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Detecting long-term growth trends using tree rings: a critical evaluation of methods

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Abstract

Tree-ring analysis is often used to assess long-term trends in tree growth. A variety of growth-trend detection methods (GDMs) exist to disentangle age/size trends in growth from long-term growth changes. However, these detrending methods strongly differ in approach, with possible implications for their output. Here, we critically evaluate the consistency, sensitivity, reliability and accuracy of four most widely used GDMs: conservative detrending (CD) applies mathematical functions to correct for decreasing ring widths with age; basal area correction (BAC) transforms diameter into basal area growth; regional curve standardization (RCS) detrends individual tree-ring series using average age/size trends; and size class isolation (SCI) calculates growth trends within separate size classes. First, we evaluated whether these GDMs produce consistent results applied to an empirical tree-ring data set of *Melia azedarach*, a tropical tree species from Thailand. Three GDMs yielded similar results – a growth decline over time – but the widely used CD method did not detect any change. Second, we assessed the sensitivity (probability of correct growth-trend detection), reliability (100% minus probability of detecting false trends) and accuracy (whether the strength of imposed trends is correctly detected) of these GDMs, by applying them to simulated growth trajectories with different imposed trends: no trend, strong trends (−6% and +6% change per decade) and weak trends (−2%, +2%). All methods except CD, showed high sensitivity, reliability and accuracy to detect strong imposed trends. However, these were considerably lower in the weak or no-trend scenarios. BAC showed good sensitivity and accuracy, but low reliability, indicating uncertainty of trend detection using this method. Our study reveals that the choice of GDM influences results of growth-trend studies. We recommend applying multiple methods when analysing trends and encourage performing sensitivity and reliability analysis. Finally, we recommend SCI and RCS, as these methods showed highest reliability to detect long-term growth trends.

Keywords: age/size trend, climate change, dendrochronology, detrending, growth trends, regional curve standardization, tree growth, tree ontogeny, tree-ring analysis, tropical forests

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Introduction

Worldwide, forests store and process large quantities of carbon (Pan *et al.*, 2011). Changes in the growth rates of forest trees affect their net uptake or loss of carbon and may therefore have large consequences for the global carbon cycle (Bonan, 2008). Tree-ring analysis yields long-term growth data – covering centuries (Koutavas, 2013) to millennia (Salzer *et al.*, 2009; Esper *et al.*, 2012) – that can be used to detect such growth changes or trends. Tree-ring analysis has been widely applied for this purpose on boreal and temperate tree species (e.g. Briffa *et al.*, 1998; Fritts, 2001; Esper *et al.*, 2010; Villalba *et al.*, 2012) and more recently, there is an increasing attention to use this tool for assessing long-term growth trends in tropical tree species (Rozendaal *et al.*, 2010; Bowman *et al.*, 2013; Zuidema *et al.*, 2013; van der Sleen *et al.*, 2014).

Tree-ring series contains information on tree-growth responses to different drivers that vary on different time scales (e.g. from years to centuries). Year-to-year variations in growth rates are often driven by interannual fluctuations in, for instance, precipitation and temperature (Schöngart *et al.*, 2006; Subedi & Sharma, 2013), while decadal-scale variations may be induced by, for instance, responses to changes in light availability due to canopy dynamics (Brown & Wu, 2005; Baker & Bunyavejchewin, 2006). Long-term variations – spanning several decades to centuries – may reflect responses of trees to gradual environmental changes (e.g. in precipitation, temperature, or CO_2 concentration), but may also reflect age/size dependent trends in growth (i.e. caused by the ontogenetic development; cf.

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Briffa & Melvin, 2011). Detecting long-term growth trends using tree rings requires disentangling these ontogenetic and short-term environmental signals from changes driven by gradually shifting environmental conditions. This removal of the age/size trend is also called standardization (e.g. Fritts, 2001; Briffa & Melvin, 2011) or detrending (e.g. Bontemps & Esper, 2011) of the tree-ring series.

Over the past decades, various growth-trend detection methods (henceforth referred to as GDMs) have been developed to detect environmental growth changes in tree-ring series and correct for the inherent age/size trends in growth (cf. Briffa *et al.*, 1998; Esper *et al.*, 2002; Biondi & Qeadan, 2008). While having similar aims – correcting for the age/size trend to reveal externally forced growth responses – GDMs differ largely in their approach; as illustrated in Fig. 1 for the four most widely applied GDMs. GDMs correct for the age/size trends in quite different ways: by detrending growth of trees using curves that describe the age/size

This is most similar to our GLS approach, except that we're using DBH

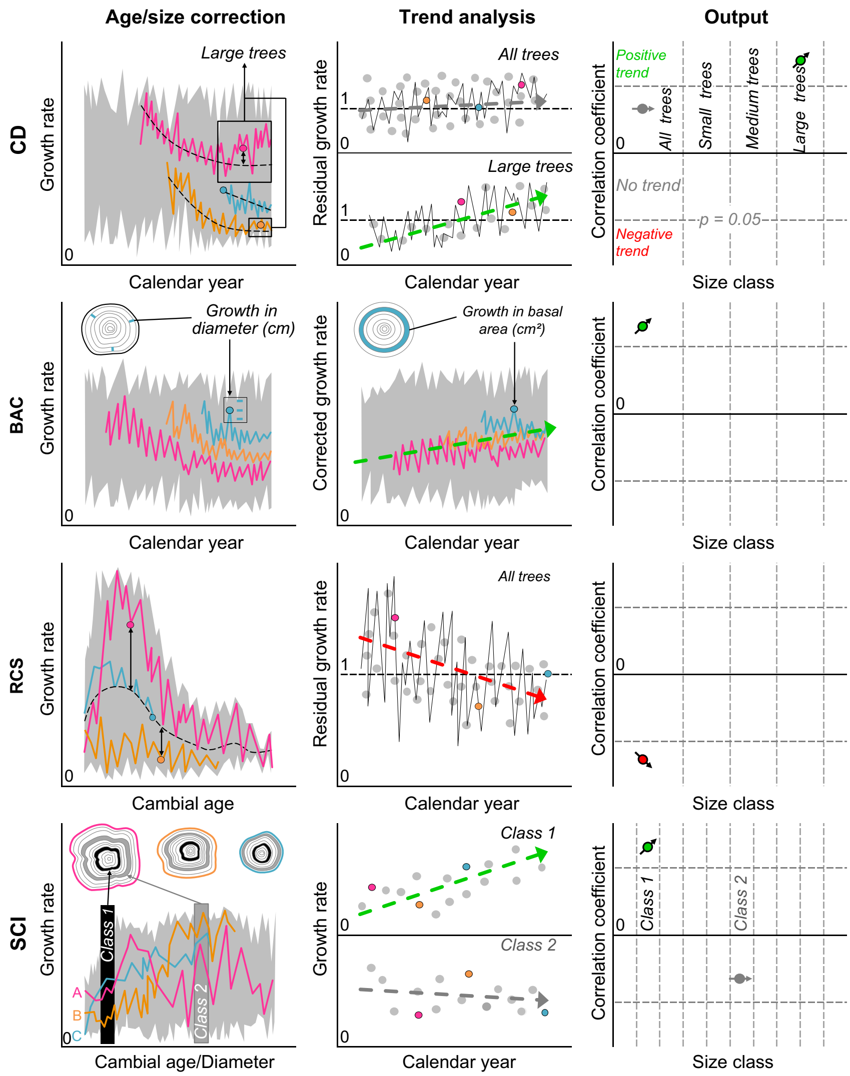

Fig. 1 Schematic representation of four growth-trend detection methods (GDM) most commonly used to analyse long-term growth changes using tree rings: conservative detrending (CD), basal area correction (BAC), regional curve standardization (RCS) and size class isolation (SCI). The first column indicates how GDMs disentangle the age/size trend (i.e. the ontogenetic signal) from long-term growth changes. See the Methods section for more detailed explanation of the methods. The second column shows how trends are computed: either on raw or on residual growth rates over time, using Spearman's rank correlations. The third column represents how we present detected trends in this study: grey dot = no growth change; green = temporal growth increase; and red = growth decrease. Results are presented for all trees (i.e. for all measured tree rings) or per size category: small trees = trees 0–27 cm diameter; medium = 27–54 cm; and large = trees >54 cm diameter.

