Critical note on the application of the “two-third” spline

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1. Introduction

Detrending is inherent to the dendrochronology discipline. Removal of the age trend in ring widths is standard practice and a required procedure prior to any statistical analysis to infer climate-growth relationships. There are three general approaches how to detrend ring-width measurements, neither of which is better or worse than the other two approaches per se. It always depends on the research question and the tree-ring material:

The first way to detrend is following a deterministic approach (Cook and Kairiukstis, 1990). Here, a data-adaptive mathematical function with a predefined shape is fit to each ring-width series individually, i.e. each tree-ring series is detrended with its own unique growth model. The most commonly used deterministic growth trend models are the modified negative exponential curve, and the generalized negative exponential “Hugershoff” curve. These growth models fit a monotonic decreasing or unimodal curve to the ring-width series and are typically used to detrend open-canopy stands with undisturbed trees. To overcome the so-called segment length curse, i.e. low-frequency climate variability cannot be investigated on time-scales longer than the segment lengths of the studied tree-ring series (Cook et al., 1995), one can follow the biological approach, i.e. regional curve standardization (RCS; Briffa et al., 1992a; Briffa and Melvin, 2011; Esper et al., 2003). In RCS all tree-ring series are first aligned according to their biological age and a mean growth curve is determined. Each individual tree-ring series will then be detrended by this one biological growth model, the regional curve. In a final step the time series are re-aligned to their calendar dates. Through systematic (temporally clustered) over- or under-estimating of the actual growth values the resulting mean chronology is now capable of resolving lower frequencies that a deterministic approach would not be able to retain.

The third approach is stochastic detrending. Here, digital filters are used for curve fitting. The most commonly used filter is a cubic smoothing spline with a known frequency cutoff at a given frequency. Splines were introduced to dendrochronology to detrend tree-ring series from closed-canopy forests that do not follow a monotonic decreasing trend of open-canopy grown trees but that are affected by stand competition and disturbance pulses (Cook and Peters, 1981). “At that time, Cook was concerned that an artificial frequency distribution might be induced by using splines of the same stiffness for initial detrending of..."
the ring-width series. For this reason and in order to leave more low frequency in the long series, Cook and Holmes decided to express spline stiffness as a percent of series length rather than by a fixed stiffness” (Holmes et al., 1986). Cook (1985) argued that a good stiffness is a spline with a 50% frequency cutoff at two-thirds (to three-quarters) of an individual series. Setting the 50% frequency cutoff to $n/N$ of an individual series length is based on the “trend in mean” concept by Granger (1966) where the lowest resolvable frequency cycle from a trend in a series equals $1/N$, with $N$ being the series length. Variability at lower frequencies (< $1/N$) may appear as a trend because the cycle is incomplete (Cook, 1985). The two-third option (2/3S) thus seemed like a good trade-off between keeping as much low frequency in a tree-ring series as possible, while ensuring that the age trend operating on the frequency $1/N$ is adequately dealt with (Cook & Kairiukstis, 1990).

The first prominently application of the 2/3S was the climate reconstructions of Scandinavia (Briffa et al., 1990) and Western North America (Briffa et al., 1992b) With the integration of the Dendrochronology Program Library into the R environment decades later (dplR, Bunn, 2008) the 2/3S was set as the default for detrending with a cubic smoothing spline. Since 2017, 160 tree-ring publications applied this detrending (as of July 31st 2019), which is 32% of all publications (160 out of 505) that used a cubic smoothing spline for detrending. Another 34% applied a spline with a 50% frequency cutoff at 30 years or lower (i.e. a 30-year or more flexible spline). 23% used splines stiffer than 30 years, (12%: 40–90 years, 7%: ~100–130 years, 4%: >130 years), and 6% applied age-dependent spline smoothing (Melvin et al., 2007). In 9% of the publications the stiffness of the cubic smoothing spline, was not reported. Some publications used multiple spline rigidities. Of the publications that used the 2/3S detrending 34% reconstructed a climate parameter, and 63% performed some sort of ecological analyses, either on different groups during the 20th century or a common period (46%), or investigating climate-growth relationships on one chronology (17%). 3% were archeological publications. In 41% of the 2/3S publications the ring-width series were pre-whitened before further analysis and 12% of those re-introduced the pooled auto-correlation to the final chronologies (using the ARSTAN chronology). I performed this meta-analysis in Google Scholar using the search terms (“tree-ring” OR “tree ring”) AND “spline”.  

