Canadian Journal of Forest Research

Applications of computed tomography (CT) scanning technology in forest research: A timely update and review

Journal:	<i>Canadian Journal of Forest Research</i>
Manuscript ID	cjfr-2018-0537.R2
Manuscript Type:	Review
Date Submitted by the Author:	07-Jun-2019
Complete List of Authors:	Beaulieu, Jean; Université Laval, Sciences du bois et de la forêt Dutilleul, Pierre; McGill University, Plant Science; McGill University, Mathematics and Statistics
Keyword:	X-ray computed tomography (CT) scanning, Wood density, Annual growth ring, Moisture content, Scale of resolution
Is the invited manuscript for consideration in a Special Issue? :	Not applicable (regular submission)

SCHOLARONE™
Manuscripts

1 **Applications of computed tomography (CT) scanning technology in forest research: A timely**
2 **update and review**

3
4

5 Jean Beaulieu^{1,*} and Pierre Dutilleul²

6
7

8 ¹ Département des sciences du bois et de la forêt, Faculté de foresterie, de géographie et de
9 géomatique, Université Laval, 1030 Avenue de la Médecine, Québec, QC G1V 0A6, Canada

10

11 ² Department of Plant Science, McGill University, Macdonald Campus, 21,111 Chemin
12 Lakeshore, Sainte-Anne-de-Bellevue, QC H9X 3V9, Canada

13

14 *Author for correspondence (jean.beaulieu@sbf.ulaval.ca).

Draft

Abstract: Organic materials of woody plants are complex, and show internal, structural and morphological variations due to genetic and environmental influences. Variability can be observed in stems, branches, leaves, and roots. Non-destructive and non-invasive technologies have been proposed to assess this variability. Computed tomography (CT) scanning, originally designed for medical diagnostics, gives access to the measurement of wood properties *in situ* (e.g., wood density, moisture content, internal defects, annual growth) and crown traits that characterize branching pattern geometry and canopy space occupancy for small-size trees. Since Wei et al.'s (2011) review on the assessment of wood quality for optimized manufacturing processes using a CT scanner, several important developments occurred, which motivated the preparation of an update. We provide technical clarifications about the scales of observation and resolution; report on recent studies where CT scanning was applied with research objectives beyond wood quality assessment for an optimized manufacturing of forest products; and stress the importance of analytical procedures for the graphical and quantitative analyses of CT scanning data (images and numbers) and the need of specialized algorithms and software. With this review, readers are expected to be well informed of the avenues offered by CT scanning technology in forest research in general.

Keywords: X-ray computed tomography (CT) scanning, wood density, annual growth ring, moisture content, scale of resolution

Introduction

Woody plants produce raw organic materials (cellulose, hemicelluloses, and lignin) that are highly variable in quantity and quality. Their properties are determined through a complex process controlled by internal and external signals (Mauriat et al. 2014), along major developmental steps which begin with the differentiation of vascular cambium into secondary xylem mother cells followed by cell division, cell expansion, cell wall thickening, programmed cell death, and heartwood formation (Plomion et al. 2001).

Variation in wood exists at several scales and positions in the stem and crown: first, within annual growth rings in temperate zones (i.e., the early versus latewood, which are produced during the first and second parts of a growing season); second, from pith to bark and from stump to apex (i.e., the juvenile versus mature wood, in direct relation with cambial age); and third, between normal and reaction woods (i.e., clear wood versus wood formed in response to gravity). The annual ring structure, as part of the early wood-latewood pattern, which is easily observed in tree species growing in temperate or boreal regions (Fig. 1), is caused by the active and dormant states of the vascular cambium, which are mainly triggered by changes in photoperiod and temperature (Fromm 2013). The early wood is generally characterized by vessels or tracheids of large size in association with thin cell walls, whereas the latter are thicker and radial lumen diameters are much smaller in latewood (Panshin and de Zeeuw 1980). In general, wood density in conifers is positively correlated with the proportion of latewood (Zobel and van Buijtenen 1989).

Juvenile wood forms a core extending outward from the pith, where wood characteristics undergo rapid and progressive changes in successively older growth rings. It differs from mature wood in that it has generally a lower percentage of latewood, lower specific gravity, shorter tracheids with larger fibril angles, and occasionally large amounts of reaction wood caused by its larger flexibility, than mature wood (Zobel and Sprague 1998; Mansfield et al. 2007).

To grow, trees take a large amount of water from the soil into their roots and all wood in living trees contains either bound water or free water. Bound water is found within cell walls, and penetrates the amorphous regions of the cellulose microfibrils. At the fibre saturation point (FSP), cell walls are saturated with water. Above FSP, no more water can be added to the cell

walls and if further water is to be absorbed, it is found in the cell lumina as free water (Lindgren et al. 2016). The cell walls of heartwood are usually saturated with water, whereas cell lumens, pit openings and cell wall voids are filled with water in sapwood.

The characterization of wood properties inside a tree stem and the branch attributes (Pernestål et al. 1995; Tian et al. 1995; Brännström 2005; Molteberg and Høibø 2007; Antony et al. 2010) has motivated the development and use of a plethora of measurement techniques. Many of these are based on X-ray technology: computed tomography (CT) scanning (Lindgren 1991a, 1991b; Fromm et al. 2001; Espinoza et al. 2005; Freyburger et al. 2009; Colin et al. 2010a; Duchateau et al. 2013); microdensitometry (Helama et al. 2008; Jacquin et al. 2017); and others (Wimmer et al. 2002; Defo et al. 2009). Rarely, though, was a three-dimensional (3-D) analysis of the data actually performed. When this was the case, the focus was on the detection of branch knots, known as rameal traces (Colin et al. 2010a; Duchateau et al. 2013; Krähenbühl et al. 2014; Song et al. 2017), and of reaction wood in the tree stem (Pont et al. 2007). More recently, progress has been made on the quantitative side, through the measurement of tree growth via wood density variations within and among annual rings (Manceur et al. 2012; Beaulieu et al. 2016), which can produce 3-D maps of means of estimated wood densities (Dutilleul et al., 2014); see Fig. 2 for an example. As wood density and moisture content largely affect the efficiency of manufacturing processes, much emphasis is put on the development of methods and devices that are able to assess them (see Wei et al. 2011 and Jacquin et al. 2017 for reviews concerning CT scanning and microdensitometry, respectively). Other factors such as the localization of pith and internal defects (Longuetaud et al. 2004) are also the key to optimize manufacturing processes and value of forest products.

Wei et al. (2011) performed a review of the use of X-ray CT scanning technology in the context of optimizing the manufacturing of forest products. Given the rapid development and applications of the technology in the past few years, we present a review of the recent use of X-ray CT scanning in the forest sector, while providing complementary details on the technological aspects and broadening the scope of application. Our review includes biological aspects related to tree growth (i.e., annual ring widths) and light interception by the crown (i.e., leaf canopy and branching pattern), among the topics of discussion.

Description of CT scanning technology and data

Computed tomography (CT) scanning is a non-invasive and non-destructive imaging technology, originally designed for diagnostic purposes in medicine (Kalender 2000). The technology was progressively introduced to soil science (Ketcham and Carlson 2001) and plant science (Dutilleul et al. 2005), including an early wood science application by Onoe et al. (1984). In simple and general terms, it is based on the absorption of X-rays by the sample that is CT scanned, because there is an X-ray source inside any CT scanner (e.g., medical or macro versus micro; see below).

