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Original article

CRUST: Software for the implementation of Regional Chronology Standardisation: Part 2. Further RCS options and recommendations

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ABSTRACT

A number of processing options associated with the use of a "regional curve" to standardise tree-ring measurements and generate a chronology representing changing tree growth over time are discussed. It is shown that failing to use pith offset estimates can generate a small but systematic chronology error. Where chronologies contain long-timescale signal variance, tree indices created by division of the raw measurements by RCS curve values produce chronologies with a skewed distribution. A simple empirical method of converting tree-indices to have a normal distribution is proposed. The Expressed Population Signal, which is widely used to estimate the statistical confidence of chronologies created using curve-fitting methods of standardisation, is not suitable for use with RCS generated chronologies. An alternative implementation, which takes account of the uncertainty associated with long-timescale as well as short-timescale chronology variance, is proposed. The need to assess the homogeneity of differently-sourced sets of measurement data and their suitability for amalgamation into a single data set for RCS standardisation is discussed. The possible use of multiple growth-rate based RCS curves is considered where a potential gain in chronology confidence must be balanced against the potential loss of long-timescale variance. An approach to the use of the "signal-free" method for generating artificial measurement series with the 'noise' characteristics of real data series but with a known chronology signal applied for testing standardisation performance is also described.

Introduction

In Part 1 (Melvin and Briffa, 2014) of this 2-part discussion of the CRUST program for standardising tree-ring data, we focussed on the concept and application of the signal-free implementation of Regional Curve Standardisation (SF RCS). We demonstrated the advantages this offers over the use of simple RCS by describing a number of experiments with known tree-growth forcing signals applied in different contexts to simulated and actual tree-ring data sets. SF RCS was shown to capture introduced step changes of signal as well as long-term signal trends with minimal or no distortion in many cases. In this Part 2, we discuss a number of other issues with the use of RCS and present several further examples that suggest specific implementations available within CRUST. We discuss the use of pith-offset estimates; the use of ratios or differences to calculate indices; and the estimation of chronology confidence. We also discuss the application of RCS where the measurement data from various sources are combined and the use of multiple RCS curves to overcome some problems encountered in RCS. Some other CRUST options are mentioned and potential users of CRUST are referred to online versions of the program manual, installation instructions and program code which contain a more detailed list of specific CRUST implementation options.

The use of pith offset estimates

When trees are hollow, the boles are partly rotten, or where coring fails to hit the centre of a tree, ring measurements do not start at the pith. The missing radius between first measured ring and pith can be estimated either by using diameter measurements or by interpolating the distance to the geometric centre of the tree, using the curvature of the innermost rings of the sample (Nicolussi et al., 1995, Section 4.1; Esper et al., 2003). The approximate rate of growth near the centre of the tree can be used to estimate the number of years between pith and the first measurable ring (Bräker, 1981) producing pith offset estimates (PO). The PO of cores from living trees can be consistently larger than the PO obtained from the cross sections normally taken from sub-fossil trees (Luckman

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and Wilson, 2005). From experience with tree cores, the accuracy of missing-radius estimates is generally no better than ±10% and where there is suppressed growth in the early sections of some trees PO of the number of missing years may be even less accurate than this.

It is common practice with RCS, where PO are not available, to assume that the first measured ring of each tree has a ring age of one. Relative to this presumption, the use of PO for trees where rings do not reach the pith will change the position (with regard to ring age) of each tree's contribution to the RCS curve and also the position along the RCS curve from which each tree's expected growth values are selected. An extreme example is provided in the case of a hollow tree where, without PO, the small rings of old age are averaged with the larger rings of early growth from other trees thus erroneously reducing the magnitude of the early section of the true RCS curve. In this situation the series of small rings from the hollow tree are then detrended using the initial (faster growth rate) section of the RCS curve. With reasonably estimated PO data, the small rings of the hollow tree are averaged into the lower growth rate section of the RCS curve which is then more correctly used to detrend the measurements from the slower-growing outer section of the tree. Thus the use of PO tends to increase the magnitude of the early parts of the RCS curve, accentuate the early period of juvenile growth and, more correctly, increase the overall slope of the RCS curve.

Not using PO for individual trees will produce a less accurate RCS curve, increased chronology noise, and the potential for wider error bars in the chronology. As well as increased noise generally, a failure to use PO will likely introduce a systematic, "end-effect", bias into a chronology. This is because, after an initial increasing phase, ring width tends to reduce with increasing ring age and the difference created by using PO is to increase the overall slope of the RCS curve. This change of slope is transferred to the series of tree indices; earlier indices having lower values and later indices having higher values, relative to indices created without the use of PO. For the central part of a long chronology, where the first and last sections of overlapping series of tree indices are averaged together, the artificial increases and decreases of slope may cancel. In this case the change in the slope of the RCS curve will have little net effect on chronology indices (Esper et al., 2003; Melvin, 2004). At the modern end of the chronology, where the final portions of all tree index series are averaged together, the slope of the RCS curve becomes more critical and, even with data from large numbers of trees, there can be a resulting systematic bias in the chronology introduced by the omission of PO data.

Fig. 1 shows some examples of the differences created when using and not using PO, in both RCS curves and corresponding chronologies. Measurement sets were standardised using one-curve SF RCS and the results without using pith offset estimates are shown in blue and with the use of pith offset estimates shown in red. The Torneträsk maximum latewood density (MXD) (S88G1112A.mxd) measurements (Melvin et al., 2012) were used to produce Fig. 1a and d. For these MXD data, the central portion of the RCS curve (corresponding to ring ages 50–300 years) is approximately a straight line (Fig. 1a) and using/not using PO shows little effect on the slope of tree-index series. The change in indices is restricted to rings <50 old and this is noticeable in the chronology differences in the period 1750–1800 (Fig. 1d) when sample counts are rapidly increasing. The Torneträsk tree-ring width (TRW) (S88G0812.raw) measurements (Melvin et al., 2012) were used for Fig. 1b and e. The use of PO changes the slope of the RCS curve (Fig. 1b) and the increased slope produces a small reduction in the chronology indices in the final century (Fig. 1e) and an increase in values in the 18th century. The Dulan TRW (Sheppard et al., 2004) data (file name chin005.rwl) provide another, more extreme example (though these data were not originally processed using RCS). These data are from multiple cores from many trees that can exhibit a strip-bark-like growth form in old age. The RCS curve without PO is roughly horizontal (Fig. 1c) and the chronology (Fig. 1f) has a large downward slope. Using PO, simply based on the earliest measured ring of each tree, produces a sloping RCS curve and a chronology which is consistent with others from the region (see Yang et al., 2014, Figure SMB7).

Because the RCS curve is "smooth" and has no high-frequency component, the use of PO only affects the medium- and low-frequency variance of the chronology (on multi-decadal time scales and longer). Some previous work has concluded that the use of PO makes little difference to the resulting chronologies (e.g. Esper et al., 2003; Luckman and Wilson, 2005), at least for the specific examples these authors explored. However, their conclusions were based on correlation analyses. Correlation, with its implicit data-series normalisation and high weighting of individual extreme values, is not suitable for the evaluation of the small (i.e. relative to the amplitude of high-frequency signals) difference in low-frequency variance between chronologies produced with or without PO data.

In RCS where PO are used, it is necessary to use a smoothing curve that is sufficiently "flexible" to follow the relatively rapid changes in the magnitude of radial tree growth in the first decades of growth and a "stiff" curve to smooth the oldest rings (Melvin et al., 2007). The juvenile maximum in TRW can occur as early as the first decade (e.g. see Fig. 1c) and most of the changes created by the use or not of PO may be lost by using smoothing that is too stiff e.g. a spline with cut-off frequency 10% of the maximum tree length as used by Esper et al. (2003), or the negative exponential and straight lines discussed by Briffa and Melvin (2011, Section 5.6.1).

The use of PO can produce notable differences in the shape of the RCS curve with corresponding changes produced in the resulting chronologies (e.g. Esper et al. (2007), Figure S3 or Briffa and Melvin (2011), Figure 5/11). When using linear regression to reconstruct climate, the relative slopes and means of the predictor chronologies and predictand climate series are critical and any systematic chronology bias over the most recent century will translate into differences in reconstructed climate. Because the chronology error generated by not using PO is generally a systematic positive bias it could become particularly relevant in the context of large regional or hemispheric-mean reconstructions (e.g. Briffa, 2000; D'Arrigo et al., 2006; Esper et al., 2009). In such cases much of the high- and medium-frequency variance in different predictor chronologies is not common and will be largely removed in the averaging. However, even a relatively small difference in chronology slope over the calibration period could become significant for large regional reconstruction where it is consistent over many sites.

Of course, the use of PO will have no effect if the RCS curve is a horizontal line. A systematic end-effect bias is not always apparent and was not found by us in the case of MXD data from Icefields, western Canada (Luckman and Wilson, 2005). However, there remains a high probability that in many situations the use of PO will change the values of tree indices and the chronology to some extent. Though failure to use PO may result in only a small, medium-frequency end effect bias in RCS chronologies this may still influence subsequent climate reconstructions. Using PO will, therefore, improve chronology accuracy where tree counts are limited and will remove the potential for one type of "end effect" bias. It is recommended that the pith offset information should be recorded as a routine part of tree-ring sampling and PO recorded during the measurement process. Wherever possible, PO should be used in RCS processing.

