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Using X-ray CT based tree-ring width data for tree growth trend analysis

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ABSTRACT

Changes in the environment influence the growth of tree species in Europe. Understanding the drivers of these growth changes is important to predict further growth and adapt forest management. To disentangle the different drivers of growth changes, it is common practice to apply mixed modeling techniques to tree-ring width series. Mixed modeling requires precise, replicated and well cross-dated tree-ring width series. The goal of this study was to compare a recently developed ring width measuring method based on X-ray Computed Tomography images (CT scan) with the standard LINTAB measuring method and to examine whether the same growth trends are detected with both methods using common beech (*Fagus sylvatica*) and sessile oak trees (*Quercus petraea*) as a case study. Although the CT scan method has a lower resolution than LINTAB measurements, it is of interest since it measures wood density in addition to ring width and it is less laborious in comparison to standard ring width measuring methods. No significant differences in ring width were found between the two measuring methods. The small non-significant difference between the two methods could largely be explained by the drying of cores needed for CT scanning. The same growth trends were detected with both methods: for common beech and sessile oak in Southern Belgium. These findings suggest that ring widths measured on CT scan images can be used as input for long-term modeling of tree growth changes for the targeted tree species.

1. Introduction

Tree growth has been changing in European forests over the last decades (Becker et al., 1994; Bergès et al., 2000; Dittmar et al., 2003; Piovesan et al., 2008; Charru et al., 2010; Kint et al., 2012; Latte et al., 2015). Climate change, increased carbon dioxide and ozone concentration, and increased nitrogen deposition have been identified as drivers of these growth changes (Matyssek et al., 2010; Bontemps et al., 2011; Babst et al., 2013; Reyer et al., 2013). Understanding how tree growth changes over time is essential to adapt forest management to future predicted climate change (Lindner et al., 2010). This forest management adaptation is important since forests deliver important ecosystem services such as wood production and carbon sequestration (Thorsen et al., 2014).

Tree-ring series are true archives of the past, storing information on tree growth change drivers which are acting at different time scales. Inter-annual fluctuations in growth may be related to yearly variations in temperature or precipitation, while on longer time scales environmental change and tree aging may influence tree growth. Understanding the drivers of past growth changes will help to predict possible growth changes in the future. By applying a mixed modeling strategy to tree-ring width (TRW) series, the relative importance of these different drivers of growth change can be disentangled (Martínez-Vilalta et al., 2008; Kint et al., 2012; Aertsen et al., 2014). Analyzing tree growth trends requires accurate measurement of TRW, which is an essential condition in this and other fields of dendrochronology (Grissino-Mayer, 1997). Also replication is important for dendrochronology: by increasing the number of samples, possible anthropogenic (e.g. management) and non-

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Table 1
Location and characterization of the four forest sites where trees were cored.

Site	Coordinates	Elevation (m.a.s.l.)	Slope (°)	Orientation	Beech trees	Oak trees
Marche-en-Famenne	50°27′N 5°6′E	400	5	South-east	2	9
Libin	50°6′N 5°1′E	360	5	North	10	8
Nassogne	50°6′N 5°3′E	260–300	0	–	12	8
Couvin	50°2′N 4°44′E	300	5	East	3	6

anthropogenic (e.g. climate change) signals stored in tree-rings are enhanced, and errors due to missing rings or measurement errors are reduced (Fritts, 1976; Grissino-Mayer, 1997). Another premise of dendrochronology is cross-dating; i.e. by comparing growth variation within and among trees in a particular tree population the correct dating of TRW series is assured (Fritts, 1976). Black et al. (2016) showed that cross-dating is important to retain low- and high-frequency variability in TRW series. The abovementioned dendrochronological principles, i.e. accuracy, replication and cross-dating of the TRW measurements, determine the validity and the explanatory power of TRW series (Fritts, 1976; Maxwell et al., 2011), and the method used to measure TRW will influence these. Dendrochronology requires TRW measuring methods that are accurate and fast in order to obtain high numbers of precise TRW measurements.

Currently, several methods exist to measure TRW. These methods differ in resolution, degree of sample preparation, work load and cost, all of which directly or indirectly influence the accuracy, replication and cross-dating of the TRW series. The decision on which TRW measuring method will be used is mostly based on practical arguments, such as: experience, visibility of tree-ring boundaries and availability of measuring devices. Little research exists that compares accuracy of different TRW measuring methods (Maxwell et al., 2011; Arenas-Castro et al., 2015). To our knowledge, there are no studies available that evaluate the effect of the applied TRW measuring method on the outcome of TRW data based analysis, such as growth change modeling.

In addition to conventional TRW measurements with LINTAB (Speer, 2010) or Velmex, a recently developed method by Van den Bulcke et al. (2014) uses 3D X-ray CT scan images (hereafter called CT scan) to measure TRW based on micro-density profiles (De Ridder et al., 2010). 3D X-ray images of increment cores are produced by the CT scanner from which wood density profiles can be extracted. Maximum core length and resolution are determined by the amount of processed cores in one scan, as well as the physical limitations of the system (see, Dierick et al., 2014). Ring boundaries can be detected semi-automatically based on the density profile by setting a threshold in density. Furthermore, given the 3D nature of the images, a correction for structure direction by correcting ring and grain angle is applied. Conventional cross-dating procedures, as described above, are used to ensure correctly dated TRW series and in addition, density-based pattern matching can be applied to detect errors in TRW series (De Mil et al., 2016).

Measuring TRW with the CT scanner has the advantage that TRWs are measured semi-automatically resulting in less laborious work in comparison to LINTAB TRW measurements (Maes et al., in prep.). Note that semi-automated ring detection is also possible with Windendro and Co-recorder on flatbed scans of tree cores. Besides, CT scan images can be stored allowing re-measurement. In addition to TRW also density is measured with the CT scanner, although samples need to be dried which might influence the TRW measurements, due to shrinking. In this paper we will investigate if measuring TRW with the CT scanner (at a resolution of 110 μm) can increase the replication without impeding precision or cross-dating accuracy of measurements. We will compare two ways of measuring TRW. (i) Method 1: conventional method, tree-rings measured with the LINTAB system with a measuring accuracy of 10 μm; (ii) Method 2: tree-rings measured on CT scan images with a resolution of 110 μm using semi-automatic detection of ring borders based on wood density profiles.

