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Seascorr: A MATLAB program for identifying the seasonal climate signal in an annual tree-ring time series ☆

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A B S T R A C T

A common research task in dendroclimatology is identification of the monthly or seasonal climate signal in an annual time series of indices of ring width. A MATLAB function, `seascorr`, is introduced as a general statistical tool for identifying the signal. Monthly time series of primary and secondary climate variables are input to the function along with a tree-ring time series and specifications for seasonal groupings. The relationship of the tree-ring series with the seasonalized primary climate variable is summarized by simple correlations. The relationship with the secondary climate variable is summarized by partial correlations, controlling for the influence of the primary climate variable. Confidence intervals on sample correlations and partial correlations are estimated with the help of Monte Carlo simulation of the tree-ring series by exact simulation, which preserves the spectral properties of the observed series. Results are summarized in graphical and statistical output. The function is illustrated with examples from Tunisia and Russia.

1. Introduction

Tree-ring reconstructions of precipitation, temperature, streamflow, and other climatic variables are an important resource in the study of the natural variability of climate (e.g., Touchan et al., 2008; Cook et al., 2007; Woodhouse et al., 2006). A preliminary step in such reconstructions is identification of the seasonal climate signal in the series. Depending on tree species, setting, and climatic regime, tree growth may respond to different types of climate variables, and to the climate of different seasons. The climate signal is typically assessed with some form of bivariate or multivariate statistical analysis of an annual tree-ring series and monthly and seasonal climatic series. The climate variables are often precipitation (*P*) and temperature (*T*), both of which can be linked conceptually to tree-growth variations and are widely available as long time series from instrumental records (Fritts, 1976).

A simple approach to identification of the seasonal signal is to graph correlations of the tree-ring series with monthly *P* and *T* for several (typically 12 or more) months leading up to and including the probable last month of the growth year of the tree (Fritts, 1976). Statistical significance and physical interpretation of the correlations may be complicated by several factors, including autocorrelation and non-normality of variables, and intercorrelation of *P* and *T*. Principal components analysis (PCA) is sometimes applied to decouple the various climatic series (Fritts et al., 1971). Early studies rely on theoretical distributions to assign statistical significance to correlations (e.g., Guiot et al., 1982). Later studies incorporate bootstrapping for this purpose, and also address possible temporal instability of relationships (e.g., Guiot, 1991; Fritts, 1999; Biondi and Waikul, 2004).

In this paper we introduce a MATLAB function to summarize the seasonal climate signal in a tree-ring series. The scenario of application is an annual tree-ring series and a monthly climatic time series. Two climatic variables—designated as primary and secondary—are used in the analysis. These climate variables may be *P* and *T*, but the analysis is generally applicable to any pair of monthly climate variables physically related to tree growth. Although the method uses correlations, it differs in several ways from other existing methods. First is a focus on the signal integrated over months. Second is the use of partial correlations to separate confounding influence of the intercorrelation of primary and secondary climate variables. Third is the use of exact simulation (Percival and Constantine, 2006) to build confidence intervals for correlations and partial correlations: simulations of the tree-ring series are generated such that they retain the spectral properties of the observed series. We describe the methods and illustrate with applications to data from Tunisia

☆ Code available from server at http://www.iamg.org/CGEditor/index.htm.

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and Russia. Code available from server at http://www.iamg.org/CGEditor/index.htm.

2. Methods

2.1. Correlations

Let x_1, x_2, and x_3 be annual time series covering a common period of N years. Further, consider x_1 and x_2 to be seasonalized (for a specific season) primary and secondary climate variables, and x_3 a tree-ring series. For example, x_1 might be summer total (July–September) precipitation, x_2 summer average maximum daily temperature, and x_3 a standard tree-ring chronology (Cook, 1985). The linear relationship between x_1 and x_3 is summarized in `seascorr` by the simple (Pearson) correlation coefficient (Wilks, 1995), denoted here as r_{13}. Likewise the simple correlations for the other pairs of variables are denoted as r_{12} and r_{23}. The linear relationship between x_2 and x_3 with the influence of x_1 removed is summarized by the partial correlation (Mardia et al., 1979) $r_{23.1}$, where the subscripts before the dot denote the variables being correlated and the subscript after the dot denotes the variable being "controlled for." Following Panofsky and Brier (1968), the partial correlation is related to the individual simple correlations by

$$r_{23.1} = \frac{r_{23}-r_{12}r_{13}}{\sqrt{1-r_{12}^2}\sqrt{1-r_{13}^2}}. \tag{1}$$

The intent in using the partial correlation is to remove the influence of x_1 on the assessment of the importance of x_2 to x_3. Eq. (1) shows that the partial correlation between x_2 and x_3 is zero if the simple correlation between x_2 and x_3 is just equal to the product of the individual bivariate correlations of x_1 with x_2 and x_3. In practice—and in `seascorr`—r_{23} is computed as the simple correlation between the residuals from two linear regressions: regression of x_3 on x_1, and regression of x_2 on x_1 (Panofsky and Brier, 1968; Mardia et al., 1979).