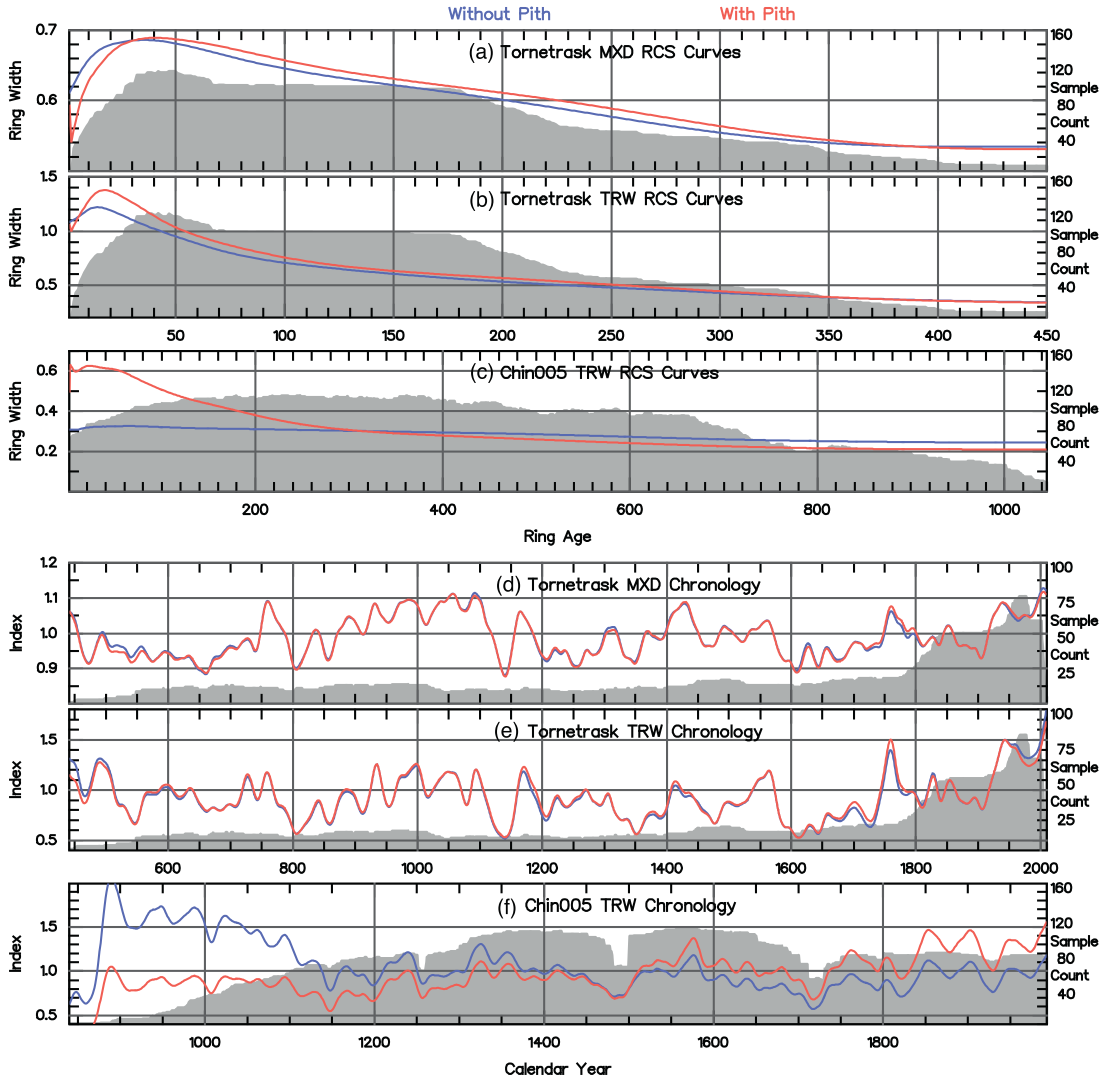

Fig. 1. Here measurement sets are standardised using one-curve SF RCS without using pith offset (PO) estimates (blue) and using PO (red). The RCS curves of both with and without PO estimates are shown by ring age in (a), (b) and (c) and the chronologies generated are shown in (d), (e) and (f). The Torneträsk MXD measurements were used in (a) and (d), the Torneträsk TRW measurements were used in (b) and (e), and the Dulan TRW measurements were used in (c) and (f). Sample counts are shown with grey shading and chronologies have been smoothed with a 50-year spline for display.

Indices by ratios or differences

Skewed distribution of tree-indices

Subtracting 'expected' growth curve values from TRW measurements, referred to here as taking "differences", removes the influence of tree age but creates tree indices whose variance is generally dependent on the local mean of the measurements (Cook and Peters, 1997). Where standardisation involves an expected growth curve fitted to the measurements of each tree, dividing measurements by the expected values (taking "ratios") also removes the influence of age but it also goes some way to reducing, or correcting, the relationship between local chronology mean and variance in the resulting indices. Ratios appear to be a better analogue for the processes of tree-ring growth than differences. The climatic control of tree growth is via photosynthesis and annual variations in climate will produce variations in carbon production rates that are roughly proportional to foliage mass, though there are other processes involved (Melvin, 2004, Section 4.1). For MXD measurements the relationship between local chronology mean and variance is less apparent (Melvin et al., 2012; Briffa et al., 2013) and indices created as differences do not generally require the variance correction needed for TRW indices (e.g. Bräker, 1981; Grudd, 2008). A disadvantage of using ratios of TRW and MXD is that, because they are 'fractional deviations', the indices may have a noticeably skewed probability distribution. This is because maximum ring width (or density) is unbounded while minimum ring width cannot be less than zero. If ratios are used, where the fitted detrending curve closely follows the local mean of growth rate of each tree (e.g. when most of the low-frequency variance is being removed), the probability distribution for indices produced as ratios is not strongly skewed and the dependence of variance on local mean is not great (see blue line of Fig. 3).

Cook and Peters (1997) describe the bias associated with using ratios with curve-fitting standardisation methods that produce "poorly fitting" detrending curves. Where the fitted curve approaches too closely to zero, the use of ratios can generate extremely large and unrealistic index values, so creating bias in the final chronology. For this reason when using ratios (e.g. in program ARSTAN, Cook, 1985) it is necessary to examine the fit

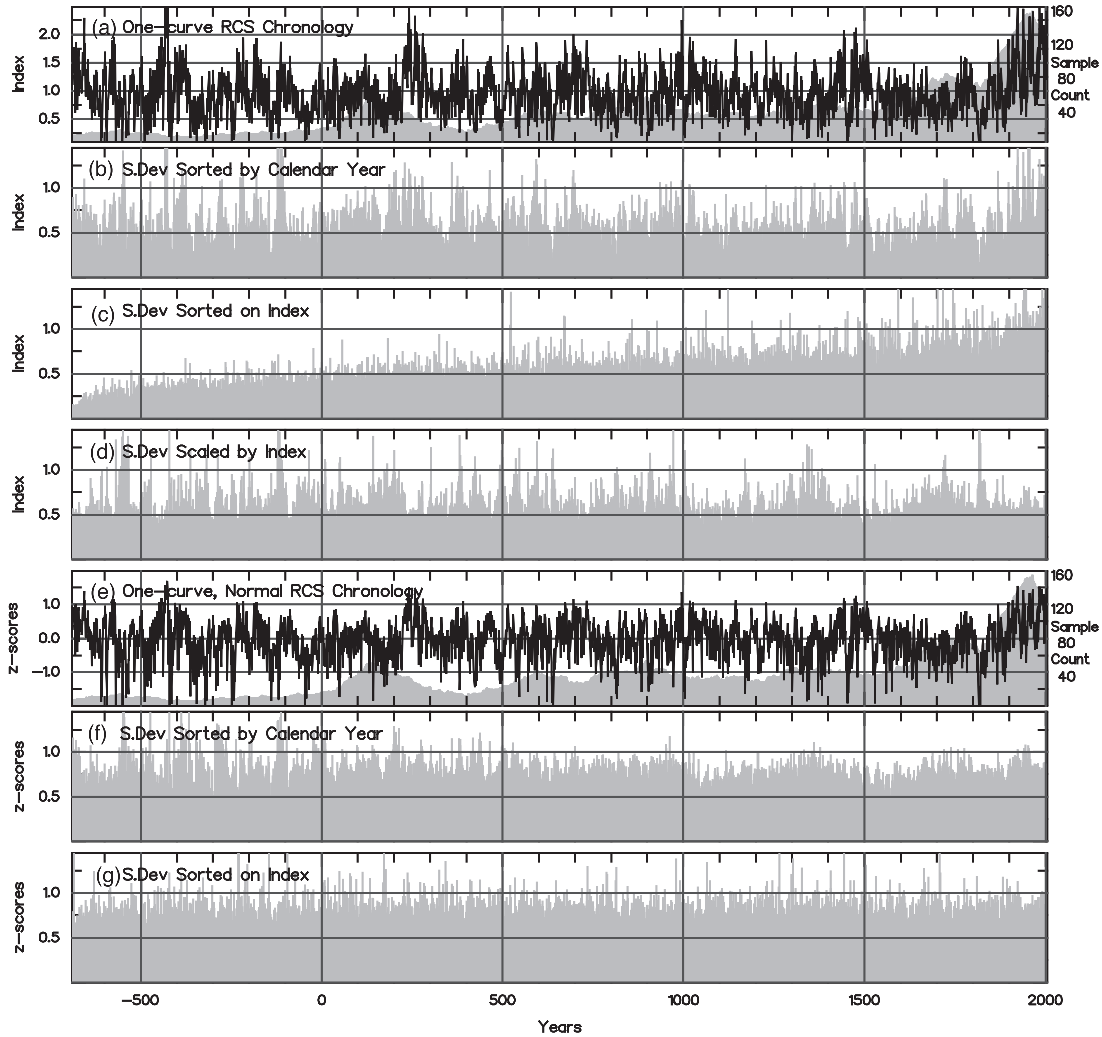

Fig. 2. One-curve SF RCS is used to standardise TRW data from Yamal (Briffa et al., 2013). (a) Chronology indices plotted by year and tree counts (grey shading), (b) standard deviation for each chronology year, (c) standard deviations sorted by chronology index size, and (d) standard deviations sorted by chronology index value and scaled by chronology index size. Alternatively, a chronology was created using one-curve SF RCS with tree-indices transformed to have a normal distribution. (e) The chronology created after conversion of tree-index distribution to normal and tree counts, (f) standard deviations of the normal-distribution chronology plotted by year, and (g) standard deviations of the normal-distribution chronology sorted by chronology index value.

