A forward modeling approach to paleoclimatic interpretation of tree-ring data

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Abstract. We investigate the interpretation of tree-ring data using the Vaganov-Shashkin forward model of tree-ring width formation. This model is derived from biophysical first principles of conifer wood growth, and explicitly incorporates a nonlinear daily-timescale model of the multivariate environmental controls on tree-ring growth. The model results are shown to be robust with respect to primary moisture and temperature parameter choices. When applied to the simulation of tree-ring widths from North America and Russia from the Mann et al. [1998] and Vaganov et al. [2005] data sets, the forward model produces skill on annual and decadal timescales which is about the same as that achieved using classical dendrochronological statistical modeling techniques. The results suggest that the Vaganov-Shashkin forward model may be used to develop improved proxy error estimates and climate reconstructions, and to predict the fingerprint of transient climate change on temperate conifer forests.
1. Introduction

A key element of climate change detection and attribution efforts is the determination of the natural variability on time scales bracketing those of anthropogenic influences on climate. In the absence of direct observations, especially prior to the rise of globally-distributed direct observations in the mid 19th century, we rely on the so-called “proxy” climate indicators, which are often derived from geological or biological archives, and are interpreted by means of statistical relationships and chemical or biophysical principles. One of the most widespread kinds of natural paleoclimatic archives are tree-rings; data now exist from over 2000 sites on six continents [World Data Center-A (WDCA) for Paleoclimatology, 2003]. The collection and interpretation of these datasets is based in biological principles of tree growth (e.g. Schweingruber [1988]; Cook and Kairiukstis [1990]; Fritts [1991]). Subsequent analysis of derived paleoclimate observational networks incorporating tree-ring records and other proxy data has produced hemispheric and global-scale paleoclimatic reconstructions over the past few centuries to millennia (e.g. Mann et al. [1998, 1999]; Stahle et al. [1998]; Briffa et al. [2001]; Jones et al. [2001]; Esper et al. [2002]; Cook et al. [2002]; Mann and Jones [2003]).

Two major uncertainties lie in the statistical development, analysis and interpretation of tree-ring width data for paleoclimate studies. First, there are non-climatic influences on tree-ring records, including tree biology, size, age and the effects of localized forest dynamics [Cook and Kairiukstis, 1990]. Successful elimination of these influences is now routinely achieved via careful site selection, sampling, data analysis and a posteriori tests to ensure that the tree-ring record is dominated by the single climate variable of interest. Perhaps of more concern is that tree-ring data reflect a nonlinear, response to multivariate
climate forcings. This represents a problem for both single-variable paleoclimatic reconstructions via linear statistical calibration of the tree-ring proxy data, and for prediction of the effects of climate change scenarios on tree biology and forest ecology. In both situations, statistical relationships - which may represent linearizations of nonlinear processes (see section 2) - are difficult to validate for long period processes and for times outside the instrumental era and may not hold for paleoclimate or climate change experiments. For example, the application of statistical calibrations to an independent time period with a fundamentally different climatic regime, e.g. with comparable temperatures but a general shift in water balance, may consequently lead to an erroneous climate reconstruction [LaMarche et al., 1984; Graybill and Idso, 1993; Briffa et al., 1998; Vaganov et al., 1999; Barber et al., 2000; Kirdyanov et al., 2003; Anchukaitis et al., 2005a]. Hence the nature of trees as a biological archive of environmental conditions raises questions about the validity of linear, statistical approaches to interpretation of the data.

Introduction of a process model of tree-ring growth, from which tree-ring formation is represented via first principles of tree biology and climate data, permits us to investigate these issues directly. Here we investigate the potential of the Vaganov-Shashkin model of tree-ring formation [Shashkin and Vaganov, 1993; Vaganov et al., 1990, 2005] to accurately simulate trees growing in a variety of environmental conditions. Although there are several other process models of tree growth and ring formation (e.g. Fritts et al. [1999]; Foster and LeBlanc [1993]; Misson [2004]), our interest in a robust if low order forward model with a prognostic variable directly comparable to standard proxy observations led us to work with the Vaganov-Shashkin model. The tree-ring process model, which is briefly reviewed in section 2, is applied to the simulation of the actual tree-ring chronology data described
in Section 3. Performance of the model is reported in Section 4. The implications of the results are discussed in Section 5; conclusions are summarized in Section 6.

2. Model Description

2.1. General principles

The Vaganov-Shashkin model has two distinguishing features. Firstly, it deals with rates of growth of cells as if their formation in the cambium is influenced exclusively by the physical environment. This is a major simplification of present knowledge of wood biology, made for the purpose of simplifying the model and reducing the number of parameters. Secondly, it deals explicitly with the dynamics of cell growth, division, and maturation in a dedicated “cambial block” that is described elsewhere (Vaganov et al., 2005). This cambial block is driven by and is connected with the growth block. Thus the model simulates not only the width of conifer tree rings but also aspects of their internal structure, reflecting intra-seasonal environmental fluctuations.