2.2. Significance of correlations

Confidence intervals for correlations and partial correlations are derived by Monte Carlo simulation. Series x_3 is simulated m times, where m is some large number ($m>1000$), and correlations and partial correlations are computed using the simulated x_3 in place of the observed x_3. The empirical cumulative distribution functions (cdfs) of the resulting m simulation-based correlations and partial correlations are used to establish the desired confidence intervals. Empirical nonexceedance probabilities for the simulation-based correlations or partial correlations are computed by the Weibull formula (Stedinger et al., 1992),

$$p(r_{(i)}) = \frac{i}{m+1}, \tag{2}$$

where $r_{(i)}$, $i=1,2,\ldots,m$ are the ranked ($i=1$ is lowest, or most negative) correlations of x_1 with the m simulations of x_3, and $p(r_{(i)})$ is the empirical probability of an absolute correlation less than or equal to $r_{(i)}$. The $\alpha=0.05$ thresholds for significance of a sample correlation are set at the 0.025 and 0.975 probability points of the cdf defined by Eq. (2); the $\alpha=0.01$ thresholds are set at the 0.005 and 0.995 probability points. Nonexceedance probabilities by Eq. (2) are also computed and output for all sample correlations and partial correlations. These probabilities are computed by linearly interpolating the rank, i for the sample statistics. If a sample correlation or partial correlation happens to be outside the range of the corresponding simulation-based correlations the rank is set to 1 for large negative correlation and m for large positive.

The simulations of x_3 are generated by exact simulation from nonparametric spectral estimates (Percival and Constantine, 2006) using the circulant embedding formulation of Dietrich and Newsam (1997). Series x_3 is regarded as a realization of length N years of some stationary Gaussian generating process whose spectrum can be estimated from the sample x_3. The first step is estimation of the spectrum of x_3 through computation of the direct Fourier transform (DFT) and periodogram (Bloomfield, 2000). Preparation of x_3 for periodogram analysis in `seascorr` consists of: subtraction of sample mean; tapering of 5% of each end with a raised-cosine filter (Bloomfield, 2000); shifting back to a mean of exactly zero; padding with zeros to a length twice the next highest power of 2 larger than the length of x_3; and rescaling such that the variance of the tapered and padded series equals the variance of the original x_3. If we let X_t be the adjusted version of x_3, the spectral weights are computed as

$$S(k) = \left|\sum_{t=0}^{2M-1} X_t e^{-i2\pi f_k t}\right|^2, \quad k=0,\ldots,2M-1, \tag{3}$$

where M is the next highest power of 2 larger than the length of x_3, $2M$ is the length of X_t, and $f_k = k/(2M)$ is frequency in cycles/year.

Circulant embedding by the Dietrich and Newsam (1997) algorithm begins with sampling a set of $4M$ independent standard Gaussian random variables $Z_0, Z_1, \ldots, Z_{4M-1}$ and generating the complex-valued sequence

$$\mathcal{V}_k = (Z_{2k} + iZ_{2k+1})\sqrt{S_k/(2M)}, \quad 0 \le k \le (2M-1). \tag{4}$$

The DFT of this sequence,

$$V_t = \sum_{k=0}^{2M-1} \mathcal{V}_k e^{-i2\pi f_k t}, \quad t=0,\ldots,(2M-1), \tag{5}$$

is a complex series V_t. The first M elements the real and imaginary parts of V_t are two independent realizations of length M of the generating process for x_3 (Percival and Constantine, 2006). These realizations are then truncated so that their length equals the length of x_3.

2.3. Seasonal grouping

The correlation analysis described in Section 2.1 is repeated for each of 56 seasons specified by the ending month of tree-ring growth and four season lengths, m_j, $j=1,2,3,4$. The seasons are the m_j-month period ending in each of the 14 months leading up to and including ending month of tree-ring growth. For example, if growth is specified as complete in September and the season lengths are {1,3,6,12}, correlations are computed for individual months from August of the previous year through September of the growth year, 3-month seasons ending in August of the previous year through September of the growth year, and so forth. The 56 seasons accordingly comprise 14 seasons for each of the four specified season-lengths.