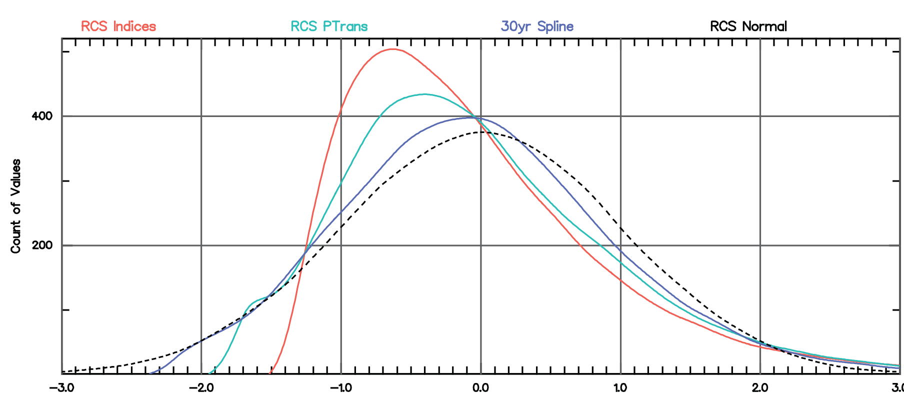

Fig. 3. The distribution of tree-indices created using the Yamal data (Briffa et al., 2013). Indices were normalised (by subtraction of the mean and division by the standard deviation) and counts for each 0.01 range from −3.0 to +3.0 were smoothed with a 60-year spline. Tree-indices from alternative standardisation methods are compared: one-curve SF RCS tree indices (red), one-curve RCS with power transform and tree indices created as differences (cyan), and signal-free 30-year spline standardised tree indices (blue). The distribution of similarly processed randomly generated numbers (one for each tree index) with a normal distribution is also shown (dashed black).

of each detrending curve to the underlying measurements and to correct or remove any problematic values manually. Cook and Peters (1997) proposed a solution to avoid this problem: first using a power transform to correct the variance and then using differences to create tree indices. An alternative method to prevent excessively high index values, used in the implementation of the signal-free approach for curve fitting methods (Melvin and Briffa, 2008), is to replace those values of the fitted curve which are below a minimum value (e.g. the thickness of two rows of cells) with the minimum value. Options are available within CRUST to implement either approach. When using RCS the inherent lack of a specifically tailored fit of standardisation curve to individual series of measurement data leads to an expectation that indices (whether produced as differences or ratios) will be notably skewed.

Example of skewed RCS chronology indices

Here we examine the problem of the skewed probability distribution function for RCS chronology indices and the associated dependence of local chronology variance on chronology mean. An example is shown in Fig. 2. Fig. 2a shows the chronology index values and tree counts over time for a chronology created using one-curve SF RCS applied to the data set of Yamal TRW measurements (Briffa et al., 2013). Fig. 2b and c show the standard deviation about each calendar year's mean index and the same standard deviations sorted by ascending chronology value. The clear dependence of standard deviation on index size (Fig. 2c) is largely removed when the standard deviations are scaled by division by the mean index values (Fig. 2d). For example, Fig. 2b shows the 20th century, in particular, as having large yearly standard deviations but after scaling by the high chronology index values of the 20th century, the association between mean and standard deviation is no longer apparent (see also the discussion of the EPS calculation for RCS in Section 'Calculating more appropriate EPS values for RCS chronologies'). If differences rather than ratios are used to produce ring-width indices, they are not fractional deviations and scaling by the chronology values may not be appropriate.

Fig. 2e–g show the same data except that the chronology was created here using tree indices that have been transformed to have a normal distribution prior to averaging by calendar year [see Section 'Tree-index transformation to normal']. Some dependence of standard deviation of each year on sample count in that year is still apparent, e.g. in the higher values of standard deviations before 500 CE in Fig. 2b and f. This is a separate problem which can be reduced using sample-count-based variance correction techniques (e.g. Osborn et al., 1997) also available in CRUST.

The skewed distribution problem is further illustrated in Fig. 3 (see also Briffa et al., 2013, SM5 section PY2). In this example the Yamal measurements have been standardised in three different ways; firstly using a signal-free 30-year high-pass spline with indices generated as ratios, secondly using one-curve SF RCS with indices generated as ratios, and thirdly using a power transform of the measurement data followed by simple RCS with indices created as differences following Cook and Peters (1997). The tree indices contributing to each chronology have been normalised, by subtracting the overall mean and dividing by the overall standard deviation, and counts for each 0.01 of index range from −3.0 to +3.0 have been smoothed using a 60-year spline for display. The distribution of similarly processed randomly generated numbers (one for each tree index) with a normal distribution is also shown for comparison.

When using RCS to retain long timescale variance and creating tree indices by division, because expected growth curves are not closely fitted to individual sample series of measurements, there is a wider distribution of tree-indices with a more noticeable skew than when using innately more flexible curve fitting methods (compare the red and blue lines of Fig. 3). Index values below the mean have a narrower range than those above the mean and this skew is what tends to produce a positive relationship between chronology index value and associated standard deviation (see Fig. 2c). Many of the methods used to process and interpret chronology indices (e.g. the correlation and regression techniques frequently used in dendroclimatology) have an underlying presumption that the series involved are at least approximately normally distributed.

Esper et al. (2003) and Büntgen et al. (2004) illustrate and discuss the use of the power transform and using differences in the context of RCS. The power transform was originally proposed as a means to overcome the problem of a standardisation curve approaching zero (Cook and Peters, 1997). This should rarely occur when using RCS. The RCS curve should not approach too closely to zero because the value for each tree age comprises the average of measurements from multiple trees. However, care is needed when smoothing the RCS curve. If too-flexible a smoothing technique is used at the poorly replicated (old-age) end of the mean-ring-width-by-age curve this problem might be encountered (Melvin et al., 2007). The distribution of tree indices generated using power transform and differences is less skewed than the distribution of RCS indices generated as ratios (compare the cyan and red curves in Fig. 3). Büntgen et al. (2004) point out that the difference between (simple) RCS and power transformed RCS chronologies, when used to reconstruct temperature, is a systematic bias. While it is an improvement over simple RCS using ratios, the power transform using differences only partially corrects the index non-normality problem (see SM Figure SM1 and associated discussion). Fig. 3 shows that both simple and power transformed RCS indices are positively skewed.

Using ratios will only remove the relationship between variance and mean in tree indices when the detrending curves follow the local mean of growth rate in individual trees closely. Indices produced using a 30-year spline have a distribution that is much closer to symmetrical (the blue line in Fig. 3) but these index series represent only the relatively high-frequency chronology signal variance. When using ratios with RCS, where more low-frequency signal variance is retained, the resulting skewed distribution produces a marked relationship between chronology value and chronology standard deviation. The use of the power transform does not correct this problem. Here we recommend that, consistent with the use of a multiplicative model, RCS is implemented using ratios to generate tree-index series. A simple method is now proposed that explicitly corrects the problem that such indices, and the resulting chronology values, have a markedly skewed distribution.

Tree-index transformation to normal

If the history of changes in some climate variable is reconstructed from a chronology of tree growth indices using linear scaling, the climate estimate will have the same probability function as the scaled chronology. The use of fractional deviations in the signal-free method suggests the need for transformation of index values so that they are distributed similarly to the predictand climate series, which by default is assumed here to be approximately normal. (The option to transform tree indices to have a normal distribution is built into CRUST along with the option for users to supply a list of random numbers with a distribution appropriate to their predictand data.) This transformation should take place after the standardisation procedures. Rather than transform the mean chronology indices directly, it is preferable to transform the distribution of the total of individual tree indices prior to averaging across calendar years to form the chronology. This approach is more robust because where there may only be a few hundred chronology indices there are often several thousand or more tree index values from constituent trees. A simple, empirical method of transforming tree indices so that they have a normal distribution is as follows.

A series of random numbers, one for each tree index, is generated with a normal distribution. These are sorted to obtain values in ascending sequence. The tree indices are ranked into ascending order to produce two parallel series; similarly ranked tree indices and random numbers. Each tree index value is then replaced with the value of the random number with the same relative position (i.e. the largest random number replaces the largest tree index, next largest etc). The relative size of tree indices (i.e. larger than or smaller than) will be unchanged whilst they are given values that have a normal distribution. The now normally-distributed tree-indices are then averaged by calendar year to create the chronology. The chronology indices, as the average of normally distributed tree indices for each year, may not have a mean of zero and a standard deviation of 1.0 and may need to be normalised by subtracting the mean and dividing by the standard deviation to achieve this.

