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# Detrending climate data prior to climate–growth analyses in dendroecology: A common best practice?

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ABSTRACT

Tree growth varies closely with high–frequency climate variability. Since the 1930s detrending climate data prior to comparing them with tree growth data has been shown to better capture tree growth sensitivity to climate. However, in a context of increasingly pronounced trends in climate, this practice remains surprisingly rare in dendroecology. In a review of *Dendrochronologia* over the 2018–2021 period, we found that less than 20 % of dendroecological studies detrended climate data prior to climate-growth analyses. With an illustrative study, we want to remind the dendroecology community that such a procedure is still, if not more than ever, rational and relevant. We investigated the effects of detrending climate data on climate–growth relationships across North America over the 1951–2000 period. We used a network of 2536 tree individual ring-width series from the Canadian and Western US forest inventories. We compared correlations between tree growth and seasonal climate data (Tmin, Tmax, Prec) both raw and detrended. Detrending approaches included a linear regression, 30-yr and 100-yr cubic smoothing splines. Our results indicate that on average the detrending of climate data increased climate–growth correlations. In addition, we observed that strong trends in climate data translated to higher variability in inferred correlations based on raw vs. detrended climate data. We provide further evidence that our results hold true for the entire spectrum of dendroecological studies using either mean site chronologies and correlations coefficients, or individual tree time series within a mixed-effects model framework where regression coefficients are used more commonly. We show that even without a change in correlation, regression coefficients can change a lot and we tend to underestimate the true climate impact on growth in case of climate variables containing trends. This study demonstrates that treating climate and tree-ring time series "like-for-like" is a necessary procedure to reduce false negatives and positives in dendroecological studies. Concluding, we recommend using the same detrending for climate and tree growth data when tree-ring time series are detrended with splines or similar frequency-based filters.

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## 1. Introduction

The study of climate–growth relationships in dendroecology traditionally relies on the standardization of tree-growth (TG) data (Cook, 1987; Fritts, 1976). Standardization procedures typically start with the detrending of individual tree–ring series in order to remove biological growth trends (Cook, 1985; Cook and Peters, 1981; Melvin and Briffa, 2008). Initially, biological growth trends were dealt with by applying an a priori deterministic curve - i.e., a mathematical function with a constrained shape, such as generalized or modified negative exponential curves or straight lines with a null or negative slope. As the discipline expanded into closed-canopy forests, with more frequent disturbances and stronger tree-to-tree competition, more flexible solutions were needed to deal with randomly occurring slow or fast increases and decreases in growth. Cubic smoothing splines were introduced as a novel detrending method (Cook and Peters, 1981). Splines belong to the group of stochastic detrending methods (they can have any (random) shape) and the family of digital filters that have certain controllable frequency-altering characteristics. That is, variability at specific wavelengths is removed, dampened, or retained, regardless of its cause (growth trend, or disturbance), by defining a 50 % frequency response cutoff at a wavelength of N years, colloquially termed N-year spline (Cook and Peters, 1981). Regardless of the detrending method (e.g., exponential or spline curves), ring-width residuals are then computed by either dividing or subtracting the observed data by those predicted through the detrending model. Due to naturally high levels of autocorrelation within tree–growth series (the growth level of a tree in a given year is strongly correlated to the growth level in the previous year), detrended time series are often further pre–whitened using autoregressive models (Cook and Kairiukstis, 1990). The resulting tree–ring indices are then correlated against climate data that are, compared to TG data, usually not treated, filtered, or detrended (Appendix A).

Removing low–frequency variability not only from tree-ring series, but also from climate time series through adapted detrending methods has been shown to strengthen climate–growth relationships (Fritts and Lough, 1985; Lyon, 1936). Routinely following such a procedure is particularly relevant when using TG series detrended with a flexible spline in a climate change context, where trends in climate are becoming more and more pronounced (IPCC, 2021; World Meteorological Organization, 2020, 2019). An additional key reason why trends should be removed in climate-growth analyses is the potential for violation of the demand for observations to be temporally independent in commonly applied statistical tests, such as linear regression or correlation analysis. Yet, the transformation of climate data prior to climate-growth analyses remains surprisingly rare in the literature. We reviewed 256 papers published in *Dendrochronologia,* one of the primary journals featuring tree-ring studies (Battipaglia et al., 2020; Eckstein and Schweingruber, 2009), between February 2018 and February 2021 (volumes 47–65). We identified 133 papers investigating climate-growth relationships, out of which only 24 (i.e., ~ 18 %) transformed (detrended) climate data prior to analyses (Appendix A). Climate detrending methods primarily consisted of high-pass filtering, such as cubic smoothing splines (n = 6) or first difference detrending (n = 14), the latter usually applied as an additional test to compare with non-detrended climate data. Of the 55 papers that applied a cubic smoothing spline to detrend the tree-ring data, only 11 % (n = 6) used the same spline stiffness to detrend climate data.

Our study aims to illustrate the rationale and relevance of detrending climate data prior to climate–growth analyses in dendroecological research using a geographically and ecologically unbiased tree-ring dataset from the systematic forest inventories of Canada and the Western United States (US). These trees and forests, among many others, are experiencing rapid warming through anthropogenic greenhouse gas emissions (IPCC, 2021) and their ability to adapt to this environmental change is uncertain (Babst et al., 2019; Beck et al., 2011; Charney et al., 2016; Hellmann et al., 2016). They are hence an excellent test case to explore how detrending climate data affects inferred climate–growth relationships. Our specific objective is to investigate the effects of detrending local climate time series on climate–growth relationships in trees across North America over the 1951–2000 period. We investigate if (i) detrending climate data strengthens climate–growth correlations and if (ii) this strengthening increases as the strength of the trend in the climate data increases.

## 2. Material and methods

### 2.1. Study area and tree-growth data

Our study encompasses all the Canadian provinces and the interior western US (30–70°N, 50–140°W, Fig. 1A), the latter including Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, and Wyoming. We extracted TG data from the Canadian and Western US forest inventories (Fig. 2A). Forest inventories are based on sampling designs that systematically monitor forested conditions over a large geographical extent. Such design-based sampling preclude the emergence of spatial and thus ecological bias when assessing climate–growth relationships and climate change impacts on forests (Charru et al., 2017; DeRose et al., 2017; Evans et al., 2022; Girardin et al., 2016; Klesse et al., 2018; Mérian et al., 2013; Nehrbass-Ahles et al., 2014; Ols et al., 2022). Despite a low number of cored trees per plot, when individual tree-ring samples are crossdated, the lack of replication at the plot level (only one tree sampled in most cases) is by far outweighed by the level of replication in space (gridded inventories) and time (new measurements every year and re–measurements).

In Canada, the dataset consisted of tree–ring increment cores sampled at either 1 m (in the Quebec province) or 1.30 m (all other provinces) above ground level. Trees were sampled from 2001 to 2010 as part of the Canadian National Forest Inventory (NFI) program (Natural Resources Canada, 2008). The NFI consists of a system of permanent sample plots located on a national grid. Within each NFI plot, up to twelve trees (diameter at breast height > 5 cm) were sampled (Fig. S1). These samples were then mounted, sanded, and crossdated (Yamaguchi, 1991), and each annual ring was measured using either a VELMEX measuring device (Velmex Inc. Bloomfield, NY, USA) interfaced with a computer or the Coorecorder/CDendro software suite with a flatbed scanner (Larsson, 2013). For each tree–ring width series, crossdating and measurements were statistically verified using COFECHA software (Holmes et al., 1986). This verification procedure was applied at the levels of individual plots, of multiple–plot aggregates (e.g., 1.0° 9 1.0° grids), and of ecoregions (Olson et al., 2001). The quality of year assignments of tree–ring width measurements was also verified against existing networks of tree–ring chronologies (see Girardin et al., 2021 for more details).