trend [conservative detrending (CD) or regional curve standardization (RCS)], by expressing growth rate in basal area instead of diameter [basal area correction (BAC)], or by comparing growth rates inside fixed age or size classes [size class isolation (SCI)]. Trend analyses are then performed on the detrended data, on the corrected growth rates, or on the raw growth rates. Given the large differences in approach between GDMs, it is pertinent to (1) evaluate whether GDMs yield consistent output when applied on a single data set, (2) assess the sensitivity and accuracy of GDMs to detect growth trends, that is, the probability and strength of correct trend detection and (3) quantify their reliability, that is, 100% minus the probability that erroneous growth trends are detected. While individual GDMs have been evaluated and weaknesses have been noted for several GDMs (e.g. Esper *et al.*, 2003; Biondi & Qeadan, 2008; Briffa & Melvin, 2011), only in rare cases have studies applied and compared multiple GDMs (e.g. Briffa *et al.*, 1992; Esper *et al.*, 2010; Andreu-Hayles *et al.*, 2011). A comparative analysis and critical evaluation of the most commonly used GDMs in tree-ring research are therefore needed.

Here, we critically evaluate the performance of the four most widely applied GDMs (shown in Fig. 1). We first reviewed the available literature on the application of these GDMs in temperate, boreal, subtropical and tropical tree-ring studies. Then, we assessed their consistency, sensitivity and reliability using a combination of measured and simulated growth data. To evaluate the consistency in results across GDMs, we applied the four GDMs on tree-ring series from a tropical species from Thailand. Next, we applied these GDMs on simulated growth data with imposed growth trends to assess their sensitivity, accuracy and reliability. We simulated five growth-trend scenarios: two with strong positive and negative growth trends, two with weak trends and one with no growth change. Finally, we discuss differences in sensitivity, accuracy, consistency and reliability of GDMs and provide recommendations for GDM choice in tree-ring studies.

Materials and methods

Growth-trend detection methods

We performed a literature review to document which GDMs are most commonly used in tree-ring studies. Published papers were collected using Scopus and Google Scholar with one, or a combination, of the following search terms: tree rings; dendrochronology; dendroecology; long-term growth trend; climate change; CO_2 fertilization; tree growth; climate–growth responses; basal area increment (BAI); RCS; age classes; and CD. We then selected publications in which GDMs were used and for each publication in this selection we noted the GDM(s) applied, the period covered by growth-trend analyses, study species and site, and growth trend(s) detected.

Below, we describe the methods and assumptions of the four most widely used GDMs: CD, BAC, RCS and SCI. In Figure 1 we provide a schematic overview of the crucial steps within the application of each of these GDMs: ‘age/size correction’ shows how the ontogenetic trend is accounted for in the raw data; ‘trend analysis’ indicates the chronology construction and regression analysis; and ‘output’ indicates how we present results of the trend analyses. Over time, several variations and new methods have been developed to cope with the (supposed) limitations of each GDM: signal-free standardization (Melvin & Briffa, 2008), age-band decomposition (Briffa *et al.*, 2001), C-method standardization (Biondi & Qeadan, 2008), or the integration of different methods into mixed-effect models (e.g. Girardin *et al.*, 2008; Nock *et al.*, 2011). Although these variations exist, in this study we focus on the four most widely applied GDMs in their most basal form.

In conservative detrending (henceforth CD), a mathematical function is fitted to individual ring series (Fig. 1; see ‘age/size correction’) to account for the decrease in ring width with tree age (i.e. the ontogeny) and residual growth is then calculated around these functions. The fitted functions can be (rigid) splines (e.g. Kienast & Luxmoore, 1988; Andreu-Hayles *et al.*, 2011) or ‘conservative curves’ (i.e. negative exponential, linear regression, or horizontal lines; cf. Wang *et al.*, 2006; Koutavas, 2013). Residuals are calculated by dividing measured ring widths by the fitted function. This method assumes that the fitted functions describe the decrease in ring width with age of each individual, while fully or partially maintaining the long-term growth trends. Long-term growth trends are then calculated over the residual chronology (the average residual per year) and related to calendar year (Fig. 1, see ‘trend analysis’).

In the BAC, the age/size trend is removed by converting diameter growth (in cm yr^{-1}) to BAI ($cm^2\ yr^{-1}$; Fig. 1). This method assumes that growth in BAI shows no trend in mature trees, contrary to diameter growth that often shows decreases with increasing tree size (Martínez-Vilalta *et al.*, 2008; Silva *et al.*, 2010). For each tree, BAI is calculated and growth trends in time are computed over the BAI chronology (Fig. 1).

In the RCS, an average age/size trend is calculated to describe the ontogeny, that is, the ‘regional curve’, and individual tree-ring series are then divided by this average curve (cf. Esper *et al.*, 2003; Cole *et al.*, 2010). To establish the regional curve, ring widths of all individuals are first aligned to cambial age (years from the pith; Fig. 1, see age/size correction) and average growth rates are calculated for each age. A mathematical smoothing function is fitted through these averages per age to describe the relationship between growth and age (i.e. the regional curve). Ring widths of individual trees are then divided by the expected growth for each cambial age. This process assumes that the age/size trend of the species is realistically described by the tree-ring series and that the regional curve is independent from long-term growth trends induced by environmental changes. Temporal trends in growth are calculated over the residual chronology, related to calendar year (Fig. 1, see ‘trend analysis’).

In the SCI, the age/size trend in growth is not accounted for by curve fitting or data transformations. Instead, growth trends are analysed directly within an ontogenetic stage, that is within the same age or size classes for extant large/old trees and extant small/young trees (Landis & Peart, 2005; Rozendaal *et al*., 2010; van der Sleen *et al*., 2014). Growth of small trees is thus compared with growth of large trees when they were small (Fig. 1, see 'age/size correction'). For instance, growth rates at a diameter of 12 cm can be compared between extant small and extant large trees and related to their corresponding calendar years to evaluate growth-changes over time (e.g. Rozendaal *et al*., 2010; Zuidema *et al*., 2011; Fig. 1, see 'trend analysis'). This method assumes that trees within a size class present similar growth rates and comparing growth within a size class thus removes the effect of the age/size trend. Trends are calculated over the raw growth data, in diameter growth or BAI, related to calendar year (Fig. 1, see 'trend analysis').

Empirical tree-ring series: Melia azedarach

We applied the four GDMs on tree-ring series for *M. azedarach* A. Juss (Meliaceae, henceforth called *Melia*) to evaluate the consistency of results between methods. *Melia* is a deciduous, long-lived pioneer (up to 120 years) known to form conspicuous and cross-datable annual rings (Vlam *et al*., 2014b). We collected increment cores of 90 *Melia* trees (three to four cores per tree) in the Huai Kha Khaeng Wildlife Sanctuary, west-central Thailand (between 15°50′ to 16°00′N and 99°00′ to 99°28′E), in an undisturbed and unlogged area of the forest. Core surfaces were prepared, scanned at 1600 dpi with a flatbed scanner (Epson Expression 10000 XL, Epson America Inc., Long Beach, CA, USA), and ring widths were measured using WINDENDRO (version 2009a Regular, Regent Instruments Canada Inc., Quebec, Canada). Average ring widths for the different radii were converted to diameter increment prior to trend analysis. More detailed descriptions of the study site, sampling methods and ring measurement procedures are given in Vlam *et al.* (2014b) and in Appendix S1.

Simulated tree-ring series

We simulated virtual growth trajectories that mimicked the growth characteristics of *Melia*, to allow for comparison of GDM outputs between measured and simulated data. Individual tree-ring series were simulated based on the following variables for *Melia*: the age trend in BAI, response to annual climatic variation and the temporal autocorrelation of tree growth. In addition, we included stochastic variation in the tree-growth simulations. A constant annual mortality chance of 1% was applied randomly for all simulated trees, independent of size class. Virtual tree-ring series were simulated for a period of 108 years (from 1901 to 2009). Every year, 300 new individuals were 'recruited' (at 1 cm diameter), thus creating a large amount of surviving series (>10 000) in the year of 'sampling' (i.e. in 2009). A full description of the tree-growth model is included in Appendix S2.