The growth block of the Vaganov-Shashkin tree-ring model uses the principle of limiting factors (e.g. Frötsch [1991]) to calculate conifer tree-ring formation integrated over the growing season from daily temperature, precipitation, and sunlight. The daily growth rate on a specific day \( t \) is modeled as

\[
G(t) = g_E(t) \min[g_T(t), g_W(t)]
\]

(1)

where \( g_E(t) \), \( g_T(t) \), and \( g_W(t) \) are the daily growth rates due to solar radiation, near surface air temperature, and soil water balance, respectively. Dependence of growth on solar radiation \( g_E(t) \) is a function of latitude, declination angle and hour angle [Gates, 1980, Eq. 6.10]. The effects of the eccentricity of the Earth’s orbit around the Sun and of
atmospheric transmissivity have been neglected. The minimum function permits tree-ring formation to vary in effective functional dependence between temperature, moisture and sunlight on daily through seasonal timescales. The daily growth rate is used to calculate the cellular growth rate \( V_i(t) \):

\[
V_i(t) = V_{0,i} G(t),
\]

where the index \( i \) indicates the position in the cambial zone of the growing cell, and \( V_{0,i} \) is the dependence of growth rate on position. Radial cell size at position \( i \) is expressed as

\[
D_i = D_0 + aV_i,
\]

where \( D_0 \) is the initial cell size (equivalent to the size of a cambial cell after division) and \( a \) is a scale factor which is determined by anatomy of a standardized tracheidogram [Fritts et al., 1991]. In Nature, tree ring width (\( TRW \)) is determined by the sum of the radial cell sizes of all the cells produced during the growing season:

\[
TRW = \sum_{i=1}^{N} D_i.
\]

In the version of the model that we used for this study, however, \( TRW \) is estimated via the normalized number of non-cambial cells \( N \) formed that year. This is possible because there is always a strong linear relationship between \( N \) and \( TRW \) [Gregory, 1971; Camerero et al., 1998; Wang et al., 2002; Vaganov et al., 1985, 2005]. Hence, in the model simulation,

\[
TRW = \frac{N}{\langle N \rangle_i},
\]

where \( \langle .. \rangle_i \) indicates the time average over the simulated time interval.

Simulated tree-ring width chronologies may be directly compared to actual standardized tree-ring width data. A schematic overview of the structure of the growth block of the
model, its inputs and prognostics is given in Figure 1. Model parameters not varying in
time and their assumed values are given in Table 1. Below we describe the component
functions contributing to $G(t)$ in the form (1); more detail is found in the literature [Fritts,
1991; Fritts and Shashkin, 1995; Fritts et al., 1999; Shashkin and Vaganov, 1993; Vaganov,

2.2. Growth response to temperature

Experimental data [Fritts, 1976; Kramer and Kozlowski, 1979; Gates, 1980; Lyr et al.,
1992] suggest that the dependence of the growth rate function on temperature $g_T$ may be
subdivided into three segments: (1) rising growth rates with increasing temperatures be-
low a growth-optimal temperature range; (2) relatively constant rates within an optimal
range of temperatures; and (3) decreasing growth rates above that temperature range.
This also represents the typical behavior of other biological systems. A polynomial func-
tion has been suggested [Vaganov et al., 1990; Fritts, 1991] which is approximated in the
Vaganov-Shashkin model by a piecewise linear function (Figure 1). Between the minimum
temperature for growth $T_{min}$ and the lower end of the range of optimal temperatures $T_{opt1}$,
the growth rate linearly increases with temperature. Between $T_{opt1}$ and $T_{opt2}$, growth rate
is optimal at a constant level, then decreasing linearly between $T_{opt2}$ and the maximum
temperature for growth $T_{max}$. Beyond $T_{max}$, growth does not occur.

Following studies by Lindsay and Newman [1956], Landsberg [1974], Valentine [1983],
Cannell and Smith [1986], and Hanninen [1991], growth in the model is initiated each year
when the sum of daily temperatures over a specified time period $t_{beg}$ reaches a defined
critical level $T_{beg}$ (Table 1). In the cambial model simulations, as in nature, cambial cells
grow and divide when they reach a critical cell size $D_{crit}$. They lose the ability to divide
and move to a stage of enlargement when the growth rate (as calculated by the model's growth block) falls below a critical level, followed by a cell wall thickening stage. At the end of the growing season, the remaining cells in the cambial zone become dormant and represent the initial number of cells for the subsequent growing season.