In a first step, we will look if the two TRW measuring methods agree closely. This includes quantifying the effect of drying the cores prior to scanning, which is required if in addition to TRW correct density estimates are of interest. In a second step, the effect of TRW measuring method on growth trend modeling is evaluated. We examine whether the same long term growth trends are detected using data from the two TRW measuring methods.

2. Materials and methods

2.1. Tree-ring data

54 and 62 cores from beech (*Fagus sylvatica*) and oak trees (*Quercus petraea*) respectively, were collected in the winter of 2014 with a 5 mm increment corer (Suunto) at 1 m above ground (58 trees in total, 2 cores per tree). Cored trees were (co)dominant and growing in even-aged stands. Trees were located in four forest sites in the Ardennes region in the South of Belgium (Table 1), more particularly in mature stands on well-drained brown acidic soil (WRB: Dystric Cambisol). Elevation ranges from 260 to 400 m above sea level (m.a.s.l.) and slope ranges from 0 to 5 °.

Collected tree cores were stored in paper straws to dry. The steps followed for measuring TRW on CT scan images and LINTAB are visualized in Fig. 1.

The cores were first scanned with the X-ray CT scanner (NanoWood CT facility, Ghent University) at a resolution of 110 μm. This resolution was sufficient for the tree species in this study (see also De Mil et al., 2016). For other tree species with smaller rings resolution can be adjusted (see a.o. Van den Bulcke et al., 2014, 2009). Prior to scanning, cores were put in a custom-made cardboard holder (in one holder 33 cores of 60 cm fit, when scanning at 110 μm) and oven-dried for 24 h at 103 ± 1 °C. Nanowood (Dierick et al., 2014) is a multi-resolution system built at the Ghent University Centre for X-ray Tomography (UGCT) and is controlled by a generic LabView interface. After scanning, reconstruction was performed with the Octopus Reconstruction software package (Vlassenbroeck et al., 2007), licensed via InsideMatters (www.insidematters.be). Next, the X-ray CT toolchain was used to indicate tree-rings (De Mil et al., 2016). A correction for grain and tilt angle was applied to the digital cores. Density profiles were used to automatically indicate tree-ring boundaries. For beech maximum density values were used as tree-ring boundaries. For oak minimum density values were used, as wood density did not increase until the end of the growing season (Fig. 2). Falsely indicated rings or not indicated rings were removed or added by inspecting the CT scan images and during the cross-dating process.

After scanning the cores, visibility of tree-rings was increased by microtoming the surface to be able to measure TRW with LINTAB

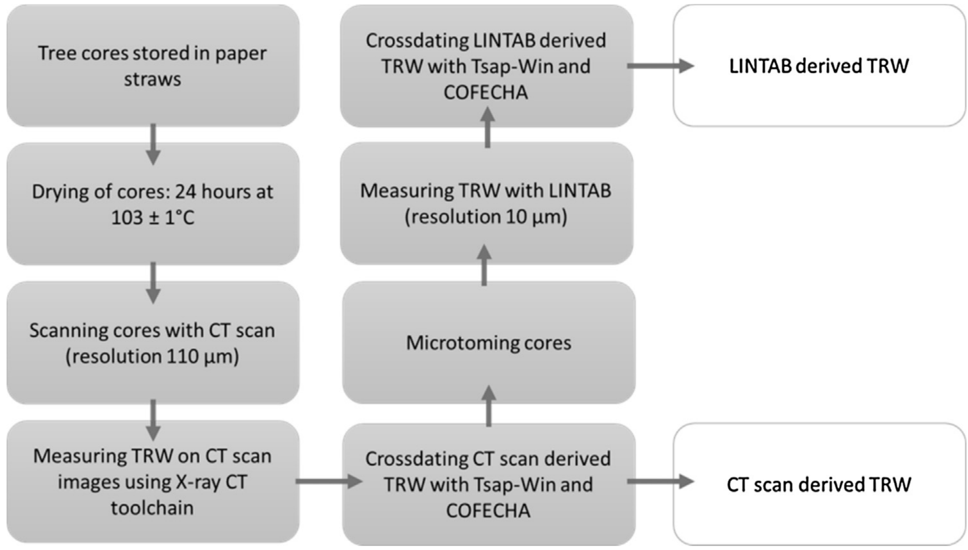

Fig. 1. Flow chart of preparation and measuring steps for TRW data measured on CT scan images and LINTAB. See De Mil et al. (2016) for specifications on the X-ray CT toolchain.

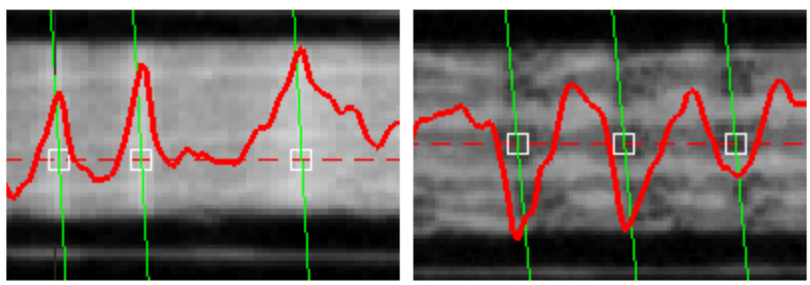

Fig. 2. CT scan images with density profile in red for beech (left) and oak (right). Green lines represent the detected ring boundaries by detection of maxima and minima in wood density for beech and oak, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.).

(Gärtner and Nievergelt, 2010). For beech, additional sanding was needed to enhance the contrast between growth ring boundaries. TRWs were measured with a LINTAB 6 table at a resolution of 10 µm in combination with TSAP-Win software (Rinntech, Germany). In order to ensure correctly dated series, COFECHA in combination with Tsap-Win was used for the two TRW measuring methods (Holmes, 1983; Grissino-Mayer, 2001; Rinn, 2003).