Specifically, more than one CT image are usually produced from the CT scanning session of one sample, and these images (in the so-called X-Y plane) are maps of CT numbers, for successive sections of the sample (along the Z-axis, which is perpendicular to the X-Y plane). The data for those maps are contained in matrices or 2-D arrays of large size (e.g., 512 x 512 or even more), and each of the data is a CT number, computed for each parallelepiped rectangle or voxel (3-D extension of a pixel) into which the volume (i.e., a much larger parallelepiped rectangle) containing the CT scanned sample (including the surrounding air) is divided. A CT number (CTN, expressed in Hounsfield units, HU) is calculated (Kalender 2000) as a ratio of two differences between coefficients of X-ray attenuation:

(1)
$$CTN (HU) = \frac{\mu_{object} - \mu_{water}}{\mu_{water} - \mu_{air}} \times 1000$$

By definition and nature, the coefficient of attenuation of air (denoted μ_{air} in eq. 1) is 0, as air is too light to absorb any amount of X-ray energy; the denser an object, the more X-rays absorbed. For a given voxel other than air, the value of the attenuation coefficient (μ_{object} in eq. 1) is computed from measurements made by detectors located in the gantry of the CT scanner, on the amount of X-ray energy that passed the voxel (i.e., penetrated and went out); the X-ray source (or 'tube') is on the opposite side inside the gantry (see Supplementary material for a macro-CT scanner, equipped with the helical scan option). The value of μ_{water} is set for pure water by calibrating the CT scanner. Let us then consider a wood cell, composed of air, water and other materials or structures such as cell walls (Fig. 1). Since a voxel in wood CT scanning will contain more than one wood cell, the μ_{object} values in eq. 1 will be weighted averages, depending on the proportions of air, water and other materials and their respective densities in

the different voxels. This also underlines the importance of wood moisture content in wood CT scanning, as already stressed and demonstrated by Lindgren (1991a, 1991b); the same principle (i.e., distinction between lighter voxels versus denser voxels) applies to the separation of leaves from branches in CT scanning datasets collected for tree crowns (Fig. 3). From eq. 1, it appears that positive and negative CTN values represent estimated densities greater and less than that of pure water, respectively. The CTN scale is linear and centered on 0, which corresponds to water, while air has the calibrated CTN value of -1000 HU (Han et al. 2009).

When a number p of $q \times q$ matrices of CTN data (i.e., p CT images) are produced for a given wood sample, the data can be arranged in a 3-D array with dimension $q \times q \times p$, and their number $q^2 p$ rapidly increases. For example, $q^2 p$ is already greater than 12×10^6 when $p = 50$ and $q = 512$, and this represents 50 CT images which cover a mere volume of 382 cm^3 when the field of view is 18 cm in diameter and the image construction interval length is 0.03 cm (Dutilleul et al. 2014). Such 3-D data arrays can be called “big data”.

Most modern macro-CT scanners are equipped with the helical CT scan option, which provides an almost perfect volumetric reconstruction from the CT images produced, contrary to the former scan and view option, in which ‘slices’ were made and could be slightly misaligned. When the helical CT scan option is used on a macro-CT scanner, the sample is installed on its side on the couch and the couch moves forward or backward, following the exam plan, while the X-ray tube is turning around the couch during a number of seconds called “exposure time”. Figure 4 presents an illustration where the Z-axis corresponds to the couch axis as well as the height of the conifer for which the crown is being CT scanned in this case. The procedure is different on a micro-CT scanner, where the sample stands up at the center of a circular plate and rotates in this position, horizontally, while the X-ray source remains in place, on the side of the plate.

Concerning the question of resolution in relation to the use of the particle “macro” versus “micro” when characterizing an X-ray CT scanner, Ketcham and Carlson (2001, Table 1) offer very clear and useful definitions based on scale of observation and scale of resolution. For high-resolution macro-CT scanning, the scale of observation is the dm and the scale of resolution is expressed in multiples of $100 \mu\text{m}$, whereas the two scales are, respectively, the mm and a few

µm for micro-tomography. Accordingly, high-resolution macro-CT scanning is suitable for wood disks, and micro-CT scanning for wood pellets, for example. More conventional macro-CT scanning (scale of observation: m; scale of resolution: mm) can be recommended for tree logs. The main difference between macro- and micro-CT scanners is likely that the X-ray tube turns around the sample installed on the couch with a helical macro-CT scanner, whereas the sample stands up on a plate and the plate rotates a number of times and by an angle increment defined by the exam plan, with X-ray emission from a fixed source on the side, in a micro-CT scanner.

In the following sections, we review recently published studies where wood properties and internal or external features of trees were assessed with CT scanning technology. Different CT scanners, from medical to high-speed industrial, were used by the researchers in these studies; the specific CT scanner models and companies are given in Table 1.

Assessment of wood properties and features

Wood density and radial growth

Density has long been considered the most important wood property because it has major influences on lumber mechanical properties (i.e., strength and stiffness) and pulp yield (Zobel and Talbert 1984; Jozsa and Middleton 1994). The CT numbers (eq. 1) are known to be indirect measures of density of the parts of an object analyzed with the technology, because the X-ray attenuation coefficient for a voxel is intrinsically related to its material density, or specific gravity. Thus, it is very naturally that CT scanning technology has started to be used to assess wood density (Lindgren 1991a; Bucur 2003).

For tree species grown in temperate and boreal regions, the annual variation in wood density makes it possible to delineate annual growth rings in CT scanning data. This is because there is generally a drastic drop in density between the wood produced at the end of a growing season and that produced at the beginning of the following one in those regions (Manceur et al. 2012; Dutilleul et al. 2014; Beaulieu et al. 2016). Using their own macro-CT scanner, which was of a different model (Table 1), a group of researchers at the INRA Nancy-Lorraine (France) Centre completed several studies to assess wood density and measure the width of annual growth rings in various tree species. The resolution of CT images (in the X-Y plane) was close to 0.2 mm/pixel,

and Freyburger et al. (2009) first calibrated equations to relate CT numbers (HU) to wood density ($\text{kg}\cdot\text{m}^{-3}$) depending on the scanner settings.

Thereafter, Longuetaud et al. (2016, 2017) analyzed specific gravities in fresh and oven-dry states for five tree species. The authors also quantified within-stem variation in basic specific gravity as a function of height, to assess the representativeness of measurements usually made at breast height. The five tree species studied are three hardwood species: European beech (*Fagus sylvatica*), sessile/pedunculate oak (*Quercus petraea/robur*) and sycamore (*Acer pseudoplatanus*); and two softwood species: Douglas-fir (*Pseudotsuga menziesii*) and European silver fir (*Abies alba*). Trees were harvested in winter or at the beginning of spring, and wood discs were collected every 2 m along the stem. Discs were placed on the side and parallel to each other, separated by a foam folder, on the CT scanner couch, and scanned in fresh and oven-dry conditions. The oven-dry state was achieved after 24 h of drying at 103 °C. Temperature above 100 °C is required to remove the water, including bound water (Williamson and Wiemann 2010). The CT scanning was performed with same tube current (50 mA) for both states, but within an interval of tube voltage values higher for the fresh state (80–120 kV) than for the dry state (80 kV), to allow the emission of a greater quantity of X-rays from the source and a greater penetration of X-rays through the wood disc in the former case. Slice thickness was 1.25 mm, and as the field of view is dependent on the disc size, pixel dimensions varied from 0.18 to 0.98 mm. Eventually, the authors produced radial and vertical “2-D within-stem maps” of estimated wood density for each of the sampled trees.