2.3. Growth response to water balance

Similar to calculation of growth response to temperature $g_T(t)$, growth response to soil water balance $g_W(t)$ is expressed similarly as a piecewise-linear function of $W$ (Figure 1), which represents another approximation based on experimental data [Kramer and Kozlowski, 1979]. The soil water content $W$ itself is calculated through a balance equation for soil water dynamics [Thornthwaite and Mather, 1955; Alisov, 1956]:

$$dW = f(P) - E - Q.$$

Here, $dW$ is the daily change in soil water content, $f(P)$ is a function of daily precipitation, $E$ is daily transpiration, and $Q$ denotes daily runoff. Function $f(P)$ is expressed as

$$f(P) = \min[c_1 P, P_{\text{max}}],$$

where $P$ is the actual daily precipitation, the constant $c_1$ is the fraction of precipitation that is caught by the crown of the tree, and $P_{\text{max}}$ denotes the maximum level for saturated soil. For saturated soil, runoff $Q$ is proportional to the soil water content $W$:

$$Q = c_4 W.$$

The transpiration of water by the tree crown $E$ depends exponentially on temperature [Monteith and Unsworth, 1990]:

$$E = c_2 G(t) \exp[c_3 T],$$
where the constants $c_2$ and $c_3$ are used to describe a variety of tree species and growth conditions (Table 1). The factor $c_2 G(t)$ is related to stomatal conductance. Hence, temperature-driven growth creates an exponential increase in evapotranspiration, which can become the limiting factor in the growth rate function $G(t)$, via the water balance function $W$ (e.g. Larcher [1980]).

3. Data and Methods

3.1. Tree-ring chronologies

At present, there are over 2000 tree-ring chronologies potentially available for inter-comparison with synthetic chronologies produced by the tree-ring model [World Data Center-A (WDCA) for Paleoclimatology, 2003; Contributors of the International Tree-Ring Data Bank (ITRDB), 2002]. However, some of these chronologies were developed for purposes other than paleoclimatic reconstruction, others lack sufficient replication, and yet others were standardized in ways which might limit paleoclimatic interpretation of the data. Hence, we selected 198 tree-ring width chronologies for comparison with the tree-ring model output from two sources. Of these, 190 data series for North America are from the Mann et al. [1998] dataset. These data were screened a priori for several quality control variables [Mann et al., 2000] to produce a dataset most conducive to paleoclimate reconstruction, and represent an excellent target for this study. Data from eight sites in Russia are from published or unpublished datasets developed by Vaganov et al. [1999, 2005].
3.2. Tree-ring width simulations

Daily station records from the comprehensive Global Historical Climatology Network [Peterson and Vose, 1997] data set are used to simulate tree-ring chronologies at North American locations. Daily weather station data for Russian chronology locations is obtained by the Institute of Forest of the Russian Academy of Sciences, Krasnoyarsk, Russia (V. Shishov, pers. comm.). Missing temperature data are replaced by linearly interpolated values. Missing precipitation data were simply set to zero. In the case of more than 90 days of missing meteorological data, the year was not simulated. To account for model equilibration, all model simulations were initialized with the same default number of cambial cells and sizes, and the first modeled year’s growth was discarded. The simulated growth following a missing meteorological year was initialized using the last simulated year’s initialization file, and the first year following a meteorological hiatus was discarded as well.

Note that meteorological station proximity may not always be the best criterion for selecting the appropriate tree-ring model input. For example, the presence of orography produces spatially isentropic features into patterns of temperature and rainfall on daily to seasonal timescales, and elevation differences between tree-ring sites and meteorological stations may artificially create large differences between actual and simulated chronologies. For these reasons, we attempt to partially correct temperature for elevational differences by using an adiabatic correction (6.6°C/km; Wallace and Hobbs [1977]) for the mean elevation difference between our set of actual tree-ring chronologies and the meteorological stations. On average, chronologies are located 700m higher than stations; thus, the mean temperature correction of 4.6°C was used for all simulations. We then simulated the 190
North American tree-ring width chronologies for all meteorological stations found within a 500km search radius, and the 8 Russian chronologies using meteorological data from the nearest station [Vaganov et al., 2005]. In reporting results for each of the 190 North American sites, we use the simulation for the station found within the 500km search radius that is most significantly correlated with the given actual tree-ring width data series over the full intercomparison period available. This period averaged 1915-1981. For the eight Russian sites the meteorological station data coverage is sparser, and we report the same statistic but for correlation with the closest meteorological station.

It is important to note the rather simplistic approach taken with this application of the process model. The model itself is only a very simple depiction of tree growth [Vaganov et al., 2005]. For example, the model does not explicitly include photosynthesis, and it does not include other possibly important controls on tree growth, such as atmospheric attenuation of solar radiation, nutrient availability, CO₂ fertilization, or anthropogenic influences on growth conditions, except as mirrored in meteorological station temperature and precipitation. In addition we did not tune the model fixed parameters by region, mean climate, or species; all model runs use the parameter values listed in Table 1. However, precisely due to the simplicity of the model and experimental conditions, we can test, sensu Occam's razor, the hypothesis that observed tree-ring variations are due solely to meteorological controls, as represented in the Vaganov-Shashkin model. The same assumption implicitly underlies many uses of tree-ring data in paleoclimate reconstructions.

4. Results

4.1. Model behavior: Ulan-Ude, southern Russia
Figure 2 illustrates a single time series ring-width simulation (Ulan-Ude, Buryatia region, southern Siberia: 51.8°N, 107.6°E; 510m elevation) in terms of the intra-annual contributions of the temperature and moisture growth functions for a recent five year interval. The model's simulation of annual ring widths is compared to data from a Scots pine (*Pinus sylvestris* L.) tree-ring width chronology [Andreev et al., 1999] from the same region for the period 1922-1989 (Figure 3).