2.4. Temporal stability

The correlation analyses described in Section 2.1 are intended for summarizing relationships that are stationary, or not dependent on time. Temporally evolving relationships (e.g., Biondi, 2000) can be summarized more appropriately by other methods, such as the Kalman filter (Visser and Molenaar, 1988) and correlations in sliding time-windows (Biondi and Waikul, 2004). `Seascorr` offers two ways to check on temporal stability of relationships. First is control over the analysis period, such that the period may readily be changed and graphical outputs for different periods compared. Second is a test of the difference of correlations in specified nonoverlapping "early" and "late" subperiods. This test is applied only to the highest-correlated seasons for each of the four specified season-lengths described in Section 2.3. The test-statistic depends on two sample correlations and their respective sample sizes, and utilizes Fisher's Z-transformation of correlations to facilitate significance-testing (Snedecor and Cochran, 1989). Sample sizes for assessment of significance are adjusted downward in `seascorr` to "effective sample size," if necessary, to account for positive autocorrelation in the time series (Dawdy and Matalas, 1964). A detailed description of the test is relegated to the Supplementary materials. It should be emphasized that this test assumes that the time series being correlated are bivariate-normal distributed. This assumption is likely violated for some types of data—e.g., when the climatic series is monthly total or seasonal-total precipitation in an arid region.

3. Program description

`Seascorr` was written with MATLAB Release 2010b running under the Ubuntu Release 10.04 Linux operating system. The code was written to be platform-independent, and has been tested on Windows and OSX systems. `Seascorr` is a MATLAB function that relies on 22 lower-level user-written functions in addition to numerous built-in MATLAB functions and the MATLAB "Statistics" toolbox. Built-in function `FFT` (fast Fourier transform) is used both in periodogram computation and in the computation of V_t by Eq. (5), while the Statistics Toolbox function `normrnd` is used to generate the $N(0,1)$ sequences required by Eq. (4). Program flow proceeds in the following steps:

1. Reading of input data and specifications for seasons and analysis period.
2. Seasonalizing of monthly climate data.
3. Regression to generate versions of x_3 and x_2 with dependence on x_1 removed.
4. Computation of sample correlations and partial correlations.
5. Simulation of tree-ring series, x_3 (e.g., 1000 simulations).
6. Computation of correlations and partial correlations for simulations.
7. Testing of temporal stability of correlations.
8. Assignment of confidence levels for sample correlations and partial correlations.
9. Graphical and statistical output.

`Seascorr` can be called either with or without input arguments. Input arguments include tree-ring data, climatic data, season-lengths, ending month of growth year, period of analysis, text for labeling (e.g., units of climatic data), and program options. If called without input arguments, or in "point-and-click" mode, `seascorr` prompts the user to click on input data files and to enter other program settings in edit boxes or by menu choices. In point-and-click mode, the monthly climatic data are assumed to be in 13-column space-separated ascii files, and the tree-ring data either in a 2-column matrix (year and value) or in the standard "crn-file" format of the International Tree-Ring Data Bank. When calling `seascorr` with input arguments, or in "driver-script" mode, the user writes a short MATLAB script that sets up the input arguments and calls the function. Program options allow for control over the analysis period, exchange of "primary" and "secondary" roles of the two climate variables, and optional color or black-and-white graphics output.

`Seascorr` output includes 11 figure windows and an output argument. The key figure window has two bar charts displaying the correlations and partial correlations of the tree-ring series with the seasonalized primary and secondary climate variables. Each bar chart has 56 bars, corresponding to seasons with four specified lengths and 14 different ending months. Statistical significance at $\alpha = 0.05$ or $\alpha = 0.01$ is color coded. Ancillary graphics, in the other figure windows, include time series plots, scatterplots, and other graphics to aid in the interpretation of the correlations and partial correlations. The single output argument is a MATLAB structure variable with statistics and tables.

4. Sample applications

`Seascorr` is illustrated with data from Tunisia and Russia. All figures in this section are figure windows output by `seascorr`. The Tunisia input data are a *Pinus halepensis* standard tree-ring index and gridded monthly total precipitation (P) and monthly mean temperature (T) from Touchan et al. (2008). The tree-ring site is Sadine, Tunisia (36.1°N, 8.5°E, elevation 400 m). The climate data, from the 0.5° gridded climate data set CRU T5 2.1 (Mitchell and Jones, 2005), are an average over the box 7.5°–9.5°E and 34.5°–36.5°N. The common years of data coverage, 1903–2002, define the default analysis period[1] for `seascorr`. P and T were assigned as primary and secondary climate variables, respectively. September was specified as the ending month of tree growth, and the four season-lengths were set at 1, 3, 9, and 12 months.