To make their results comparable with those of other studies (e.g., Woodcock and Shier 2002; Plourde et al. 2015), Longuetaud et al. (2016, 2017) assessed wood density in three zones within discs. These zones are: an inside area, made of the two innermost 1-cm thick tangential bands; an outside area, including the two outermost 1-cm thick tangential bands; and the middle area, containing the remaining bands. Results showed that the radial pattern of basic specific gravity at breast height (i.e., 1.3 m or 2 m from the ground, depending on the species) varied with tree species. Basic specific gravity generally increased from pith to bark in European beech, sycamore and Douglas-fir, whereas it decreased in sessile/pedunculate oak and presented a U-shape in European silver fir. Variation in radial pattern of wood density is often observed within species and among directions within trees; see Dutilleul et al. (2014) for white spruce, and Longuetaud

et al (2016, 2017) for European beech, sessile/pedunculate oak and sycamore, for example. Specifically, the radial pattern of basic specific gravity in European beech was found to be influenced by disc size, with values of the trait increasing from the pith but decreasing towards the bark after attaining a maximum in the case of large-size trees. Differences in the radial pattern of wood density between discs of different sizes in white spruce were observed by Beaulieu et al. (2016); these differences, however, were mainly due to cambial age differences. Correlation analysis between breast-height and whole-stem estimates showed good representativeness of basic specific gravity at breast height for the whole stem on average in the three hardwood trees, but less so, with an overestimation of about 5%, for the two softwood species. Clearly, such a level of estimation and conclusions of this nature were made possible thanks to the collection and analysis of wood CT scanning data.

A group of researchers at the Norwegian Forest and Landscape Institute has been using X-ray CT scanning technology (Table 1), to obtain wood density estimates for Norway spruce (*Picea abies* (L.) Karst.). Steffenrem et al. (2009) obtained CT images of wood increment cores collected on 33-year-old Norway spruces sampled in a progeny test. These images were generated with the following settings: 150 mA (tube current), 110 kV (tube voltage), 1.0 s (scan time), filter = B50, and 1 mm (X-ray beam width). The pixel size was 0.21 x 0.21 mm². To translate CT values into wood density estimates, the authors developed an equation that they calibrated with gravimetric wood densities from 19 cubic specimens (10–60 cm³ in volume) of 11 different tree species, at 12% moisture content. Their density ranged from 355–755 kg·m⁻³. The same CT scanner settings as for the Norway spruce samples were used, except for slice thickness (X-ray beam width), which was 5 mm. Thereafter, their linear function which transformed CT values into wood density estimates at 12% moisture content was $\rho_{12} = 1062 + 1.068 \text{ CT value}$ ($R^2 = 0.998$, Root Mean Square Error = 6.3 kg·m⁻³). Annual tree growth rings were delineated in CT images with ImageJ software (Schneider et al. 2012) and computer algorithms based on the search for abrupt change from late to early wood in the density profile. Ring boundaries were also inspected and corrected manually. Eventually, wood density estimates were obtained for each annual growth ring and mean values of basal-area weighted wood density were calculated. The authors could also study genetic variation patterns and estimate genetic parameters such as narrow-sense heritability and genetic correlations among traits.

Using the same CT scanner and settings, Steffenrem et al. (2014) developed a high-throughput method to measure ring width and wood density for unprepared Norway spruce wood increment cores, also collected in forest genetic trials. Their method takes advantage of the automation capabilities of CT scanners and computer-script programs, to automatically extract data from the CT images constructed for a large number of samples and store them into a file for further analysis. The method was tested on 1600 wood increment cores with 5-mm diameter, from 240 clones at two sites. The increment cores were mounted in cassettes of balsa (*Ochroma pyramidale*) wood, and the cassettes containing the samples were acclimatized to ~12% moisture content in a climate chamber. Each CT image counted 512×512 pixels, spatial resolution was 0.22 mm per pixel, and each pixel represented a volume of wood (voxel) equal to 0.05 mm^3 . The CTN values were transformed into wood density estimates using the function developed by Steffenrem et al. (2009), and a SAS code using a macro was written to remove the CTN values corresponding to the balsa wood of cassettes in the CT image processing. For rings formed over an 11-year period, Steffenrem et al. (2014) also compared the wood density estimates obtained for 23 additional trees, from CT scanning data versus high-resolution though one-dimensional data obtained with a SilviScan instrument (Evans et al. 1995). The authors reported a good agreement between the two methods, while indicating a tendency for increasing differences in wood density estimation with increasing values, as also observed in white spruce (*Picea glauca* [Moench] Voss) by Manceur et al. (2012). The resolution achieved with Steffenrem et al. (2014)'s high-throughput method based on CT scanning did not allow them to analyze the maximum and minimum wood densities within annual rings reliably, so the early and late woods could not be distinguished clearly.

The INRA Nancy-Lorraine group also developed a procedure to measure quickly thousands of unprepared increment cores for the Forest Inventory Laboratory of the French National Institute of Geographic and Forest Information in France (Leban et al. 2016). In their procedure, several boxes containing increment cores can be CT scanned at the same time; the density profile and mean density of each wood core are obtained almost automatically; and manual intervention may be limited to the control of the position of cores. The software *CarDen* (Jacquin et al. 2019) allows the incremental measurement, from CT scanning data, of the wood density of 5-mm diameter cores stored into polycarbonate boxes.

Van den Bulcke et al. (2014) used an X-ray micro-CT scanner (Table 1) with wood cores, and obtained density profiles corrected for ring and grain directions for pedunculate oak, Scots pine (*Pinus sylvestris* L.) and teak (*Tectona grandis* L.). The authors followed the procedure developed and calibrated by De Ridder et al. (2011), to reach a 50- μm resolution. In this procedure, the wood cores are mounted in a custom-made holder made of a material with known density and an atomic composition similar to those of wood cell walls ($1.56 \text{ g}\cdot\text{cm}^{-3}$). By using this material as well as the zero density of air, De Ridder et al. (2011) directly converted the CT scanning data collected for wood cores into densities, and showed that the densities thus estimated were not significantly greater than densities determined gravimetrically and the correlation between them was high ($R^2=0.995$).

De Mil et al. (2016) used the same micro-CT scanner to develop a high-throughput 3-D system and obtain density profiles from pith to bark with wood cores. Their system includes screening and archiving software routines and automatized procedures for tree-ring detection and cross-dating through density-based pattern matching of the profiles, to find anomalies. Their toolchain was tested with 46 wood cores (5-mm diameter) of sessile oak, European beech and limba (*Terminalia superba* Engl. & Diels), a tropical brevi-deciduous tree species. The cores were dried at $103 \pm 1^\circ\text{C}$ temperature for 24 h and mounted in custom-made holders for CT scanning. The holders, in which a maximum number of 33 wood cores with a length of 50 cm or less could be stored, were CT scanned at a resolution of 110 μm . The authors concluded that a large number of structure-corrected density profiles can be generated in a short time interval by their system, with sufficient intra-annual density information for accurate tree-ring analysis.

Our own research team used the macro-CT scanner (Table 1) installed at the CT Scanning Laboratory for agricultural and environmental research on the Macdonald Campus of McGill University (Sainte-Anne-de-Bellevue, QC, Canada), to obtain wood density estimates in 3D and profiles of annual ring width for white spruce wood discs (Dutilleul et al. 2014; Beaulieu et al. 2016). The CT scanning parameter values were: 50 mA (tube current), 120 kV (tube voltage), 1 mm (X-ray beam width), combined with 18 cm (field of view) for the small-size discs and 24 cm (field of view) for the medium-size discs; no zoom factor was applied. Using the helical scan option, CT images were constructed every 0.3 mm in the tree stem direction (Z-axis), each CT image (X–Y plane) consisting of a 512 x 512 matrix of CT numbers. The helical scan option allows

multiple image constructions from CT scanning data collected in one rotation, and provides enhanced image precision (Han et al. 2008). CT numbers were converted to wood density estimates using the calibration equation developed by Lindgren (1991a) for not oven-dried wood, combined with separate SilviScan measurements (Manceur et al. 2012).