Tree growth for this site is expected to be mainly sensitive to the availability of water, although for specific time periods temperature can become an important factor. In 1985, the beginning of the growth season (which the model defines as when the temperature sum over the period of ten days has reached the critical level of $T_{\text{beg}}=60^\circ\text{C}$, Table 1) is in May (Figure 2). The growth function remains high until the end of June, due to net positive precipitation-evaporation in May and June. A relatively dry period is observed from early July until the end of August. The consequence is a net decrease in available water during that period, resulting in a drastic decrease of the growth function. Although greater precipitation is received in the fall, the growth function is subsequently limited by temperature as the growing season draws to a close. The resulting ring width over the year can, as a first approximation, be seen as the integration over the growth function and shows a relatively wide ring for this year, mainly due to favorable growing conditions until the end of June. By constrast, 1987 shows much lower precipitation within the growth season window defined by the annual cycle of temperature. Consequently, soil moisture was lower throughout the growing season, and the integrated growth function indicates a much narrower predicted tree-ring.
The observed and simulated annual tree-ring indices for the available intercomparison period 1922-1986, together with their 5-year running means, are shown in Figure 3. The correlation coefficients for annual data and 5-year averages are $r=0.58$ and $r=0.81$, respectively; both correlations are significant at the 99% level. The simulated index for the first year, 1922, does not agree with the observation due to the arbitrariness of model initialization. For other years, the agreement is generally good, with the exception of the years 1933, 1941, 1944, and 1969. The misfit to the tree ring chronology, especially in 1969, generally coincides with periods when large amounts of daily weather data are missing.

4.2. Model sensitivity: Ulan-Ude, southern Russia

To evaluate the sensitivity of the Ulan-Ude results to model parameters which define the temperature and water balance growth functions (Figure 1), we performed two additional experiments (Figure 4). For the first experiment, we varied one of the parameters $T_{\text{min}}$, $T_{\text{opt}1}$, $T_{\text{opt}2}$, and $T_{\text{max}}$, keeping all other parameters constant. The value of each of the varied four parameters (Table 1) was increased and decreased stepwise (steps of ±0.5°C) up to a change of ±5°C, and the simulations were repeated for each new parameter set, resulting in a total of 80 simulated chronologies, which could then be compared to the actual tree-ring chronology from Ulan-Ude. Similarly, the values for $W_{\text{min}}$, $W_{\text{opt}1}$, $W_{\text{opt}2}$, and $W_{\text{max}}$ were varied over a range of ±20% and the simulated chronologies compared to the actual chronology.

We found that the tree-ring width simulation for Ulan-Ude was not very sensitive to the choice of primary temperature and water budget parameters (Figures 2,4). Decreasing the parameters $T_{\text{min}}$ and $T_{\text{opt}1}$ have virtually no effect on the simulation; an increase in
any of these parameters results in slightly lower but not significantly different correlation coefficients (Figure 4a). Only a decrease of $T_{\text{opt2}}$ and $T_{\text{max}}$ result in significantly lower correlations, suggesting that lower values for the upper branch of the temperature growth function are unrealistic, consistent with experimental data (e.g. Gates [1980]; Lyr et al. [1992]). The second experiment examined the response to variation of the water balance parameters $W_{\text{min}}$, $W_{\text{opt1}}$, $W_{\text{opt2}}$, and $W_{\text{max}}$ in the same manner, to $\pm20\%$ of their original values (Table 1). As $W_{\text{opt2}}$ and $W_{\text{max}}$ are varied, correlations remain at a constant level for all experiments (Figure 4b), indicating that the soil water balance does not approach a level of saturation that would negatively affect tree-ring growth at this site at any time. The important parameters affecting model output here are $W_{\text{min}}$ and $W_{\text{opt1}}$. Increasing the values for $W_{\text{opt1}}$ does not have a significant influence, whereas increasing $W_{\text{min}}$ (the lowest soil water level for the occurrence of growth) seems to have an optimum around the original value. A decrease of either parameter by $20\%$ results in a drop of the correlation coefficient from roughly 0.6 to about 0.3, demonstrating the sensitivity of the model to the lower part of the water balance growth function (Figure 2b). This is consistent with the presumption that tree-ring growth of the investigated chronology is mainly limited by the availability of water.