We ran five different simulations, applying a gradient of imposed growth trends per decade: strong (−6%) and weak (−2%) growth decreases, no growth trends and weak (+2%) to strong (+6%) growth increases. In the weak trend simulations, we imposed linear growth trends of 0.002 per year in both directions (i.e. a 2% change per decade), and in the strong trends, we imposed growth trends of 0.006 per year (6% change per decade). These growth trends were chosen as they resemble changes reported for permanent sample plots in tropical forests (cf. Lewis *et al*., 2009). The no-trend simulations contained no growth changes, as none of the input values showed trends over time. All simulations were performed in MATLAB v8.1 (The MathWorks Inc., Natick, MA, USA).

From the >10 000 surviving simulated tree-ring series, we created a database of 100 series randomly selected to be analysed for trends using the four GDMs. We chose this sample size as it is approximately the size of the empirical *Melia* data set and similar to that of many (tropical) tree-ring studies. For every growth-trend scenario, we created a fixed random selection of trees and applied all GDMs to detect trends on this selection. By repeating this random selection 100 times, we were able to assess the sensitivity of each method, that is, the percentage of correct trend detections.

We also assessed the reliability, accuracy and consistency in trend detection for each GDMs under the different scenarios. The reliability of a GDM is defined as 100% minus the percentage of cases that erroneous growth-trends were detected. We define the accuracy of a method as how well the strength of the imposed trends is reflected in the detected trend, that is, an imposed growth trend of 6% per decade translated to a detected trend of 6% per decade. For this purpose, we calculated the (relative) slope of the detected trends by the different GDMs and whether they coincided with the imposed trends. Finally, we used the simulated data to assess the consistency in trend detection between GDMs by analysing whether GDMs detected trends similarly when applied on the same random data sets (as also performed for *Melia*). To exclude any effect of the random selection of trees on the sensitivity, reliability, accuracy and consistency calculations, we repeated these analysis ten times, using ten different 'fixed' random data sets.

Implementation of growth-trend detection methods

Growth-trend detection methods were applied to both empirical and simulated tree-ring series. We applied CD using conservative curves (negative exponential curve, linear regression, or horizontal line), fitted to the diameter increments of each measured and virtual tree-ring series, using the DPLR package in R (Bunn, 2008). Residual ring-width series were calculated by dividing measured ring widths by the fitted function, and trends were calculated over average residuals per calendar year (i.e. the chronology). BAI conversion was performed using standard formulas (cf. Phipps & Whiton, 1988; Silva *et al*., 2010; Gómez-Guerrero *et al*., 2013). BAI of all individual series was then aligned to calendar year, and trends were calculated over average BAI values per year. We applied RCS following Esper *et al*. (2003), determining the regional curve (i.e. the average age/size trend) for *Melia* by aligning all individual growth rate series to cambial age. To obtain a regional curve not driven by annual variations in growth, we smoothened the curve using a 15-year spline function. Residuals were calculated by dividing the tree-ring series by the regional curve, and trends calculated over average residuals per calendar year. For SCI, we applied classes of 4 cm diameter, that is, every ring falling in a cumulative diameter class of subsequently 4 cm (e.g. at 4 and 8 cm, etc.) was marked as a central ring (Fig. 1). To obtain growth values not driven by annual variations, growth rates per class were calculated as an average BAI of five rings: that of the central ring plus the two previous and two subsequent rings. In the case of missing rings (e.g. at the start or end of series), averages were calculated for at least four rings.

For each GDM, growth data (i.e. in either BAI or residuals) were related to calendar year to analyse long-term growth trends. For the sensitivity and reliability analysis, we tested for the presence of significant trends using Spearman's rank correlation coefficients (significance level $P < 0.05$; Fig. 1 see 'Output'), as most data were not normally distributed. For the accuracy and consistency calculations, we assessed the magnitude of the trend detected by fitting linear regression models to each data set. We then determined how strongly the imposed trends were reflected in the GDM results and whether the detected slopes corresponded to the imposed trends. For these analyses, we included all correlations, including nonsignificant ones. The strength of the detected trend was expressed in relative change per decade, that is, expressed in percentages. To calculate relative slopes for SCI and BAC, we divided each detected slope by the average growth rate. For RCS and CD, we used slopes directly as these already reflect relative growth trends. For the consistency analysis, we used the RCS as a reference method and computed the correlation between the slopes detected by the other methods and the RCS (see Appendix S3).

In the SCI, trends were calculated for each size class containing at least 10 individuals. For CD, BAC and RCS, we excluded all calendar years with less than five individuals prior to trend analysis. Furthermore, for CD, BAC and RCS, we analysed correlations for all series (all trees), but also for tree diameter at breast height (DBH) size classes separately: 0–27 cm (understory trees), 27–54 cm (small canopy trees) and >54 cm (large canopy trees). For ease of comparison, we calculated the sensitivity and reliability for the SCI as an average of all the size classes. All statistical analyses were performed using the R software for statistical computing, version 3.2.00 (R development core team 2013).

Results

The use of GDMs in literature

We found a total of 46 studies on 77 species in which GDMs were used to detect growth trends. In total, 99 data sets of unique species × location × GDM combinations were evaluated (Fig. 2 and Appendix S4). In a few cases, two or more GDMs were used on the same data

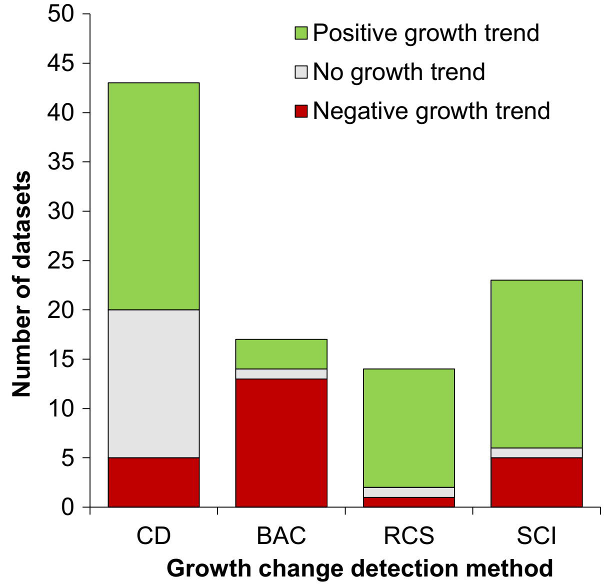

Fig. 2 Results of a literature review of the most commonly used growth-trend detection methods (GDM). A total of 46 studies on 77 species are presented, comprising of 99 data sets of unique species × location × GDM combinations. Bar colour indicates whether positive trends (green), no trend (grey), or negative trends (red) were detected. GDM abbreviations: conservative detrending (CD), basal area correction (BAC), regional curve standardization (RCS) and size class isolation (SCI).

set (e.g. Piovesan *et al.*, 2008; Esper *et al.*, 2010; Andreu-Hayles *et al.*, 2011). The studies were unevenly distributed over temperate, boreal and tropical regions, with just four studies conducted in the tropics (13 data sets).

Conservative detrending was the most widely applied GDM in all studies, with 20 studies on in total 46 data sets. In 26 of these 46 data sets, positive long-term growth trends were reported, whereas 15 data sets showed no growth trends. SCI was the most applied method for tropical species, with two studies on nine data sets.

Detecting long-term growth trends in Melia tree-ring series

We analysed growth trends in the *Melia* tree-ring series using the four GDMs to assess differences in their output. Results for CD, BAC and RCS are presented for four size categories: all trees, small (0–27 cm DBH), medium (27–54 cm) and large trees (>54 cm). For SCI, results are presented per 4-cm size class (Fig. 3) and we include a clarification on how trends were computed in SCI in a manner analogous to Fig. 1.