By construction, a tree-ring index varies around a mean of 1.0 such that the index can be roughly interpreted as a proportion of normal growth in any given year. The Sadine index ranges from a low of zero to a high of greater than 2.5, and exhibits considerable variability on interannual and decadal time scales (Fig. 1A). A histogram and Lilliefors test (Conover, 1980) suggest the index is Gaussian, an assumption in exact simulation (Fig. 1B). The periodogram shows a relatively large proportion of the variance of the index at wavelengths 5–30 year (Fig. 2). The raw-periodogram ordinates plotted are the spectral weights used in Eq. (3) for simulation of the tree-ring series.

Monthly P is significantly positively correlated ($\alpha = 0.01$) with tree-ring index in six months between October preceding the growth year and May of the growth year (Fig. 3). Correlation with P increases with increasing length of averaging period, at least through 9 months; maximum correlation is reached for the 9-month period ending with June of the growth year. Correlation with P actually declines slightly as the season length is expanded from 9 to 12 months. A scan of Fig. 3 identifies highest P correlations for "seasons" of length 1, 3, 9, and 12 months ending in October, May, June, and June, respectively (Fig. 4). The non-exceedance probabilities listed in Fig. 4 are 0.9990 for each season because the correlations for observed data are higher than those for any of the corresponding 1000 simulations (Eq. (2) with $i = m = 1000$). Scatterplots of P on tree-ring index for those seasons show that the relationships are approximately linear and not driven by outliers (Fig. 5). The correlation of tree-ring index with P for the most highly correlated seasons appear stable over time: test results indicate we cannot reject the null hypothesis that the sample correlations for the first and last halves of period 1903–2002 are from the same population (Fig. 6). In summary, an October–June P reconstruction period is suggested, though an annual (July–June) period would also be reasonable.

[1] Because correlations must be computed with aggregated climate data including months prior to the growth year, the default analysis period cannot actually begin until the first growth year two years after the start of monthly climate data—January 1901 for this example.

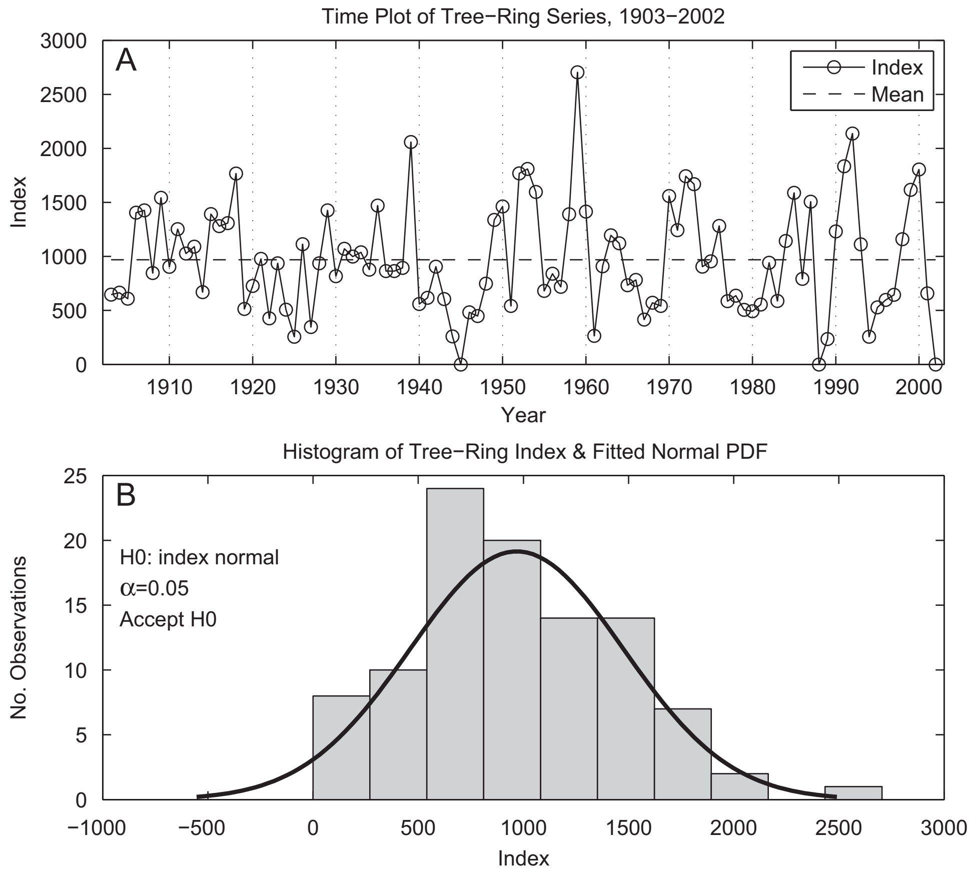

Fig. 1. Time variation and frequency distribution of Tunisia tree-ring index. (A) Time plot, 1903–2002. (B) Histogram and fitted normal probability density function. Results of Lilliefors test for normality (Conover, 1980) annotated at upper left of (B).