In the western US, the dataset includes tree–ring increment cores sampled from 2014 onwards as part of the renewed form of the Forest Inventory and Analysis (FIA) program (McRoberts et al., 2005) established in 2000 and based on a national grid with randomly sampled permanent plots. In most cases, one tree (diameter at breast height > 12.7 cm, or ~ 5 in.) was sampled per plot (Fig. S1). Tree–ring widths were measured in the laboratory with a VELMEX device (Velmex Inc. Bloomfield, NY, USA) at a 0.01 or 0.001 mm accuracy. Tree–ring width series were then visually crossdated using the marker year approach and crossdating was statistically verified against a regional chronology when available using the COFECHA software (Holmes et al., 1986).

### 2.2. Tree–growth data selection

The selection of TG series, was limited to conifer species. To reduce the presence of tree–to–tree competition and species–mixture effects on interannual tree growth variability, we further restricted TG series to samples taken from dominant or codominant living conifer trees growing in stands dominated by a single species, i.e., where the sampled

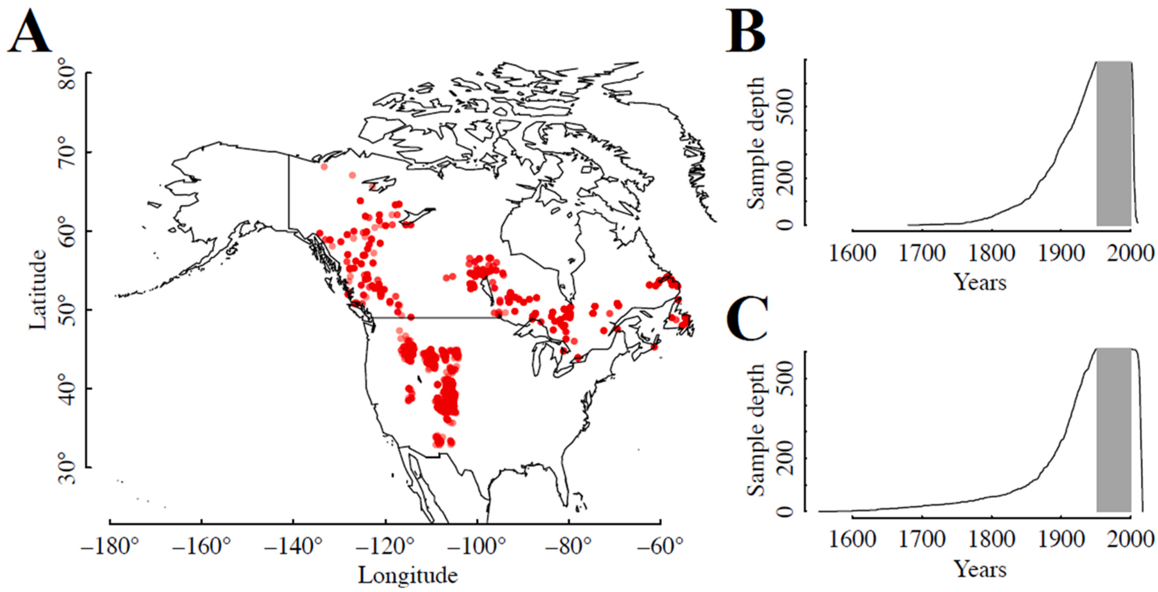


**Fig. 1.** A. Location of the 1301 selected tree–growth series. B. & C. Number of tree–ring series available for each calendar year in Canada and in the Western US, respectively. The gray shading delineates the 1951–2000 study period.

tree species accounted for more than 50 % of the stand basal area. To target decades of strong climate trends in climate–growth analyses, we selected TG series covering at least the 1951–2000 period. In total, 1301 series were selected in Canada and 612 in the Western US (Fig. 1, Table S1). The periods covered by these tree–ring data sets were 1680–2010 CE and 1552–2016 CE in Canada and the Western US, respectively (Fig. 1 B&C). The median series length for the entire dataset was 81 years (interquartile range: 59–114).

The main tree species selected were black spruce (*Picea mariana* (Mill.) Britton. et al., n = 451), subalpine fir (*Abies lasiocarpa* (Hook.) Nutt., n = 65), and lodgepole pine (*Pinus contorta* Douglas ex Loudon, n = 53) in Canada and Douglas fir (*Pseudotsuga menziesii* (Mirb.) Franco, n = 276), ponderosa pine (*Pinus ponderosa* Douglas ex P. Lawson & C. Lawson, n = 197), and lodgepole pine (n = 57) in the Western US (Table S1).

To investigate the impact of the detrending method used for TG series on climate–growth analyses, TG series were detrended using two cubic smoothing splines with a 50 % frequency cut–off at 30 and 100 years (hereafter called the 30–yr and 100–yr spline, respectively; Fig. 2B). Given the median series length of 81 years, we are aware that a substantial number of the TG series may not be adequately detrended with a 100–yr spline. Detrended series were computed as ratios of observed to predicted growth. All detrended series were then prewhitened (removal of autocorrelation within the series) using auto–regressive models (Cook and Kairiukstis, 1990). Detrending and prewhitening were performed in the R environment (R Core Teams, 2015) using the *detrend* function of the dplR package (Bunn, 2008). The two resulting sets of TG indices are hereafter referred to as TG–30 and TG–100.

### 2.3. Climate data

We included three climate variables in the analyses: minimum (Tmin) and maximum (Tmax) temperature and precipitation (Prec; Fig. 2A). Monthly temperature averages and monthly precipitation sums were extracted over the period 1950–2000 CE from the 10 km x 10 km resolved gridded ANUSPLIN database (McKenney et al., 2011), which covers Canada and the US. This climatic dataset relies on a plate–thin spline interpolation of monthly station data. In Canada, monthly data originate from the Environment Canada stations network, but some other regional networks have been added as well (e.g., summer fire weather stations, Hydro Quebec stations). In the US, monthly station data were primarily derived from NOAA's National Climatic Data Center (NCDC) network.

Seasonal maximum and minimum temperature averages and seasonal precipitation sums were computed based on monthly variables over five seasons defined as follows: previous and current year summer – June through August, previous year autumn – September through November, previous winter – December through February, current year spring – March through May. To capture the variability of climate change direction across grid cells, linear trends in seasonal climate from 1950 to 2000 and their significance were computed by regressing annually-resolved seasonal climate variables against calendar years. This was done by using the base function *lm* in R. Linear trends in climate are hereafter referred as trends. Average trends in minimum temperature ranged between + 0.004 °C.yr$^{-1}$ (previous autumn) and + 0.032 °C.yr$^{-1}$ (spring); average trends in maximum temperatures ranged between – 0.007 °C.yr$^{-1}$ (previous autumn) and + 0.035 °C.yr$^{-1}$ (spring); and average trends in precipitation ranged between + 0.040 mm.yr$^{-1}$ (previous winter) and + 0.613 mm.yr$^{-1}$ (previous autumn) (Table 1).

### 2.4. Climate–growth analyses

We conducted analyses over the 1951–2000 period at the individual–tree level using basic R functions (R Core Teams, 2015). The tree-level was preferred to site-level because of the limited number of trees cored per site in the Canadian and Western US forest inventory schemes (1–4 in most cases), which did not allow for robust site-level chronology development.