The trends detected for the *Melia* tree-ring series varied between specific methods. Three GDMs detected consistent negative growth trends over time: BAC, RCS

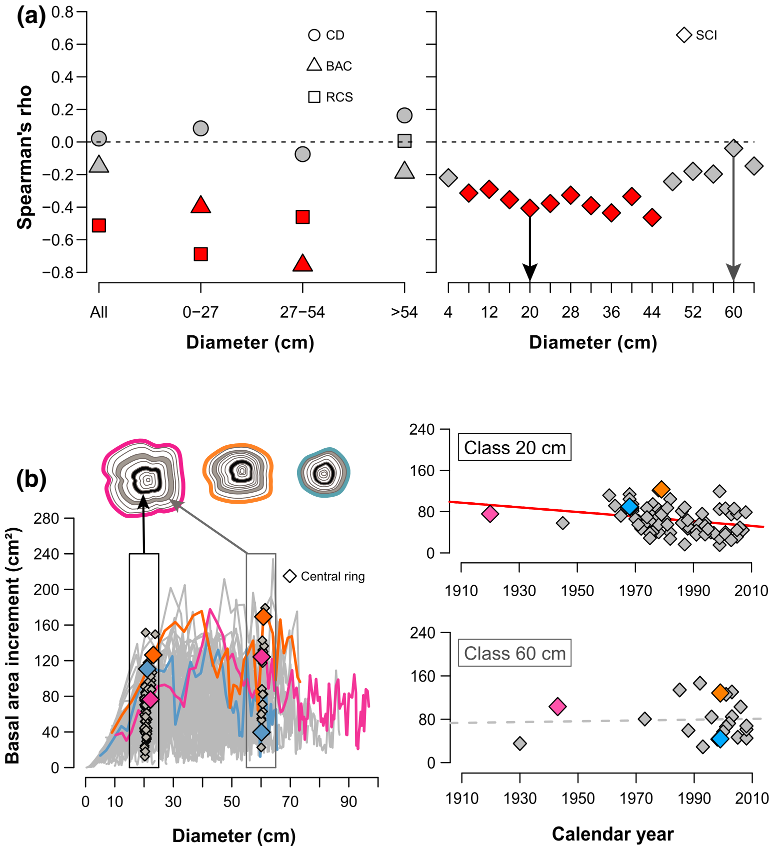

Fig. 3 Results of the analyses of long-term growth trends on the tree-ring series of *Melia azedarach*. (a) Trends detected by each growth-trend detection methods (GDM): conservative detrending (CD), basal area correction (BAC), regional curve standardization (RCS) and size class isolation (SCI). Negative trends (red) and nonsignificant trends (grey) are presented for different diameter categories (in Spearman's rho, significance level $P < 0.05$). (b) Procedure and results of the SCI method: tree growth of all – small and large – individual trees is arranged to tree size (left panel) and average growth rates (of 5 years) are calculated within specific diameter classes, for example Class 20 and Class 60 cm. For each diameter class, growth rates are then arranged to calendar year (right panel) and trends computed over time, for example in the Class 20 cm, a negative trend was detected [red dot at 20 cm (in a)].

and SCI. These trends were found for small and medium-sized trees (BAC and RCS) and for 8–44 cm diameter trees (SCI). RCS was the only method detecting trends in the category of all trees. Trends detected by BAC, RCS and SCI were highly significant (mostly $P < 0.001$). The nonsignificant results for CD in all size categories ($P > 0.05$) clearly contrasted with the highly significant results obtained by the other GDMs.

In short, three of the four methods (BAC, RCS and SCI) yielded evidence for declining growth rates over time in small and medium-sized *Melia* trees.

Detecting imposed long-term growth trends on virtual growth trajectories

We generated virtual growth trajectories mimicking the growth of *Melia*, to assess the sensitivity, reliability, accuracy and consistency of the four GDMs. The input of the model consisted of factors for the age/size trend, climate–growth relationship, growth autocorrelation (of 15 years) and stochastic variation. The modelled data mimicked the growth of *Melia* very well: modelled growth showed a similar age/size trend (and variation around it; Fig. 4a) and similar year-to-year variation (Fig. 4b) to the *Melia* data. This year-to-year variation was induced by the input factor for climate–growth relationship. We built a chronology for the modelled data – on the same way as for *Melia* (see Appendix S1) – that was highly similar to this input climate–growth factor (R^2 = 0.956, data not shown). Analysis *a posteriori* on the no-trend scenario data set showed that the age/size trend explained 18.8% of the variation in all growth data while climate explained 8.4% of the variation remaining after removal of the age/size trend (by dividing individual series by the input formula for the age/size trend). The remaining variation, not explained

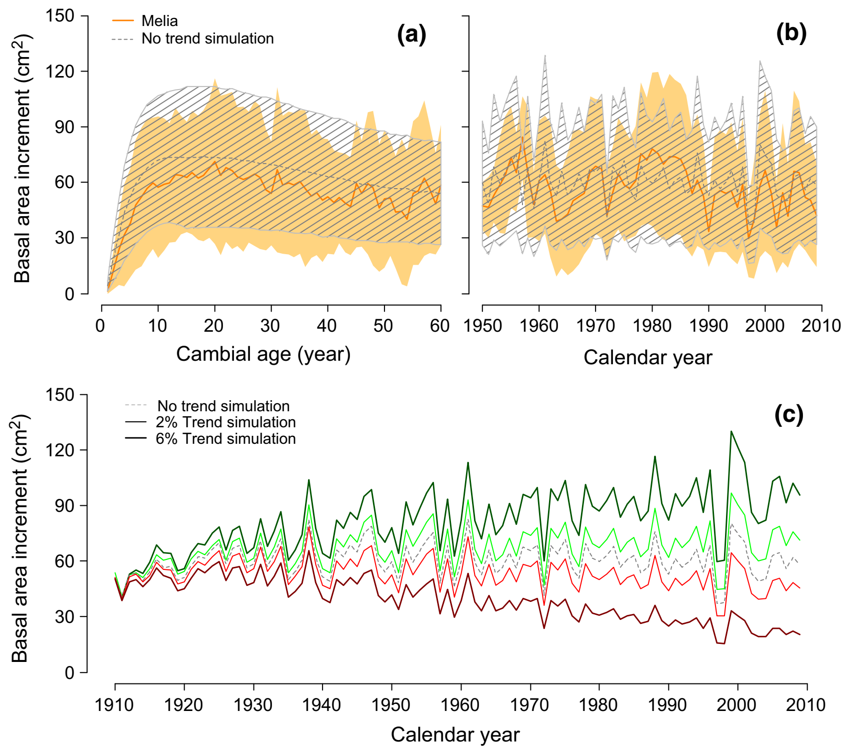

Fig. 4 Simulated growth trajectories based on *Melia azedarach* and examples of the imposed growth trends. (a) Relationship of basal area increment (BAI) per cambial age for the simulated data (in the no-trend scenario; grey) and the measured growth rates for *M. azedarach* (orange). (b) Relationship of BAI per calendar year between modelled (grey) and measured data (orange). Lines represent average BAI for all measured or simulated series and shading their SDs. (c) Relationship of average BAI per calendar year for the five imposed growth-trend scenarios: strong increases (i.e. 6% growth change per decade; dark green line), weak increases (2% change, light green), no change (grey line), weak decreases (light red) and strong decreases (dark red).

by the age/size trend or climate, can be attributed to the factor for stochastic variation and to the autocorrelation in growth. Growth in the simulated growth curves data was on average significantly autocorrelated for up to 6 years (data not shown). The simulation of positive and negative trends also clearly affected the modelled growth data (and its average variation), as shown in the mean basal area chronology for each scenario (Fig. 4c).

Next, we assessed how well GDMs detected growth trends imposed on the virtual growth trajectories. Sensitivity (i.e. percentage of imposed growth trends correctly detected) varied considerably among GDMs (Fig. 5; Table 1). On the data sets with the strongest imposed growth trends (i.e. 6% increase and decrease), BAC, RCS and SCI often correctly detected the direction of the imposed trends (Table 1). For these three GDMs, sensitivity was higher with imposed strong negative growth trends (93–100% of cases) than with positive trends (30–99%) and this difference was most evident in the SCI. CD had the lowest sensitivity, detecting almost none of the strong imposed positive trends and only 36% of the strong negative trends.