Dutilleul et al. (2014) used customized programs written in MATLAB (The MathWorks Inc., Natick, MA, USA), to extract eight "virtual cores" with 1 voxel in diameter from the 3-D array of CT scanning data collected for each wood disc, every 45 degrees from an interior point used as centre for the disc. For each of the virtual cores thus digitally extracted, a curve made of wood density estimates was produced every 0.35 mm (i.e., the field of view of 18 cm, divided by 512) for a small disc and every 0.47 mm (i.e., 24 cm divided by 512) for a larger disc. Results of graphical and quantitative analyses were reported for trees with circular versus non-circular growth. The scale of resolution of the CT scanner and the CT scanning data collected with it, combined with the computational tools developed by the authors in addition to pre-existing and new calibration procedures, allowed them to delineate reliable limits for annual growth rings. Furthermore, the size of samples (wood discs) was large enough to capture directional variation in white spruce growth rates. Growth variability in 3D could thus be assessed using 25 CT images (along the Z-axis) for each wood disc. The multidirectionality, flexibility and fineness offered by CT scanning technology in wood science was hence demonstrated.

In Beaulieu et al. (2016), we extracted digitally virtual wood cores in four orthogonal directions from the 3-D array of CT numbers collected for each of a number of small-size and medium-size wood discs, to assess statistically the main and interactive effects of direction, core size and year of growth on estimated wood density for a given wood-disc size. Each virtual wood core mimicked a cylinder of 1 voxel, 5 mm, or 12 mm in diameter, the latter two core sizes corresponding to the diameters of real wood cores usually extracted on-site from stems of standing trees in forest surveys. The graphical and quantitative analytical procedures of Dutilleul et al. (2014) were followed for each of the virtual wood cores that were extracted, including the identification of the beginning and end of annual growth rings based on the interpeak distances in estimated wood density (Manceur et al. 2012; Appendix A). Besides the assessment of effects mentioned above, the estimated wood densities as well as the variation in derived radial profiles

were in line with data obtained formerly with other means (Jessome 1977) and the types of growth ring patterns expected and described by Panshin and de Zeeuw (1980) for white spruce.

Using two CT scanners, one macro- and one micro- (Table 1), operated in Norway, Bill et al. (2012) assessed the applicability of computed tomography in archaeological dendrochronology. Both CT scanners were tested with air-dried, archaeological oak wood, and with waterlogged archaeological oak wood and archaeological oak wood treated with polyethyleneglycol as conservation treatment. The macro-CT scanner was a Siemens medical *SOMATOM Emotion* single-slice, which had also been used by Steffenrem et al. (2009) with mostly the same settings. Unlike the Siemens CT scanner which is helical, the X-ray source and detectors in the industrial Nikon XT H 225 CT scanner with micro-focus maintain fixed positions during data acquisition, while the plate on which the CT-scanned object lies is incrementally rotating 360 degrees. For each angular increment, a projection image of the sample is cast on a $45 \times 45 \text{ cm}^2$ Perkin Elmer detector panel, with a matrix of 2048×2048 pixels. The settings for the Nikon CT scanner were: 100 mA (tube current), 55 kV (tube voltage), no filtering, and 10–15 cm (field of view) for an image resolution of 50–75 μm ; this micro-focus CT scanner is equipped with electromagnetic lenses that enable a voxel resolution down to about 5 μm . Eventually, Bill et al. (2012) report that only the industrial CT scanner with micro-focus produced sufficiently clear images to allow for dendrochronological analyses. With it, the authors could separate 0.2 mm-wide tree rings, and identify the sapwood-heartwood boundary when the number of sapwood rings was sufficient, but a visual inspection was needed to distinguish between sapwood and decayed wood. However, they indicated that dendrochronological dating based on CT scanning is comparable to, but more time-consuming than, conventional dating. Their attempts to scan waterlogged and archaeological oak wood treated with polyethyleneglycol were unsuccessful, without excluding that a successful protocol could be developed for these types of materials.

Osborne et al. (2016) used a medical CT scanner (Table 1) with the purpose of estimating Douglas-fir wood density and developing a regionally applicable equation for it. Thirty 1.27-cm diameter wood cores were therefore drawn from a 30-year old coastal Douglas-fir spacing trial near Corvallis, OR, USA. In addition, 80 wood blocks of about 2.5 cm^3 each were cut from sawn lumber purchased at a local hardware store and planks from a local woodpile. The wood cores were CT scanned in a balsa wood cassette at 0%, 10% and 20% moisture contents, using a

method adapted from Steffenrem et al. (2014). The targeted 0% moisture content was achieved by drying samples in an air-circulated oven at 103 °C temperature for 24 h, the 10% moisture content by allowing samples to reach equilibrium in an environmental chamber maintained at 65% relative humidity and 20 °C temperature, and the 20% moisture content by placing the samples in a desiccator for four weeks with 95% relative humidity and 20 °C temperature. For all three moisture content levels, samples were CT scanned with 120-kV X-ray tube voltage, 1-mm slice thickness and 0.544-mm² pixel size. The X-ray tube current was set at 50 mA, 80 mA and 200 mA for the 0%, 10% and 20% moisture contents, respectively. After each CT scanning session, the weight (nearest 0.1 g) and volume (nearest 0.1 mm³) of the wood cores and blocks were measured, and their density was estimated. Eventually, the authors developed a linear model to relate wood density to the CT number value (HU), X-ray tube current, moisture content and the interaction between CT number value (HU) and moisture content ($R^2=0.966$). They concluded that their results confirm the efficacy of a medical X-ray CT scanner to rapidly collect data in order to robustly predict Douglas-fir wood density, but their model may be specific and apply only to Douglas-fir and the CT scanner they used.

Other internal features

Pith, sapwood and heartwood

Locating the pith in CT scanned logs is important because to model knots, for example, the distance from the pith in a CT image is required. Andreu and Rinnhofer (2003) located the pith of spruce logs by considering it as the center of concentric annual growth rings, themselves identified in CT images with the use of filters to reduce noise. They scanned logs with a prototype industrial CT scanner (Table 1), allowing a pixel resolution of 1.55 x 1.55 mm², an intensity resolution of 4096 grey levels per pixel, and an image size of 512 x 512 pixels. Thus, they took CT images every 20 mm with a scanning transversal feeding speed of 1.5 m·min⁻¹. Thereafter, the researchers used the method of Duda and Hart (1972), based on a Hough transformation, to localize the pith over 270 images of a rather bent log under the assumption that annual growth rings are concentric circles. They compared their results with the exact position of the pith within each image, and found a distance error with a mean of 2.2 pixels and a standard deviation of 1.2 pixels.

The INRA Nancy-Lorraine Centre research group developed a series of algorithms to delineate several internal features in tree logs. Among them, they designed a method to automatically locate the pith from CT images regularly spaced within logs of Norway spruce trees sampled in two stands of the Vosges Mountains in northeastern France (Longuetaud et al. 2004). The logs were scanned at Luleå University of Technology in Skellefteå, Sweden, with a medical Siemens CT scanner (Table 1). A total of 18,700 CT images (512 x 512 pixels, 4096 grey levels) were constructed every 10 mm for 42 4.5 m-long logs taken from 12 trees. The resolution in the X-Y plane varied between 0.68 and 0.88 mm/pixel, depending on the diameter of the log. To locate the pith, the researchers used the Hough transform method, as Andreu and Rinnhofer (2003) had done before them. The underlying assumption of the method (i.e., annual growth rings are circular and hence, centered on the pith) is not always met but the method is nevertheless robust to departures, except when slices contain knots. The algorithm developed by Longuetaud et al. (2004) can treat both clear wood sections and those containing whorl branches, by the application of corrections to knotty slices. They reported that the mean distance between automatically detected pith positions and the reference manually detected ones was about 0.75 mm and the accuracy was less than 2 mm for more than 95% of the slices. Accordingly, they considered that their algorithm was precise enough to be used for automatic detection of pith in other studies.