First, we computed four sets of climate data that include 15 seasonal variables each (3 variables × 5 seasons): one set with raw data (hereafter C–raw), one set with climate data detrended using a linear regression (C–lin), and two sets with climate data detrended using cubic smoothing splines, with a 50 % frequency cut–off at 30 and 100 years, respectively (C–30 and C–100; Fig. 2B). The detrending of climate data followed the same procedures as that of TG data. Climate indices were computed using ratios (division) for precipitation data and residuals (subtraction) for temperature data, some temperature series being incompatible with ratio procedures (contrasting positive vs. negative values). Unlike TG series, detrended climate series usually have very little temporal autocorrelation. Here, 903 (2.9 %) out of 31, 140 climate time series (519

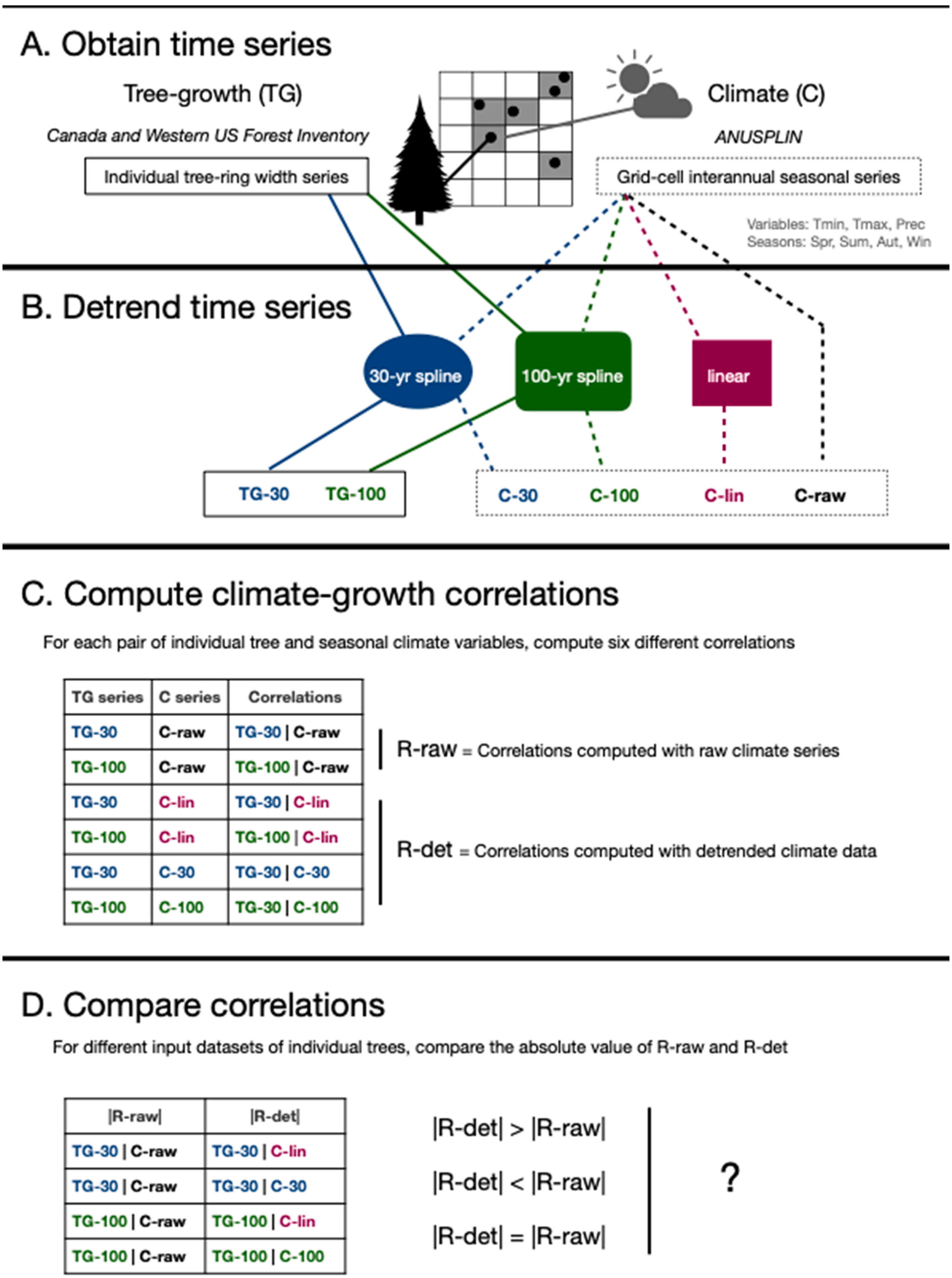


**Fig. 2.** Visual summary of the Material and Methods Section.

**Table 1**
Statistics on the distribution of trends in seasonal climate variables across sites of TG series covering the 1951–2000 period. Trends are indicated in °C.yr$^{-1}$ for seasonal minimum (Tmin) and maximum (Tmax) temperature averages and in mm.yr$^{-1}$ for seasonal precipitation sums (Prec). Seasons include previous year summer (pSum), autumn (pAut), and winter (pWin), and current year spring (Spr) and summer (Sum). Statistics include minimum, first quantile, median, third quantile, and maximum values. Bold font indicates the highest absolute value in absolute terms for a given variable and quantile.

| Var. | Season | Min. | 1st Qu. | Median | Mean | 3rd Qu. | Max |
|---|---|---|---|---|---|---|---|
| Tmin | pSum | -0.009 | 0.009 | 0.015 | 0.014 | 0.021 | 0.041 |
| | pAut | -0.020 | -0.005 | 0.006 | 0.004 | 0.012 | 0.039 |
| | pWin | **-0.058** | 0.002 | 0.017 | 0.021 | **0.051** | **0.083** |
| | Spr | -0.017 | **0.025** | **0.034** | **0.032** | 0.043 | 0.070 |
| | Sum | -0.009 | 0.007 | 0.014 | 0.012 | 0.018 | 0.040 |
| Tmax | pSum | -0.016 | 0.001 | 0.009 | 0.009 | 0.017 | 0.032 |
| | pAut | -0.034 | -0.013 | –0.007 | -0.007 | -0.002 | 0.013 |
| | pWin | **-0.038** | 0.005 | 0.014 | 0.019 | 0.032 | **0.084** |
| | Spr | -0.011 | **0.025** | **0.036** | **0.035** | **0.043** | 0.074 |
| | Sum | -0.015 | 0.002 | 0.008 | 0.008 | 0.016 | 0.030 |
| Prec | pSum | -0.345 | 0.221 | 0.436 | 0.494 | 0.758 | 1.542 |
| | pAut | -0.538 | 0.194 | **0.590** | **0.613** | **0.925** | 3.443 |
| | pWin | **-1.453** | **-0.333** | –0.052 | 0.040 | 0.271 | **4.151** |
| | Spr | -0.625 | 0.034 | 0.407 | 0.465 | 0.765 | 3.780 |
| | Sum | -0.360 | 0.139 | 0.385 | 0.436 | 0.704 | 1.478 |

grid cells × 3 climate variables × 5 seasons × 4 four sets of data) had an absolute first–order autocorrelation (|AR1|) > 0.3, which is less than what would be expected by chance alone. Detrended climate series were therefore not prewhitened.