The dashed-black line in Fig. 3 shows the distribution of RCS indices after their transformation to have a normal distribution. The problem, that the values of indices below the mean have a smaller spread than the indices above the mean, has been corrected. The one-curve RCS chronology created from normally distributed tree-indices (Fig. 2e) has fewer extremely high values and more extremely low values that the uncorrected chronology (Fig. 2a). The standard deviation of the chronology values (Fig. 2f) has a mean slightly less than 1.0 because of the averaging. The relationship between mean and standard deviation (Fig. 2c) has been corrected by the transformation (Fig. 2g). A reason for the use of this transformation is the non-linearity of fractional deviations and it may not be appropriate where the data are non-stationary. Further discussion of the use of this approach and the underlying assumptions when processing various versions of TRW and MXD chronologies from Yamalia, northern Siberia can be found in Briffa et al. (2013).

The use of ratios, or the use of the power transform with differences, has proved generally satisfactory for processing chronologies generated using curve-fitting standardisation methods. The ambition to preserve greater long-timescale climate-related variance and the corresponding adoption of RCS methods have exacerbated the problem of skewed chronology indices. Consistent with our use of a multiplicative model of tree growth, and our recommendation that RCS be implemented using ratios rather than differences, we also recommend that the subsequent need to correct the skew in the distribution of RCS chronology indices should be satisfied by transforming the resulting RCS tree-indices to have a normal distribution. We have described a simple, empirical method that must be applied to the whole of the chronology, i.e. it cannot be applied to a section of chronology and "extrapolated" to other sections. Nevertheless, we consider it an improvement over the use of non-normal chronologies. Further experimentation with other approaches, including the possibility of transformation to other 'non-normal' distributions where relevant, is warranted. At present CRUST only has the facility to transform indices to a normal distribution.

Chronology confidence

We now turn to the issue of assessing chronology confidence in the context of RCS. Here we are concerned with two major stages of RCS implementation: errors associated with constructing an RCS curve and errors associated with the averaging of tree indices to form a chronology. The chronology error can be considered separately for each of these aspects of chronology construction. When considering chronology confidence we may ask firstly, "How many data series are needed to build an 'acceptably accurate' RCS curve?" and secondly "How many data series are needed in each calendar year to obtain an 'acceptably accurate' estimate of tree growth in that year?"

How many trees are needed to build an RCS Curve?

An important requirement in developing an RCS curve is that rings of a particular age (i.e. part of the RCS curve) come from different periods in time so that when aligned by ring age and averaged together, the climate induced variability from different periods cancels out, leaving an RCS curve that accurately represents expected growth as a function of tree age (Briffa et al., 1992, 1996). If, for example, all the young rings are predominately from one period in time, the common growth signal of that period may not be efficiently removed from the early section of the RCS curve. The same is true for all sections of the RCS curve. There needs to be a "reasonable" representation of growth from different time periods for all ring ages. What constitutes reasonable in this context cannot be answered too rigidly as the precise requirements will depend on specific research situations and aspirations. However, as an illustration, if we suggest a minimum of one tree representing each of at least 5 time periods and five age ranges (parts of the young to old sections of the RCS curve), this requires data from at least 25 trees. If, as is often the case, the distribution of sample data over time is not even, we can easily double this. This suggests a rule of thumb, that data from at least 50 trees are needed to build an RCS curve.

In producing the RCS curve, high-frequency noise (in this case including year-to-year climate variability) will be efficiently reduced by averaging rings from different calendar years and is further removed by the smoothing of the curve of mean-growth values ordered by ring age when producing an RCS curve (Melvin et al., 2007). The medium and low-frequency variance of the common forcing signal is not so efficiently removed and it is necessary to use large numbers of sub-fossil tree data to build a sufficiently accurate RCS curve. When using a chronology built solely from living trees, provided there is an adequate distribution of tree ages, the use of the signal-free method as described in Melvin and Briffa (2014) will reduce the climate-related bias of all but the longest-timescale (the slope over the chronology length) and enable 50 trees to be sufficient to build an accurate RCS curve.

How many trees are needed in each year?

There is a problem in natural forest situations that the rates of growth of individual trees can vary appreciably because of varying micro-site conditions (Fritts, 1976, p. 280). Factors such as rooting depth, soil type, aspect, and site elevation can all affect local rates of tree growth over the whole of a tree's life, while local competition can constrain the growth of an individual over many decades. The effects of such non-climate growth influences are presumed to be noise that is superimposed on the common forcing or "climate signal" that varies on different time scales from year-to-year up to many centuries. Sufficient samples are needed in each year for the effects of this background noise and the random selection of different samples (e.g. from a fast growing tree rather than a slow growing tree) on the estimate of the mean chronology value to be reduced to an acceptable level.

Wigley et al. (1984) and Briffa and Jones (1990) describe a statistical metric for gauging how well the common growth signal is expressed in a chronology: the Expressed Population Signal (EPS). The EPS value refers to the proportion of "common" signal in the chronology e.g. an EPS of 0.85 indicates that 85% of the chronology variance is common signal while 15% of the chronology variance is residual noise. The calculation of EPS uses the mean correlation of all inter-tree index series (*rbar*). The *rbar* calculations should not be based directly on "within-tree" series correlations which are normally much higher than "between-tree" correlations (Briffa and Jones, 1990, Section 3.6.2). Either the "effective chronology signal" can be used (see Briffa and Jones, 1990, Equation 3.43) or the measurement data for each tree can be averaged prior to standardisation and subsequent *rbar* calculation (Wigley et al., 1984).

The longer the (common) period over which *rbar* is calculated, the longer the timescales of chronology variability that are assessed. Analysis intended to assess temporal changes in signal strength might calculate *rbar* over a moving window rather than using a single common period (e.g. 50-year running segment lengths might be used). Where the period of comparison is so short, only correspondingly short-period (high-frequency) coherence between sample index series is assessed. In the normalisation implicit in *rbar* calculations, the means of each series of tree indices are set to the same value (zero) over the selected common period and consequently the noise associated with variation of the mean values of tree-index series is not accounted for in the EPS calculation. In most practical situations the calculation of *rbar* is dominated by the large magnitude of high-frequency (versus low-frequency) ring-growth variation and long-timescale chronology confidence is not assessed.

The 'normal' application of EPS calculation is not suitable for estimating the strength of common signal of RCS chronologies. The original papers describing the EPS (Briffa, 1984; Wigley et al., 1984) were written before the common adoption of RCS in the 21st century and its availability in ARSTAN (Cook, 1985) and so do not directly address the use of EPS with RCS chronologies. When using RCS, the varying mean value of tree-index series is the source of long-timescale variance. The exclusion of the long-timescale variance in the *rbar* calculation causes the EPS to seriously underestimate the level of true "noise" in RCS chronologies (Briffa and Cook, 2008; Jones et al., 2009). Here we demonstrate the underestimation of low-frequency noise in the standard EPS calculations using some of the Torneträsk TRW data (Melvin et al., 2012). Fig. 4 shows 20 years of tree-index data for each of the nine Torneträsk trees which span the years 700–750 CE. Fig. 4a shows tree index series derived from 50-year spline signal-free standardisation applied to the full data set. Fig. 4b shows tree indices derived from one-curve SF RCS. Fig. 4c shows the RCS index series after each has been normalised (by subtracting the mean and dividing by the standard deviation over the period 700–750 CE). When standardised with RCS, as expected with its greater retention of low frequency variance, there is a much wider distribution of index values in each year (Fig. 4b) than when spline standardisation is used (Fig. 4a). The normalisation (Fig. 4c) implicit in calculating *rbar* over 50-year segments removes the low-frequency variance (and associated noise) leaving a similar amount of (the higher-frequency) variance to that produced when standardising with a 50-year high-pass spline (Fig. 4a). Calculation of EPS using the between-series variability of Fig. 4c instead that of Fig. 4b, seriously under-estimates the proportion of noise in an RCS chronology.

Calculating more appropriate EPS values for RCS chronologies

Assuming that the chronology "*noise will cancel in direct proportion to the number of series averaged*" (Briffa and Jones, 1990). The number of trees needed to achieve a specified level of EPS for an RCS chronology can be estimated, as in the case for relatively high-frequency noise, by assessing a requirement to attain the same proportion of noise as that contained in a "high-frequency" chronology. This can be calculated by scaling the number of trees for a particular EPS threshold in a high-frequency chronology (e.g. as produced using a 50-year high-pass spline) by the square of the ratio of the chronology standard deviations (e.g. RCS variance divided by 50-year-spline variance both calculated over the same segment). This is equivalent to calculating the change in sample count that will "compensate" for the additional noise in the mean value of RCS tree indices and thus provide EPS calculations that are more relevant to assessing the levels of chronology confidence for RCS chronologies. To achieve an EPS of 0.9 for the 50-year segment of the spline chronology shown in Fig. 4b requires a sample depth of 5 (4.5) trees while for the RCS chronology in Fig. 4c approximately 5 times as many trees would be needed, i.e. a sample depth of 22 (22.2) trees. However, there is an additional complication that, because RCS-generated TRW indices are fractional deviations, the standard deviation is proportional to the chronology index value (see Section 'Example of skewed RCS chronology indices'). This problem is removed either by scaling the standard deviations by the chronology values or transforming tree-indices to have a normal distribution (see Section 'Tree-index transformation to normal').