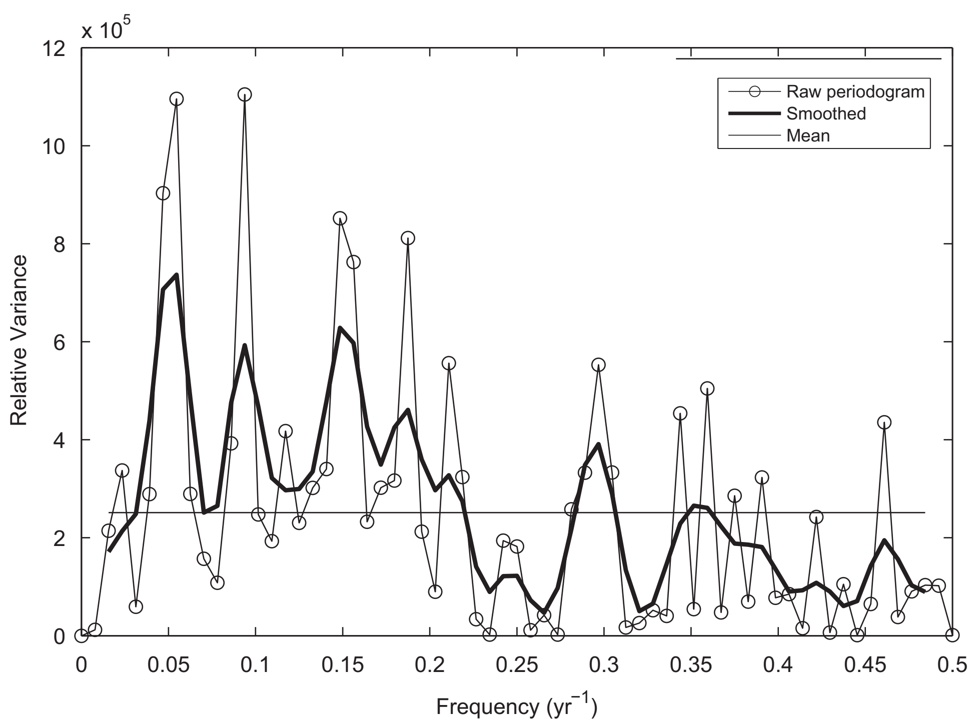

Fig. 2. Spectrum of Tunisia tree-ring index, 1903–1999. Smoothing by five-weight binomial filter.

May is the only month identified with a significant T response (Fig. 3, bottom). The significant partial correlation implies additional influence of May T on growth beyond that explainable by covariation of P with T. Monthly P and T for the Tunisia data are significantly negatively correlated ($\alpha = 0.05$) in 10 months of the year, including May (Supplementary materials).