The 2/3S is a reasonable and good starting point to detrend an individual series. But on closer inspection in a standard dendrochronological setting it seems less optimal. First, the 2/3S method runs counter to one of the key strengths of the spline detrending approach. When detrending with a cubic smoothing spline, one has full control over the frequency-removing characteristics of the detrending curve for each individual series. Choosing a cubic smoothing spline with a 50% frequency cutoff at $n$ years, one knows exactly that the original variability at a frequency of $n$ years is reduced by 50%, that there is no variability left at frequencies greater than $\sim3n$, and that only the variability in the frequency domain approximately $<1/3n$ years remains unchanged from the raw tree-ring series (Cook and Peters, 1981). Making the spline stiffness dependent on the dataset characteristics, i.e. applying a different stiffness to each individual according to its segment length, gives away this control. Furthermore, when choosing the spline-detrending approach one does not assume a general shape of the growth curve, as assumed in the deterministic and biological detrending approaches, but treats the possible growth curve shape as a purely stochastic and frequency-based function of the ring widths. From a time-series analysis point of view it is seems problematic to choose different filters for different individuals, to use a stiffer filter for a tree-ring sample with many rings compared to the filter for a sample with fewer rings.

Second, applying the 2/3S method to a tree-ring dataset with samples from living trees with varying ages will introduce a temporal frequency bias within a chronology. The oldest and longest samples forming the early part of the resulting chronology are detrended with a stiffer spline (retaining more low frequency) compared to the most recent end of the chronology, where the youngest and shortest samples are detrended with a more flexible spline that removes more low frequency. It is to be mentioned that auto-regressive modeling (“pre-whitening”) and the re-introduction of pooled auto-correlation circumvents the introduction of a temporal frequency bias. This segment length-dependent bias was hinted at in Briffa et al. (1992b) and Cook (1985) already wrote about this potential problem in his discussion: “A drawback of the 2/3S criterion is the way in which shorter series will have less resolvable long-period variance compared to longer series. This problem is implicit when detrending any ensemble containing variable length series. On this basis, it is desirable that the minimum length in a tree-ring ensemble be a large fraction of the maximum or useful length of the final chronology.” During the development of his tree-ring network in the eastern United States it was thus required that all tree-ring series go back to at least 1800, and the oldest samples date back to at least 1700 (the oldest ones rarely dating back further than ~1630; Cook, personal communication).

A similar problem exists when the two-third spline detrending is applied to multiple groups with varying mean segment lengths. A subsequent analysis (climate-growth correlation or regression) will be influenced by this frequency bias (as already pointed out e.g. in Cailleret et al., 2019). The 2/3S spelled out means to detrend e.g. group A with a ~120-year spline, group B with a ~80-year spline, and group C with a ~40-year spline and subsequently try to make inferences on e.g. climate-growth relationships and differences between three groups that have potentially vastly different low frequency characteristics influencing regression and correlation coefficients. Again, pre-whitening will remove any persistence in the data and thus also low frequency differences (Cook, 1985). However, re-introducing group-specific pooled auto-correlation here also re-introduces different auto-correlation structures, thus low-frequency characteristics.

In this study I will visualize the impact of this temporal frequency bias on chronologies and common dendrochronological analyses with the help of artificial data with known frequencies and amplitudes. In the first part I will show the impact of the 2/3S detrending within a dataset that might be used to reconstruct climate. In the second part I will show the impact of the 2/3S detrending when analyzing climate-growth relationships of different groups with different mean segment lengths. In the third part I will use publicly available tree-ring data as well as the data structure of the above-mentioned meta-analysis to provide a quantification how much these two biases potentially influence real world datasets and potentially have influenced results of publications.

2. Material and methods

2.1. Part 1: Frequency bias within a chronology affecting climate reconstructions

2.1.1. Artificial climate data

I generated sine waves with a mean of 0 and an amplitude of 0.05 and wavelengths of 200, 100, 30, and 10 years, respectively and added normal distributed white noise with a mean of 1 and standard deviation of 0.1 (Fig. 1). I repeated this process 200 times, where the initial position of each sine wave is randomized. For the remainder of the manuscript these repetitions will be referred to as climate runs.