For a high-frequency chronology where:

rbar = the mean between-tree index-series correlation coefficient
n = the number of trees
1.0 − *rbar*) = the fraction of noise
($n \times rbar$) = the magnitude of common signal

EPS is the proportion of chronology variance represented by the common signal, calculated (following Briffa and Jones, 1990, Equation 3.4.4) using:

$$\mathrm{EPS} = \frac{(n \times rbar)}{[(n \times rbar) + (1.0 - rbar)]}.$$

To take account of the additional long-timescale variance in an RCS chronology and the consequent increase in the number of samples needed to reduce the RCS chronology standard deviation to the level of the standard deviation of a high-frequency chronology (e.g. 50-year high-pass spline), the *rbar* calculation is made using the RCS "adjusted count" (n_{adj}). Because the standard deviation varies considerably from year to year the standard deviations are calculated here as the mean of standard deviations for each year over the time span (window) used in the *rbar* calculation:

$$n_{\mathrm{adj}} = n \times \frac{\text{50-year-spline variance}}{\text{RCS variance}}.$$

EPS for RCS is estimated by

$$\mathrm{EPS}_{\mathrm{RCS}} = \frac{(n_{\mathrm{adj}} \times rbar)}{[(n_{\mathrm{adj}} \times rbar) + (1.0 - rbar)]}.$$

Note that here the error associated with representation of the RCS curve itself is not incorporated in the EPS calculations.

The Torneträsk TRW chronology is used to demonstrate these EPS calculations. Running (50-year windows) *rbar* values calculated for 50-year spline (black) and for one-curve RCS (red) chronologies are shown in Fig. 4d. The EPS (Fig. 4e) was calculated for the 50-year spline chronology (black) and for an RCS chronology with *rbar* calculated over 50-year moving windows (red). Adjusted EPS was also calculated (blue). The unadjusted EPS suggests that the chronology is acceptably reliable (using the often quoted criterion of EPS > 0.85) after 400 CE while the adjusted EPS suggests that the reliability of the chronology is limited in the period before 600 and also between 1000 and 1440 CE. The number of trees during both periods drops below 50. The running *rbar* values are inherently "noisy" and increasing the window length for calculation EPS would reduce this noise. Where interest is focussed on a specific timescale, an adjusted EPS can be calculated for specific filter lengths. An option to select the filter length used for EPS calculation for RCS is built into CRUST.

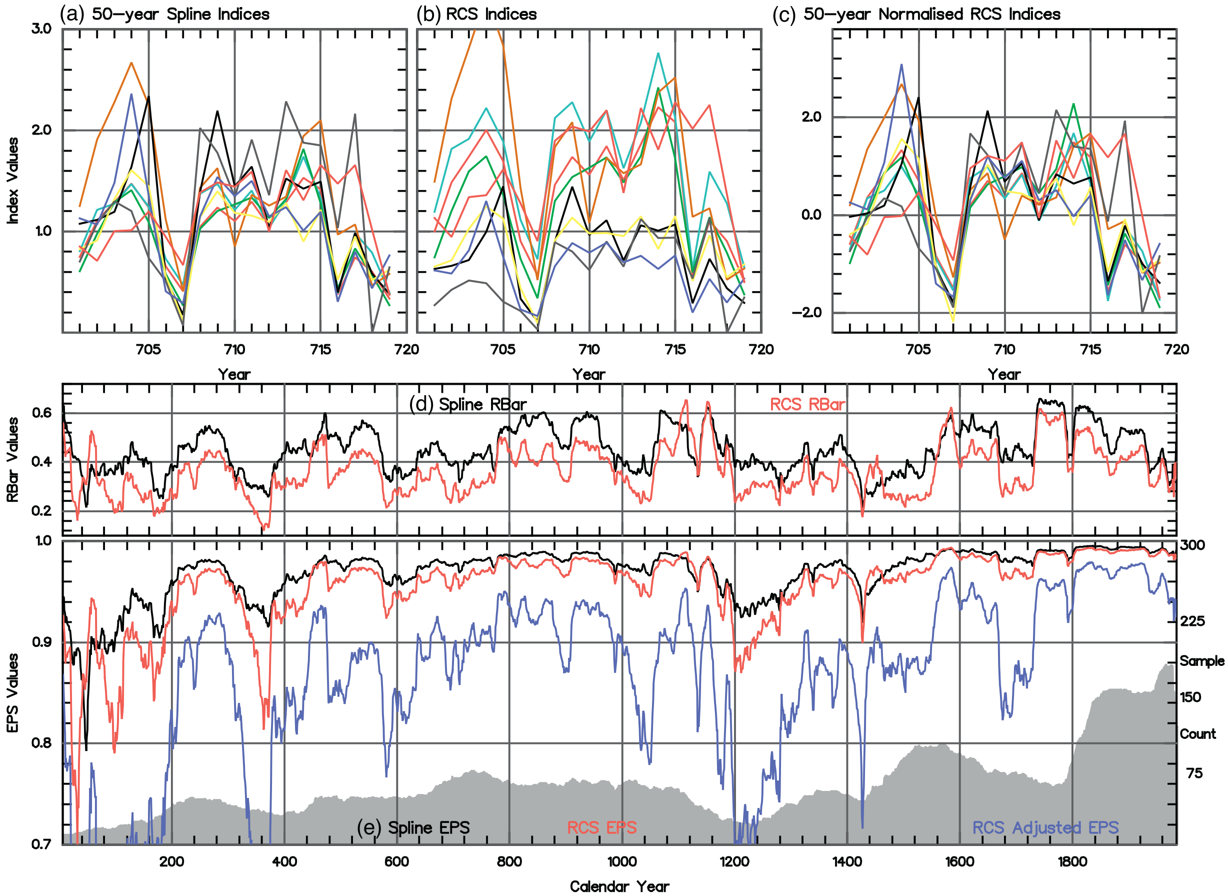

Fig. 4. Plots of indices for 20-year segments from 11 trees from the Torneträsk AD TRW chronology which include the common period 1150 to 1199 AD: (a) tree indices derived from a 50-year spline standardisation, (b) tree indices derived from one-curve SF RCS standardisation, and (c) SF RCS tree indices which have had their mean value, over the period 1150 to 1199, subtracted. For the CE portion of the Torneträsk TRW chronology, (d) shows the Rbar calculated using 50-year spline standardisation (black) and two-curve SF RCS chronology (red). (e) shows EPS calculated for the 50-year spline chronology (black), EPS calculated for the RCS chronology (red), and adjusted EPS calculated for the RCS chronology (blue).

Combining sub-samples of data from different sources or sites

It is a basic requirement of simple RCS that the data being processed represent a homogeneous sample through time (Briffa et al., 1992, 1996, 2013). Mixing data from trees from sources with notably different mean growth rates under the same climate conditions has the potential to produce serious chronology bias when the proportions of data from different sub-samples varies over time. Combining sub-sample data sets into one for RCS processing assumes that the different sub-samples contain similar common forcing signals and come from populations of trees with similar age-related growth curves. To explore the potential for bias when constructing long, compound chronologies, it is informative to test the data from different sub-samples of trees, e.g. sub-fossil, archaeological and living-tree samples or samples from neighbouring sites, for compatibility. There are several issues that need to be considered when assessing compatibility between data sets.

A simple assessment based on comparing the means of the measurement data requires the removal of two confounding factors. Firstly, the effects of the common-forcing signal must be removed because differing forcing regimes are expected to produce differing ring measurements, e.g. temperature sensitive tree rings would be expected to be larger in a warm period than in a cool period. Comparing the count weighted means of sub-sample data over a common period can achieve this. Dividing each measurement by the chronology index also removes the effect of variation in common forcing signal of tree growth over time: in other words using signal-free measurements. A major advantage of this is that it does not require the selection of a common analysis period. Secondly, the effect of differing ring age needs to be taken into account because TRW and MXD measurements reduce with increasing ring age. Measurements can be converted to values that would be expected at a specific ring age by rescaling: dividing the measurements by the actual ring-age value of the RCS curve and multiplying by the "different" ring-age value of the RCS curve. Alternatively tree-index series, which have had the effect of changing ring age removed, can be used.

Combining the different sub-sample data sets into one, processing the combined data with one-curve SF RCS, and dividing series of tree indices by the appropriate-year chronology index produces series of signal-free tree indices. These indices have had both the age-related and the common-signal-related variance removed. This then allows a valid, direct comparison of the mean values of the different sub-sample signal-free tree indices and will reveal the existence of differences and the potential for bias between data sets. Examples of just such comparison and adjustment by rescaling of differently sourced TRW and MXD data sets are described for the Torneträsk (Melvin et al., 2012) and Polar Urals (Briffa et al., 2013) regions. Procedures are available in CRUST to assist with the evaluation and "correction" of sub-sample biases.

The use of multiple RCS curves

In RCS, expected growth is expressed as a function of tree age and below we only consider trees with full circumferential growth. In this there is an implicit assumption that in an unchanging climate all trees have similar growth rates over their lifetime. In a forest, if trees of the same age have differing diameters, then we would expect a larger diameter tree to have a faster growth rate. Hence diameter in combination with age becomes a superior predictor of tree growth rate than age alone. It would be equally valid to use tree diameter as an estimator of expected growth rate using diameter-based RCS curves (see Melvin, 2004, Chapter 4 for a detailed discussion). If trees of roughly the same diameter have differing ages, then we would expect a younger tree to have a faster growth rate than an older tree and hence age in combination with diameter is a superior predictor of tree growth rate than diameter alone. The combination of age and diameter is a measure of growth rate. Because fast growing trees tend to continue growing rapidly whilst slowly growing trees tend to continue to grow slowly tree growth rate tends to be a superior predictor of expected growth than either age or diameter alone.