We then computed Pearson correlation coefficients between each of the two detrended TG datasets (TG–30 and TG–100) and two of the climate datasets (C–raw and C–lin). In addition, we computed correlations between TG–30 and C–30 and between TG–100 and C–100 (Fig. 2C). The ensemble of correlation coefficients between TG–30 and the three climate datasets are hereafter referred to as TG–30|C–raw, TG–30|C–lin, and TG–30|C–30. Similarly, correlation coefficients computed with TG–100 are hereafter referred to as TG–100|C–raw, TG–100|C–lin, and TG–100|C–100 (Fig. 1C). We further denote R–raw as the general term for all correlation coefficients computed with raw climate data and R–det as those calculated based on detrended climate data. In total 117,090 correlation coefficients were computed (1301 TG series × 3 climate variables × 5 seasons × 6 detrending combinations). We accounted for false discovery rates by using the Benjamini and Hochberg (1995) method and the *p.adjust* function in R (Fig. S2).

### 2.5. Analytical approach

To examine the effect of detrending climate data on the strength of climate–growth correlations, we tested the difference between the mean absolute value of R–det and the mean absolute value of R–raw (|R–det| vs. |R–raw|; Fig. 2D) using a two–tailed paired sample t–test (Student, 1908). This test, performed for each seasonal climate variable, is a statistical procedure used to determine whether the mean difference between two sets of correlations is significantly different from zero – i.e., whether |R–det| < |R–raw| or |R–det| > |R–raw|. The absolute value of correlations was used so that results could be compared regardless of the sign of the correlation (e.g., positive or negative). To ensure meaningful results, we restricted t–test analyses to climate seasons and variables with at least 30 pairs of |R–det| vs. |R–raw| observations (for number of pairs per climate variable and season t-test see Fig. S2). We excluded about 6 % of all possible pairs from the analysis where a switch in sign from R–raw to R–det was observed. This mostly occurred when R–raw was close to 0. Each t–test analysis was computed for two input datasets, one including all TG series (set A) and one restricted to only TG series of sites where we found a significant ($P < 0.05$) trend in the focal seasonal climate variable (set B). We considered including two additional types of input dataset, one restricted to TG series significantly ($P < 0.05$) correlated with C–raw (set C) and another restricted to TG series not significantly ($P < 0.05$) correlated with C–raw (set D). However, the number of TG series in set C was not sufficient to perform robust t–tests (less than 30 pairs in most cases; Fig. S3) and the set D was similar at 99.2 % to set A (i.e., most TG series did not correlate significantly with raw climate), which resulted in identical t–test results for sets A and D (Fig. S3). In total, we computed 60 t-tests for set A and set B. Their associated $P$ values were so skewed towards very small values (n [< 0.05] = 73) that correction for false discovery rate by the Benjamini and Hochberg (1995) method left their distribution unchanged (Fig. S4). We therefore decided to use uncorrected $P$ values.

To investigate the effect of trends in climate time series on the impact of detrending climate data on climate–growth relationships, we compared the difference |R–det| – |R–raw| against the trend of the focal climate variable for each seasonal climate variable.

### 2.6. Supplementary analysis

We repeated the analysis above with 828 chronologies from the International Tree Ring Data Bank (ITRDB, Zhao et al., 2019) that span the entire 1951–2000 period and climate data extracted from CHELSA (Karger et al., 2017) to investigate whether the effect of detrending climate data on correlation changes is similar when working with mean site chronologies. Here, we focused on the TG–30|C–raw and TG–30|C–30 scenarios. Site chronologies were averaged with Tukey's bi-weight robust mean. We also repeated the analysis covering only the 1971–2000 period to show the effect of treating climate and tree-ring data like-for-like for a shorter period length of 30 years that is commonly used in moving-window analyses. In such shorter periods correlation coefficients are more volatile by nature and climate trends can be stronger.

Modern analytical frameworks such as mixed-effect models usually report regression coefficients instead of correlation coefficients. Therefore, we also report changes in regression coefficients using linear regression before and after detrending climate data. We show this analysis for both individual tree-ring time series (North American NFI data) and mean site chronologies (ITRDB).

## 3. Results

### 3.1. Effect of detrending climate data on the value of climate–growth correlations

#### 3.1.1. Set A – analyses including all TG series

In 28 out of 60 t-tests, detrending climate data significantly strengthened climate–growth correlations (|R–det| > |R–raw|) by 4.2 % on average, relative increases ranging between 0.6 % and 13 % (Fig. 3A). Correlation changes for TG-30 and temperature variables (regardless of season) were stronger and much more consistently positive than for TG100 (Fig. 3A). These patterns held true regardless of the detrending method applied to the climate data (linear or spline detrending) – e.g., results for TG–30|C–lin were similar to those obtained for TG–30|C–30. In 18 out of 60 t-tests, roughly half of which involved temperature variables and half precipitation variables, detrending climate had no impact on climate-growth correlations. No clear pattern emerged regarding the seasonal climate variables and the type of TG- and C-detrending involved. In the remaining 14 out of 60 t-tests, detrending climate data significantly weakened climate-growth correlations (|R–raw| > |R–det|) by 3 % on average, relative decreases ranging between – 0.01 and – 7.6 %. These cases mostly (57 %) involved correlations between TG-100 and previous summer and autumn precipitation variables. However, most of the TG series included in set A did not correlate significantly to raw climate data.

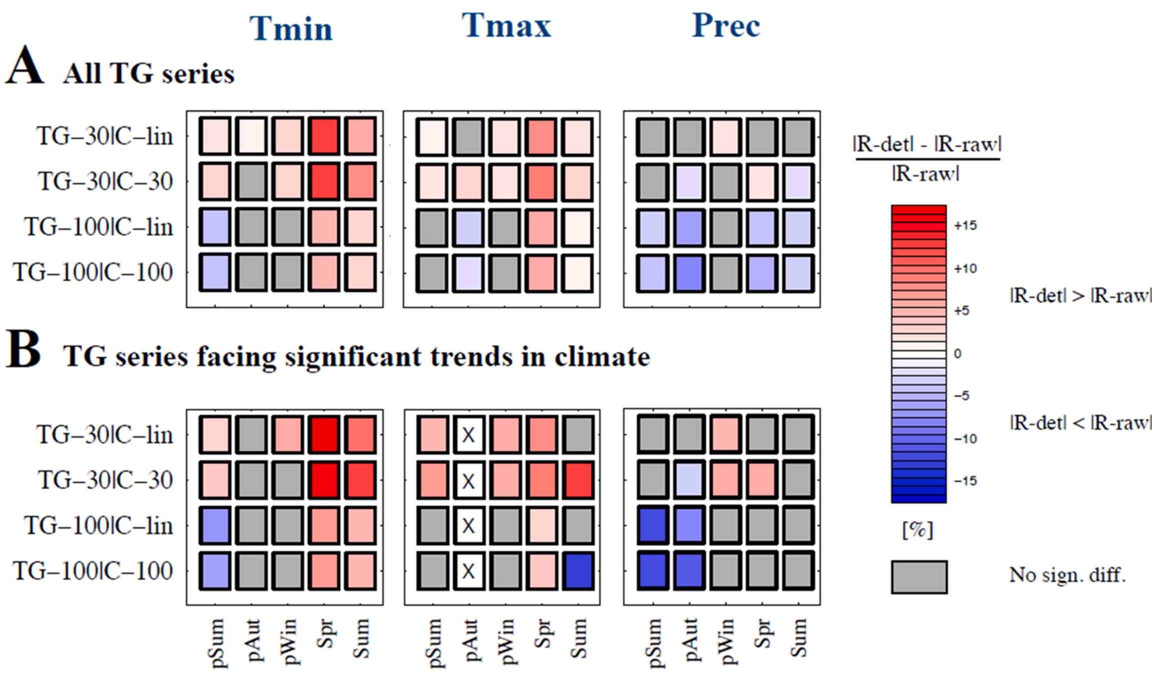


**Fig. 3.** Difference between the mean of |R–det| and the mean of |R–raw| over the 1951–2000 period for different detrending of tree–growth (TG–) and seasonal climate (C–) data. Differences in absolute mean were investigated using two–tailed paired sample t–tests. T–tests were computed for two input datasets: A. all TG series (set A); B. TG series sampled at a site where the seasonal climate in focus shows a significant trend (set B); Red rectangles indicate comparisons with a significantly ($P < 0.05$) higher mean for |R–det| compared to |R–raw|, blue rectangles comparisons with a significantly ($P < 0.05$) higher mean for |R–raw|, and gray rectangles comparisons with a non–significant difference between the two means. White rectangles with a black cross indicate cases for which the t-test could not be computed (less than 30 TG series verifying the selection criterion that is here sampled at sites where trends in previous autumn maximum temperature were significant).