2.1.2. Artificial ring-width data

To obtain realistic growth shapes I defined for each series a modified negative exponential curve or straight line based on individual Douglas-fir ring-width series of the International Tree-Ring Data Bank (>10,000 series). I generated growth curves for all segment lengths between 30 and 600 years for each year between 1400 and 1970. Those series were multiplied with the artificial climate time series.

The series were subsequently detrended via division with the dplR package in R using a cubic smoothing spline with a 50% frequency response cutoff at 300, 200, and 100 years, respectively, and a spline
where the 50% frequency response cutoff was equal to two thirds of each segment length (i.e. the 2/3S detrending, Fig. 2, Bunn et al., 2019).

2.1.3. Ring-width sampling

To mimic real dendrochronological sampling scenarios, I resampled 100 ring-width time series following a gamma distribution with a mean of 200 and standard deviation (SD) of 100, 200, and 300 years. The minimum and maximum age sampled were set to 100 and 600 years, respectively. The standard deviation of 100 imposes a right-skewed distribution with the majority of samples entering the chronology between 1800 and 1900, whereas the wider standard deviations have a more equal sample distribution over time (Fig. 3). For each climate run I

Fig. 1. Exemplary decomposed (a) and composite (b) climate run.

Fig. 2. a), d) and g) Three exemplary growth curves of 500-, 300- and 120-year long ring-width series (dashed black line) with multiplied climate signal (grey line). Overlaid are the growth models inferred from the 2/3S (dark blue), 300-y spline (light blue), 200-y spline (yellow) and 100-y spline (brown). b), e), and h) show the residuals between the spline detrending curves and the original growth curve. c), f) and i) show the effect of correctly tracking or mis-fitting the growth curve on the resulting ring-width indexes. In the central panel the 2/3S and 200-year spline are effectively the same. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).
repeated each sampling scenario 100 times. Mean chronologies were calculated with Tukey’s biweight robust mean. Because there is essentially no noise in the ring-width data (\( r_{bar} > 0.90 \) in all detrending options) no variance stabilization with decreasing sample size is needed (Frank et al., 2007), which could – depending on the exact method chosen – also influence the results. The different sampling scenarios impose different effective chronology lengths. In the scenario with a standard deviation of 100-years (100SD) all iterations have a sample replication of five. The dashed (dotted) vertical lines show where the 200- and 300-year SD subsampling scenario reach sample replication of 5.

**2.1.4. Statistical analysis**

The main purpose of the following tests is to show the influence of the four different detrending options on recoverable low frequencies of the original climate signal, as well as to show the temporal stability of the low-frequency amplitude and correlation.

First, I bandpass-filtered the composite climate series and ring-width chronologies by fitting cubic smoothing splines with a 50% frequency cutoff at 90 and 110, and 190 and 210 years, respectively. The former isolates variability in the 100-year frequency domain, the latter in the 200-year frequency domain. Then I calculated running standard deviations (SD) over a window length of 100 and 200 years, respectively, shifted by one year on both filtered time series. The obtained series reflect variability on the two chosen time scales. In a last step I divided the resulting ring-width variability by the climate variability. The resulting amplitude (or more correct: SD) ratio shows how much of the original standard deviation of the climate signal was retained by the detrending procedure. In the best case the ratio stays stable over time.

Additionally, I investigated the spectral coherence between the climate and tree-ring series with the mtm.coh function of the R package multitaper (Rahim, 2014). Magnitude Squared Coherence reports the common variance between two time series through a linear relation at given power spectra estimates (Thomson, 1982). Here, I also chose 200-year window lengths offset by 25 years and specifically looked at the coherence in the 200-, 100-, 30- and 10-year frequency spectra. The first analyzed period is 1525–1724 and the last period is 1800–1999.

**2.2. Part 2: Frequency bias during the climate calibration period**

The same climate runs and tree-ring series were used as described above. Artificial ring-width series were detrended only with the 2/3S. I subsampled the population with mean ages of 3/2-\( x \) years, a standard deviation of 1/3\( x \) and a minimum age of \( x \) years, where \( x \) and thus the effective spline stiffness during the analysis period was 30, 40, 50, 60, 70, 80, and 90 years, respectively. I performed linear regression of the seven groups to the original climate series over the 1950–1999 period, i. e. the common period of all groups, mimicking classic climate-growth relationship analyses. To investigate differences in regression slopes between the seven spline groups I used the Tukey HSD (Honestly Significant Difference) test on the median regression slopes and correlation coefficients between and within the 200 climate runs. I also tested if a trend in the climate data has an effect on overall regression slopes and differences between groups.