4.3. Simulation of actual ring-width chronologies

A third set of results demonstrates generalized model behavior, as represented by the quality of simulation of the entire set of 198 chronologies described in Section 2. We calculate the significance of correlations between all simulated and actual chronologies on annual and decadal (11-year running mean) timescales (Table 2; Figure 5), taking into account the reduction in effective degrees of freedom due to autocorrelation and temporal
averaging [Trenberth, 1984; Donaldson and Tryon, 1987]; for each chronology, we report the process model correlation having the highest significance within the 500km search radius over the full intercomparison period. Figure 5 shows the map of the significance of correlations between the 198 simulated and real tree-ring chronology data series. A good fit is found across the entire data set, which includes chronologies from the arid western US, Siberia as well as from the humid, warm eastern United States, and several different species of trees. Table 2 shows the correlation of the 190 North American simulated chronologies on annual and decadal timescales, and for the two epochs (1915–1959 and 1960–1981) of the average common 1915–1981 intercomparison timeframe. The average correlation for all stations over the full period is 0.47. 176 of 190 annual scale correlations between process-modeled and observed tree-ring width chronologies are significant at the 95% confidence level, with an average correlation of 0.49. Furthermore, the annual correlations are stable with respect to the two chosen epochs (Table 2): the correlation averages are 0.46 and 0.43 in each of these periods. On decadal timescales, the average correlation is 0.61 for all modeled chronologies, the average of the 42 of 190 correlations significant at the 95% confidence level is 0.79.

4.4. Skill intercomparison: Process and statistical modeling

A fourth set of results allows us to assess the process model skill relative to that of multivariate linear statistical models developed using a standard dendroclimatological approach (e.g. Guiot [1990]; Fritts [1991]; Cook et al. [1999]). For each of the pre-whitened 190 North American chronology data series, for all sites within the same 500km search radius used for the process modeling study, the statistical model is constructed by selecting the predictors from monthly values of standardized temperature and precipitation for 16 con-
tinuous months, from prior-year June through current growing-season year September. Monthly averages were derived from the same set of daily meteorological station records used in the process modeling study; if more than 3 months of data were missing from a given year, then the entire year was marked as missing. Principal component analysis was used to reduce each resulting set of 32 predictor variables to a smaller number of robust predictors using a 50% cumulative variance criterion. The Akaike information criterion is used to select the most robust regression model. To test the calibration of each statistical model, the most recent one-third of the available meteorological data is withheld from statistical calibration for verification purposes; this resulted, on average, in 1917–1960 calibration and 1961–1981 verification periods. As with the process model simulations described above, the most significant correlation found within the search radius over the full intercomparison period (averaging 1917–1981) is reported. We did not apply and report this approach for the 8 Russian data series, because only single nearest meteorological station data were available.

A summary of the statistical modeling results is in Table 3. Scatter plots of the correlation of process model and statistical models with the actual tree-ring width chronologies for annual and decadal averages, and across development and verification periods, are shown in Figure 6; a summary of the modeling intercomparison is in Table 4. The statistical approach was able to define successful models for 184 of the 190 North American chronologies, with an average correlation of 0.55. 181 of 184 chronologies were simulated with an average correlation of 0.55 at the 95% confidence level. Average correlations for calibration and verification epochs are 0.60 and 0.37, respectively (Table 3). On decadal
timescales, the average correlation is 0.67 for all modeled chronologies, and is 0.80 with 56 of 184 chronologies significantly correlated at the 95% level.

An additional way of quantifying the model intercomparison is to ask how often (i.e. in how many locations) the process model produces higher correlations than the statistical model. That is, what is the percentage of points above the 1-1 line in the panels of Fig. 6 and is it significantly different from 50%? This comparison of the process and statistical modeling results is presented in Table 4 for all chronologies modeled by both statistical and process modeling approaches, and specifically for on those comparisons by epoch which are at or above the 95% confidence level for a given epoch. Results for the entire period of study (~1916-1981) show that the process and statistical models are each able to explain, on average, about 25-30% of the variance in the tree-ring observations (Fig. 6a). In the first epoch (~1916-1960), which is the calibration period for statistical modeling, and for all chronologies modeled by both statistical and process models, the statistical model clearly outperforms the process model (Fig. 6b, Table 4), with only 23% of correlations above the 1:1 line. However, in the second epoch (~1961-1981), which is the verification period for the statistical model, statistical modeling skill is no different than that of the process model (Fig. 6c, Table 4); now 59% of correlations are above the 1:1 line. For just the comparisons that were at or above the 95% confidence level (black filled circles in Figure 6), the correlations of the process and statistical models are indistinguishable within uncertainty.

5. Discussion
5.1. Process model skill

We believe process model skill in simulation of tree-ring width chronologies without chronology-specific tuning comes from three major features. First, the model uses realistic, nonlinear functional forms to represent the dependence of trees on soil moisture and temperature (Figure 1). As illustrated for the Ulan-Ude site, the explicit incorporation of the principle of limiting factors permits the model to flexibly respond to multivariate controls on tree growth throughout the year (Figures 1-4). Second, the model incorporates a simple yet effective water balance model that calculates net change in water availability due to runoff, evapotranspiration, and demand (Fig. 1). In many locales, this, combined with the modeled predetermination of the number of cambial cells at the start of the growth season, permits effective and realistic intraseasonal switches of the growth-limiting environmental control between temperature and moisture for temperate and subarctic sites (Table 2). Third, the use of daily-resolution input data to drive the model permits flexible responses to rapid changes in environmental controls on growth; in particular, it can accurately determine the beginning and end of the growing season (e.g., Figure 2). The generally excellent aggregate results (Figures 5, 6; Tables 2-4) are likely due to these process modeling features.