#### 3.1.2. *Set B – analyses restricted to TG series sampled at sites with significant trends in seasonal climate*

TG series sampled at sites with significant trends in the target seasonal climate variable represented 28.4 % of the dataset. We identified 2813, 1342, and 1379 'TG series-season' combinations (out of 6505) of significant trends in Tmin, Tmax, and Prec, respectively. In 25 out of 56 t-tests, detrending did not affect the strength of climate–growth relationships (Fig. 3B). In 23 out of 56 t-tests, detrending significantly strengthened climate-growth correlations (|R–det| > |R–raw|) by 7.4 % on average, relative increases ranged between + 0.1 and + 16.8 %. Similar to Set A, these t-tests mostly included correlations computed between TG–30 and seasonal temperatures (Tmin and Tmax), particularly C-30 (Fig. 3B). These patterns were observed regardless of the detrending method applied to the climate data. In only 8 out of 56 t-tests, detrending climate data significantly weakened climate-growth correlations by 9.9 % on average, relative decreases ranging between 0.3 and − 12.6 %. These t-tests mostly involved correlations based on TG-100 and previous summer and autumn precipitation (Fig. 3B). Lastly, t-tests could not be computed in 4 cases due to a lack of data (less than 30 time series with significant trends in previous autumn Tmax; Fig. S2).

### 3.2. *Link between linear trends in climate and the effects of detrending climate data on climate–growth relationships*

The variance of the |R–det| – |R–raw| differences increased with increasing linear trend in the seasonal climate variable, regardless of the climate variable (Fig. 4), i.e., absolute changes were larger on average with larger climatic trends. This result was more pronounced when a linear (C–lin) or 100–yr spline (C–100) detrending was applied to the climate data (Fig. 4A–C–D). In the C-30 comparison we found notable changes in the correlations in cases without linear trend in the climate time series (Fig. 4B), i.e. there was no wedge-shaped pattern around the origin of the plot as in the other three comparisons (Fig. 4A-C-D). The absolute difference between |R–det| and |R–raw| ranged between − 0.36 and + 0.27, with extreme values of − 0.2 and + 0.2 found for almost all climate variables and seasons (Fig. 4).

All presented observed effects and results using individual tree time series are supported by the re-analysis using mean site chronologies of the ITRDB (Fig. S5). The general pattern, as well as the magnitude of maximum changes for Tmin (+0.20), Tmax (+0.13), and precipitation (+0.10), are indistinguishable from the pattern shown in Fig. 4B.

The effect of detrending climate data on correlations using a shorter period of 30 years results in an even more pronounced pattern of correlation changes (Fig. S6), with a stronger fanning out with increasing trends in the climate data and stronger correlation changes.

Our analysis of changes of regression coefficients shows a strong positive linear relationship with the changes in correlation coefficients (Figs. S7, S8). However, and more interestingly, there is a significant positive offset (all intercepts $p < 0.05$). This means that even in the absence of correlation changes absolute regression coefficients systematically increase after detrending climate data. Therefore, not detrending climate data likely leads to an underestimation of climate impacts on tree growth.

## 4. Discussion

We investigated the effects of detrending climate data on climate–-growth relationships for conifer trees growing in Canada and the Western US as well as for site chronologies of the ITRDB from across the globe. In the context of accelerating climate change, our results highlight that the detrending of climate time series can significantly influence the strength of inferred TG response to climate. This influence: (i) is mainly observed for temperature variables and is positive, but shows slightly negative effects with precipitation (Fig. 3), (ii) is more common when tree-ring series are detrended with a flexible 30-year spline

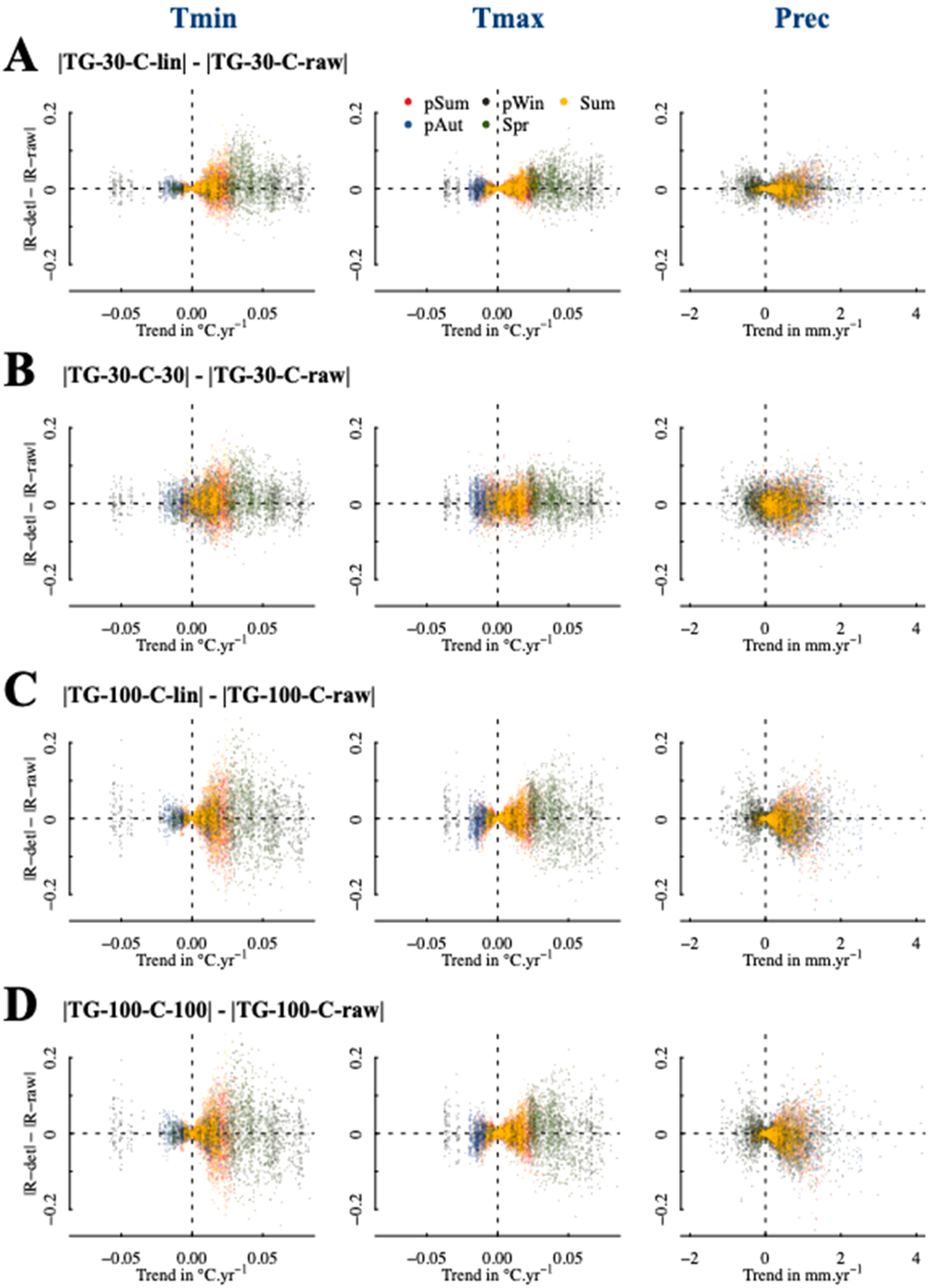


**Fig. 4.** Difference between |R–det| and |R–raw| as *a* function of trends in local seasonal climate over the 1951–2000 period. The differences are displayed for different detrending procedures on tree–growth (TG–) and climate (C–) time series. Climate variables tested include average seasonal minimum and maximum temperatures (Tmin and Tmax) and precipitation sums (Prec). Results for different climate seasons are indicated by different colors and seasons span from previous year summer through current year summer. Cases where R–det and R–raw differed in sign were excluded from analyses.