2.2. Environmental data

For the tree growth modeling, additional variables were measured in circular plots (18 m radius) centered around the cored trees. The following forest structural variables were measured in each plot: crown projection area of the cored tree (CPA, m^2), height of the cored tree (m), total CPA of trees with diameter at breast height (DBH) > 15 cm in plot (TotCPA, m^2), total basal area of trees with DBH > 15 cm in plot (TotBA, m^2), basal area of trees larger than cored tree (BAL, m^2) and the ratio between the diameter of the cored tree and the average diameter of trees with DBH > 15 cm in plot (ddg). CPA is measured by mapping the crown border in the four cardinal directions. Dendrometrical variables were measured with FieldMap equipment and software in the winter of 2014 (http://www.fieldmap.cz) Site quality was characterized by measuring pH (5:25 soil:solution, 0.01 M $CaCl_2$), organic C and N content, bulk density (g/cm^3) and texture on a soil sample of the mineral soil horizon (depth ranges from 10 to 15 cm) taken in the South-East direction relative to the cored tree in each plot.

2.3. Statistical methods

2.3.1. Evaluation of method agreement

The effect of measuring method on cross-dating is checked by looking at the COFECHA output for the two measuring methods. Default settings of COFECHA are used for cross-dating: (i) 32 smoothing spline with 50% wavelength cutoff, (ii) 50 year segments lagging 25 years, (iii) autoregressive modeling, (iv) log transforming series, (v) critical correlation level of 0.3281 (see Grissino-Mayer, (2001)). The cross-dating accuracy for the two measuring methods is evaluated by the following variables based on COFECHA output: average correlation with master series and percentage of 'A' flagged segments (i.e. number of flagged segments/total number of segments × 100). 'A' flags indicate that 50 year segments of a particular core have a correlation with master chronology outside of the 99% confidence interval.

In order to evaluate the effect of measuring method on TRW series, raw TRW chronologies are built for the period 1930–2014 for both species and methods, using a robust mean to remove extreme values when averaging the chronology (Mosteller, 1977; Wigley et al., 1984). Chronologies are characterized and evaluated by: average growth rates (AGR), inter-series correlation (Rbar) and expressed population signal (EPS), which is a measure for statistical quality of the chronology based on Rbar and the number of samples. Rbar and EPS are calculated on detrended series. Detrending was performed using a cubic smoothing spline (50% frequency cut-off at 15 years) in order to remove low frequency variability due to biological elements (e.g. tree aging) or stand dynamics (Cook and Peters, 1981).

Table 2
Bias, precision and accuracy measures. With Aj the TRW measured with LINTAB on non-dried samples (method 4), Ej the TRW measured with measuring method 1, 2 or 3 and j the jth ring and n the total number of measured rings.

Bias	Precision	Accuracy
$ME = \frac{1}{n}\sum_{j=1}^{n}\left(E_j - A_j\right)$	$var = RMSE^2 - ME^2$	$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(E_j - A_j)^2}$

The degree of agreement between the two methods at TRW level is evaluated with the bias (i.e. mean difference between TRW LINTAB and TRW CT scan), root mean square error (RMSE) and number of outliers. The number of outliers was calculated as the number of years in which the absolute difference of TRW measured with LINTAB versus CT scan is 2.5 times larger than the mean absolute difference of the series (Grissino-Mayer, 1997). Finally, the difference between the two methods is plotted in function of the TRW measured with LINTAB to determine whether the difference between measuring methods is related to width of the rings.

To test whether or not a significant difference exists between the two TRW measuring methods, a post-hoc Tukey test was performed on a mixed model where measured TRW is modelled in function of measuring method. In order to take the relatedness of rings grouped per core into account, a random intercept for each core per method was used in the mixed model. Since we are dealing with autocorrelated data with growth in year t related with growth in year t-1, a second-order autoregressive covariance structure for the error terms is added to the model. By doing this, error terms are forced to be decreasingly correlated as the rings are further apart. This approach results in estimates of confidence intervals of the parameters that are not influenced by the autocorrelation present in the data (Pinheiro and Bates, 2000; Martin-Benito et al., 2011).

2.3.2. Evaluation of shrinkage effect on tree-ring width measured on CT scan images

The effect of core drying, required when in addition to TRW also wood density is of interest, is evaluated by measuring TRW on a subsample of 14 randomly selected cores of beech and oak each. TRW of these cores was measured four times: (1) on CT scan images of cores conditioned at 20 °C and 65% relative humidity, (2) on CT scan images of oven-dried cores (24 h at 103 ± 1 °C), (3) with LINTAB on oven-dried cores (24 h at 103 ± 1 °C) and (4) with LINTAB on air-dried cores. Bias, precision and accuracy measures (Table 2) were calculated for the measuring methods 1, 2 and 3 separately with TRW measured with LINTAB of non-dried cores (method 4) as a reference.

2.4. Effect of TRW measuring method on tree growth change detection

2.4.1. Growth change modeling

The evaluation of the effect of TRW measuring method on the detection of growth change is done by modeling the tree growth based on LINTAB and CT scan TRW measurements. Basal area increment (BAI, cm^2) is used to model radial tree growth:

$$BAI_t = \pi(R_t^{2} - R_{t-1}^{2})$$

with R the tree radius at the end of the growing season (derived from raw undetrended TRW measurements, averaged per tree) and t the year of ring formation. The first thirty years of all TRW series were eliminated from the analysis to exclude juvenile growth. In addition, growth modeling was started from the year for which data from at least five trees is available (1930 for both beech and oak). For the modeling, BAI increment was log transformed because of the heavily skewed distribution. BAI was modelled in function of previous year diameter (D_p, cm). This previous-year diameter is a better proxy for development time since mature tree growth is more driven by tree size than by cambial age itself (Wykoff, 1990; Mencuccini et al., 2005; Bontemps et al., 2009). The relationship between BAI and previous year diameter is described by: intercept, slope associated with D_p (instantaneous growth rate, growth rate of a tree with diameter zero) and the curvature associated with D_p^2 (change in growth rate as tree size increases) (Singer and Willett, 2003).