There are three important sources of uncertainty in the process model simulations. The first of these is that the quality of simulations varies with tree taxon (results not shown); pines, firs and junipers are best simulated by the model. The second is the quality and accuracy of local precipitation data. For example, moisture-stressed Russian tree-ring width chronologies that were successfully simulated using weather station data as model input were not simulated well using NCEP reanalysis data [Kistler et al., 2001] instead
of station observations. This is likely to be due to the well-known, poor representation of precipitation on small spatial scales in the NCEP reanalysis (e.g. Hagemann and Gates [2001]). The third is that no model parameters were tuned in this study. However, we have found [Anchukaitis et al., 2005a, b)] that we can improve simulations of Eastern and Southeastern US trees to levels observed in the western US in this study merely by a priori adjustment of one parameter – the water drainage coefficient A (Table 1) – to reflect local conditions more accurately.

Given these strengths and weaknesses we are encouraged that the aggregate process model results indicate skill which is roughly equal to that of classical cross-verified statistical modeling techniques (Tables 2-4). For the entire comparison dataset (N=184), we find that the statistical model is highly significantly ahead during the calibration period, so much so as to also be ahead for the whole period and the decadal period. However, the process model skill is about the same as that of the statistical model during the verification period, so the statistical model’s “wins” in the calibration and full periods may reflect its artificial skill. This interpretation is supported by the skill similarity when only correlations for each epoch significant at or above the 95% level are averaged (Figure 6, Table 4), although it is also worth noting that the complete set of 184 statistical modeling results passed the multiple tests for robust regression described in section 4.4. We feel justified in drawing the weak conclusion that neither method is decisively more skillful.

5.2. Model stability

Results for a range of environments, species, timescales and epochs suggest that the Vaganov-Shashkin process model is capable of simulating a wide variety of tree-ring records and their response to climate forcing, as represented by sunlight, temperature,
and precipitation. Experiments exploring a wide range of temperature and water budget parameter space suggest that the model output, ring width index, is not especially sensitive to the choice of these parameters. Rather, the shape of the moisture and temperature growth functions is likely the key element for accurate modeling of the response to moisture availability (Figs. 1-4). The generality of the model and its relative insensitivity to tuning parameters are also demonstrated by high correlation with actual tree-ring data from the warm, arid southwest US; cold, moist Siberia; and to a lesser extent, the warm, moist southeastern US (Fig. 5). We further note that the results shown here do not depend sensitively on meteorological station search radius: average results for 200km search radii, not shown, were similar to those presented in Fig. 5.

For the aggregate tree-ring dataset studied here, the process model appears to simulate annual and decadal climate variability about as well as standard statistical transfer function methods calibrated on monthly climate data (Tables 2,3; Fig. 6). Decadal-scale skill may derive from the predetermination by prior conditions of the number of cambial cells available at the start of the growing season in the simulation model, or it may be due to the nonlinear form of the model. More study is needed to fully characterize the origins of the decadal skill in the process model results. However, process model skill appears to be more temporally stable than that of linear statistical models, whose form and skill may be dependent on the period chosen for its calibration (Tables 2-4; Fig. 6b,c).

5.3. Model applications

Based on the skill demonstration presented here, there are a number of important applications of the Vaganov-Shashkin model which may be pursued in the future. For instance, the residuals of the fit of the simulated chronologies to the tree-ring width observations...
could be used to define patterns influencing chronology and/or model error in space, time and frequency. We have shown (Fig. 6d) mechanistic support for interpretation of decadal tree-ring variations as climatically-driven in a significant fraction of the tree-ring dataset studied here. Hence, in particularly well-observed regions, decadal-scale error functions (corresponding to non-climatic factors) for tree-ring width records might be identified. This would represent a significant step toward validating and improving statistically-based but ultimately subjective data standardization techniques and identifying decadal climate variability reliably. With the error functions of model and data better resolved, especially on interannual to decadal timescales, we can investigate the inversion of data and model for simultaneous temperature and precipitation reconstructions. GCM output could be used to hindcast probabilistically the natural variability in growth of conifer forest ecosystems and carbon budgets on a global scale. Similarly, climate change forecasts may be transformed into a global conifer forest change “fingerprint”, and the results compared to ongoing satellite observations of the terrestrial ecosystem. These latter applications would require a simulation model expanded to include the effects of changing atmospheric concentrations of carbon dioxide on tree growth.

6. Conclusions

We have found the Vaganov-Shashkin model capable of accurately simulating intraseasonal to interdecadal climate variability, as expressed in variations in tree-ring width, for large regions of North American and Russia. The process model is relatively insensitive to parameter estimation, as shown by the good simulation of actual tree ring width chronologies from a variety of environments using a single fixed set of tuning parameters. The overall skill of the process model is not different from the verification skill of sta-
istical models typically used in dendroclimatology. Skillful simulation of decadal-scale
tree-ring variability suggests that the process model may be suitable for estimating tree-
ring chronology uncertainty, reconstructing multivariate paleoclimate fields, and assessing
the effects of anthropogenic change on the growth of temperate conifer forests.