(Fig. 3), and (iii) generally increases in variability and magnitude with stronger linear trends in climate (Fig. 4).

The observed greater sensitivity to detrended temperature time series was most pronounced for current year spring and summer variables (Fig. 3). This was particularly true when TG series were detrended with a 30-yr spline, i.e., a detrending method removing any low frequency and hence longer-term trends (Fig. 3A, Fig. 4A-B) and emphasizes that high–frequency ring–width variability is better explained by high–pass filtered climate data (Fritts, 1976; Fritts and Lough, 1985; Lyon, 1936). Given that our TG series were on average 93 years long (101 and 90 years in Canada and the Western US, respectively), a 30–yr spline may be more appropriate for approximating age effects on radial tree growth (Cook, 1985). In comparison, a spline with a cut–off at 100 years may be too stiff, so that ontogenetic effects as well as other disturbances (such as stand dynamics) may still be present and can potentially distort climate–growth relationships.

We reported a systematic strengthening of correlation coefficients for temperature variables, yet we observed a rather stable-to-weakened sensitivity of tree–ring indices to detrended seasonal precipitation variables – in comparison to their sensitivity to raw precipitation time series (Fig. 3). This might seem somewhat surprising given that tree growth at high latitudes has been reported to be increasingly driven by soil moisture conditions (Babst et al., 2019; Choat et al., 2012; Trahan and Schubert, 2016). However, precipitation time series generally have strong interannual variability and weak-to-no linear trend, so that high–pass filtering might have little impact on the strength of climate–growth correlations. A decrease in absolute correlation after detrending climate time series (Figs. 3 and 4) can also point to spuriously high correlations that were initially amplified by common trends or shared lower frequency variability in the absence of an actual meaningful relationship between climate and growth at the inter-annual time scale. Another strategy to safeguard against spurious correlations, which is commonly applied in dendrochronological climate reconstructions, is to take first-differences or apply other high-pass filter techniques to both tree-ring and climate time series (e.g., Buckley et al., 2018; D'Arrigo et al., 2015). Ultimately, climate-growth correlations should be very similar whether the analysis is performed with both high-pass filtered TG and climate data, or with raw climate data and TG data that were detrended to contain the full spectrum of high- to low-frequency variability.

Using a large-scale dendroecological dataset, we showed that the stronger the trend in climate data, the greater variability in the difference between the strength of climate correlations using detrended vs. raw climate data (Fig. 4). The pattern and magnitude are supported by additional analyses using site chronologies of the ITRDB (Fig. S5). In a controlled setting using simulated time series, Klesse (2021) also revealed a negative effect of increasing trends in climate data on correlations with spline-detrended TG series, when climate data are not detrended. Both these examples underline the importance of detrending climate data prior to climate-growth analyses. This becomes particularly important for the frequently applied moving-window analyses (e.g., Wilmking et al., 2020) that use 30-year or even shorter periods to investigate temporal stability in climate-growth responses. Trend distortions on correlation coefficients are much more pronounced in such short periods (Fig. S6) and if not properly accounted for likely influence results and interpretations of these type of analyses. Even though the effect of the two detrending procedures applied on climate data (linear vs. spline) in our study was quite similar for a given detrending procedure for TG data (Fig. 3A), we strongly recommend, as a rule, using the same detrending for climate and TG data, especially when TG series are detrended with a flexible cubic smoothing spline, as is commonly done in dendrochronological literature (Klesse, 2021). Splines are tools derived from time–series analysis and should be treated as mathematical functions removing desired wavelengths from time series (not biological age or size trends in the series). Following time–series analysis theory (Shumway, 1988), if TG and climate data are to be detrended with splines, these splines must have the same characteristics (i.e., retain, dampen, and remove similar frequency domains) to avoid interfering with the estimation of climate–growth relationships. We illustrate this in Fig. S9 and show that in the presence of lower frequency variability in the climate time series, correlations with tree growth are lower with increasing difference in the flexibility of the detrending method of the growth time series and climate time series. The biggest differences in absolute correlations in our hypothetical example (Fig. S9) are of the same order of magnitude as in our observations with |R-det| - |R-raw| $\geq$ 0.2 (Fig. 4), which is considerable given commonly reported climate-growth correlations.

The reason the differences between TG-100|C-lin and TG-100|C-100 are relatively small, is that on a 50-year time scale the 100-yr spline almost behaves like a straight line and removes less than ~10 % variability on the wavelength of 50 years (cf. Fig. 3.6 in Cook and Kairiukstis, 1990) in addition to the linear trend. The longer the climate time series and the analyzed period, the larger the potential differences between a straight linear fit and a 100-yr spline will become, and hence differences in |R-raw| and |R-det| between those two methods will also increase.

Detrending climate time series that do not contain a linear trend over the study period (i.e., |trend| < 0.001 °C.yr$^{-1}$ or < 0.01 mm.yr$^{-1}$) with a linear method did not alter climate–growth correlations (|R–det| – |R–raw| ranging between –3.57 $\times 10^{-3}$ and +3.45 $\times 10^{-3}$; Fig. 4A & C). Detrending the same trend-free climate time series with a 30–yr spline, however, will dampen some of its remaining "mid–frequency" variability (c.f. Fig. S9D). The 30-yr spline removes all variability of wavelengths longer than 90 years, dampens 30–yr frequencies by half, and preserves full variability at 10 years. Any variability on the wavelength of 50 years will be dampened by ~90 %, whereas the 100-yr spline only dampens about 10 % of variability on this wavelength (Cook and Kairiukstis, 1990). This likely is why in the TG-30-C-30 scenario changes in climate–growth correlation coefficients varied considerably (|R–det| – |R–raw| ranging between –0.112 and +0.112; Fig. 4B) even without any climate trend, and the effects of climate data detrending appear to be more homogeneous along the gradient of climate trends. However, even without a change in correlation coefficients, the effect on regression coefficient is systematically positive (Figs. S7, S8) leading to an underestimation of the true impact of climate on growth. This is logical, because high-pass filtering almost always decreases the standard deviation of a time series, thereby increasing the product of cor(climate, growth) and sd(growth)/sd(climate), which is the equivalent notation of the simple linear regression coefficient.

The climate data we used contained little autocorrelation and therefore did not need prewhitening. Future studies that work with other climate variables that contain possibly higher levels of autocorrelation, such as the Palmer Drought Severity Index (PDSI) (Katz and Skaggs, 1981), should also test how the prewhitening of climate data influences climate-growth correlations. Analyses conducted on time series having significant first order autocorrelation will necessarily violate assumptions of independence of samples when determining the significance of relationships. Further, it would be valuable to investigate the impact of detrending climate data on climate–growth relationships for other climate–sensitive wood characteristics such as annual and intra–annual tree–ring density, lumen size, and stable isotope ratios (see for instance Briffa et al., 2004; D'Arrigo et al., 1992; Kirdyanov et al., 2003).