The model was built in two stages, using the same approach as in Kint et al., 2012 and Aertsen et al., 2014. In a first stage the BAI was modelled in function of development stage (Dp and Dp^2), forest structural variables and site quality variables. A multiple linear regression, with criteria variance inflation factor < 5 and Pearson correlation > 0.75, was used to identify those variables that have the best relation with BAI (Zuur et al., 2009). Selected forest structural variables are: BAL (m^2), TotBA (m^2), TotCPA (m^2) and CPA (m^2) for beech and tree height (m), CPA (m^2) and ddg for oak. The following site quality variables were selected: C/N, C and pH for beech and pH, C and bulk density (g/cm^3) for oak. After the selection of possible explanatory variables, the methodology of Zuur et al. (2009) was used to build the base model (Mb), which describes the BAI in function of the previous year diameter (Dp). First, the optimal random structure is determined by comparing nested models with random intercept for forest site and tree; and random slope for Dp and Dp^2 (restricted maximum likelihood (REML) fitted models). Then, the optimal fixed effect structure is determined by backward elimination of fixed effects (Dp, Dp^2 and selected site and forest structural variables).

$$\begin{aligned} Mb: \ln(BAI_{fs,i,t}) &= \alpha + \beta T_{i,t} + \gamma F_i + \delta S_i + a_i + b_i T_{i,t} \\ &+ c_{fs} + d_{fs} T_{i,t} + \xi_{fs,i} \end{aligned} \quad (1)$$

where BAI $_{fs,i,t}$ is the basal area of tree i in year t located in forest site fs; $T_{i,t}$ is a vector related to the tree's development stage (Dp and Dp^2). By including this both in fixed and random parts, both common and individual tree growth trajectories are modeled; α and β are intercept and slope related to $T_{i,t}$; a_i and b_i are tree specific random intercept and slope related to $T_{i,t}$; c_{fs} and d_{fs} are forest complex specific random intercept and slope related to $T_{i,t}$; F_i and S_i are the vectors of the preselected forest structural variables and site quality variables; γ and δ are the associated fixed effect estimates related to F_i and S_i; and finally $\xi_{fs,i}$ is the error term.

Common historical growth change related to the calendar date is not included in the base model Mb. The Mb model describes the individual tree BAI. By adding a linear, quadratic, cubic or natural cubic spline term of year to the base model Mb, the date model Md models common historical growth through time.

$$Md: \ln(BAI_{fs,i,t}) = Md = Mb + \lambda Y_i (2)$$

where λ is the vector of fixed effects estimated associated to calendar year. The date model allows us to study long-term growth changes caused by exogenous factors operating at a broad scale.

Fixed and random effects were selected by applying likelihood ratio tests and comparing Akaike and Bayesian Information Criteria (AIC and BIC) between nested models. The final models were

Table 3
COFECHA results for TRW measuring methods LINTAB and CT scan; correlation with master series: average correlation of individual cores with master series; % of 'A' flagged segments: number of flagged segments/total number of segments × 100.

	Beech		Oak	
	LINTAB	CT scan	LINTAB	CT scan
Correlation with master series	0.597	0.585	0.584	0.580
% of 'A' flagged segments	1.29	4.55	5.96	7.62

Table 4
Characterization of TRW chronology for the period 1930–2014; AGR: average growth rate; Rbar: interseries correlation; EPS: expressed population signal. [1] calculated on detrended data.

		AGR [mm]	Rbar [1]	EPS [1]
Beech	LINTAB	2.338	0.352	0.958
	CT scan	2.270	0.348	0.957
Oak	LINTAB	1.834	0.382	0.972
	CT scan	1.785	0.367	0.970

fitted with restricted maximum likelihood (REML) and model performance was evaluated with pseudo-R^2 of full and marginal model (i.e. only considering fixed effects) and relative root mean squared error (rRMSE, calculated for response i.e. $\ln(BAI_{i,t})$). The pseudo-R^2 was calculated as the correlation between the response (i.e. $\ln(BAI_{i,t})$) and model predictions.

The effect of measuring method on the detection of long term growth changes was evaluated by applying this two-step modeling approach (step 1: Mb and step 2: Md modeling) on BAI data derived from TRW data measured with LINTAB and a second time with TRW data measured on CT scan images. All statistics were performed in R (version 3.2.5) (R Development Core Team, 2016) with packages "nlme", "spline", "dplr" and "multcomp" (Bunn, 2008; Hothorn et al., 2008; Pinheiro et al., 2016).

3. Results

3.1. Evaluation of agreement between methods

3.1.1. Overall effects of method on cross-dating accuracy and tree-ring chronologies

The cross-dating accuracy as evaluated by COFECHA is presented in Table 3. The average correlation with the master series does not differ largely between the two measuring methods. The percentage of 'A' flagged segments is higher for the CT scan method for both species. Number of flagged segments varied between 2 and 16 and number of evaluated segments between 154 and 218.

The raw TRW chronologies based on LINTAB versus CT scan measurements are visualized in Fig. 3 for the two studied species. The raw TRW chronologies show similar growth patterns despite the different measuring method. Raw TRW chronologies based on CT scan measurements show lower TRW in comparison to the LINTAB based raw TRW chronologies for both species.

Chronology characteristics are presented in Table 4 for beech and oak using the two methodologies. For both tree species the average growth rate (AGR) is higher on LINTAB compared to CT scan, with an average difference of 0.068 mm and 0.049 mm for beech and oak, respectively, for the period 1930–2014. The EPS is high for both tree species and methods (considering the threshold of 0.85 defined by Wigley et al., 1984). Rbar values indicate similar interseries correlation for both species and measuring methods.

3.1.2. Agreement of measuring method at TRW level

Looking more into detail to the differences in TRW measurements of the two methods we see that the bias between LINTAB and CT scan measurement is negative (Table 5). So TRW measurements on LINTAB are higher than on CT scanner. The number of outliers is 1% higher for oak in comparison to beech.