The same INRA Nancy-Lorraine Centre research group developed an algorithm that enabled the automatic detection of the boundary between heartwood and sapwood within fresh Norway spruce logs from northeastern France (Longuetaud et al. 2007). Sapwood is usually denser than heartwood because of a greater moisture content in the former, and this difference was used to separate sapwood from heartwood in the stacks of CT images; the algorithm is also robust against the presence of knots. Logs were about 4.5-m long, as in Longuetaud et al. (2004); the CT images of two logs from each of four trees were used to calibrate the algorithm; and CT images from eight other trees were used to validate it. Results were validated by comparing sapwood-heartwood boundaries identified manually by three experienced operators, with those detected automatically by the algorithm. In experimental conditions detailed in the paper (Longuetaud et al. 2007), the mean of errors was calculated to be 1.8 mm. Differences in accuracy were observed between bottom and top logs, and were likely related to the

corresponding change in branch morphology. The authors concluded that their algorithm can be applied efficiently only if the densities of heartwood and sapwood are sufficiently contrasted.

Boukadida et al. (2012) enhanced the algorithm initially developed by Longuetaud et al. (2004) to automatically detect the stem pith within X-ray CT scans of logs, and implemented it as the plug-in *PithExtract* for the ImageJ software (Schneider et al. 2012). They validated it with 125 logs of 15 hardwood and two softwood species. The algorithm uses adaptive thresholds and a final smoothing operation, among other options. The logs were air-dried for several months before CT scanning (Table 1). The settings were 80 kV (tube voltage), 50 mA (tube current) and 1.25 mm (slice thickness), and each CT image constructed every 1.25 mm counted 512x512 pixels, with a side length varying from 0.20 to 0.98 mm depending on the log shape and diameter (2.6–36.0 cm). The pith trajectory was manually recorded on each log using ImageJ software (Schneider et al. 2012) and the plug-in *Gourmands* (Colin et al. 2010a). Boukadida et al. (2012) compared their automatic detection data with the manual measurements, and reported that the automatic detection of pith location was accurate for most of the logs, with an overall mean error of 1.69 mm, and was more accurate than in other studies. The accuracy of the automatic pith detection procedure was significantly better when CT images were processed downwards (i.e., from the top to the bottom of the log), rather than upwards. The reason would be that in upward processing, the algorithm might follow a secondary pith in the presence of a fork, for instance. The authors also indicated that the pith detection accuracy should be assessed in an industrial context, with CT images of lower resolution.

Knots and rameal traces

Knot geometry and distribution within a log determine largely the products that can be derived as well as their value. X-ray CT scanning technology allows, in a non-destructive way, the estimation of the number of knots, their size as well their location inside the log. Image analysis algorithms based on knot models are generally used to characterize knot structure from the data gathered for CT scanned logs (Grundberg 1994). For Norway spruce logs, Oja (2000) evaluated the accuracy of knot parameters measured automatically in CT images constructed every 10 mm; see Table 1 for the CT scanning equipment. Results included the descriptions of the outer shape, heartwood border, pith location, and knot structure. Each knot was described by 10 parameters, which provided a very precise characterization of the knot structure of a stem

(Oja 2000). Following CT scanning, the logs were sawn. Saw pattern was noted, together with the log position during sawing. From this information, virtual logs were built and submitted to a simulation sawing software, to obtain images of boards. The diameter of knots was measured on these boards and compared with those measured on real sawn boards. In the end, this study showed that CT scanning technology allows an accurate detection of knots in terms of position and number, and that knot diameter can be measured with a mean error of 2 mm.

Researchers at the INRA Nancy-Lorraine Centre also developed algorithms aimed at detecting knots in CT images automatically. Longuetaud et al. (2012) presented an improved algorithm to automatically detect and measure knots in CT images of softwood beams. The algorithm combines a connex component analysis and a 3-D distance-based transformation. The method was tested on dried square beams of Norway spruce and silver fir. Six of seven wood beams were CT scanned (Table 1), with the following settings: 50 mA (tube current), 120 kV (tube voltage), 2 cm·s⁻¹ (couch speed), and 3.75 mm (X-ray beam width and interval between slices). The seventh wood beam was CT scanned using 50 mA (tube current), 120 kV (tube voltage), and 1.25 mm (X-ray beam width and interval between slices). Each CT image comprised 512 x 512 pixels, each with 0.74 x 0.74 mm² size. The DETAIL filter, available with the CT scanner, was applied in the image reconstruction of wood beams. The knot shape and size were manually recorded using ImageJ software (Schneider et al. 2012) and the plug-in *Gourmands* developed by Colin et al. (2010a). The outputs of the algorithm and the manual measurements of knots made on the same images were compared. Results showed that the algorithm was able to detect 85% of the knots present in a wood beam, with errors of 2.9 mm and less in knot maximum diameter. Correlations with manual measurements were high, with mean R^2 values of 0.86, 0.87, 0.59, and 0.86 for inclination, maximum diameter, length, and volume, respectively.

In 2014, Krähenbühl et al. proposed a fully automatic procedure to segment wood knots from CT images of wet sapwood. Their algorithm first exploits the knot distribution per whorl branch in a stem, to isolate each knot within a specific zone. Then, it uses a robust curvature estimation of 2-D digital contours, and takes advantage of the geometric properties of the knot shape and knot-sapwood interface. The authors tested this algorithm on images of three conifer species: Norway spruce, European silver fir, and Scots pine, and compared the results with those

obtained with three other algorithms. They reported that their algorithm provided the best precision for each species.

The INRA Nancy-Lorraine Centre research group also developed an algorithm to automatically segment knots in wet logs. They developed it as a plug-in of the ImageJ software and called it *TEKA*. The algorithm uses stacks of images sliced tangentially to annual growth rings from pith to bark, to segment knots (Roussel et al. 2014). In each tangential slice, the knot pith is detected and its diameter is estimated by analyzing the gray-level variations around a pixel used as center. The authors validated their algorithm on 125 knots from 16 wet logs of five softwood species: Douglas-fir, European silver fir, European larch, Scots pine, and Norway spruce. The logs were CT scanned (Table 1). The thickness of CT images (512 x 512 pixels) was 1.25 mm, and their resolution ranged from 0.4 to 0.8 mm/pixel, depending on the log diameter. Each knot was also manually delineated with plug-in *Gourmands* (Colin et al. 2010a) of the ImageJ software (Schneider et al. 2012), thus allowing comparison with results of the knot detection algorithm regarding knot diameters and positions. The authors found that the statistics values (RMSE: 3.37 mm, bias: 0.81 mm, R^2 : 0.85) were almost identical for heartwood and sapwood, and detected only a few, small differences between species. They also indicated that compared to previously published algorithms, *TEKA* does not seem more accurate but works as well for sapwood as for heartwood, unlike other algorithms (Roussel et al. 2014).

Johansson et al. (2013) designed an algorithm to detect knots in both heartwood and sapwood, with a high detection rate, in CT images of logs from Scots pine and Norway spruce tree stems. The algorithm, which can be seen as a follow-up to Grundberg and Grönlund's (1992) work, segments the knots with variable thresholds on cylindrical shells or concentric surfaces following approximately the annual growth rings. Knot detection was based on 10 concentric surfaces, with a minimum of five located in the heartwood. Ellipses were fitted to knots, and the fitted ellipses that could be matched through at least three successive heartwood concentric surfaces were considered to correspond to knots. Parameterized knots were obtained by regression from the matched knot ellipses. The algorithm was validated using logs from the Swedish Stem Bank (Grönlund et al. 1995), which contains data from several hundreds of logs. These logs were CT scanned (Table 1) and the CT images (512 x 512 pixels, 10-mm thick) are stored. A simulation software produced images with a quality similar to that of the images produced with the high-

speed industrial CT scanner that had been used in reality. The pith position, bark-wood border and sapwood-heartwood border were identified using Hough transforms (Longuetaud et al. 2004) and a series of filters, with the pith as origin. Reference measurements of knots on physical boards (Grönlund 1995) or reference measurements made in high-quality CT images were used in validation. The algorithm detected between 88% and 94% of all reference knots, and appears to be robust, with only about 1% of falsely detected knots for both species. However, the accuracy is not comparable to that achieved in others studies (Grundberg and Grönlund 1999, Oja 2000, Longuetaud et al. 2012), because of the lower quality of images for a high-speed industrial CT scanner.