## 5. Conclusion

Our analyses suggest that detrending climate data should be more broadly applied in dendroecology. This study based on individual tree ring-width time series from North American NFIs as well as site mean chronologies from the ITRDB indicated that we can expect a slight strengthening of correlations primarily for temperature comparisons and less so for precipitation. Our results corroborate recent theoretical work (Klesse, 2021) showing the stronger the trend in the climate data the larger the possible effect of detrending both time series equally. The rationale for detrending climate data is not new (1930s) but seems to have been largely ignored (Appendix A). Thus, the relevance of detrending climate data is increasingly clear in a time of rapidly changing climate (set A vs set B), particularly when tree-ring data are treated with a flexible detrending method.

## Declaration of Competing Interest

The authors declare no conflict of interest.

## Data availability

Data will be made available on request.

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## Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.dendro.2023.126094.

## References

Babst, F., Bouriaud, O., Poulter, B., Trouet, V., Girardin, M.P., Frank, D.C., 2019. Twentieth century redistribution in climatic drivers of global tree growth. Sci. Adv. 5, eaat4313 https://doi.org/10.1126/sciadv.aat4313.

Battipaglia, G., De Micco, V., Gärtner, H., 2020. Most recent trends in tree-ring sciences: from local to global, from molecule to forest stands, from days to millennia. - Editorial to the special issue "TRACE 2019". Dendrochronologia 63, 125758. https://doi.org/10.1016/j.dendro.2020.125758.

Beck, P.S.A., Juday, G.P., Alix, C., Barber, V.A., Winslow, S.E., Sousa, E.E., Heiser, P., Herriges, J.D., Goetz, S.J., 2011. Changes in forest productivity across Alaska consistent with biome shift. Ecol. Lett. 14, 373–379. https://doi.org/10.1111/j.1461-0248.2011.01598.x.

Benjamini, Y., Hochberg, Y., 1995. Controlling the false discovery rate: a practical and powerful approach to multiple testing. J. R. Stat. Soc. Ser. B Methodol. 57, 289–300. https://doi.org/10.1111/j.2517-6161.1995.tb02031.x.

Briffa, K.R., Osborn, T.J., Schweingruber, F.H., 2004. Large-scale temperature inferences from tree rings: a review. Glob. Planet. Change, Glob. Clim. Chang. Late Quat. 40, 11–26. https://doi.org/10.1016/S0921-8181(03)00095-X.

Buckley, B.M., Hansen, K.G., Griffin, K.L., Schmiege, S., Oelkers, R., D'Arrigo, R.D., Stahle, D.K., Davi, N., Nguyen, T.Q.T., Le, C.N., Wilson, R.J.S., 2018. Blue intensity from a tropical conifer's annual rings for climate reconstruction: an ecophysiological perspective. Dendrochronologia 50, 10–22. https://doi.org/10.1016/j.dendro.2018.04.003.

Bunn, A.G., 2008. A dendrochronology program library in R (dplR. Dendrochronologia 26, 115–124. https://doi.org/10.1016/j.dendro.2008.01.002.

Charney, N.D., Babst, F., Poulter, B., Record, S., Trouet, V.M., Frank, D., Enquist, B.J., Evans, M.E.K., 2016. Observed forest sensitivity to climate implies large changes in 21st century North American forest growth. Ecol. Lett. 19, 1119–1128. https://doi.org/10.1111/ele.12650.

Charru, M., Seynave, I., Hervé, J.-C., Bertrand, R., Bontemps, J.-D., 2017. Recent growth changes in Western European forests are driven by climate warming and structured across tree species climatic habitats. Ann. For. Sci. 74, 1–34. https://doi.org/10.1007/s13595-017-0626-1.

Choat, B., Jansen, S., Brodribb, T.J., Cochard, H., Delzon, S., Bhaskar, R., Bucci, S.J., Feild, T.S., Gleason, S.M., Hacke, U.G., Jacobsen, A.L., Lens, F., Maherali, H., Martínez-Vilalta, J., Mayr, S., Mencuccini, M., Mitchell, P.J., Nardini, A., Pittermann, J., Pratt, R.B., Sperry, J.S., Westoby, M., Wright, I.J., Zanne, A.E., 2012. Global convergence in the vulnerability of forests to drought. Nature 491, 752–755. https://doi.org/10.1038/nature11688.

Cook, E.R., 1987. The decomposition of tree-rings series for environmental studies. Tree Ring Bull. 47, 37–59.

Cook, E.R., Peters, K., 1981. The smoothing spline a new approach to standardizing forest interior tree-ring width series for dendroclimatic studies. Tree Ring Bull. 41, 45–53.

Cook, E.R., Kairiukstis, L.A., 1990. Methods of Dendrochronology - Applications in the Environmental Sciences, first ed. Springer, Netherlands.

Cook, E.R., 1985. A Time Series Analysis Approach to Tree Ring Standardization, University of Arizona, School of Renewable Natural Resources.

D'Arrigo, R., Wilson, R., Wiles, G., Anchukaitis, K., Solomina, O., Davi, N., Deser, C., Dolgova, E., 2015. Tree-ring reconstructed temperature index for coastal northern Japan: implications for western North Pacific variability. Int. J. Climatol. 35, 3713–3720. https://doi.org/10.1002/joc.4230.

D'Arrigo, R.D., Jacoby, G.C., Free, R.M., 1992. Tree-ring width and maximum latewood density at the North American tree line: parameters of climatic change. Can. J. . Res. 22, 1290–1296. https://doi.org/10.1139/x92-171.

DeRose, R.J., Shaw, J.D., Long, J.N., 2017. Building the forest inventory and analysis tree-ring data set. J. For. 115, 283–291. https://doi.org/10.5849/jof.15-097.

Eckstein, D., Schweingruber, F., 2009. Dendrochronologia—a mirror for 25 years of tree-ring research and a sensor for promising topics. Special Section: 25 year anniversary of the italian institute of dendrocronologia. Dendrochronologia 27, 7–13. https://doi.org/10.1016/j.dendro.2009.01.001.

Evans, M.E.K., DeRose, R.J., Klesse, S., Girardin, M.P., Heilman, K.A., Alexander, M.R., Arsenault, A., Babst, F., Bouchard, M., Cahoon, S.M.P., Campbell, E.M., Dietze, M., Duchesne, L., Frank, D.C., Giebink, C.L., Gómez-Guerrero, A., García, G.G., Hogg, E. H., Metsaranta, J., Ols, C., Rayback, S.A., Reid, A., Ricker, M., Schaberg, P.G., Shaw, J.D., Sullivan, P.F., GaytÁn, S.A.V., 2022. Adding tree rings to North America's national forest inventories: an essential tool to guide drawdown of atmospheric $CO_2$. BioScience 72, 233–246. https://doi.org/10.1093/biosci/biab119.

Fritts, H.C., 1976. Tree Rings and Climate, first ed. Academic Press, London.

Fritts, H.C., Lough, J.M., 1985. An estimate of average annual temperature variations for North America, 1602 to 1961. Clim. Change 7, 203–224. https://doi.org/10.1007/BF00140506.