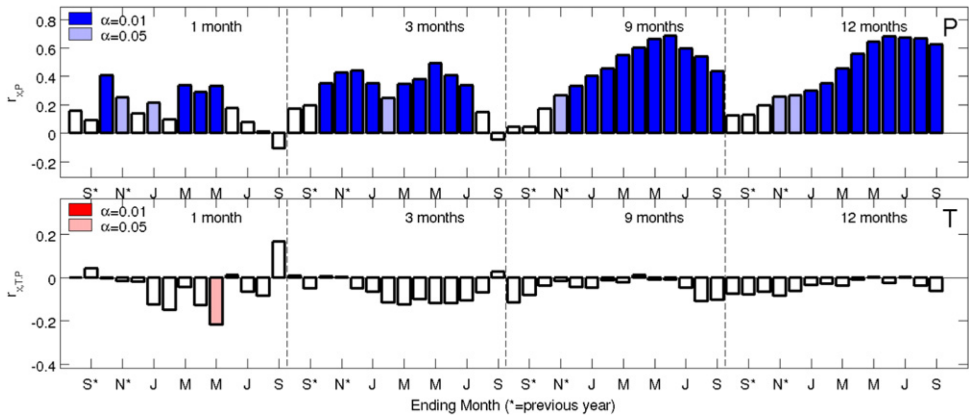

Fig. 3. Correlations and partial correlations of Tunisia tree-ring series with seasonalized climate variables. (Top) Simple correlations with the primary climate variable, *P*. (Bottom) Partial correlations of tree-ring index with secondary climate variable, *T*.

```
HIGHEST-CORRELATED SEASONS
 (Tree rings with P)

Analysis period: 1903-2002
1000 simulations

--------------------------------
       Ending       Nonexceedance
 m     Month    r    probability
--------------------------------
 1      Oct#   0.40      0.9990 **
 3      May    0.49      0.9990 **
 9      Jun    0.68      0.9990 **
 12     Jun    0.68      0.9990 **
--------------------------------
# after month means "previous year"
m-month seasons with given ending month
r is highest correlation for each m

For complete list of correlations and
partial correlations that are plotted
in Figure 1, type 'Result.S{i}' at
  command prompt, where i is 1, 2, 3 or 4.

LIST OF FIGURE WINDOWS
  1) bar charts -- tree ring vs climate
  2) bar chart -- P vs T
  3) time plot and histogram, tree ring
  4) spectrum of tree-ring series
  5) acf of tree-ring series
  6) lag-1 autocorrelation comparison
  7) climogram
  8) scatter plots, tree-ring vs P
  9) time plots of tree rings and P
 10) this summary text window
 11) difference-of-correlation test
      (early vs late sub-periods)
```

Fig. 4. Summary `seascorr` figure window. Listed are the seasonal groupings of *P* most highly correlated with Tunisia tree rings. One or two asterisks flag significant correlations at 95% or 99%. Summary window also lists the other figure windows and gives instructions for obtaining statistics from the MATLAB command window.

In the above example, with a setting of 1000 simulations `seascorr` required 20 s of cpu time on a 2.16 GHz PC with 4 MB RAM and a 250-GB hard drive. With 10 000 simulations the required cpu time was 152 s.

For regions where tree growth is primarily controlled by temperature variability, the default roles of *P* and *T* as primary and secondary climate variables can be readily exchanged to focus the analysis on temperature relationship with tree growth. In Fig. 7 we show such an application with a *Larix sibirica* tree-ring chronology from the Yamal Peninsula, Russia (Hantemirov and Shiyatov, 2002; Briffa et al., 2008) and regional climate data. We use temperature data from the CRUTEM3 (Brohan et al., 2006) and precipitation data from the CRU TS3.0, corresponding in both cases to the grid box closest to 70°E and 70°N. We used a regularized expectation maximization approach with ridge regression (Schneider, 2001) to impute 1.27% of missing temperature values at this grid point in this dataset, which allows us to evaluate climate/tree growth relationships over the period 1903–1996, using an annual window spanning the prior October to the growing season November. This analysis (Fig. 7) shows a statistically significant relationship with summer growing season temperatures, with the strongest correlations in July. Significant seasonal (3-month) correlations are also consistently identified for the summer (MJJ and JJA). Larger seasonal windows, however, do not show consistently significant relationships, and there is no evidence that ring width is correlated with mean annual temperature. These findings agree with those of Briffa et al. (2008), although their correlation analysis over a shorter period (1950–1994) showed a stronger monthly correlation in June. Splitting the time period of analysis, following Sections 2.3 and 2.4 above, reveals no temporal instability between ring width and summer temperature, and therefore no sign of a "divergence effect" (D'Arrigo et al., 2008). Positive-sign partial correlations with precipitation amount are detected by `seascorr` in the prior winter (OND), possibly indicating that snowfall can have a secondary influence on subsequent summer growth.

5. Comparison with other programs

Two other programs that can be used to identify the months of significant *P* and *T* influence on tree growth are the C++ program `DENDROCLIM2002` (Biondi and Waikul, 2004) and the DOS program `PRECON` (Fritts, 1999). `Seascorr` differs from these programs in its Monte Carlo approach to significance levels, and its focus on the integrated (over months) climate signal. Other differences include `seascorr's` suite of diagnostic plots of climate and tree-ring series (see Appendix A) and access to the MATLAB graphics environment, which allows direct export of figures in graphics formats suitable for presentation and publication. The other available programs do offer some analyses not included in `seascorr`. For example, `DENDROCLIM2002` can be used to study the time-evolution of the relationship between tree rings and climate with more temporal precision.