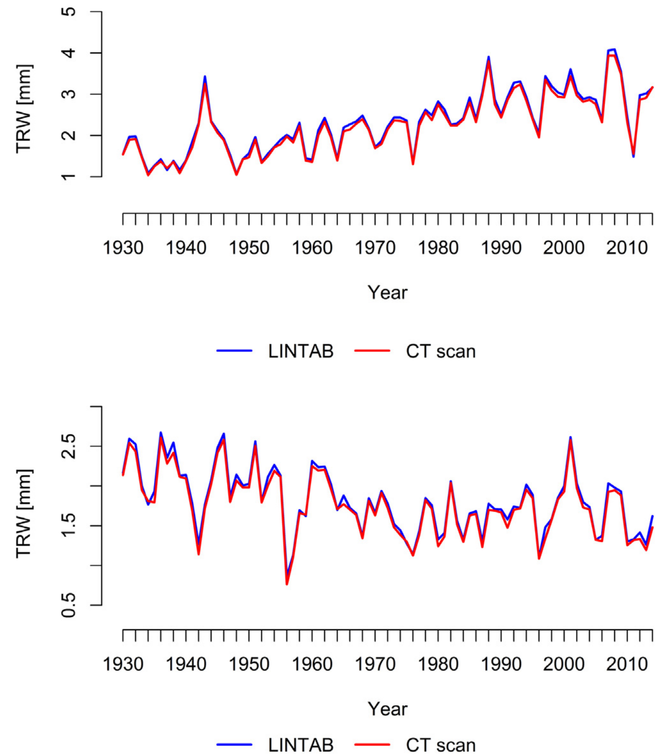

Fig. 3. Raw TRW chronologies for LINTAB versus CT scan measurements for beech (above) and oak (below) for the period 1930–2014. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 5
Comparison of TRW measurements measured with LINTAB and CT scanner.

	Bias[mm]	RMSE[mm]	Nr of outliers [%]
Beech	−0.069	0.163	5.38
Oak	−0.052	0.160	6.36

Table 6
Results of post-hoc Tukey test on mixed model TRW ~ method with random intercept for cores and second order correlation structure for year.

	Test	Estimate	Std.Error	z value	Pr(> |z|)
Beech	CT scan-LINTAB = 0	−0.067	0.063	−1.059	0.290
Oak	CT scan-LINTAB = 0	−0.055	0.041	−1.344	0.179

The difference between the two measuring methods has a weak negative correlation with the width of the rings (Fig. 4). A small significant spearman rank correlation of −0.35 and −0.19 (both, $p < 0.001$) is found for beech and oak, respectively.

The post-hoc Tukey test indicates no significant differences between the two methods (Table 6).

3.2. Effect of oven-drying prior to TRW measurements on CT scan images

The bias, variance and RMSE for respectively the TRW measuring methods: (1) CT scan images of cores conditioned at 20 °C and 65% relative humidity (CT_con) (2) CT scan on oven-dried cores *(24 h at 103 ± 1 °C,* CT_dry) and (3) LINTAB on oven-dried cores *(24 h at 103 ± 1 °C,*Lint_dry) is presented in Table 7. The measuring method LINTAB on air-dried cores is taken as the reference TRW measuring method. The RMSE decreases from CT_dry to CT_con to Lint_dry,

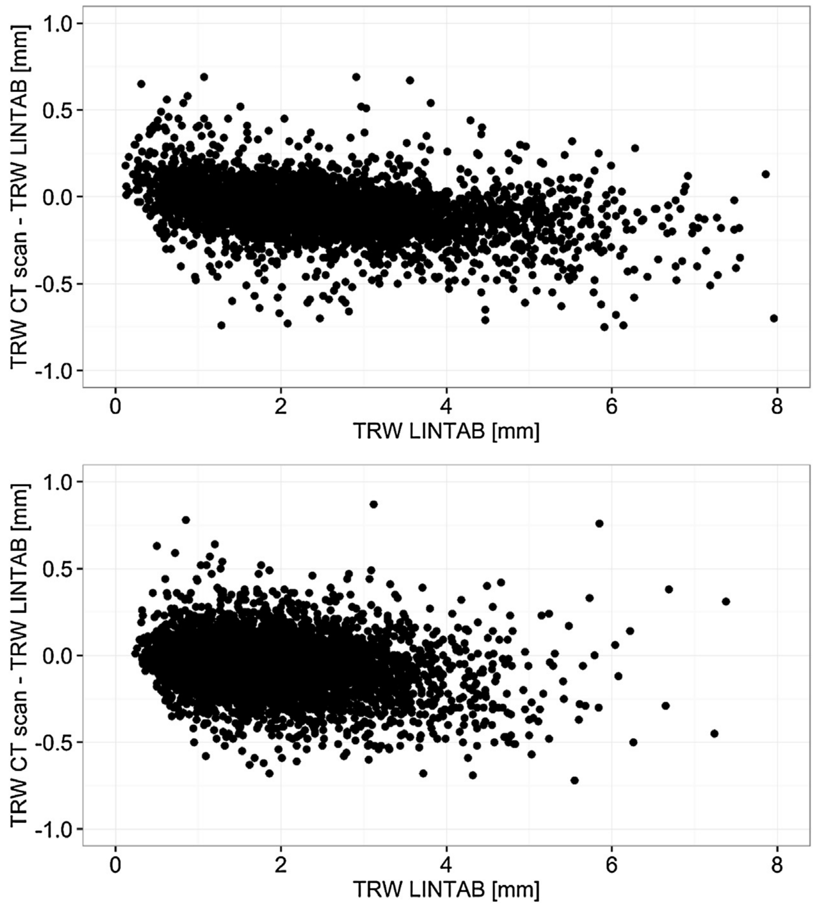

Fig. 4. Difference of TRW measured on CT scan and TRW measured on LINTAB is plotted in function of TRW measured on LINTAB for beech (upper panel) and oak (down panel).

indicating that Lint_dry has the highest accuracy. The lower accuracy in CT_dry is mostly attributable to the higher bias in CT_dry since variance of CT_dry and CT_con is similar. The drying of the samples prior to scanning thus increases the bias with 42% (beech) and 48% (oak) whilst the measuring precision is not influenced by drying. The higher variance of CT_con and CT_dry in comparison with Lint_dry indicates that the precision of the CT scanner is lower compared to the Lint_dry. Comparing the two tree species, a higher bias and lower variance is observed in beech in comparison to oak on the CT_con and CT_dry method.