Sensitivity decreased for all GDMs when detecting weak imposed growth trends of 2% increase or decrease, compared to the strongest (6%) simulated trends. For BAC and RCS, sensitivity was intermediate, with trends correctly detected in 36–67% of the simulations, whereas SCI had a lower sensitivity of 7–23%. Again, CD had the lowest sensitivity, varying between 2% and 6%.

In the no-trend simulations, reliability was high for CD, RCS and SCI – varying between 85% and 96% of correctly detected ‘no trends’ – and was lower for BAC (67%; Table 1). Erroneous trend detection also occurred in the 2% increase and decrease scenarios (Fig. 5), but overall, reliability was high in all simulations with imposed growth trends (Table 1). For BAC, the lower reliability in the no-trend scenarios, compared to the other methods, was not reflected in the scenarios with imposed trends: reliability was high, with >97% of trends correctly detected.

The accuracy of trend detection (i.e. correctly detecting the strength of the imposed trends) also varied between GDMs. CD showed nearly no differences in the strength of detected trends between increasing,

Table 1 Sensitivity and reliability of four growth-trend detection methods (GDM) applied to a range of growth changes imposed to simulated tree-ring series

		Imposed growth trend (per decade)					
GDM		−6%	−2%	0	2%	6%	Mean
CD	Sensitivity	36.4 ± 6.4	5.5 ± 2.9	95.9 ± 1.8	1.5 ± 1.2	0.8 ± 1.2	28.0
	Reliability	98.6 ± 1.1	98.7 ± 1.2	95.9 ± 1.8	97.9 ± 1.1	99.4 ± 0.7	98.1
BAC	Sensitivity	100.0 ± 0.0	66.9 ± 4.6	66.7 ± 4.3	56.5 ± 3.6	98.9 ± 1.0	77.8
	Reliability	100.0 ± 0.0	98.9 ± 0.9	66.7 ± 4.3	97.4 ± 1.4	100.0 ± 0.0	92.6
RCS	Sensitivity	100.0 ± 0.0	37.6 ± 3.7	85.3 ± 4.0	35.6 ± 3.7	86.3 ± 4.0	69.0
	Reliability	100.0 ± 0.0	99.2 ± 1.0	85.3 ± 4.0	99.7 ± 0.5	100.0 ± 0.0	96.8
SCI	Sensitivity	93.2 ± 0.6	23.4 ± 1.8	93.9 ± 0.5	7.1 ± 0.9	30.5 ± 1.3	49.6
	Reliability	100.0 ± 0.0	99.9 ± 0.1	93.9 ± 0.5	98.5 ± 0.2	99.6 ± 0.2	98.5

Sensitivity refers to the percentage of correct detection of the imposed growth trend. Reliability is 100% minus the percentage of erroneous growth-trend detections. Values are presented as an average of 10 analyses ± SDs. For SCI, the results are presented as the average of all size classes and for the other methods, for the 'all trees' size category.
CD, conservative detrending; BAC, basal area correction; RCS, regional curve standardization; SCI, size class isolation.

decreasing and no-trend scenarios: detected slopes varied between 0.0% and 1.0% growth-change per decade (Fig. 6; Table S4 in Appendix S3). The other GDMs appear to underestimate the detection of positive trends: in the scenarios with 2% growth increases, growth trends were detected varying between 0.4% and 1.1% per decade and in the 6% increase scenarios between 1.7% and 3.5%. In the scenarios with growth decreases, on the other hand, BAC and SCI overestimated the imposed trends, for example in the 6% decrease scenario, growth decreases of >11% were detected (Fig. 6; Table S4 in Appendix S3). It is also clear that both BAC and SCI show a higher spread of detected trends, that is, wider distribution of detected slopes, compared to the RCS (Fig. 6).

Consistency in detecting trends was high between BAC and RCS: the detected trends showed high correlations for all different scenarios (average $R^2 = 0.678$; Table S5 in Appendix S3). The slopes detected by SCI correlated less strongly with the RCS ($R^2 = 0.192$), while for CD, the detected slopes did not correlate at all ($R^2 = 0.022$). For more detailed results on the consistency, see Appendix S3.

In short, sensitivity varied between methods: detection of trends was good when 6% trends were imposed but lower with the 2% trends. Reliability was high on the simulations with imposed growth trends but erroneous trends were detected in the no-trend simulations, with results varying between GDMs. Accuracy also varied between GDMs: in CD nearly none of the imposed trends were detected and the remaining methods tended to underestimate the imposed positive trends, while overestimating the negative trends. Finally, methods are rather consistent in detecting trends when applied on the same data sets.

Discussion

Long-term growth trends for M. azedarach

Three of the four GDMs applied to detrend a single tree-ring data set yielded similar results: long-term decreases in growth for *Melia* trees in similar ranges of tree size (Fig. 3). Application of CD did not yield trends over time. The negative growth trends are consistent with findings from Nock *et al.* (2011) who studied the same tree species at the same site. They calculated trends in BAI over different size classes, with a method that combines BAC and SCI, using a mixed-effect model.

Identifying the causal drivers of decreasing growth rates is difficult (Clark & Clark, 2011) and multiple factors have been suggested: increased drought periods, increasing temperatures and closing of the canopy after disturbances (e.g. Nock *et al.*, 2011; Middendorp *et al.*, 2013). In addition, biases due to sampling design (Nehrbass-Ahles *et al.*, 2014) or related to the nature of tree-ring data (Brienen *et al.*, 2012) could also lead to the detection of (apparent) trends. For instance, the 'juvenile selection effect' (cf. Landis & Peart, 2005; Rozendaal *et al.*, 2010) could create negative growth trends in a light-demanding species such as *Melia*, where adult trees are probably the successful, fast-growing individuals from the past. In addition to these issues, we show here that the choice of growth-trend detection method also influences the probability of detecting trends.

Applying CD did not yield significant trends for *Melia* in any of the size classes. This lack in trend detection is to be expected for CD (Briffa *et al.*, 1992) as the functions fitted to individual ring series may not differentiate between age/size trends and trends induced by