**2.3. Part 3: Actual tree-ring data**

I used 4545 publicly ring-width datasets from the International Tree Ring Data Bank (ITRDB, https://www.ncdc.noaa.gov/paleo-search), from Babst et al. (2013) and Klesse et al. (2018, both: https://www.bgc-jena.mpg.de/geodb/projects/Data.php) to investigate how the 2/3S affects the temporal frequency bias in average tree-ring datasets. Therefore, each dataset was detrended using the standard 2/3S setting, as well as with a fixed spline at 2/3 of the median segment length. I calculated the spline ratio by dividing the median segment length in a given year by the overall median segment length and smoothed the ratio by a running mean with a 200-year window, respectively. I used the same bandpass filtering settings as described in part 1 to calculate amplitude ratios between the 2/3S and fixed spline detrended chronologies in the 200-year spectrum. I then applied a mixed-effects model using the lme4 package (Bates et al., 2015) to explain the amplitude ratio:

\[
\log(AR_{st}) \sim \beta_0 + \beta_1 \log(MSR)_{st} + \beta_3 \log(MSR)_{st} + \log(SR)_{st} + \gamma_s + \epsilon_{ts}
\]

where \( AR \) is the amplitude ratio at time \( t \) and site \( s \) and SR and MSR are the spline ratio and the mean spline rigidity, respectively. \( \gamma_s \) is a random intercept modification for each site. I repeated the analysis after removing 234 sites from that analysis that could be classified as outliers in the random effects structure (>1.5 times the interquartile range).

I will also give an overview of summary statistics of the 95 publications that used the 2/3S without auto-regressive modeling. To obtain an estimate for the average spline length for ecological comparisons I took 2/3 of the median segment lengths of the groups, which was usually either reported in a table, or was otherwise extracted from a sample replication graph. For climate reconstructions I extracted the median series length from the sample replication graph and the “maximum” series length at the point where either the EPS or SSS cutoff was reported, or the sample replication drops below 5. I divided the “maximum” segment length by the median segment length to obtain an approximation of the maximum spline ratio as described above. The ITRDB analysis above revealed that the actual measured maximum spline ratio is approximated quite well by this rough estimate (\( R^2 = 0.54 \)).
3. Results

3.1. Part 1: Temporal frequency bias within a chronology affecting climate reconstructions

Amplitude ratios of both the 100-year and 200-year frequency domain are stable in all chronologies detrended with the 100-year spline (Fig. 4). As expected, the amount of recoverable frequency amplitude is much lower in the 200-year frequency domain (Fig. 4b) compared to the 100-year frequency domain (Fig. 4a; 10% vs. 40%). Also, the 200-year and 300-year spline chronologies show quite stable variability in the 100-year domain back to the central year 1550, with both chronologies recovering ~75% and ~80% of the original forced variability, respectively. In the 200-year domain both detrendings show a slight trough in amplitude ratio in the middle compared to the start and end of the chronology. The 200-year spline recovers ~40% of the original variability and the 300-year spline ~65% (Fig. 4b).

In contrast, the 2/3S chronologies display a uni-directional drift in recovered low frequency with decreasing values towards the present. In the 100-year frequency domain and the 200SD and 300SD scenarios, amplitude ratios are comparable to that of the 300-year spline chronologies. But from 1750 onwards there is a notable decrease from 80% to 70%, which is even below that of the 200-year spline chronologies. In the 100SD scenario that decrease already sets in around 1600 and the amplitude ratio decreases to 60%, which equals a relative decrease of 25% ((60–80)/80). The decrease of resolved low-frequency is even stronger in the 200-y frequency domain (Fig. 4b). In the 100SD scenario the amplitude ratio decreases constantly from 60% around the central year of 1600 to 35%. This equals a 42% relative decrease from the past (1500–1699) to present (1800–1999), or, a 71% relative increase from present to past. The 200SD (300SD) scenarios show a 33% (25%) relative decrease over the same period.