Girardin, M.P., Guo, X.J., Metsaranta, J., Gervais, D., Campbell, E., Arsenault, A., Isaac-Renton, M., Harvey, J.E., Bhatti, J., Hogg, E.H., 2021. A national tree-ring data repository for Canadian forests (CFS-TRenD): structure, synthesis, and applications. Environ. Rev. 29, 225–241. https://doi.org/10.1139/er-2020-0099.

Girardin, M.P., Bouriaud, O., Hogg, E.H., Kurz, W., Zimmermann, N.E., Metsaranta, J.M., de Jong, R., Frank, D.C., Esper, J., Büntgen, U., Guo, X.J., Bhatti, J., 2016. No growth stimulation of Canada's boreal forest under half-century of combined warming and $CO_2$ fertilization. Proc. Natl. Acad. Sci. USA 113, E8406–E8414. https://doi.org/10.1073/pnas.1610156113.

Hellmann, L., Agafonov, L., Ljungqvist, F.C., Churakova (Sidorova), O., Düthorn, E., Esper, J., Hülsmann, L., Kirdyanov, A.V., Moiseev, P., Myglan, V.S., Nikolaev, A.N., Reinig, F., Schweingruber, F.H., Solomina, O., Tegel, W., Büntgen, U., 2016. Diverse growth trends and climate responses across Eurasia's boreal forest. Environ. Res. Lett. 11, 074021 https://doi.org/10.1088/1748-9326/11/7/074021.

Holmes, R.L., Adams, R.K., Fritts, H.C., 1986. Tree-ring chronologies of Western North America: California, Eastern Oregon and Northern Great Basin with procedures used in the chronology development work including users manuals for computer programs COFECHA and ARSTAN,Natural History Reports, Laboratory of Tree-Ring Research, University of Arizona, Tucson, AZ.

IPCC, 2021. Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press.

Karger, D.N., Conrad, O., Böhner, J., Kawohl, T., Kreft, H., Soria-Auza, R.W., Zimmermann, N.E., Linder, H.P., Kessler, M., 2017. Climatologies at high resolution for the earth's land surface areas. Sci. Data 4, 170122. https://doi.org/10.1038/sdata.2017.122.

Katz, R.W., Skaggs, R.H., 1981. On the use of autoregressive-moving average processes to model meteorological time series. Mon. Weather Rev. 109, 479–484. https://doi.org/10.1175/1520-0493(1981)109<0479:OTUOAM>2.0.CO;2.

Kirdyanov, A., Hughes, M., Vaganov, E., Schweingruber, F., Silkin, P., 2003. The importance of early summer temperature and date of snow melt for tree growth in the Siberian Subarctic. Trees 17, 61–69. https://doi.org/10.1007/s00468-002-0209-z.

Klesse, S., 2021. Critical note on the application of the "two-third" spline. Dendrochronologia 65, 125786. https://doi.org/10.1016/j.dendro.2020.125786.

Klesse, S., DeRose, R.J., Guiterman, C.H., Lynch, A.M., O'Connor, C.D., Shaw, J.D., Evans, M.E.K., 2018. Sampling bias overestimates climate change impacts on forest growth in the southwestern United States. Nat. Commun. 9, 5336. https://doi.org/10.1038/s41467-018-07800-y.

Larsson, L., 2013. CooRecorder and Cdendro Programs of the CooRecorder/Cdendro Package.

Lyon, C.J., 1936. Tree ring width as an index of physiological dryness in New England. Ecology 17, 457–478. https://doi.org/10.2307/1931846.
McKenney, D.W., Hutchinson, M.F., Papadopol, P., Lawrence, K., Pedlar, J., Campbell, K., Milewska, E., Hopkinson, R.F., Price, D., Owen, T., 2011. Customized spatial climate models for North America. Bull. Am. Meteorol. Soc. 92, 1611–1622. https://doi.org/10.1175/2011BAMS3132.1.
McRoberts, R.E., Bechtold, W.A., Patterson, P.L., Scott, C.T., Reams, G.A., 2005. The enhanced forest inventory and analysis program of the USDA forest service: historical perspective and announcements of statistical documentation. J. For. 3, 304–308.
Melvin, T.M., Briffa, K.R., 2008. A "signal-free" approach to dendroclimatic standardisation. Dendrochronologia 26, 71–86. https://doi.org/10.1016/j.dendro.2007.12.001.
Mérian, P., Pierrat, J.-C., Lebourgeois, F., 2013. Effect of sampling effort on the regional chronology statistics and climate–growth relationships estimation. Dendrochronologia 31, 58–67. https://doi.org/10.1016/j.dendro.2012.07.001.
Natural Resources Canada, 2008. Canada's National Forest Inventory Ground Sampling Guidelines: Specifications for Ongoing Measurement.
Nehrbass-Ahles, C., Babst, F., Klesse, S., Nötzli, M., Bouriaud, O., Neukom, R., Dobbertin, M., Frank, D., 2014. The influence of sampling design on tree-ring-based quantification of forest growth. Glob. Change Biol. 20, 2867–2885. https://doi.org/10.1111/gcb.12599.
Ols, C., Gschwantner, T., Schadauer, K., Bontemps, J.-D., 2022. Unexpected negative effect of available water capacity detected on recent conifer forest growth trends across wide environmental gradients. Ecosystems 25, 404–421. https://doi.org/10.1007/s10021-021-00663-3.
Olson, D.M., Dinerstein, E., Wikramanayake, E.D., Burgess, N.D., Powell, G.V.N., Underwood, E.C., D'amico, J.A., Itoua, I., Strand, H.E., Morrison, J.C., Loucks, C.J., Allnutt, T.F., Ricketts, T.H., Kura, Y., Lamoreux, J.F., Wettengel, W.W., Hedao, P., Kassem, K.R., 2001. Terrestrial ecoregions of the world: a new map of life on earth: a new global map of terrestrial ecoregions provides an innovative tool for conserving biodiversity. BioScience 51, 933–938. https://doi.org/10.1641/0006-3568(2001)051[0933:TEOTWA]2.0.CO;2.
R Core Teams, 2015. R: a Language and Environment for Statistical Computing.
Shumway, R.H., 1988. Applied Statistical Time Series Analysis. Prentice Hall, New Jersey.
Student, 1908. The probable error of a mean. Biometrika 6, 1–25. https://doi.org/10.2307/2331554.
Trahan, M.W., Schubert, B.A., 2016. Temperature-induced water stress in high-latitude forests in response to natural and anthropogenic warming. Glob. Change Biol. 22, 782–791. https://doi.org/10.1111/gcb.13121.
Wilmking, M., Maaten-Theunissen, M., van der, Maaten, E., van der, Scharnweber, T., Buras, A., Biermann, C., Gurskaya, M., Hallinger, M., Lange, J., Shetti, R., Smiljanic, M., Trouillier, M., 2020. Global assessment of relationships between climate and tree growth. Glob. Change Biol. N./a. https://doi.org/10.1111/gcb.15057.
World Meteorological Organization, 2019. Statement on the State of the Global Climate in 2018 (No. 1233), Geneva, Switzerland.
World Meteorological Organization, 2020. Provisional Statement of the State of the Climate 2019, Geneva, Switzerland.
Yamaguchi, D.K., 1991. A simple method for cross-dating increment cores from living trees. Can. J. For. Res. 21, 414–416. https://doi.org/10.1139/x91-053.
Zhao, S., Pederson, N., D'Orangeville, L., HilleRisLambers, J., Boose, E., Penone, C., Bauer, B., Jiang, Y., Manzanedo, R.D., 2019. The International Tree-Ring Data Bank (ITRDB) revisited: Data availability and global ecological representativity. J. Biogeogr. 46, 355–368. https://doi.org/10.1111/jbi.13488.