The observation that the rate of reduction of ring width over time is greater for fast-growing trees than for slow-growing trees (partly a consequence of rate of change of diameter) suggests that the 'average' RCS curve may not be optimum for representing expected-ring width in trees with widely varying growth rates. The assumption that one curve fits all trees can lead to systematic bias in tree-index series; where the tree-index series of faster-growing trees have a negative slope and those of slower-growing trees have a positive slope (Melvin, 2004; Briffa and Melvin, 2011). It is possible, where sufficient samples are available, to consider the use of multiple RCS curves, each representing a different growth-rate class. Because growth rate is a "reasonable" predictor of expected growth rate, growth rate is the metric we use to separate trees into multiple RCS curves.

Rathgeber et al. (1999) proposed using the first 50 years of tree growth to evaluate and remove the within-site variation of the mean growth rate of trees. Melvin (2004) used the early years of growth of each tree to evaluate the rate of growth for each tree and found that the RCS curve for each growth rate tended to the same value as tree age increased. Subsequent work has shown that using the mean growth rate of the tree over the full time span, after removing the mean age affects, produces multiple RCS curves which do not tend to converge. In CRUST the growth rate of each tree is assessed over its full life span, relative to the growth rate of an unsmoothed RCS curve created using the measurement data from all trees: the ratio of the diameter increment of the tree is expressed relative to the diameter increment of the single RCS curve, using the common age range. Trees are sorted by relative growth rate and near equal (as much as possible) numbers of trees are allocated to each multiple RCS curve (note: CRUST will only use multiple RCS if there are data from 40 or more trees in each RCS curve).

When an RCS curve is created by averaging all the measurements from a set of trees and those measurements are each divided by the appropriate age RCS curve value then the mean of the complete set of tree indices created will be ~1.0. When using multiple RCS curves, the sub-chronologies formed by averaging sets of tree indices, created using their own sub-set RCS curve will each have a mean of ~1.0. Averaging together the tree index series of these sub-chronologies will lose some of the low-frequency variance in the overall chronology that the RCS technique is intended to preserve. Consistent with our multiplicative model, the mean value of tree-index series (as calculated using one-curve RCS) can be reinstated by rescaling the means of the series of indices from each tree to have the value that they would have had if only one RCS curve were used. This procedure produces a multiple-curve RCS chronology that contains as much low frequency variance as a one-curve RCS chronology.

Using a single RCS curve to standardise the complete measurement dataset will preserve the maximum long-timescale changes in the mean growth rates of all trees but will often result in a chronology that suffers from systematic biases: e.g. modern sample bias, or the slope problem discussed above; or where subsets of data are not homogeneous. The use of multiple growth-based RCS curves can remove much of this bias but at the cost of losing some of the potential long-time scale climate-related changes in mean growth rates. When multiple growth-rate based RCS curves are used the slope bias caused by the differing growth rates of trees (and less-well fitting RCS curves) is corrected. The removal of long-timescale variance will also substantially reduce the amplitude of both modern sample bias and any sample homogeneity problems. The CRUST user has a choice of either creating a chronology which has some long-timescale variance removed but has been largely corrected for "modern sample bias" and has reduced homogeneity problems or of retaining all the long-timescale variance. These points are now illustrated using example data sets.

The Yamal trees

The Yamal trees (Briffa et al., 2013) were standardised using three-curve SF RCS with tree indices transformed to have a normal distribution. Fig. 5a shows the mean signal-free measurements plotted by ring age for the three separate sub-samples (i.e. each for a different growth rate). The slowest growth rate trees create a much shallower RCS curve than do the fastest growth rate trees. Use of a single RCS curve (black), with too shallow a slope for the fastest growth rate trees and too steep a slope for the slowest growth rate trees, would generate tree indices with a slope bias whereas the use of three separate RCS curves reduces this bias. In Fig. 5b–d chronologies have been smoothed with a 50-year spline for display purposes. The three sub-chronologies, generated using the different growth rate RCS curves, are shown in Fig. 5b. Where sample counts are sufficient (>7 shown as thicker lines) the sub-chronologies generated from trees with widely differing growth rates have similar values. Separate sub-chronologies created after each series of tree indices is rescaled to have the same mean as it would have had were one-curve RCS used are shown in Fig. 5c. These chronologies clearly illustrate the differences in relative growth rate (slow, medium and fast) of the three sub-samples of trees. When the tree indices from these three growth rates are averaged into a single chronology (Fig. 5d) the chronologies created without rescaling (blue) and after resetting their means to the values they would have had were one-curve RCS used (red), are remarkably similar much of the time. The main difference between these chronologies is in the most recent 400 years, where the chronology with means reset has a steeper slope than the chronology with means of 1.0. Sample counts by calendar year for each chronology (slow, medium and fast growth rate trees) show that in the 20th century there were more of the fast growing trees and in the 16th and 17th centuries there were more of the slow growing trees, and the changing counts of fast and slow growing trees has created the differences (see Fig. 5e). The difference in sample count could be the result of improved growing conditions (increased summer temperature) or it could result from sample selection; specifically "modern sample bias" where faster growing living trees are selected preferentially for sampling. That the slow and medium growth rate trees (there are insufficient fast growing

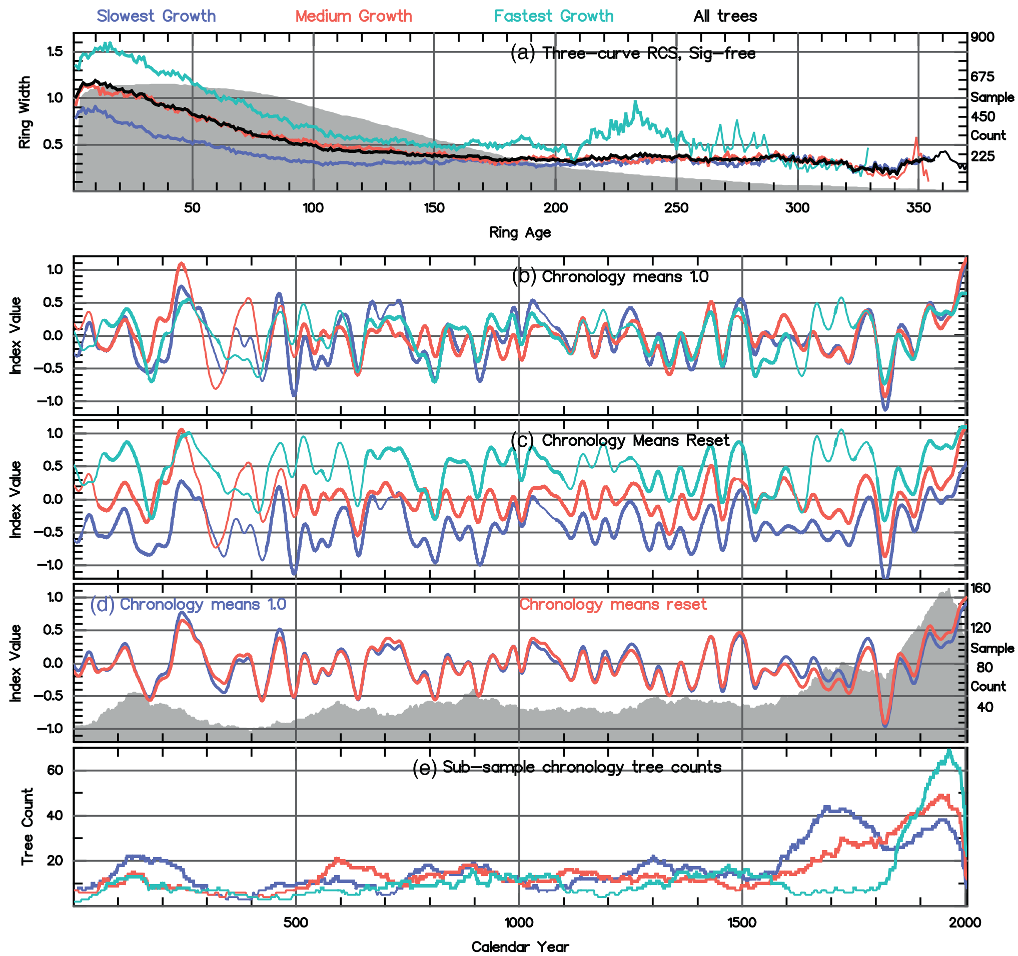

Fig. 5. The Yamal TRW measurements (Briffa et al., 2013) were standardised using three-curve SF RCS with tree indices transformed to have a normal distribution. The unsmoothed single RCS curve (black) and each of three different growth-rate RCS curves are shown in (a) along with the total sample counts (grey shading). For display the chronologies have been smoothed with a 50-year spline and narrow lines are used where sample counts are below 7. The three individual sub-sample chronologies, slowest growth rate (blue), medium growth rate (red) and fastest growth rate (cyan) are shown in (b). The means of indices for each tree were reset to the values they would have had were one-curve RCS used and the sub-chronologies created from these are shown in (c). The two alternative chronologies: one with tree means unchanged (blue) and one with tree means reset (red) are shown in (d) along with the total sample counts (grey shading). Sample counts for each of the three sub-sample chronologies are shown in (e) with narrow lines indicating where sample counts are below 7.

trees in the 16th and 17th centuries for comment) both display the same growth rate change suggests that much of the difference between the sub-chronologies in Fig. 5d is the result of modern sample bias on the chronology made from trees whose means have been reset and this bias would also apply to the case of a one-curve RCS chronology.