The moisture content of a log is known to affect the CT scanning results for it, as wet wood has higher density than the same wood sample in dry condition. Thus, knot detection becomes more difficult when logs are only partially dried out. Fredriksson et al. (2017) tested the algorithm developed by Johansson et al. (2013) on partially dried logs of jack pine (*Pinus banksiana* Lamb.) and white spruce (*Picea glauca* (Moench) Voss), to evaluate its capacity to detect knots with such challenging material. Twenty logs of each of the two softwood species were CT scanned (Table 1). CT images were constructed every millimetre along the logs, which were collected on 32-year-old trees from a Nelder spacing design. As in Johansson et al. (2013), the pith was detected using Hough transforms (Longuetaud et al. 2004), and sapwood-heartwood and outer space borders were delineated using filters and an upgrade of the Longuetaud et al. (2007) algorithm, due to Baumgartner et al. (2010). The automatic knot detection (including geometry, size, position, and end point) performed by the algorithm was compared to manual reference knot measurements. Results showed that knot detection was affected by the heartwood shape. It was also shown that the knot detection rate was high for logs having well defined heartwood-sapwood borders, whereas it was low for those having irregular heartwood-sapwood borders. Accordingly, a decision can be made on whether or not to trust the knot models that follow from the collection and analysis of CT scanning data, and the authors concluded that using this criterion to sort logs could potentially aid both sawmills and researchers in their application of CT-based log models.

Berglund et al. (2014) investigated the potential value increase of Norway spruce sawn timber by rotating logs to their optimum position prior to sawing, compared with sawing all logs in

573 horns-down position. This study followed earlier work by Berglund et al. (2013), in which log
574 breakdown had been simulated for about 800 Norway spruce and 600 Scots pine logs. Data used
575 for simulations come from the Swedish stem bank and formerly CT-scanned logs (Table 1). The
576 CT images described the log shape, pith location, heartwood border and knots. The authors used
577 the software of Nordmark (2005) to simulate log curve sawing in each rotation angle from -180°
578 to 180° , the rotation angle of 0° corresponding to the horns-down position. Simulations included
579 prices corresponding to different quality grades influenced by knot position and size. Berglund
580 et al. (2014) found that there is a potential value increase when a rotation aimed to maximize
581 the value of each log is applied instead of processing all logs in the horns-down position. The
582 authors indicated, however, that the potential value increase depends on the rotational error of
583 the sawing machine and the price differences between quality grades. They concluded that for a
584 Scandinavian sawmill processing Norway spruce and Scots pine logs, there is a potential value
585 increase in the CT scanning of logs in real time.

586
587 Stängle et al. (2015) tested whether value-optimized log rotation can be performed for
588 European beech, based on the knowledge about internal knottiness derived from CT scanning.
589 Nineteen trees were therefore felled in two stands in South West Germany, and cross-cut into
590 three 4.1-m long logs. The 57 logs were CT scanned (Table 1). Resolution was 1.1 mm and 5 mm
591 in the axial and longitudinal directions, respectively. In preliminary analysis of the CT images, the
592 authors detected the pith location using the algorithm of Boukadida et al. (2012), and retained
593 33 logs for further analyses. The CT images were examined visually to locate the knots and
594 measure their dimensions manually. The 33 logs were then reconstructed in 3D, from the
595 derived information about the shape of the logs and the position, geometry and direction of the
596 knots in a log, and virtually sawn in 12 rotational angles, using the simulation software *InnoSIM*
597 (Song and Usenius 2007). Each virtual board was graded automatically. Current market prices
598 for sawn wood of each quality grade and the by-products were used to estimate the value
599 increase that would result from the optimized log rotation. Stängle et al. (2015) concluded that
600 changing the log rotational angle led to large differences in the volume and value of product
601 yield, as calculated from the sawing simulations, and that potential optimization of volume and
602 value per log was highest for logs of low quality. Based on their results, the authors also
603 indicated that using a CT scanning system to detect log internal defects would allow better
604 performance of hardwood sawmills in the future.

605

606 Rais et al. (2017) reported the results of a study aimed at demonstrating that the value of sawn
607 boards can be increased by the knowledge of log internal knottiness. The researchers sampled
608 20 Douglas-firs originating from two experimental plots in Germany. Thirty-six 4.1 m-long logs
609 from these trees were CT scanned (Table 1), at a speed of 120 m·min⁻¹. The *CT Log* equipment
610 includes an X-ray sensor that covers a surface of 1478 mm × 752 mm and an X-ray source with
611 225 kV voltage and 12 mA current. The CT images were reconstructed using the Katsevich cone
612 beam reconstruction algorithm (Katsevich 2004), which eventually provided 3-D images of the
613 logs with a cross-sectional resolution of 1 mm and a longitudinal resolution of 10 mm. Knots
614 were detected using an algorithm which analyzes the concentric surfaces drawn around the
615 previously extracted pith positions (Johansson et al. 2013). Afterwards, the logs were sawn and
616 the boards were visually graded. Detailed knot data was recorded for the entire length of each
617 board, thus allowing the computation of a knot area ratio. Plastic labels installed at the two
618 extremities of a log were visible in the CT images, and allowed the reconstruction of the original
619 position of each board within the log and the comparison of knots on virtual boards with those
620 measured manually. It was also possible to evaluate the error in knot area ratios estimated from
621 the CT images. The authors found a good correlation between the three largest knot area ratios
622 measured by CT scanning and from the manual measurements made on boards. They concluded
623 that sawmill owners can process logs in a better way and produce final products with increased
624 added value, in particular by using a CT scanner to optimize sawing (Rais et al. 2017).

625

626 The presence of sprouts and related defects affects wood quality in oak, causing reduction in
627 timber value species (Colin et al. 2010b). Epicormic branches, which develop from latent buds,
628 are of concern for lumber value, as they alter the lumber grade. Song et al. (2017) used the
629 measurements of branching-related traits made from CT images of logs, to study the genetic
630 architecture of branching in pedunculate oak (*Quercus robur* L.) through a quantitative trait
631 locus (QTL) analysis. The authors retrieved logs from a systematic thinning applied in an oak
632 clonal test, where clones were produced by the rooted cutting technique. One-meter long logs
633 were cut between 40 cm and 140 cm in height, in two ramets of 166 offspring belonging to the
634 same full-sib family (i.e., a controlled cross between a female and a male parent). They were CT
635 scanned (Table 1) at the Xylosciences platform of the INRA Nancy-Lorraine Centre, with 2.5-cm
636 thick slices at the rate of 150 images per meter. The observed branching traces, which included

(1) primary latent buds, (2) knots of sequential branches, (3) knots of epicormic branches, and (4) secondary latent buds, were manually marked on the CT images. Images of virtual logs in 3D were also constructed. Thus, it was possible to define and evaluate a total of 13 branching descriptors, and carry out a genetic architecture study for these branching traits. The authors indicated that they could detect highly significant QTLs related to latent buds and epicormic branches. They also indicated that the number and effects of these QTLs suggest moderate genetic determinism in the formation of latent buds and the development of epicormic branches. Finally, they found high phenotypic variation in all the branching traits and correlations among some of them (Colin et al. 2010b).