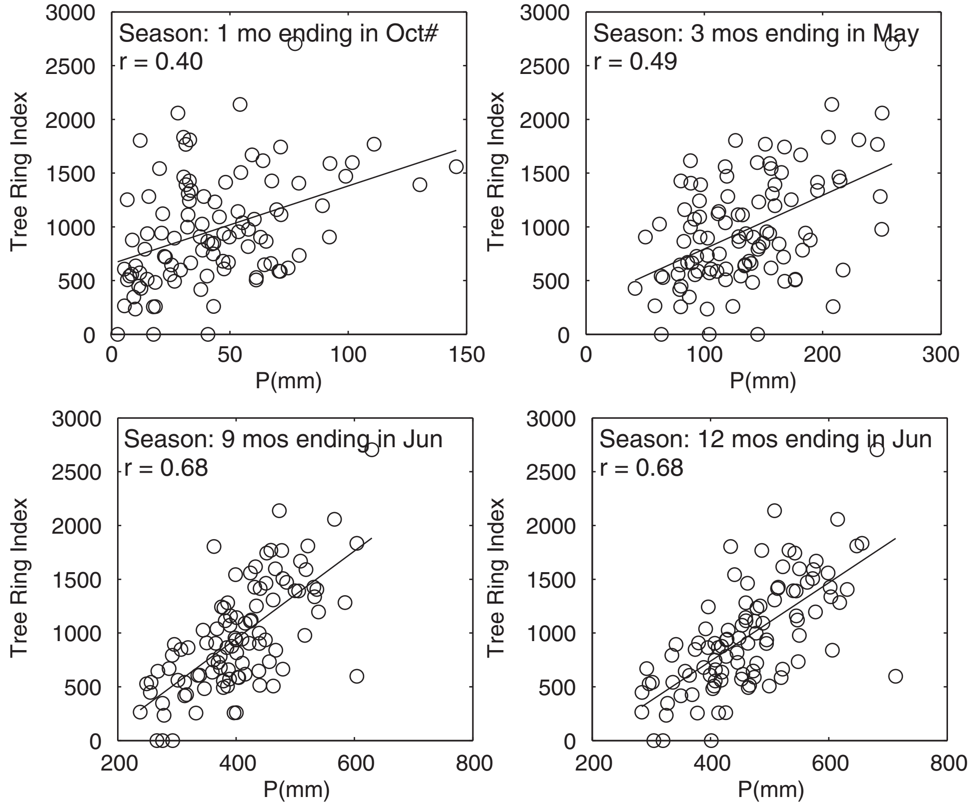

Fig. 5. Scatterplots of tree-ring index on seasonalized primary climate variable for most highly correlated seasons.

TEMPORAL STABILITY OF CORRELATION FROM EARLY TO LATE SUB-PERIOD

Full = 1903-2002, Early = 1903-1952, Late = 1953-2002

Season[a]		Correlation[b]			Sample Size[c]		Test Results[d]	
Months	length	Full	Early	Late	N_1	N_2	ΔZ	p
Oct*	1	0.40	0.31	0.46	50	50	-0.1712	0.406
Mar-May	3	0.49	0.46	0.52	50	50	-0.0743	0.719
Oct*-Jun	9	0.68	0.67	0.69	50	50	-0.0311	0.880
Jul*-Jun	12	0.68	0.68	0.68	50	50	-0.0022	0.991

[a] Season: start & end months and number of months in season; asterisk denotes year preceding tree-ring year.

[b] Correlation: Pearson correlation of tree-ring index with primary climate variable for full-period, early-period, and late-period.

[c] Sample Size: N_1 and N_2 are the effective sample sizes for the correlations computed on early and late sub-periods, respectively. Effective sample size is fewer than the number of observations if both time series have positive lag-1 autocorrelation. Autocorrelations for the assessment computed on the full analysis period. Sample-size adjustment after Dawdy and Matalas (1964).

[d] Test Results: The test statistic (ΔZ) is the difference between transformed correlations for the early and late periods, following Panofsky and Brier (1968) and Snedecor and Cochran (1989). The last column is the p-value for a test of the null hypothesis that the population sample correlations for the early and late period are the same. A significant difference in sub-period correlations is indicated by a small p (e.g., $p<0.05$).

Fig. 6. `Seascorr` figure window summarizing test of difference of correlation in early and late subperiods.