Four chronology versions were created using the Yamal trees, with the data processed using one-curve, two-curve, three-curve and four-curve SF RCS. The means of tree indices were not reset and tree indices were converted to have a normal distribution (see Fig. 6a). To further examine the reasons for the loss of long-timescale variance involved with the use of multiple RCS, for each chronology, time series were created using only the mean value of each series of tree indices (Fig. 6b) and alternatively only the slopes of each series of tree indices (Fig. 6c). For the means, the values of each series of tree indices were replaced by a horizontal line, the series mean. For the slopes, the values of series of tree indices, after the mean was removed, were replaced by a least squares fitted sloping line, the series slope. For the full chronologies, the two-, three- and four-curve RCS versions are similar while the one-curve RCS chronology has a notably larger slope than the others over the post 1600 period. The two-, three- and four-curve RCS chronologies created only from the means of series of tree indices are also similar while the one-curve RCS chronology created from the means of tree indices shows the increased slope post 1600 very clearly (Fig. 6c). The four chronologies created from the slopes of tree index series are all similar (Fig. 6c) suggesting that the predominant effect of multiple RCS is to change the relative means of series of tree indices. Power spectra plots of the four full chronologies are shown in Fig. 6d. The loss of low-frequency variance does not occur until the period is beyond the average length of the trees (~150 years) and almost all of the loss occurs in the change from using one to two RCS curves, with little change from the progression to three or four RCS curves.

The processing used in producing Fig. 6 was repeated using a set of data from the Tibetan Plateau (Yang et al., 2014). Again most of the loss of long-timescale variance occurs with the change from one-curve to two-curve RCS. This Tibetan chronology has a homogeneity problem, the trees used for constructing burial chambers (before 500 CE) were much slower growing than contemporary trees sampled at higher altitudes. This effect was corrected with the use of multiple RCS curves (Yang et al., 2014). The power spectrum

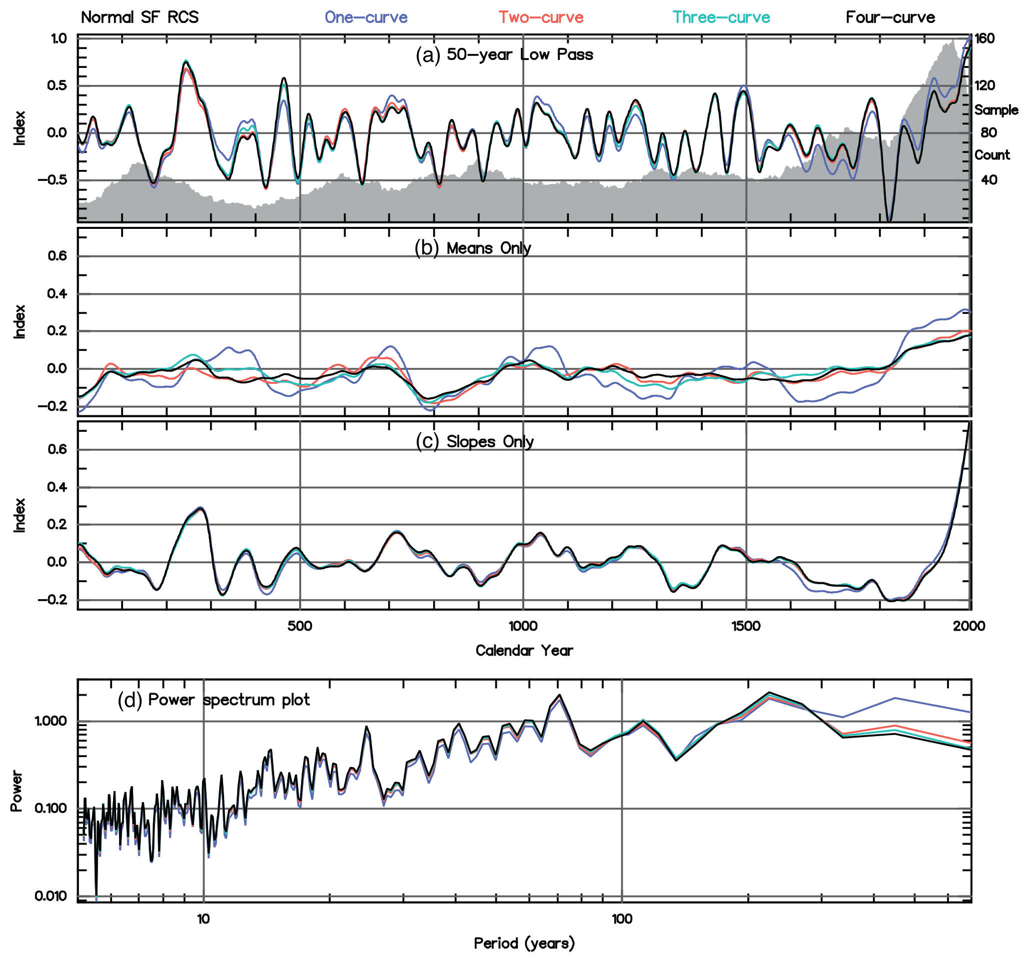

Fig. 6. (a) Four chronologies are shown, each based on TRW data from Yamal (Briffa et al., 2013) using one-curve, two-curve, three-curve and four-curve SF RCS, all with tree-indices transformed to have a normal distribution. The individual values of each series of tree indices were replaced by the appropriate series mean value (i.e. the index series for each tree was replaced by a horizontal line) and separate chronologies created by averaging these mean values (b). The mean value of each series of tree indices was subtracted from the series, the residual values were replaced by a least-squares-fitted sloping line, and separate chronologies were created by averaging the values of the sloping straight lines (c). All chronologies have been smoothed here with 50-year spline for display. Tree counts are shown with grey shading in (a). The power spectra for the four full chronologies (from a) are shown in d).

plot (Fig. 7d) again shows that most of the loss of long-timescale variance occurs at a period beyond the average lifespan of the trees (here ~660 years). In these trees there is a progressive loss of long-timescale variance from chronologies created using only the mean values of tree index series as the number of multiple RCS curves is increased from two to four (Fig. 7b) while the variance associated with the slopes of tree indices (Fig. 7c) is remarkably constant during the increase of RCS curves from one to four. These examples demonstrate the value of using multiple RCS curves and using the means and slopes of tree-index series to explore the source of the long-timescale variance within a chronology. The use of two-curve RCS appears to remove modern sample bias from both of these example chronologies. The effect of using multiple RCS curves on the standard deviations of chronologies derived from the means and slopes of tree-index series for both these example chronologies are illustrated in SI (see Figures SM2 and SM3).

Generating artificial ring measurements

Series of unprocessed ring measurements contain an age-related growth signal, a chronology signal and "noise" (see Part 1, a conceptual RCS model). Dividing measurements by the chronology signal produces series of signal-free measurements. If a chronology of signal-free measurement is standardised using RCS (with unchanged parameter settings) this will generate a "null" chronology. If signal-free measurements series were randomly selected and given artificial start dates we would expect a chronology created from these series to be a "null" chronology with larger variance (representing residual noise) where sample counts are lower. Prescribed artificial signals can be added (by multiplication) to the age-related-growth curve and error contained by series of SF measurements.

A set of measurement data containing 1200 samples was created by the random selection (with replacement) of series of SF measurements which were generated from the Yamal data (Briffa et al., 2013) using one-curve SF RCS. The series of measurements (each series representing one tree) were allocated start dates that were evenly distributed through time to form a 2000 year-long chronology. An artificial sine wave signal of period 1000 years and with amplitude ±0.5 was created. This signal was converted to represent a fractional deviation; the negative values were replaced using the formula:

$$\text{New value} = \frac{1.0}{2.0 - \text{Old value}}.$$

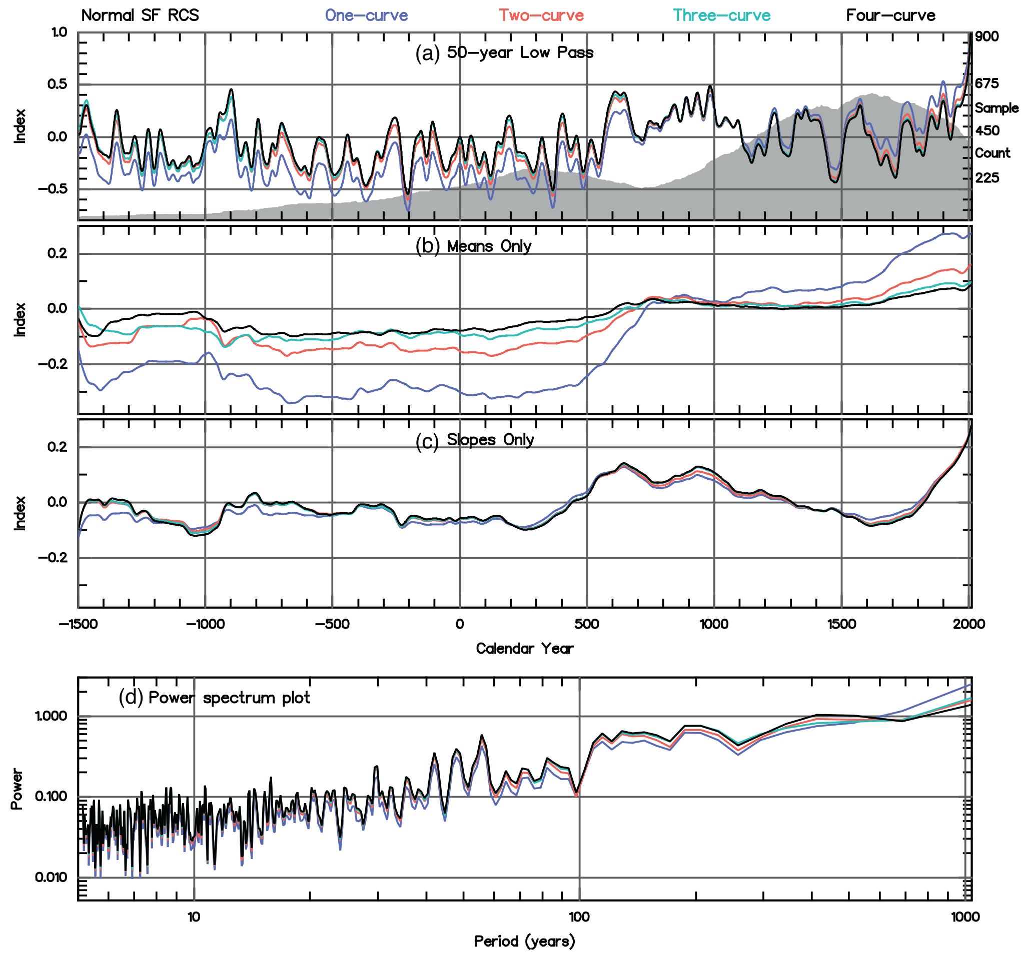

Fig. 7. As for Fig. 6 but using TRW data from the northeast Tibetan Plateau (Yang et al., 2014).

The artificial measurements were multiplied by the appropriate calendar-year values of the adjusted sine wave. Chronologies were created from these measurement series by standardising them using one-curve (Fig. 8a), two-curve (Fig. 8b) and three-curve (Fig. 8c) SF RCS with all tree indices in each case converted to have a normal distribution. Sample counts are shown as grey shading (Fig. 6a) and the artificial common signal is shown with red lines. The amplitude of the sine wave is fully preserved using one-curve RCS (Fig. 8a) but the amplitude is progressively reduced using two-curve (Fig. 8b) and three-curve (Fig. 8c) RCS. This demonstrates a loss of long-timescale variance caused by allowing the chronologies created using separate RCS curve to retain their mean of 1.0. The period of the sine wave is roughly four times the mean length of the trees and the slopes of series of tree indices are unable to preserve variance on timescales corresponding to this (and longer) periods. The three chronologies (smoothed with a 500-year spline) are plotted together in Fig. 6d to highlight the differences and to show the progressive loss of long-timescale variance associated with the use of multiple RCS curves.

The above process was repeated but this time the value of each series of tree indices created using multiple RCS curves was rescaled to have the same mean value that they would have had, if one-curve RCS had been used (CRUST option “mean single”, gtr = 2). The chronologies, smoothed with a 500-year spline, are plotted in Fig. 6e. Resetting the means of individual trees has recovered the lost amplitude of the long-timescale sine wave signal and the smoothed chronologies are very similar to the imparted sine wave signal.

Additional CRUST features

Although we recommend the use of growth-rate based multiple RCS curves, CRUST contains other options for sorting trees into multiple RCS curves; sort by tree age, sort by final tree diameter, or to use unsorted data. Because the decay of ring-width may be associated with the increase of diameter, the option to evaluate diameter-based RCS curves and chronologies has been incorporated within CRUST. Melvin (2004) found that diameter-based RCS curves were neither better nor worse than age-based RCS curves. The use of basal-area increment (BAI) as an alternative to TRW for dendroclimatic standardisation has been addressed by many papers (e.g. Frelich et al., 1989; Briffa, 1992; Biondi and Qeadan, 2008). An assumption of constant basal area increment does not tend to fit the progression of measurements from individual trees even after ignoring the juvenile period. The use of BAI-based RCS curves to generate chronologies does not appear to be an improvement over TRW based chronologies. The option to convert TRW into basal area increment is available in CRUST in order to facilitate further experimentation with the use of BAI. The detailed User Manual for CRUST is available at http://www.cru.uea.ac.uk/cru/papers/melvin2013dendrochronologia/.

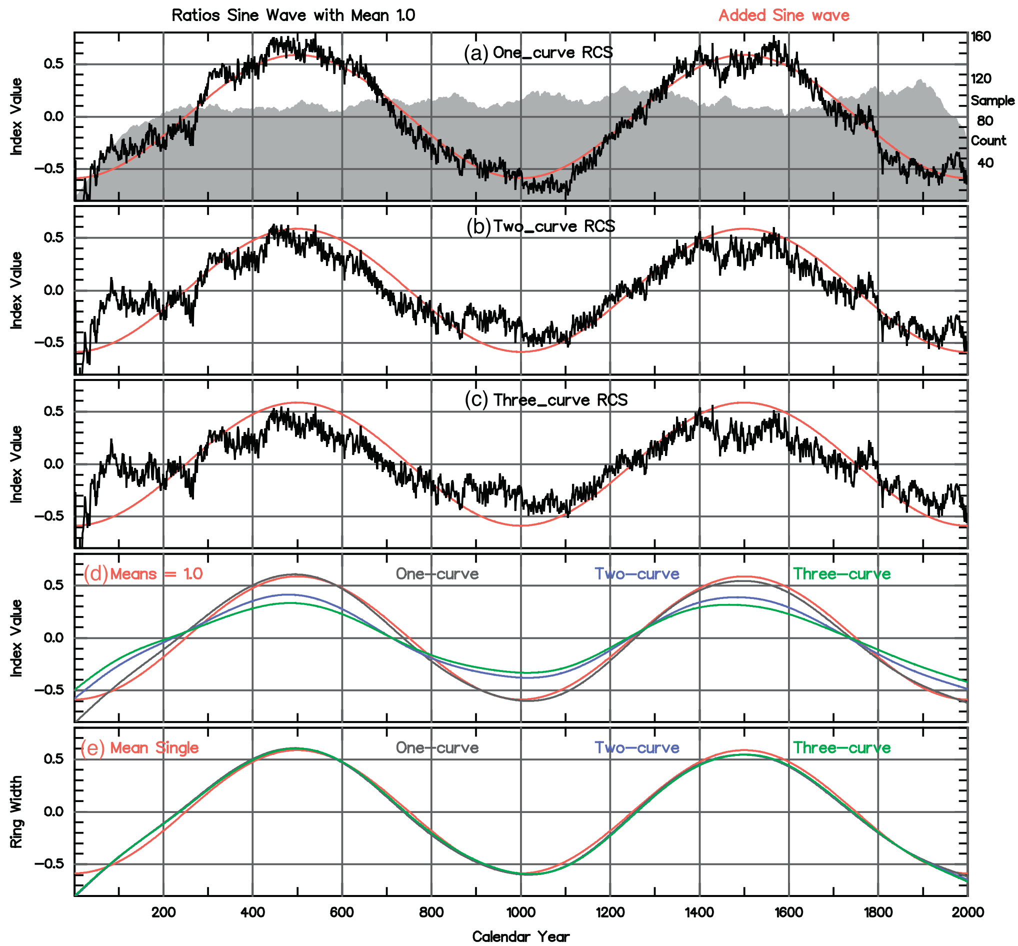

Fig. 8. Measurement data were generated by the random selection (with replacement) of 1200 series of signal-free measurements from the Yamal TRW data set. These series were allocated start dates which were evenly distributed through time. An artificial signal comprising a sine wave with a period of 1000 years and amplitude 1.0 (smooth red line in (a) to (e)) was converted to fractional deviations (values below 1.0 = 1.0/(2.0 – value)) and added to the measurement data by multiplication to form a 2000 year-long chronology. This chronology was standardised using one-curve (a), two-curve (b) and three-curve (c) SF RCS with tree indices converted to have a normal distribution. The three chronologies were smoothed with a 500-year spline and are plotted superimposed in (d). The standardisation of the two-curve and three-curve RCS was repeated but with each tree-index series rescaled to have the same mean value as it would have had using one-curve RCS standardisation (CRUST option "mean single", gtr = 2). These chronologies along with the one-curve chronology were smoothed with a 500-year spline and are plotted in (e). Sample counts for each year of this artificial data set are shown as grey shading in (a).

Conclusions

We have tried to describe a number of the principal options in the use of SF RCS and the CRUST program. It is not our intention to be prescriptive in the use of CRUST, but we believe that an ensemble of detrending experiments should be performed to get an idea of how sensitive the final chronology versions are to subjective methodological choices. In this paper we have pointed to a number of implementation issues associated with the use of RCS. It is for the user to experiment and choose specific applications of RCS that are appropriate for their needs. Our experience to date with RCS standardisation leads us to make the following recommendations for using SF RCS in CRUST:

1. Pith offset estimates should always be used when using the RCS method.
2. Tree indices should be created as ratios by the division of measurements by RCS curve values.
3. Correction of the skewness of RCS generated chronologies should be made by changing the distribution of tree-indices (e.g. to a normal distribution).
4. An "adjusted" version of the EPS calculation should be used to account for the additional long-timescale variance associated with RCS chronologies.
5. The mean value of signal-free tree indices should be used to evaluate the homogeneity of sub-samples of tree-ring measurements from different contexts.
6. Where sufficient trees are available, the use of multiple growth-rate based RCS curves should be used to evaluate (and where necessary remove) the effects of modern sample bias.
7. Signal-free measurement series with an added common signal can be used to generate artificial measurement data sets with the noise characteristics of actual measurement data

Acknowledgments

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.dendro.2014.07.008.

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