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study was supported by NOAA grants NA86GP0437 and NA16GP1616 to MAC, AK,
MNE and BKR, and an Alexander von Humboldt Foundation Feodor Lynen Fellowship
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importance of early summer temperature and date of snow melt for tree growth in the


### Table 1. Tree-ring model parameters used throughout this study

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_{\text{min}}$</td>
<td>Minimum temperature for tree growth (°C)</td>
<td>5.0</td>
</tr>
<tr>
<td>$T_{\text{opt1}}$</td>
<td>Lower end of range of optimal temperatures (°C)</td>
<td>18.0</td>
</tr>
<tr>
<td>$T_{\text{opt2}}$</td>
<td>Upper end of range of optimal temperatures (°C)</td>
<td>24.0</td>
</tr>
<tr>
<td>$T_{\text{max}}$</td>
<td>Maximum temperature for tree growth (°C)</td>
<td>31.0</td>
</tr>
<tr>
<td>$W_{\text{min}}$</td>
<td>Minimum soil moisture for tree growth, relative to saturated soil (v/vs)</td>
<td>0.04</td>
</tr>
<tr>
<td>$W_{\text{opt1}}$</td>
<td>Lower end of range of optimal soil moistures (v/vs)</td>
<td>0.2</td>
</tr>
<tr>
<td>$W_{\text{opt2}}$</td>
<td>Upper end of range of optimal soil moistures (v/vs)</td>
<td>0.8</td>
</tr>
<tr>
<td>$W_{\text{max}}$</td>
<td>Maximum soil moisture for tree growth (v/vs)</td>
<td>0.9</td>
</tr>
<tr>
<td>$T_{\text{beg}}$</td>
<td>Temperature sum for initiation of growth (°C)</td>
<td>60</td>
</tr>
<tr>
<td>$t_{\text{beg}}$</td>
<td>Time period for temperature sum (days)</td>
<td>10</td>
</tr>
<tr>
<td>$l_r$</td>
<td>Depth of root system (mm)</td>
<td>1000</td>
</tr>
<tr>
<td>$P_{\text{max}}$</td>
<td>Maximum daily precip. for saturated soil (mm/day)</td>
<td>20</td>
</tr>
<tr>
<td>$c_1$</td>
<td>Fraction of precipitation penetrating soil (not caught by crown) (rel. unit)</td>
<td>0.72</td>
</tr>
<tr>
<td>$c_2$</td>
<td>First coefficient for calculation of transpiration</td>
<td>0.12</td>
</tr>
<tr>
<td>$c_3$</td>
<td>Second coefficient for calculation of transpiration</td>
<td>0.175</td>
</tr>
<tr>
<td>$\Lambda$</td>
<td>Coefficient for water drainage from soil</td>
<td>0.001</td>
</tr>
</tbody>
</table>

### Table 2. Correlations with North American chronologies: Process model results. a

<table>
<thead>
<tr>
<th>Signif. level</th>
<th>annual averages</th>
<th>first epoch</th>
<th>second epoch</th>
<th>decadal</th>
</tr>
</thead>
<tbody>
<tr>
<td>all</td>
<td>0.47(190)</td>
<td>0.46(190)</td>
<td>0.43(190)</td>
<td>0.61(190)</td>
</tr>
<tr>
<td>p &lt; 0.10</td>
<td>0.48(176)</td>
<td>0.51(155)</td>
<td>0.58(111)</td>
<td>0.75(65)</td>
</tr>
<tr>
<td>p &lt; 0.05</td>
<td>0.49(170)</td>
<td>0.53(138)</td>
<td>0.61(84)</td>
<td>0.79(42)</td>
</tr>
<tr>
<td>p &lt; 0.01</td>
<td>0.51(134)</td>
<td>0.55(107)</td>
<td>0.66(46)</td>
<td>0.85(9)</td>
</tr>
<tr>
<td>p &lt; 0.001</td>
<td>0.53(101)</td>
<td>0.59(68)</td>
<td>0.70(19)</td>
<td>(0)</td>
</tr>
</tbody>
</table>

a Numbers in parentheses indicate number of averaged correlations.