Table 7
Bias, variance and RMSE of TRW measurements methods. Evaluated methods (1) CT_con = CT scan images of cores conditioned at 20 °C and 65% relative humidity, (2) CT_dry = CT scan images of dried cores (24 h at 103 ± 1 °C) and (3) Lint_dry = LITNAB on dried cores (24 h at 103 ± 1 °C). The measurements of air-dried samples on LINTAB are used as reference. A subsample of 14 cores is used for both beech and oak.

	Evaluated method	beech	oak
BIAS	CT_con	−0.0338	−0.0271
	CT_dry	−0.0587	−0.0530
	Lint_dry	−0.0382	−0.0474
VARIANCE	CT_con	0.0178	0.0216
	CT_dry	0.0165	0.0230
	Lint_dry	0.0106	0.0105
RMSE	CT_con	0.1377	0.1494
	CT_dry	0.1412	0.1606
	Lint_dry	0.1099	0.1129

3.3. *Tree growth change modeling*

The parameter estimations and model evaluation of the date model based on TRW measured on LINTAB versus CT scan images are presented for beech in Table 8. Both models have random intercept and random slope associated with Dp at forest site and tree level. The estimates of fixed effects associated to Dp (slope) and Dp^2 (curvature) are positive and negative, respectively, in both models. The estimates describe the relationship between tree growth and size: tree growth increases until a certain maximum is reached, afterwards tree growth declines. No fixed effects of forest structural variables or site quality variables were kept in the final model. A natural cubic spline of year with 2 knots located at 1958 and 1986 (33.33th and 66.66th quantile of year) is included as fixed effect in the model. The estimates of this spline are similar for both models. Relatively high pseudo-R^2 of the full model indicates a good fit of both models. The lower pseudo-R^2 of the marginal models indicates that the fixed effects could not explain a large part of the variability in BAI and was thus captured by the random effects. The rRMSE is comparable and acceptably low for both models.

The modelled long term growth trends based on TRW data from LINTAB and CT scan is presented in Fig. 5. The full line represents the growth change through time of a tree with constant Dp (value from 1930 is taken), indicating a growth increase from 1930 to 2014. The detected long term growth trends are similar for models built with TRW measured on LINTAB or CT scan data.

The date models built for oak based on TRW data from LINTAB and CT scan are presented in Table 9. For both models, a random intercept and random slope related to Dp for individual trees

Table 8
Parameter estimates and model evaluation of the model for beech, which is a date model Md for ln(BAI) based on TRW measured on LINTAB and CT scan images.

Fixed effects	Beech model based on TRW LINTAB (n = 1353)				Beech model based on TRW CT scan (n = 1353)			
	Estimate	SE	Df	p > |t|	Estimate	SE	Df	p > |t|
Intercept	0.8651	0.2466	1322	0.0005	0.8412	0.2579	1322	0.0011
Dp	0.1031	0.0146	1322	<0.001	0.1044	0.0152	1322	<0.001
Dp^2	−0.0017	0.0003	1322	<0.001	−0.0017	0.0003	1322	<0.001
ns(year,1)	1.0497	0.1745	1322	<0.001	1.0216	0.1721	1322	<0.001
ns(year,2)	1.6144	0.3648	1322	<0.001	1.6003	0.3595	1322	<0.001
ns(year,3)	1.4175	0.2376	1322	<0.001	1.4182	0.2337	1322	<0.001

Random effectforest site	Intercept	Dp	Intercept	Dp
	0.147	4.39×10^{-6}	0.150	4.757×10^{-6}

Random effect tree	Intercept	Dp	error	Intercept	Dp	Error
	0.669	0.026	0.394	0.693	0.026	0.379

Model evaluation	R^2f	R^2m	rRMSE	AIC	R^2f	R^2m	rRMSE	AIC
	0.64	0.20	12%	1124	0.65	0.19	12%	972

Dp (previous year diameter, cm); ns(year, 1),ns(year, 2) and ns(year, 3) estimates for cubic spline of year with 2 knots.

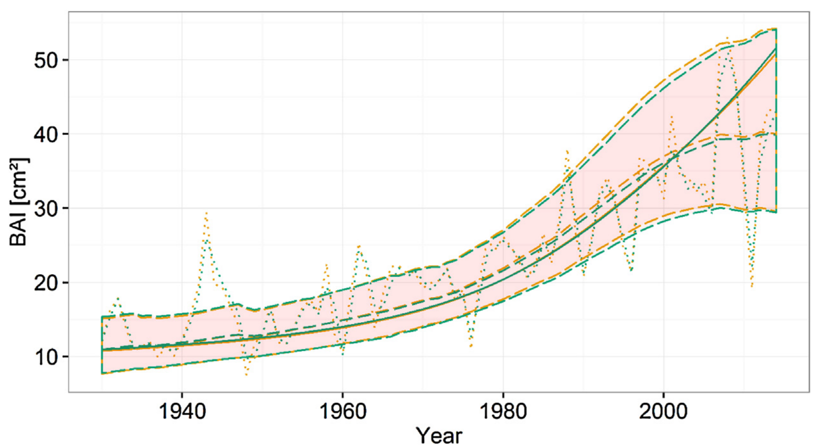

Fig. 5. Long term growth changes of beech modelled using TRW measurements of LINTAB (yellow) and CT scan images (green). Dots represent the observed average BAI. Dotted line represents the predicted BAI using average yearly values of Dp (previous year diameter, cm). Full line represents the growth change of a tree with constant Dp (average value from 1930 is taken). 95% confidence intervals of mean prediction are shaded in red for both methods. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 9
Parameter estimates and model evaluation of the Oak model, which is a date model Md for ln(BAI) based on TRW measured on LINTAB (left) and TRW measured on CT scan images (right).