Moisture content

Water content and distribution

Fromm et al. (2001) assessed water content in Norway spruce and pedunculate oak (*Quercus robur* L.) stems and annual growth rings, as mapped after high-resolution CT scanning. This was achieved by repeating CT scanning of the same discs in field-fresh and dry conditions, and estimating water content from the density differences between paired images. Twenty spruce and oak trees were sampled. Branch and stem discs with 5-cm thickness were collected at various heights, and deep frozen immediately in dry ice before being transported to the laboratory. Discs were CT scanned (Table 1), in fresh state first and then in dry state after oven drying at 103°C. The settings were: 210 mA (tube current), 120 kV (tube voltage), 1 mm (X-ray beam width), and pixel size (0.35 x 0.35 mm²) in the CT images. The authors reported that the radial water and density profiles in oak differ substantially from those in spruce, for which clear density and water peaks in each annual ring and a strong reduction of water content are shown in the heartwood. In contrast, the decrease of water in the heartwood is much smaller for oak than for spruce, and significant differences in water content between sapwood rings could not be found for oak.

Johansson and Kitefew (2010) used CT scanning technology to gain knowledge about and understanding of the capillary characteristics in three tree species: aspen (*Populus tremula* L.), pedunculate oak and Scots pine. The authors first conditioned for two weeks at 20°C and a relative humidity of 65% seasoned boards of oak and low-temperature-dried boards of aspen and pine with an approximate moisture content of 12%. They then prepared separate sapwood

and heartwood, oak and pine specimens from the boards. For aspen, because it is difficult to distinguish visually (before CT scanning) sapwood from heartwood in the dry state, it was assumed that the CT scanned specimens contained both sapwood and heartwood, which were separated in the analysis of CT scanning data subsequently. Specimens were regrouped in batches of 6 to 8. Their end-grain section (i.e., the face showing growth rings) was placed in contact with a metal grid in a water basin, and immersed down to a depth of 5 mm. All batches were CT scanned (Table 1), before being immersed in water and several times during the 14-day experimental period. Before each CT scanning session, each of the batches was wrapped in plastic to prevent the drying of specimens during CT scanning. Each CT scan, in the longitudinal direction of wood specimens at 5-mm intervals, resulted in a matrix of 512×512 pixels. Each pixel corresponded to a parallelepiped rectangle with dimensions $0.63 \times 0.63 \text{ mm}^2$ in the cross-section plane, and 5 mm in the longitudinal direction. Water uptake was estimated from changes in wood density over time, jointly with a theoretical model that determines the capillary characteristics of wood in relation to its structure. Results showed that aspen sapwood absorbs much more water, and has a much higher capillary rise height than sapwood in oak and pine. Moreover, the comparison between empirical results and results obtained from the theoretical model of capillary water movement indicated that not all the cells were active in the capillary water absorption, possibly because some of the cells were impermeable or totally blocked by extractives and tyloses or because the pits were aspirated (Johansson and Kitefew 2010).

Sandberg and Salin (2012) measured moisture profile development in Norway spruce via capillary water sorption, by CT scanning and CT image processing. They sampled 20 trees from two contrasting sites, one dry and the other with a good supply of ground water. Thirty-two-mm thick boards were sawn from the logs and dried at 12% moisture content during 84 h. Wood specimens (200-mm long, 32-mm thick) were cut from the boards. Before CT scanning, the wood specimens were placed in a climate chamber for a period of two months, to reach an equilibrium moisture content of 12%. Wood specimens were placed in a basin, on bars of stainless steel in 5-mm deep tap water, for end-grain sorption (Johansson and Kitefew 2010). They were CT scanned (Table 1) after 1, 3, 7, and 14 days at Luleå University of Technology in Skellefteå, Sweden. The settings were: 50 mA (tube current), 110 kV (tube voltage), and 10 mm (X-ray beam width), and the constructed CT images had 512×512 pixels. As reference with a

known moisture content level, the authors used wood specimens, oven-dried at 130 °C until they reached a stable weight. Because wood swells during water sorption, images were geometrically transformed so that the immerse cross-section matches the dry reference cross-section. An algorithm developed by Lindgren (1992) was used to determine moisture content from pairs of images (transformed and dry reference). Moisture content was measured in both sapwood and heartwood. The authors compared their results to theoretical profiles obtained by percolation simulation, and reported that the amount of water absorbed could be expressed as a linear function of the square root of time (Sandberg and Salin 2012). The slopes of the lines differed between sapwood and heartwood, and varied depending on the growth conditions of the trees. They concluded that the percolation simulations generally show good agreement with the measured results for sapwood.

In 2013, Li et al. combined X-ray micro-CT scanning technology (Table 1) and a method of electrical resistance moisture content measurement for solid wood, plywood and oriented strand board panels, to study the moisture content distribution in wood products. They validated their CT scanning procedure with gravimetrically-recorded moisture contents of solid wood. Solid defect-free wood specimens (50 x 50 x 15 mm³) were prepared from birch (*Betula* spp.), poplar (*Populus* spp.) and Scots pine heartwood and sapwood. After being conditioned in a control room at 65% relative humidity and 20 °C temperature until constant mass was reached, they were weighed and CT scanned. They were then immersed in a container filled with demineralized water, and weighed and CT scanned after 1, 4, 8, 24, and 48 h of immersion, using the micro-CT scanner at Ghent University Centre for X-ray Tomography, UGCT (Van den Bulcke et al. 2014). Thereafter, the specimens were oven-dried, weighed and CT scanned again; each time, a plastic vial containing demineralized water was CT scanned along. The CT images were reconstructed with Octopus software (Vlassenbroeck et al. 2007). In the end, Li et al. (2013) reported a strong relationship between moisture contents estimated from CT scanning data and with the gravimetric method ($R^2=0.994$), and indicated that X-ray CT scanning technology can accurately monitor moisture content and its distribution in wood products.

In the study of Longuetaud et al. (2016), discussed in the *Wood density and radial growth* section, wood density and moisture content as well as related within-stem properties were mapped for three hardwood and two softwood tree species, and the authors analyzed the

relationships among wood traits. The other properties studied included: the moisture content, the relative water content of lumens, and the volumetric fractions of cell walls, total water, free water, and gas. The objective was to determine which property was the most complementary to basic wood density, in order to discriminate species. A total of 115 trees sampled at dormant stage were used. Discs were collected every 2 m from each tree stem and a radial cut using a bandsaw was made at the same azimuthal position for all discs. For CT scanning, the discs of the same tree were placed vertically and parallel to each other on the couch. The middle slice of each scanned disc was extracted from the stack of CT images, and the disk contour and pith location as well as the opening angle and azimuth of the radial cut were determined manually on the images. The polar coordinates of each pixel were calculated, as well as the corresponding specific gravity in fresh and dry states; the discs were divided into tangential bands of 1 cm in fresh state, and the width in dry state was adjusted to account for the shrinkage of the disc after drying (see next subsection). The radial variation of specific gravity was examined, which allowed the evaluation of water-related variables. The authors could map radial and vertical wood properties, and highlight species-specific patterns. They finally reported that basic specific gravity and the relative water content of lumens were relatively complementary, and therefore were suitable for species characterization and discrimination (Longuetaud et al. 2016).

Longuetaud et al. (2017) studied species-specific patterns of radial and vertical variations in the relative water content of lumens in the same five tree species. They showed that the relative water content of lumens generally increased from inner to outer area, but wet sapwood was clearly distinguishable only for the two coniferous species. Vertical variations were strongly species-dependent, usually with nonlinear patterns. When comparing the average water content of lumens in the stem with that at breast height, the authors concluded that the latter was not representative of the whole stem. Moreover, vertical variations in the values of this trait were affected by radial variations. Finally, the authors recommended that further research be conducted about the relative water content of lumens in relation to sap flow measurements, in order to understand better the hydraulic functions of wood.