### Table 3. Correlations with North American chronologies: Statistical model results. a

<table>
<thead>
<tr>
<th>Signif. level</th>
<th>annual averages</th>
<th>first epoch</th>
<th>second epoch</th>
<th>decadal</th>
</tr>
</thead>
<tbody>
<tr>
<td>all</td>
<td>0.55(184)</td>
<td>0.60(184)</td>
<td>0.37(184)</td>
<td>0.67(184)</td>
</tr>
<tr>
<td>p &lt; 0.10</td>
<td>0.55(183)</td>
<td>0.61(181)</td>
<td>0.55(76)</td>
<td>0.75(94)</td>
</tr>
<tr>
<td>p &lt; 0.05</td>
<td>0.55(181)</td>
<td>0.61(178)</td>
<td>0.59(61)</td>
<td>0.80(56)</td>
</tr>
<tr>
<td>p &lt; 0.01</td>
<td>0.56(170)</td>
<td>0.62(167)</td>
<td>0.63(27)</td>
<td>0.84(15)</td>
</tr>
<tr>
<td>p &lt; 0.001</td>
<td>0.57(134)</td>
<td>0.63(148)</td>
<td>0.66(10)</td>
<td>(0)</td>
</tr>
</tbody>
</table>

a Numbers in parentheses indicate number of averaged correlations.
Table 4. Comparison of process and statistical model results\textsuperscript{a}

<table>
<thead>
<tr>
<th>Epoch</th>
<th>All comparable simulations</th>
<th></th>
<th>95% conf. level simulations</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Process</td>
<td>Statistical</td>
<td># $r_P &gt; r_S$</td>
<td>Process</td>
</tr>
<tr>
<td>~1916-1981 annual</td>
<td>0.47(\pm)0.0087</td>
<td>0.55(\pm)0.0078</td>
<td>52(184)(\pm)6.8</td>
<td>0.49(\pm)0.0083</td>
</tr>
<tr>
<td>~1916-1960 annual</td>
<td>0.46(\pm)0.0011</td>
<td>0.60(\pm)0.0084</td>
<td>42(184)(\pm)6.8</td>
<td>0.51(\pm)0.011</td>
</tr>
<tr>
<td>~1961-1981 annual</td>
<td>0.43(\pm)0.017</td>
<td>0.37(\pm)0.017</td>
<td>109(184)(\pm)6.8</td>
<td>0.62(\pm)0.018</td>
</tr>
<tr>
<td>~1916-1981 decadal</td>
<td>0.61(\pm)0.018</td>
<td>0.67(\pm)0.016</td>
<td>73(184)(\pm)6.8</td>
<td>0.69(\pm)0.064</td>
</tr>
</tbody>
</table>

\(\text{\textsuperscript{a} Epochs are averaged across statistical and process epochs for all comparable simulations.}

Ranges give ±1 standard error in mean correlation values. For 95\% confidence level comparisons, numbers in parentheses give number of comparisons. \# $r_P > r_S$, number of correlations for which the process modeling result was better than the statistical modeling result. Theoretical standard errors for $r_P > r_S$ are equal to $\sqrt{N}/2$.}
Figure 1. Schematic representation of the growth block of the Vaganov-Shashkin tree-ring model (see section 2). Daily model inputs (solar radiation, temperature, and precipitation) are italicized.
Figure 2. Seasonal soil moisture and temperature controls on simulated tree-ring growth at Ulan-Ude, southern Siberia, 1985-1989. (a) Annual growth response function $G(t)$ (dashed line) normalized to 100%, and cumulative number of tracheids (wood cells) per ring (solid line). (b) Daily temperature (grey) and precipitation (black) data used to drive the model; vertical scale is in degrees Celsius (temperature) and in millimeters/5 (precipitation). (c) Soil moisture calculated by the water balance component of the model (volume/volume ratio).
Figure 3. Observed and Simulated tree-ring width indices, Ulan-Ude, 1922-1986. Annual (thin lines) and 5-year mean (heavy lines) correlations are $r=0.58$ and $r=0.81$, respectively, both significant at the 99% level for the effective numbers of degrees of freedom.
Figure 4. Sensitivity of model simulation to temperature and water balance to parameter choices, Ulan-Ude, 1922-1986. (a) Sensitivity of the correlation between simulated and real tree-ring width chronology as a function of the four temperature parameters $T_{\text{min}}$, $T_{\text{opt1}}$, $T_{\text{opt2}}$, and $T_{\text{max}}$. (b) Sensitivity of the correlation between simulated and real tree-ring width chronology as a function of the four precipitation parameters $W_{\text{min}}$, $W_{\text{opt1}}$, $W_{\text{opt2}}$, and $W_{\text{max}}$. 
Figure 5. Correlation significance map for simulation of 198 tree-ring width chronologies from North America and Russia for the ~1915-1981 comparison period. Significance levels (considering effective degrees of freedom): >99% (black; n=138; 70% of correlations), >95% (grey; n=175; 88% of correlations), <90% (white; n=6; 12% of correlations).
Figure 6. Correlation of the process and statistical model results with actual North American tree-ring chronologies. Correlations are plotted for chronologies for which both successful process and statistical model simulations were made (N=184; open circles) and for chronologies for which both process model and statistical model correlations reached the 95% confidence level for each intercomparison shown (N varies: see Table 4; closed circles). a) Process model vs. statistical model correlation, annual values, full ∼1916-1981 intercomparison period; solid 1:1 line indicates equal model skill. b) As in a), except for ∼1916-1960 calibration epoch. c) As in a), except for ∼1961-1981 verification period. d) As in a), except for decadal-scale (11-year running mean) correlations.