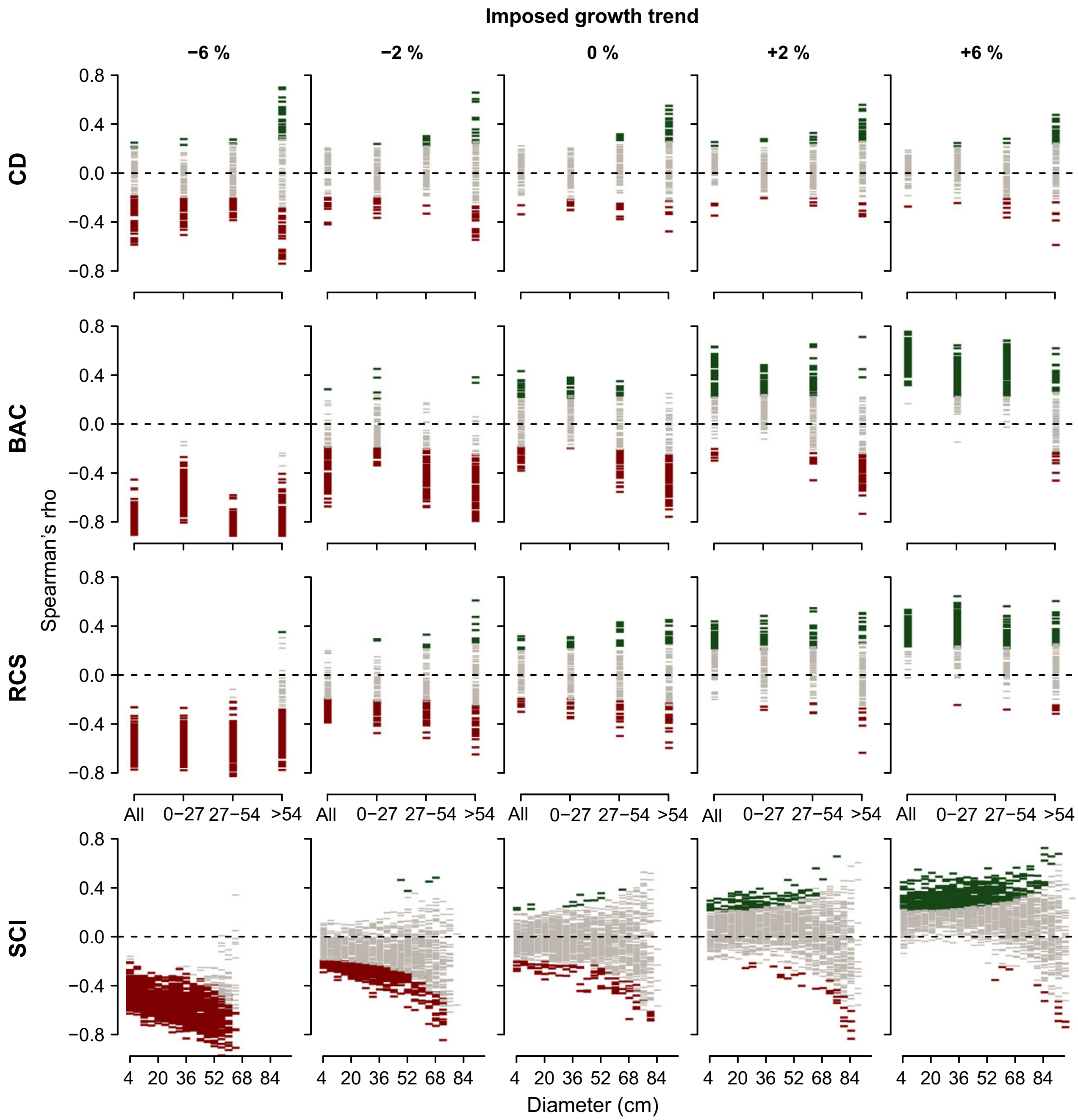

Fig. 5 Results of the analyses with simulated growth trajectories for four growth-trend detection methods (GDM). Significant negative (red) and positive trends (green), and nonsignificant trends (grey) are presented per GDM (in Spearman's rho, significance level $P < 0.05$) for different diameter categories. Results are presented for one subset of 100 times 100 trees per imposed trend. GDM abbreviations: conservative detrending (CD), basal area correction (BAC), regional curve standardization (RCS) and size class isolation (SCI).

climatic influence (Cook *et al.*, 1995). Furthermore, this lack in trend detection may have been reinforced by the relatively short length of our ring series (i.e. lifespan of *Melia* ~100 years). On long series, function fit is mostly determined by the age/size dependent growth trend in the series, whereas on short series, function fit is relatively more influenced by values at the end or beginning of a series, hampering the detection of trends. This pattern of lower trend detections on short series also emerged from the literature review: trends were detected by CD in 90% (19 of the 22) of studies working with long series, that is, lifespans >130 years, while in just 43% (9 of the 21) of studies with short series (Appendix S4).

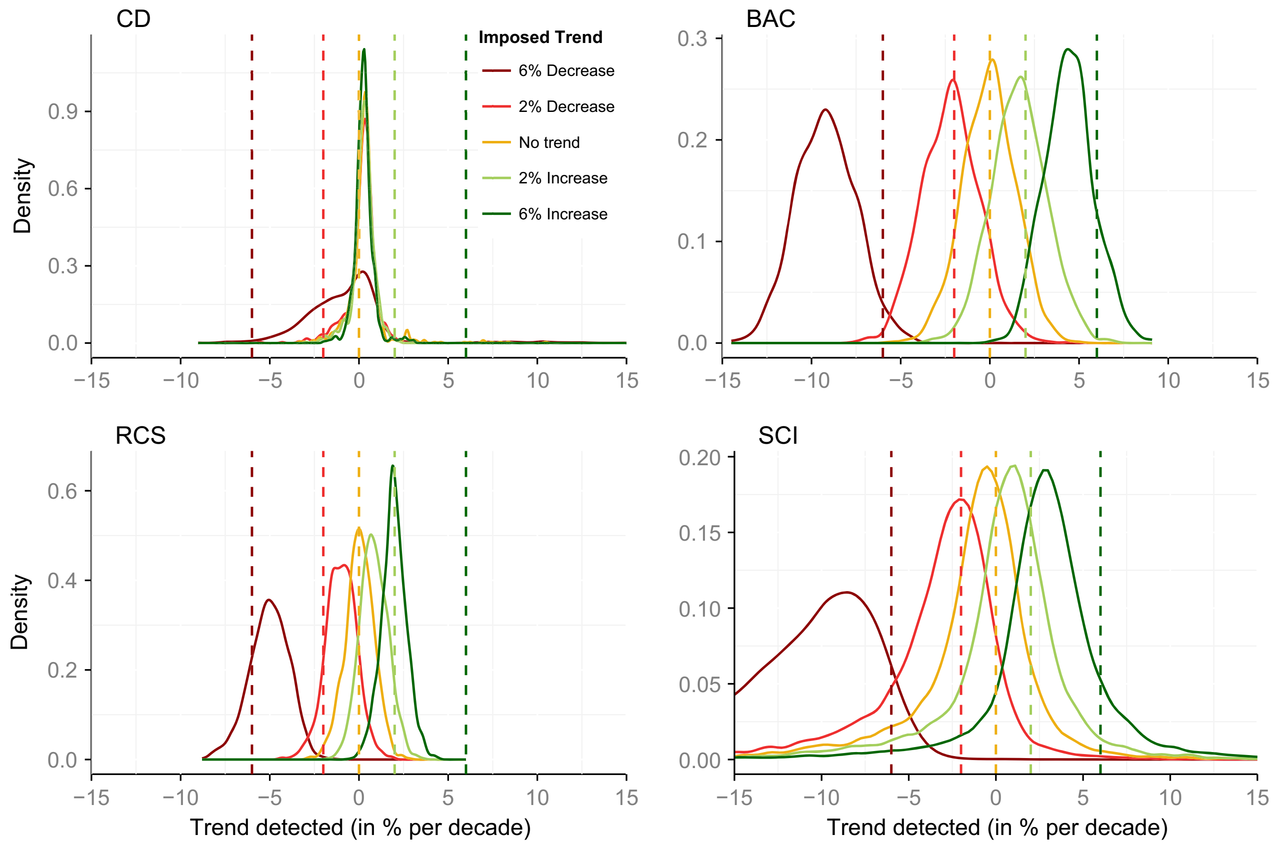

Fig. 6 Comparison of slopes detected by the growth-trend detection methods (GDMs) for each of the imposed growth-trend scenarios and runs. Coloured lines show the distribution of all slopes detected by the GDMs (as a Kernel density plots) and the vertical dotted lines the corresponding imposed growth trends. GDM abbreviation: conservative detrending (CD), basal area correction (BAC), regional curve standardization (RCS) and size class isolation (SCI).

The results on the *Melia* ring series indicate that GDM choice influences the detection of long-term trends. This influence was also suggested by Esper *et al.* (2010) using multiple detrending methods on boreal trees. These differences in trend detection between methods suggest that results of studies using a single method should be interpreted with care.

Sensitivity, reliability, accuracy and consistency of growth-trend detection methods

If different GDMs yield similar results, this may be reassuring, indicating that the detected trend is likely. Yet, this does not imply that growth trends were correctly detected or that they were present in the tree-ring series in the first place. We addressed these issues by applying the four GDMs on simulated growth trajectories that had imposed growth trends. These growth-trend scenarios, with either negative, no or positive trends as input, demonstrated that GDMs vary in their sensitivity (i.e. power to detect imposed trends), accuracy (i.e. how well the strength of trends are detected) and reliability (i.e. 1- the probability of detecting erroneous trends). Sensitivity was reasonably high when strong growth trends (of 6%) were imposed, but decreased when imposed trends were weaker (2%; Table 1). The accuracy of trend detection also differed between GDMs, with a higher tendency to detect (or overestimate) imposed negative trends than for positive trends (Fig. 6). Similarly, the reliability of trend detection was high in the scenarios with strong trends, but was lower for the weak or no-trend scenarios (Table 1). In the following section, we discuss specific results for each of the GDMs.