The non-stationarity in low-frequency coherence between climate and 2/3S detrending can be also be seen in Fig. 5. All four detrending options have high coherence in the high-frequency domains of 30 and 10 years (blue and green lines in Fig. 5). While the fixed spline chronologies of the SD100 scenario (solid lines) have stable coherence in the 100- and 200-year frequency domain (black and red lines Fig. 5) between 1725 and 1875 there is a stronger drift from higher to lower coherence in the 2/3S chronology. For the SD200 and SD300 scenarios this drift is notably smaller, but still present. One can also observe a negative dip in the coherence in the 200-year spline (and 300-year spline) panel during the last (last two) time step 1800–1999 (1775–1974 and 1800–1999) that probably results from detrending the shortest time series containing only 100–150 years with a too stiff spline (see also Fig. 2h and 2i). These too stiff spline growth curves lead to an accumulation of increased ratios between standard deviations of detrended individual ring-width and the climate run in the outermost 200–300 years (Fig. 6 c; onwards from 1800, which shows the standard deviation for the 1700–1899 period) and especially the last 150 years (onwards from 1900, Fig. 6f and g). The 100-year and 2/3S spline detrending do not suffer from this problem (Fig. 6a, e, d and h). This “end effect problem” occurs also after power transformation and detrending by subtraction, and cannot be solely attributed to dividing raw ring widths by very small estimated growth curve values (not shown). Additionally, the 200- and 300-year splines seem often too stiff to be able to correctly follow the early decreasing part of the growth curves (Fig. 6b, c, f and g), leading to decreasing low-frequency coherence in the early part of the chronology (first four time steps of dashed and dotted lines in Fig. 5). The same problem can occur in the early part of the 2/3S detrending with spline stiffnesses greater.

Fig. 4. Amplitude ratios of the differently sampled and detrended chronologies in the 100-year frequency domain (a) and 200-year frequency domain (b). An amplitude ratio of 0.5 means that 50% of the original climate variability has been retained in the detrending process. The thin (thick) solid lines represent results with the 100-year spline (2/3S), the dashed (dotted) lines represent amplitude ratios of the 200-y (300-y) spline chronologies. 100SD (200SD, 300SD) scenarios are shown in blue (orange, green). The shading around the 100SD chronologies denotes the interquartile range of amplitude ratios. For visibility purposes the other uncertainties are not shown. The vertical black (grey) lines show where sample replication of all (half of the) iterations is above five. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).
Fig. 5. Mean magnitude squared coherence between 10,000 (100*100) detrended ring-width and 100 climate time series over a 200-year period plotted at each central year. Spectral coherence is shown for 200-year (black), 100-year (red), 30-year (green) and 10-year (blue) frequencies. The solid, dashed, and dotted lines show coherence for the 3 sampling scenarios with a 100-, 200-, and 300-year standard deviation, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

Fig. 6. a) to d) 200-year running standard deviations of individual detrended ring-width series divided by the running standard deviation of one individual climate run. SD ratios are standardized by the overall mean of the SD ratio for each detrending. e) to h) show the SD ratios obtained with a 100-year running standard deviation. a) and e) show results for the 100-year spline, b) and f) for the 200-year spline, c) and g) for the 300-year spline, d) and h) for the 2/3S. Please note the different y-axis ranges between the left and right panels.
than 200 years (before 1800 in Fig. 6d).

3.2. Part 2: Frequency bias between chronologies of varying mean ages

Using the 2/3S to investigate climate-growth relationships between groups with different mean ages will likely introduce distorted results (Fig. 7). There are significant differences in regression slopes (and thus correlation coefficients) across multiple climate scenarios. The group that was initially detrended with an average 2/3S stiffness of 30 years (the 30-year group) yields significantly different results from all other groups. The 40-year group is significantly different from all but the 50-year group, which in turn is significantly different from the 90-year group. There are no significant differences between the 60-, 70-, 80- and 90-year groups (Fig. 7a). Differences between groups stay the same independent of the climate trend (Fig. 8). It becomes also clear that for any given climate run (as shown by the vertically stacked points representing the four median regression slopes of the 30-, 50-, 70- and 90-year groups), the more flexible spline yields always a smaller regression slope compared to the next stiffer spline. Because all climate series have highly similar standard deviations the regression slopes can be proportionally translated to correlation coefficients.