Fixed effects	Oak model based on TRW LINTAB (n = 1949)				Oak model based on TRW CT scan (n = 1949)			
	Estimate	SE	Df	p > |t|	Estimate	SE	Df	p > |t|
Intercept	22791.8	9730.1	1913	0.0193	25751.4	9884.7	1913	0.0093
Dp	0.1150	0.0150	1913	<0.001	0.1210	0.0150	1913	<0.001
Dp^2	−0.0020	0.0000	1913	<0.001	−0.0020	0.0000	1913	<0.001
ddg	0.8950	0.1990	29	<0.001	0.8510	0.1980	29	<0.001
year	−34.4190	14.778	1913	0.02	−38.9530	15.0130	1913	0.0095
$year^2$	17.3210	7.4810	1913	0.0207	19.6370	7.6000	1913	0.0098
$year^3$	−0.0030	0.0010	1913	0.0215	−0.0030	0.0010	1913	0.0102

Random effect tree	Intercept	Dp	error	Intercept	Dp	error
	0.591	0.021	0.344	0.610	0.022	0.355

Model evaluation	R^2f	R^2m	rRMSE	AIC	R^2f	R^2m	rRMSE	AIC
	0.59	0.29	12%	877	0.56	0.27	13%	1027

Dp (previous year diameter, cm), ddg (ratio diameter cored tree and average diameter trees with DBH > 15 cm in plot), $year^2$ is ($year^2$/1000) and $year^3$ is ($year^3$/1000).

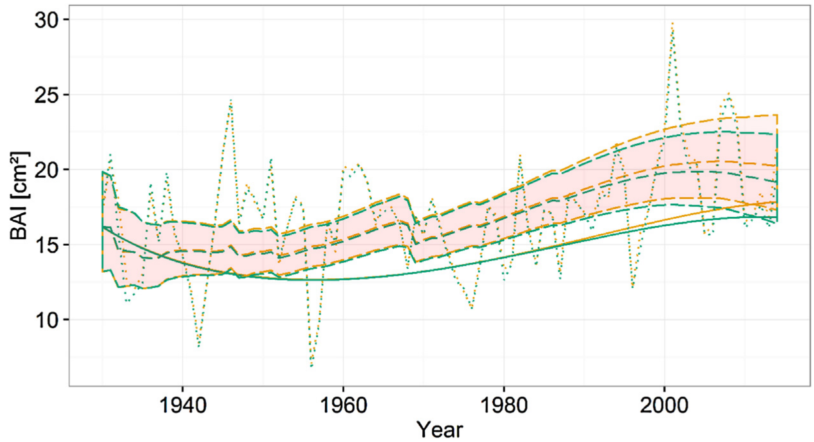

Fig. 6. Long term growth changes of oak, modelled using TRW measurements of LINTAB (yellow) and CT scan images (green). Dots represent the observed average BAI. Dotted line represents the predicted BAI using average yearly values of Dp (previous year diameter, cm). Full line represents the growth change of a tree with constant Dp and ddg (average values from 1930 are taken, ddg: ratio diameter cored tree and average diameter trees with DBH > 15 cm in plot). 95% confidence intervals of mean prediction are shaded in red for both methods. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

is included. Dp^2 was only significant as fixed effect, indicating that individual trees have similar change in growth as tree size increases. Only the forest structure variable ddg was kept in the final date models. The positive estimate indicates that growth increases as ddg increases. A cubic polynomial of year was included in both date models. Similar to the beech date models, the model evaluation parameters are good.

The long term growth trend predicted for oak based on data measured with LINTAB and CT scan are presented in Fig. 6 in yellow and green respectively. The full line shows the long term growth trend, this is the predicted BAI of a tree under constant growth conditions (i.e. Dp and ddg values from 1930) over time. This long term growth trend shows a decrease in growth until 1956, after that year the growth of oak increases again. By 2014, the BAI slightly exceeds the BAI of 1930. The model based on LINTAB data indicates a slightly higher growth increase for a tree with constant diameter than the model based on CT scan data (10% versus 4%) relative to 1930. The lower estimate for the fixed factor year for the model based on CT scan data results in a higher difference between the predictions of model based on LINTAB versus CT scanner with time.

4. Discussion

4.1. Agreement of TRW measuring methods

The COFECHA output indicates that cross-dating is good with both measuring methods for the two species: the correlations with the masterseries are above 0.5 (Grissino-Mayer, 2001). The percentage of flagged segments is higher for the CT scanner. The flagged segments were checked and no dating errors were found. Cross-dating accuracy is thus equally good for the two measuring methods. The chronologies based on LINTAB and CT scan data show similar characteristics (EPS and Rbar) and growth patterns for the two tree species. But the TRW for the chronologies based on CT scan measurements are a bit lower compared to the LINTAB. This difference is confirmed by the bias calculated on the raw data (Table 5).

The number of outliers and the variance of oak is slightly higher in comparison to beech (Tables 5 and 7). This might be the consequence of the predefined threshold in density for ring border demarcation. For oak this was set to the minimum in wood density, though this minimum does not always coincide with the border between late and early wood cells. A modification of this threshold to the inflection point closest to the minimum wood density point could possibly reduce the variance (Table 7). Inspection of the outliers indicated that most outliers are located at rings where maximum (beech) or minimum (oak) in wood density did not coincide completely with the ring border. Manually shifting these ring borders could thus decrease the number of outliers. The accuracy of the CT scanner (with LINTAB as a reference) does not differ largely between beech and oak (Table 5 and 7). In comparison to the resolution of the CT scanner (0.110 mm), the accuracy is good. Scanning on a higher resolution, possible up to 0.035 mm, could increase this accuracy. Despite the observed bias and higher variance in the CT scan TRW measurements the post-hoc Tukey test indicates that there is no significant difference between the TRW measured with the two measuring methods (Table 6).