Conservative detrending is assumed to sufficiently remove the (negative) age/size trend in diameter growth, while maintaining long-term trends. However, several weaknesses of CD have already been noted (Briffa & Melvin, 2011) and detrending series individually has been suggested to inevitably also remove long-term trends in growth (Briffa *et al.*, 1992; Cook *et al.*, 1995). Our results confirm these suggestions, as CD showed the lowest sensitivity and accuracy of the four methods (Table 1; Figs 5 and 6), implying that imposed growth trends were completely removed from most simulated growth trajectories (Table 1). Additionally, CD was the least consistent method in detecting trends, that is, slopes detected by CD showed nearly no correlation with slopes detected by the RCS (Appendix S3). Although these weaknesses have been noted, CD is still widely applied (e.g. Wang *et al.*, 2006; see Appendix S4; Villalba *et al.*, 2012). This low sensitivity is also reflected by the relatively high proportion of studies detecting no growth trends when applying CD (15 of the 43 reviewed data sets; Appendix S4), which is considerably higher than for other GDMs (Fig. 2). Similar to the *Melia* data, the complete removal of trends from the modelled data may have been reinforced by the relative short length of the simulated growth trajectories. Furthermore, the negative (exponential/linear) curves fitted in CD may also not be suitable for describing the initial growing phases of trees, when young growth years or young individuals are included. CD may thus be better suited for detecting trends on long-lived species.

Basal area correction showed high sensitivity and good accuracy in detecting growth trends (Table 1; Figs 5 and 6), and trends detected using BAC were consistent with those detected with RCS (Appendix S3). However, the reliability of BAC was the lowest of all methods, especially in the no-trend simulations (Tables 1 and 2). The frequent detection of erroneous trends by only expressing growth in basal area is worrisome, as BAC is still applied this way (e.g. Martínez-Vilalta *et al.*, 2008; Silva *et al.*, 2010) and this unreliability may lead to incorrect conclusions about growth trends. Our results suggest that BAC may not effectively disentangle age/size from long-term growth trends. Indeed, growth of *Melia* (and the simulations derived from *Melia* data) still shows a clear age trend in BAI (Fig. 4a). If the age/size trend is not correctly accounted for, trends may be induced by, for instance, changes in the relative abundances of small (slow growing) and large (fast growing) trees over time.

Simply expressing growth as basal area has the advantage of avoiding curve fitting procedures (as performed in CD and RCS; Table 2) and also because BAI is a meaningful expression of tree functioning, for example conducting xylem surface (e.g. Mendivelso *et al.*, 2013; Sterck *et al.*, 2014). However, this conversion may thus not suffice to remove the age/size trends and additional steps are necessary to account for the remaining age/size trend when using BAC. These steps may include: analysing trends inside specific size classes (e.g. only for mature trees; cf. Jump *et al.*, 2006); detrending the BAI series by an estimated BAI growth trend (the C-Method, cf. Biondi & Qeadan, 2008); or incorporating tree size explicitly (e.g. in mixed-effect models) when analysing trends (e.g. Martínez-Vilalta *et al.*, 2008; Nock *et al.*, 2011). Analysing trends inside specific size classes may indeed provide additional information, as illustrated in the trend analysis for *Melia*. When analysing trends in specific size classes, trends were detected for the small and medium size categories but not for all trees (Fig. 3). Note that with small size classes, BAC effectively becomes analogous to SCI. We also applied the C-method (cf. Biondi & Qeadan, 2008) to the simulated data. Surprisingly, this

Table 2 Strengths and limitations of four different growth-trend detection methods (GDM)

	CD	BAC	RCS	SCI
Strength				
High sensitivity (Table 1)	✗	✓	✓	✗
High reliability (Table 1)	✗	✗	✓	✓
Can be applied on untransformed growth data (Fig. 1)	✗	✓	✗	✓
Can be combined with climate–growth analysis (Fig. 1)	✓	✓	✓	✗
Limitation				
Time span ring series should extend span of the trend assessed*	✓	?	✓	?
Low detection power for larger diameter classes†	✗	✗	✗	✓
Affected by sampling biases‡	✓	✓	✓	✓

Symbols indicate whether strength or limitation is applicable: check mark = applicable; crosses = not applicable; and question marks = still unclear/not assessed. Criteria are either assessed in this study or derived from literature (as indicated). Sensitivity refers to the percentage of correct detection of imposed growth trend and reliability = 100% minus the percentage of erroneous growth-trend detections.

GDMs assessed: CD, conservative detrending; BAC, basal area correction; RCS, regional curve standardization; SCI, size class isolation.

*To avoid the trend-in-signal bias (cf. Briffa & Melvin, 2011).

†Sample size decreases with increasing diameter (e.g. for *Melia*, n = 17 at 63 cm diameter).

‡Slow-grower survivorship bias and big-tree selection bias (cf. Brienen *et al.*, 2012).

method detected solely negative trends, irrespective of the imposed trends (see for more details Appendix S5). We believe that C-method might not be suitable for short series, that is, the small trees in our data set, as it cannot account well for the ontogenetic growth trends in these small/juvenile trees (Biondi & Qeadan, 2008). We have not analysed trends using mixed-effect models, as this was beyond our scope of comparing existing and widely used methods. However, we believe that mixed-effect models, including generalized additive mixed models (GAMM), have great potential to disentangle age/size trends from long-term growth trends, as these models can simultaneously account for linear (i.e. growth trends) and nonlinear (i.e. age/size) trends in a data set (Wood, 2006; Polansky & Robbins, 2013). Such approaches are, however, rare in tree-ring studies (e.g. Martínez-Vilalta *et al.*, 2008; Nock *et al.*, 2011) and should receive more attention. Additionally, the detection of trends using BAC may be hampered as growth (in basal area) may continually increase over a tree's life (Stephenson *et al.*, 2014). If a species shows a continually increasing trend in basal area growth over its life, BAC is hampered in disentangling age/size from long-term growth trends. However, such increasing growth trend poses less of a problem for the other methods, as the age trend (or size trend) will be accounted for by the fitted conservative curves, incorporated in the regional curve or, for the SCI, trees will be selected from within a particular size class (with its corresponding 'average' growth rate).

Overall, RCS showed high sensitivity, accuracy and reliability (Table 2). However, sensitivity was below 50% in the scenarios with weak growth trends (2%; Table 1) and RCS underestimated the strength of imposed positive trends (Fig. 6). Weak (positive) growth trends over time are thus not easily detected using this method. Applying RCS requires large sample sizes (Briffa *et al.*, 1992; Esper *et al.*, 2002) and ideally species showing a 'strong' age–size relationship, to enable the calculation of a representative and 'strong' regional curve. Our light-demanding study species – and the simulated series – showed such strong age/size relationship. RCS may be less suitable for shade-tolerant species, as these species often exhibit rather weak age–size relationships (due to periods of slow or suppressed growth). Also, the period covered by the tree-ring series in RCS should ideally be longer than the period over which trends in environmental signals are assessed (Table 2; e.g. Esper *et al.*, 2002), to avoid that externally driven growth trends are incorporated into the regional curve (the 'trend in signal bias'; cf. Briffa & Melvin, 2011). In boreal and temperate regions, fossil and subfossil wood are often incorporated to extend the time span of long-term growth reconstructions (e.g. Esper *et al.*, 2012). In regions lacking fossil wood (e.g. in the tropics, due to the high decomposition rates), it is necessary to work with long-lived species when using RCS when analysing climate change effects on tree growth. For tropical studies, the combined requirements of long lifespans and strong age/size relationships imply the RCS may be better suited for long-lived pioneer species. Finally, RCS requires accurate estimations of tree ages (cambial age) to calculate the regional curve (unless the regional curve is based on diameter instead of age; cf. Bontemps & Esper, 2011). Care should thus be taken when estimating ages from increment cores that do not include the pith.