The 200 climate runs have trends ranging from -0.36 to +0.31 (median: 0, IQR -0.11 to +0.08; Fig. 8) over the last 50 years. The smaller the absolute trend in the climate data the steeper are the regression slopes across all seven groups (30-y $R^2 = 0.51$, 90-y $R^2 = 0.57$). This apparent trend in slope (and concurrently correlation) suppression with increasing climate trend should be a tell-tale sign towards a standard procedure to also detrend climate data with the same spline stiffness when detrending ring-width data with cubic smoothing splines.

3.3. Part 3: Actual tree-ring data

The fixed effects of the model explained 55.3% of the variance of the increase in low frequency due to increasing spline ratio. Including random intercept modifications, the explained variance increased to 78.7%. The amplitude ratio increases with increasing spline ratio (Table 1, Fig. 9) and decreases with longer median spline rigidities. The stiffer the median spline rigidity is the weaker is the effect of increasing spline ratio.

To put the model into context with the artificial data presented in this study, the maximum spline ratios of part 1 are 1.87 (SD100), 1.91 (SD200), and 1.77 (SD300), respectively, and the median spline rigidities are 140, 180, and 200, respectively. Modeled 200-year frequency drift would result in maximum low frequency increases of 90%, 67%, and 50%, respectively. From Fig. 4 one can see that these are obviously realistic numbers, when comparing the relative increase from the end of the chronologies to the very beginning at central years 1500–1550.

In the meta-analysis 19 of the 36 publications that reconstructed a

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**Table 1**

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Fig. 8. Median regression slopes per climate run and effective spline stiffness vs. absolute climate trend during the 1950-1999 period. For clarity, points are only shown for effective 30-, 50-, 70- and 90-year splines.
climate variable using the 2/3S without auto-regressive modeling showed a sample replication panel. Applying the above-described model to those chronologies results in an interquartile range of 200-year frequency domain relative amplitude increases of 31–100%. This means the earliest parts of the reconstructions likely have a third more, to two times as much low-frequency variability than the recent end of the chronologies. 25 of 40 publications that compared climate growth relationships between two or more groups showed the mean age of the groups either in tables or sample replication panels. Eight of which (32%) show differences in group ages that would yield significantly different regression slopes based on the analysis in part 2.

4. Discussion

The 2/3S is not an optimal option to detrend a tree-ring width dataset as it will almost always introduce temporal biases in spectral properties within a mean chronology that would not occur if the applied spline stiffness was the same for all samples. Explicitly writing out the theoretical effect of the “two-thirds spline” detrending choice supports this conclusion. Briffa et al. (1992b) said exactly this – but only in a short subclause. This temporal frequency bias will also grow stronger the more right-skewed the sample replication is (many young vs. few old samples) and the younger the young end of the sample replication curve is or the median spline rigidity in general, as could be shown in Fig. 4 and Table 1. The 2/3S detrending will also produce significantly different regression slopes and correlation coefficients in a setting where it is applied on groups with different mean ages, especially in groups younger than 100 years, where the 2/3S will effectively be a <70-year spline and the differences become more significant (Fig. 7). Proving how much these two related biases have affected actual tree-ring datasets and existing publications is not exactly possible without re-analyzing the published datasets.

However, Fig. 9 gives an approximate picture that in many datasets this effect leads to a regular increase in low frequency variability of ~25%, based on the interquartile range (IQR) of all spline ratios across all chronologies. When the maximum spline ratio is used to estimate low frequency variability increase, the modeled increase of 27–45% (IQR) in ITRDB chronologies matches quite well that of the 31–100% increase of the published climate reconstruction datasets. This means the publications using the 2/3S have a very similar sample replication structure compared to the ITRDB and the findings can be extrapolated to most of existing tree-ring datasets. Applying the same model to a subset of ITRDB chronologies that fit the original sample requirement of Ed Cook’s eastern United States tree-ring network (using spline ratios between 1.15 and 1.35, and mean spline stiffness between 160 and 210 years) yields 25–45% (IQR) low frequency increase. The actual observed maximum amplitude ratio of this subset is very similar and ranges from 14% to 47% (IQR) and thus can be placed in the lower half of potential temporal frequency bias. Arguably, any percentage increase of very low absolute variability in the 200-year frequency domain still results in very low variability. The actual absolute effect size of the temporal frequency bias on published chronologies remains unquantified and certainly depends on the initial amount of low frequency variability of the climate signal and how well it is incorporated in the tree rings. In many cases the effect is presumed negligible and the big picture of results will not change. However, that does not mean that there are no publications (or datasets) where the 2/3S detrending choice might have introduced (would not introduce) spurious trends, climate extremes, or differences between groups that an analysis with a common fixed spline length would not have created (would not create). The very possibility of biases one introduces with this detrending – even if small – should advise caution against its application.