A species effect is observed, with the bias between methods being higher in beech compared to oak (Table 5 and 7). The drying of the cores, needed when in addition to TRW also wood density is of interest, explains a large part of the bias between the two methods (42% and 48% for beech and oak respectively, Table 7). Since beech trees have on average wider rings compared to the oak trees (Table 4), the effect of drying is higher in absolute value. This is confirmed by Fig. 4, which shows higher differences in TRW CT scan and LINTAB when rings become wider. This higher absolute shrinkage in beech might explain the larger bias for beech in comparison to oak. A mixed model where difference (TRW CT scan – TRW LINTAB) is modelled in function of an interaction of tree species and TRW LINTAB was built on the entire dataset in order to evaluate this. By including a random intercept for individual cores and an autocorrelation structure in the model the data structure and correlation present in the data is taken into account. A significant ($p = 0.007$) difference in tree species was found indicating that for beech the difference in TRW measured by the two methods is 0.0258 mm higher compared to oak. Besides, a stronger increases in difference is found when rings become wider for beech compared to oak ($p < 0.001$). The results confirm that the bias is species dependent and increases when rings become wider. When measuring TRW and density with the CT scan, bias could be reduced with a species specific post-processing step.

4.2. Detection of long term growth trends

For both beech and oak the same long term growth trends are detected based on TRW measurements of LINTAB and CT scanner. This indicates that both measuring methods are suitable to detect growth trends in beech and oak.

For beech a strong long term growth increase is observed between 1930 and 2014. If we filter out the age effect on growth by fixing Dp at the average diameter in 1930, BAI increased with 373.0% and 372.2% for the model based on LINTAB and CT scan TRW data respectively between 1930 and 2014. This observed growth increase in beech is in contrast with the observed growth decline detected since the 1960s in the paper of Kint et al. (2012) for beech growing in the North of Belgium. In other studies in Europe growth increases of beech were reported, though not of the same magnitude (Badeau et al., 1996; Bontemps and Esper, 2011). Additional analysis on the raw data showed that the five oldest trees took on average 12 years to increase DBH from 20 to 25 cm, the five youngest trees increased DBH from 20 to 25 cm in only 5 year, which supports the modeled growth trend. In further research, environmental and climatic data and information on shifts in forest management, more particularly in the thinning regime, all factors that may affect tree growth, will be added to the date model. This will allow to study if part of the long term growth trend can be explained by these variables, but this is beyond the scope of this paper. Besides, inclusion of measurement of additionally sampled trees will increase model performance. The growth increase relative to the start point of the different spline intervals for a tree with a fixed Dp is as follows. For the first spline interval (1930–1958) the detected increase is 25% with respect to 1930 in both models. In the second interval (1958–1986) the growth increase is 52% and 50% higher compared to the relative growth increase of the previous spline interval (1930–1958), for the model based on LINTAB and CT scan data respectively. In the third spline interval (1986–2014) the growth increases again in comparison to the two previous spline intervals. For this spline interval the growth model based on LINTAB data detects a less sharp relative growth increase, 111% versus 115% in comparison to the growth model based on the CT scan data (see also Fig. 5 and Table A1 in Appendix A). Since for the period 1930–2014 the difference in detected long term growth trend is only 0.8% higher for the model based on LINTAB data and the modeled growth change in the three spline intervals is of the same magnitude for both models, we can conclude that the same growth trends are detected with the two TRW measuring methods.

For oak, the two TRW measuring methods detect the same cubic growth change with time. The modeled decline in growth between 1930 and 1956 for oak is in line with other literature (Delatour, 1983; Thomas et al., 2002). In these studies oak growth decline was related to a combination of factors such as extreme winter frost, drought, and insect outbreaks. The detected growth decline remains when the years 1942 and 1956, which show extreme low growth probably related to extreme low temperatures in early spring in these years, are removed from the dataset. Addition of climatic and environmental data and info on shifts in forest management to the models would give us more insight to the detected negative growth trends, which will be part of future research as mentioned earlier. The detected overall growth increase, from 1930 to 2014 for a tree with constant diameter, is 6% higher for the model based on TRW data of LINTAB. This difference between detected growth trend by model based on LINTAB compared to CT scan data is slightly higher compared to the observed difference in the beech models (i.e. 0.8%) but is still acceptable.

5. Conclusion

Measurement of TRW with LINTAB and CT scanner agree sufficiently close for both beech and oak to model growth change. The non-significant bias between the two methods can be attributed largely to the drying of cores needed if wood density in addition to TRW is measured with the CT scanner. The precision of the TRW measurements with the CT scanner can possibly be further improved by scanning at higher resolution and by optimizing the automated ring border demarcation based on wood density. We conclude that both TRW measurement methods deliver precise and well cross-dated measurements that are very similar to each other. With the CT scanner, replication can increase if time is a limiting factor since this method is less time consuming compared to the LINTAB (Maes et al., in prep.).

Modeling of growth trends is not influenced by the methods used to measure TRW. The same long term growth trends are detected with LINTAB and CT scan TRW data. For beech an increase in growth is detected since 1930 in the Southern region of Belgium. A slight growth decrease until 1956 and growth increase afterwards is detected for oak. In future research the possible influence of change in forest management as well as climatic and environmental variables to the detected growth trends will be investigated to get more insight in the processes behind the detected growth changes.

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Appendix A.

Table A1
Predicted growth by beech growth models. Relative growth interval%: (predicted BAI at end of spline interval/predicted BAI at beginning of spline interval) × 100. Contribution of interval to overall growth increase% = (relative growth interval/predicted relative growth 1930–2014) × 100.

	Spline interval	Relative growth interval%	Contribution of interval to overall growth increase%
LINTAB	1930–1958	125.75	26.58
	1958–1986	177.64	37.55
	1986–2014	211.77	44.77
CT SCAN	1930–1958	125.13	26.50
	1958–1986	175.02	37.06
	1986–2014	215.61	45.66

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