The SCI method was not very sensitive but showed high reliability (i.e. detecting few trends erroneously; Table 1 and Fig. 5), detected the imposed trends rather accurately (Fig. 6) and was consistent with the RCS (Appendix S3). Splitting the data into diameter classes reduces sample size, as trends are calculated on average growth values per tree and not on individual ring measurements. Sample size may be particularly low in smaller diameter classes, due to missing piths when coring, and in large diameter classes if only a small portion of trees are large. The low sensitivity of SCI may be explained by these reduced sample sizes and working with SCI thus requires sampling relatively large numbers of trees (Table 2). Furthermore, SCI requires including both large and small trees, which is not always possible as many (tropical) species show periodic absence of recruitment (e.g. Vlam *et al.*, 2014a). Another limitation of SCI is that determining size classes is a subjective process that may lead to analyses of trends over a variety of classes for different species (e.g. Rozendaal *et al.*, 2010), making comparisons between these analyses more difficult. Additionally, the output of SCI is less suitable for establishing climate–growth relationships (Table 2), which hampers assessing which environmental factors may explain growth trends. Despite its limitations, SCI showed low detection of erroneous trends, that is, SCI is a reliable method. We argue that the reliability of a method is important, as a conservative method is preferred over an unreliable method. Finally, another advantage of SCI is that it directly evaluates growth trends on raw measurements and therefore is not influenced by (subjective) decisions on curve fitting that are necessary for CD and RCS (Table 2).

Overall, the four tested GDMs differed in their sensitivity, reliability, accuracy and consistency. These results show that detection of long-term trends (spanning several decades to centuries) is affected by method choice and suggest that the age/size trend may not be completely removed in some methods. GDM sensitivity and accuracy varied, with CD not detecting trends while the other methods underestimate positive trends while overestimating negative trends. This stronger detection of negative trends can in part be explained by the fact that growth cannot be negative in our modelled data or in real tree-ring data. Growth reductions over time force growth data nearer to zero, reducing variation in growth data over time. The contrary is true for the growth increase scenarios (see Fig. 4c), in which growth variation increases. We believe that the lower variation in growth in the decrease scenarios implies trends are more easily detected, thus leading to the higher sensitivity and accuracy.

In our modelling approach, we attempted to assess how the variation present in tree growth affects the detection of trends (i.e. an improved power test) and determined each factor in the model using simple correlations. This approach only accounts for the stochastic variation in growth and is of course a simplification of all physiological and mechanistic factors affecting tree growth. A modelling approach based on mechanistic or physiological processes could greatly enhance the understanding of the effects climate change on tree growth and how to detect them. Furthermore, our finding should be interpreted with some care, as the growth characteristics of one tropical species do not necessarily apply to other species or other regions. Similar analyses should thus be performed on more species, including widespread and well-studied species such as Scotch Pine (*Pinus sylvestris*) or Douglas Fir (*Pseudotsuga menziesii*), for which long chronologies are available. Despite the limitations of our approach, we believe that it suffices when assessing the detection power of the different GDMs and that it forms an important first step in disentangling the effects of method choice on the detection of long-term growth trends.

Recommendations for growth-trend detection

Tree-ring analysis has been widely applied to detect growth trends in boreal and temperate tree species, and there is growing interest in using tree rings for the same purpose for tropical tree species (Bowman *et al*., 2013). In this study, we focused on the four detrending methods most widely used in tree-ring research to disentangle age/size trends from long-term growth trends. Below, we provide recommendations for tree-ring studies analysing trends in growth.

Our results suggest that, to detect long-term growth trends, CD is not very suitable, that BAC is not always reliable and that the RCS and SCI show good potential. Using CD, no trends were detected in the *Melia* tree-ring data and in nearly all simulated growth data. We recommend not using CD to evaluate trends, especially when working with short-lived species, and CD may be better suited when analysing climate–growth relationships. BAC showed high sensitivity and accuracy, but showed the lowest reliability (i.e. it also detected trends erroneously). This low reliability is problematic, as determining when a trend is correctly or erroneously detected in measured ring data is difficult. Great care should thus be taken if only expressing growth in basal area. Several additional steps can be taken to improve analysis with BAC, as discussed above. The high sensitivity of BAC merits assessing which of these steps effectively increase BAC's reliability.

For future tree-ring studies analysing growth trends, we recommend the use of several GDMs. We believe that combining the sensitive RCS with the reliable but somewhat conservative SCI would yield robust results. RCS showed high sensitivity and reliability and the SCI, despite its low sensitivity, was the most reliable method (i.e. the lowest erroneous detection of trends). These two methods are complementary in three aspects. First, SCI is independent of the age/size trend, whereas RCS depends on a 'strong' ontogenetic signal and may be less reliable when this signal is lacking. Second, the sensitivity of SCI depends of large sample sizes, as individuals (and not growth measurements) are the units of analysis. On the other hand, sensitivity of RCS is generally high as the individual ring measurements are the units of analysis. Thus, RCS is more suitable to detect weak growth trends and more suitable when sample sizes are relatively small. Third, the higher reliability is an important asset of SCI and – combined with its somewhat lower sensitivity – it makes SCI a high-quality, conservative method that can be used to verify the robustness of trends detected using RCS.

Detecting trends in tree growth is challenging, whether one deals with growth data derived from permanent plot studies or from tree-ring analysis (Bowman *et al*., 2013). For tree-ring data, both from temperate, boreal and tropical regions, specific limitations exist that need to be taken into account. First, many tree species show persistent temporal growth differences, that is, fast-growing individuals stay fast growers in time (e.g. Brienen *et al*., 2006). We believe that especially the RCS is sensitive to these growth differences. These differences lead to strong variation in diameter–age relationships that disproportionally affect the regional curve and therefore influence trend detection. Similarly, shade-tolerant species and species showing periods of growth suppression (e.g. slow growth due to overshadowing) may show periods of low or high growth over multiple years. To minimize the effect of these persistent growth differences on the regional curve, we recommend calculating RCS using small cumulative diameter classes (e.g. 1 cm) instead of age (cf. Bontemps & Esper, 2011).

Second, biases due to sampling strategies can potentially induce growth trends over time (Brienen *et al.*, 2012; Nehrbass-Ahles *et al.*, 2014). For instance, growth increases may be detected if slow-growing individuals within a population live longer, that is, the 'slow-grower survivorship' bias (cf. Brienen *et al.*, 2012; Table 2), but see Ireland *et al.* (2014). These slow-growing individuals will then be overrepresented in the more ancient portion of the data set, leading to apparent growth increases over time. Irrespective of the GDM used, tree-ring series should be collected according to the population structure to avoid such sampling biases as much as possible (e.g. Vlam *et al.*, 2014a). Additionally, accurate estimation of tree ages is crucial and may require working with cross-sectional discs instead of increment cores. Furthermore, we stress the importance of sampling near permanent sample plots and weather stations with long-term, high-quality data (cf. Wang *et al.*, 2006; Clark & Clark, 2011), to provide critical contextual information on the sample site and conditions (Bowman *et al.*, 2013).

Finally, detecting trends using tree-ring analysis requires working with large sample sizes (~100 trees or more per species). Large samples are needed to increase trend detection power and to obtain 'representative' subsets of the population (e.g. for a 'representative' regional curve in RCS). Also, to avoid local or regional effects on trends, sampling should preferably occur over large geographical scales (e.g. Esper *et al.*, 2012; Villalba *et al.*, 2012). In the tropics, however, acquiring and measuring large number of trees is challenging, due to low species abundance of individuals and the difficulties of working with tropical tree rings (Groenendijk *et al.*, 2014). Collecting multiple species and simultaneously analysing their growth trends (e.g. with mixed effects models) can be applied to increase the statistical power of the analysis (e.g. Kint *et al.*, 2012; Lara *et al.*, 2013). Such combined analyses are particularly powerful if sampling follows a standardized strategy (cf. Nehrbass-Ahles *et al.*, 2014). A standardized sampling and analysis protocol would allow for a meta-analysis of tree-ring studies worldwide, which is critical to assess the effects of global environmental changes on tree growth and forest dynamics.

To accurately identify long-term growth trends using tree-ring analysis, the best approach is probably to apply several detrending methods simultaneously. This approach would be especially strong if combined with simulated tree-ring series that take sample sizes into account and that mimic the variance in tree growth. Such integrative approaches are essential to determine whether detected growth trends really occured and should be extended to include more species, from boreal, temperate and tropical regions.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Appendix S1. Climate-growth relations.
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