Fixed splines are also not void of problems. Too stiff splines (50% frequency cutoff at 200 years and longer) increase the chance to underfit the actual growth curve and lead to spurious low frequency properties. This is especially problematic when stiff splines are used on shorter than 200-year old series and will lead to end effect distortions (Fig. 2 and Fig. 5, drop in coherence in the last time step). But the mis-fitting also affects the beginning of the older samples (Figs. 2,4,5, and 6). Especially when sample replication is low stiff splines will likely introduce erroneous low frequency, a possible distortion that increases in likelihood and amplitude using the 2/3S detrending during early parts with the longest segment lengths (e.g. 400 years and older). This was already highlighted in the second example in Cook (1985), where poor curve fits of the stiffest splines retained strong out-of-phase residual variability, canceling out common low-frequency variability (Fig. 2).

The age-dependent spline (ADS, Melvin et al., 2007) seems a viable alternative for this type of problem and is now the default detrending option in ARSTAN v48 and RCSsigFree2019. It would be great if this method could be implemented into dplR in the near future.

In ecological research, one usually has an assumption about how a growth curve should look like. One fits a deterministic curve, or a regional curve. In the case of stochastic detrending the curve can have any shape, but one can control the frequency-removing characteristics of the filter. The 2/3S does not fully support an ecological and assumption-driven detrending choice, because the frequency removing characteristics – that which is in our ability to control – vary from sample to sample. Span-related detrending options such as the Friedman variable span smoother (Friedman, 1984) and locally estimated scatterplot smoothing (LOESS) are probably also affected by this effect. These options also fit filters of varying stiffness depending on the length of a time series, with all the possible consequences laid out above. One might argue that the ADS and the (generalized) negative exponential curve are more flexible in the beginning compared to higher ages, thus leading to a low-frequency dampening at the beginning of chronologies. While this is true to some extent, the absolute effect of the temporal frequency bias of negative exponential detrending appears smaller compared to the bias introduced by the 2/3S (Figure S1). Ultimately, when detrending with a negative exponential curve or ADS one has a clear age-driven assumption of growth curve flexibility, and the ADS applies the same age-dependent stiffness to all samples. How much the initial spline stiffness of the ADS and missing pith offset data can impact low-frequency characteristics over time has yet to be determined. The current versions of ARSTAN v48 and RCSsigFree2019 have initial values of 20 and 50 years, respectively.

If the distribution of segment lengths is very narrow (e.g. less than 50 years) the temporal frequency bias of the 2/3S will be definitely...
negligible. However, a possible, viable, and more consistent alternative to the 2/3 would be to use a spline with a 50% frequency cutoff at a fraction (e.g. two-thirds) of x, where x is not determined for each individual sample, but based on the overall mean or median and spread of segment lengths of a site, and depending on the aim of the study (e.g., Allen et al., 2018). If the segment lengths have a wide spread one has to assure that the chosen spline stiffness is not too stiff for the youngest samples. Within one group and within a single chronology this method would not introduce a temporal frequency bias, and if determined for multiple chronologies at the same time, i.e. when x is the mean segment length of the entire dataset, this method would be also suitable for comparisons between groups. In my opinion, a good option for the dplR package would be to set the default spline stiffness to a rather flexible 50% frequency cutoff at around 30 years or smaller, essentially becoming a high-pass filter preset, because the literature review has shown that this is the most frequent fixed spline stiffness used. For stiffer splines, or for a continuation of the use of the 2/3, the researchers would then have to actively choose a different spline to fit their dataset to retain more low frequency – a big step forward in assumption-driven detrending of tree-ring widths. Ultimately, every data-adaptive individual detrending method suffers from the inability to differentiate between an individual’s growth trend and common (climatic) signal. This consequence of distorting the true size- or age-corrected interannual growth signal calls for further research into “signal-free”-like detrending applications in ecological research, such as treating year as a random intercept in mixed effects models (Clark et al., 2007; Klesse et al., 2020; Miina, 2000; Morrongiello and Thresher, 2015; van der Sleen et al., 2018).

Declaration of Competing Interest
None declared.

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Appendix A. Supplementary data
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