (June), 4–6.
- Biondi, F., 1993. Climatic signals in tree-rings of *Fagus sylvatica* L. from the central Apennines, Italy. *Acta Oecologica* 14, 57–71.
- Biondi, F., 1997. Evolutionary and moving response functions in dendroclimatology. *Dendrochronologia* 15, 139–150.
- Biondi, F., 2000. Are climate–tree growth relationships changing in north-central Idaho? Arctic, Antarctic, and Alpine Research 32, 111–116.
- Biondi, F., Cayan, D.R., Berger, W.H., 1997. Dendroclimatology of Torrey pine (*Pinus torreyana* Parry ex Carr.). *The American Midland Naturalist* 138, 237–251.
- Biondi, F., Perkins, D.L., Cayan, D.R., Hughes, M.K., 1999. July temperature during the second millennium reconstructed from Idaho tree rings. *Geophysical Research Letters* 26, 1445–1448.
- Blasing, T.J., Solomon, A.M., Duvick, D.N., 1984. Response functions revisited. *Tree-Ring Bulletin* 44, 1–15.
- Briffa, K.R., Cook, E.R., 1990. Methods of response function analysis. In: Cook, E.R., Kairiukstis, L. (Eds.), *Methods of Dendrochronology*. Kluwer, Dordrecht, The Netherlands, pp. 165–178.
- Cormen, T.H., Leiserson, C.E., Rivest, D.L., Stein, C., 2001. *Introduction to Algorithms*, 2nd Revised Edition. MIT Press, Cambridge, MA, 1180pp.
- Cropper, J.P., 1985. Tree-ring response functions: An evaluation by means of simulations. Ph.D. Dissertation, Laboratory of Tree-Ring Research, The University of Arizona, Tucson, AZ.
- Dixon, P.M., 2001. Bootstrap resampling. In: El-Shaarawi, A.H., Piegorisch, W.W. (Eds.), *The Encyclopedia of Environmetrics*. Wiley, New York, pp. 9pp.
- Efron, B., 1979. Bootstrap methods: another look at the jackknife. *Annals of Statistics* 7 (1), 1–26.
- Efron, B., Tibshirani, R., 1986. Bootstrap methods for standard errors, confidence intervals, and other measures of statistical accuracy. *Statistical Science* 1 (1), 54–75.
- Fekedulegn, B.D., Colbert, J.J., Hicks Jr., R.R., Schuckers, M.E., 2002. Coping with multicollinearity: An example on application of principal components regression in dendroecology. Research Paper NE-721, USDA Forest Service, Northeastern Research Station, Newton Square, PA, 43pp.
- Fritts, H.C., 1976. *Tree Rings and Climate*. Academic Press, London, 567pp.
- Fritts, H.C., 1999. PRECON Version 5.1: A Statistical Model for Analyzing the Tree-Ring Response to Variations in Climate. Laboratory of Tree-Ring Research, University of Arizona, Tucson, AZ.
- Fritts, H.C., Blasing, T.J., Hayden, B.P., Kutzbach, J.E., 1971. Multivariate techniques for specifying tree-growth and climate relationships and for reconstructing anomalies in paleoclimate. *Journal of Applied Meteorology* 10 (5), 845–864.
- Guiot, J., 1990. Methods of calibration. In: Cook, E.R., Kairiukstis, L. (Eds.), *Methods of Dendrochronology*. Kluwer, Dordrecht, The Netherlands, pp. 165–178.
- Guiot, J., 1991. The bootstrapped response function. *Tree-Ring Bulletin* 51, 39–41.
- Holmes, R.L., Lough, J.M., 1999. *Users Manual for Program RESPO*. Laboratory of Tree-Ring Research, University of Arizona, Tucson, AZ.
- Jolliffe, I.T., 1986. *Principal Component Analysis*. Springer, New York, 271pp.
- Morrison, D.F., 1983. *Applied Linear Statistical Methods*. Prentice-Hall, Englewood Cliffs, NJ, 562pp.
- Morzukh, B.J., Ruark, G.A., 1991. Principal components regression to mitigate the effects of multicollinearity. *Forest Science* 37 (1), 191–199.
- Press, W.H., Flannery, B.P., Teukolsky, S.A., Vetterling, W.T., 1997. *Numerical Recipes in C: The Art of Scientific Computing*, 2nd Revised ed. Cambridge University Press, Cambridge, UK, 994pp.
- Press, W.H., Teukolsky, S.A., Vetterling, W.T., Flannery, B.P., 2002. *Numerical Recipes in C++: The Art of Scientific Computing*, 2nd Edition. Cambridge University Press, Cambridge, UK, 1002pp.
- SAS Institute Inc., 2000. *SAS/STAT User's Guide*, Version 8. SAS Institute Inc., Cary, NC.
- Villalba, R., Veblen, T.T., Ogden, J., 1994. Climatic influences on the growth of subalpine trees in the Colorado Front Range. *Ecology* 75 (5), 1450–1462.