Despite the various differences in scope and method, `seascorr`, `DENDROCLIM2002` and `PRECON` all aim at least in part on identifying the individual months of most important climate influence to tree growth. `DENDROCLIM2002` and `PRECON` run on the Tunisia sample data gave results broadly similar to those of `seascorr`: precipitation in 4–6 cool-season months is most

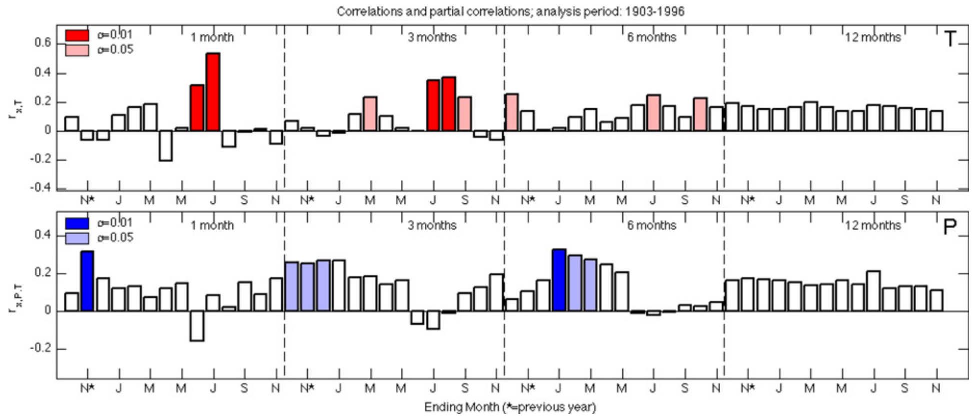

Fig. 7. Correlations and partial correlations of Yamal Peninsula tree-ring series with seasonalized climate variables. (Top) Simple correlations with the primary climate variable, *T*. (Bottom) Partial correlations of tree-ring index with the secondary climate variable, *P*.

important to tree growth, though the individual months marked as significant do not coincide exactly for all three programs. Graphics output from the programs is compared in the Supplemental material (see Appendix A).

6. Caveats and limitations

Exact simulation as applied here assumes the generating process of the tree-ring series is stationary and Gaussian. The bivariate relationships examined are also assumed to be linear. Moreover, even for linear relationships, complications can arise with interpretation of correlations when the time series are autocorrelated (Chatfield, 2004). A mismatch of autocorrelation in the tree-ring index and climate time series may indicate that the residual rather than standard chronology (Cook, 1985) should be used in `seascorr`. Diagnostic plots and statistics are produced by `seascorr` to address these issues (see Appendix A). We note also that the significance levels in `seascorr` are not "simultaneous": they have not been adjusted for multiple comparisons, as with a Bonferroni adjustment (Snedecor and Cochran, 1989). A scan of more than 20 sample correlations (e.g, as in Fig. 3) is therefore likely to identify one or more correlations significant at $\alpha = 0.05$ by chance alone. Monte Carlo sampling to establish confidence intervals can also at times produce non-intuitive results. For example, a sample correlation near the 95th percentile of simulation-based correlations may be identified as significant at $\alpha = 0.05$ in one run and not significant in the next. Moreover, the ability to detect significant relationships may be limited by the climatic data. Station, gridded or regionally averaged climate data can only approximate the climate variations where the trees are growing. Finally, because an input signal must vary sufficiently to elicit a response in the output, the climate signal for a particular season may not emerge merely because that season happens to have low climatic variability in the available time series sample.

7. Conclusion

`Seascorr` is intended as a statistical/graphical tool to supplement existing tools available for analyzing the seasonal climate signal in tree-ring data. `Seascorr` is of course useful only in the MATLAB environment, though it is platform-independent, across Unix, Windows, and Mac platforms. Its primary advantages over existing software are convenient trial-and-error assessment of possible "seasons" for reconstruction of a climate variable, a suite of ancillary diagnostic plots, and ease of export of figures in many graphics formats. The incorporation of exact simulation could be advantageous for autocorrelated tree-ring series, especially those with an autocorrelation structure not following some simple low-order autoregressive process.

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Appendix A. Supplementary materials

Supplementary materials, available from the server at http://www.iamg.org/CGEditor/index.htm, include `seascorr` running instructions, sample input data, output data, and annotated full sample graphics output for the Tunisia example. Ancillary graphics windows not shown in this paper include: (1) bar chart of correlations of *P* with *T*, (2) climograph of monthly *P* and *T*, (3) autocorrelation function of tree-ring series, (4) bar chart of lag-1 autocorrelation of *P* for the 56 seasons, (5) time plots showing covariation of the tree-ring series with *P* for the seasons with highest correlation of *P* with tree rings. The Supplementary Materials also include annotated graphical output from `PRECON` and `DENDROCLIM2002` run on the Tunisia data, and a mathematical description of the difference-of-correlation test summarized in Fig. 6.

Appendix B. Supplementary data

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.cageo.2011.01.013.

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