Moisture content and drying shrinkage

X-ray CT scanning technology has been used to measure wood moisture content during drying since the mid-1980's (Watanabe et al. 2012). Mapping moisture content locally remains difficult

765 due to the deformation, or shrinkage, which results from drying. Several techniques have been
766 proposed to increase accuracy (e.g., Lindgren 1992, Danvind and Synnergren 2001, Lazarescu et
767 al. 2010). Watanabe et al. (2012) introduced a new method to characterize the moisture content
768 distribution in cross-sections during timber drying, using CT scanning and CT image processing. A
769 measurement error could be calculated, and the moisture content distributions for annual
770 growth rings and the changes due to shrinkage during drying were also studied by the authors.

771
772 Twenty-five pieces of green timber of Pacific silver fir (*Abies amabilis* Douglas ex Loudon), 115 x
773 115 mm² in cross section and 900 mm in length, were kiln-dried over nine days. During this time,
774 pieces of timber were removed from the kiln at the intervals of 0, 1, 2, 3, 4, 7, and 8 days, and
775 CT scanned (Table 1) in Vancouver, Canada. The CT scanner was equipped with a 3.5 MeV X-ray
776 generation system, which is 22 times higher than medical CT scanners (Lazarescu et al. 2010),
777 and can therefore be called “industrial”. Lumber pieces were CT scanned at the oven-dried
778 stage. A piece of timber for which the CT images did not contain drying checks or resin pockets
779 was selected, and a cross section from the center (335 mm from an end) was analyzed. Seven CT
780 images taken during drying and one CT image in oven-dried condition were used for moisture
781 content assessment. A subset of 450 x 450 pixels (~0.25-mm resolution) of the original CT image,
782 which included the cross section of the lumber piece, was analyzed. Using the linear relationship
783 between CT number and wood density, the latter was converted from the CT number for each
784 pixel in the CT image taken in oven-dried condition. Moisture density was converted from the CT
785 number of the ‘subtracted image’ (i.e., the CT image taken during drying ‘minus’ the CT image in
786 oven-dried condition), following Fromm et al. (2001). In the absence of shrinkage during drying,
787 the water content of a pixel could be readily derived from the ratio of moisture density to the
788 estimated wood density in oven-dried condition. In the presence of shrinkage (below the fibre
789 saturation point), the CT images were geometrically transformed for comparison purposes. The
790 bidirectional elastic registration plug-in *bUnwarpJ* (Sorzano et al. 2005) to the software ImageJ
791 (Schneider et al. 2012) was used to fit the CT images taken during drying.

792
793 Hansson and Cherepanova (2012) developed an advanced CT image-processing algorithm to
794 calculate moisture content and moisture loss during low-temperature drying. They also used the
795 bidirectional elastic registration algorithm *bUnwarpJ* for simultaneous registration of the dry
796 and wet wood CT images. The dry wood CT image was elastically deformed to look as similar as

possible to the wet wood CT image, and inversely. Moisture content was calculated following Hansson (2007). To test their method, Hansson and Cherepanova (2012) cut two sapwood pieces from a board of undefined tree species, first dried them at 56/80 °C (wet bulb/dry bulb temperature) for 50 h and then at 103 °C for 24 h to reach the dry state. Ten centimetres of the middle part of each board were CT-scanned with a 5-mm slice width every 15 min, for 20 images for each period time. The distribution of moisture content was studied at each step in time, as well as the average moisture content of a selected 69.6 x 11.6 mm² core region. Thus, the moisture content loss of the core, compared to the average moisture content of the board, could be calculated. By applying their method, the authors showed changes in moisture content within wood pieces over time, and concluded that CT scanning during low-temperature drying in a climate chamber is a powerful procedure to analyze moisture loss within wood pieces.

Couceiro and Elustondo (2015) conducted a study focused on measuring the variation of wood moisture content below the fibre saturation point. During drying, wood shrinks when moisture content reaches and goes below the fibre saturation point. Because wood is an anisotropic material, it does not shrink evenly in all directions. To calculate the correct shrinkage coefficient for each pixel, Watanabe et al. (2012) proposed to use a Digital Image Correlation software (Pan et al. 2009), after CT image construction and registration. Then, Couceiro and Elustondo (2015) examined the size of wood density differences between samples in relation to the experimental error in low moisture condition. They collected six Norway spruce lumber samples (125 x 30 mm²) in a local sawmill. These were cut into 60- to 100-cm long sections, end sealed with heat resistant silicon glue, and dried in a laboratory kiln to moisture content levels between 7.1% and 19.7%. The drying schedules were designed to produce a high moisture-content gradient between the centre and the surface of the boards. The dried samples were CT scanned (Table 1), to obtain density profiles over a cross-sectional area in a knot-free part of the boards. The settings were: 120 mA (tube current), 110 kV (tube voltage), 0.8 sec scan time, and 10 mm (slice thickness). After CT scanning, three adjacent slabs were cut from the CT scanned area. The slab in the centre was oven-dried and CT scanned again for use as reference at 0% moisture content. Results showed that it is possible to use the procedure proposed by Watanabe et al. (2012) for measuring low moisture content values in small regions of wood samples. A linear regression model developed to relate wood moisture content values estimated from CT images to those obtained in oven-dry conditions provided a very good fitting ($R^2 = 0.93$) and a root mean square

error of 1.4% for moisture content values ranging from 6.5% to 25.5%. More research on the topic may still be needed, though, including the CT scanner operation itself and comparison with other methods proposed for image processing in the literature (Couceiro and Elustondo 2015).

Hansson et al. (2017) reported the results of a study aiming to compare wood shrinkage coefficients estimated from CT images in two ways: through the displacement information in the radial and tangential directions versus with *Computer-Aided Design* software. The materials used for the study were 7 Norway spruce and 10 Scots pine wood specimens, i.e., half-discs of the whole log circumference with a thickness between 1.5 cm and 12 cm. Wood specimens were CT scanned (Table 1) in green state, at equilibrium moisture content 15% and 8% state, and finally in oven-dry condition. Spruce and pine specimens were dried separately, in a laboratory-drying kiln. In order to avoid cracks, the drying schedules were slow, and with a long conditioning phase to achieve a uniform moisture content in the specimens. The CT images had a resolution of 1.28 pixels·mm⁻¹ (pixel size: 0.78 × 0.78 mm²); the depth of a voxel was 10 mm. The CT images were first registered with the intensity-based image registration algorithm, designed for the deformation and transformation aspects (Myronenko and Song 2010), and a scaling of the density values was also applied (Hansson 2007). The CT images were then imported into *Computer-Aided Design* software. Angles from the pith (visible or estimated) to the edges of the specimen were measured before and after shrinkage, as were radii from the centre of the specimen. The radial shrinkage was calculated from the radii of the specimens before and after shrinkage, and the tangential shrinkage, from the length of the arch derived from the average radius for the disc. Hansson et al. (2017) concluded that the results obtained with the two methods were consistent because the root-mean-square-error calculations showed acceptable small differences between the two measurement methods. This means the algorithm is a useful tool for estimating the shrinkage coefficients in radial and tangential direction from CT images. It provides an image analysis procedure, with which the dimensional changes during the drying and heat treatment processes can be monitored adequately.

Wood degradation

Wood is often used as building material, but when exposed without protection to outdoor conditions, it undergoes degradation. Heat treatments can improve protection against decay. However, earlywood and latewood have different chemical compositions, which influences

thermal degradation (Shchupakivskyy et al. 2014). Hamada et al. (2016) conducted a study to assess the effect of initial wood density of oak boards on their thermo-degradation, using X-ray CT scanning (Table 1). From each of five sessile oaks, two boards ($250 \times 110 \times 25 \text{ mm}^3$) were radially cut: the one close to the pith (inner heartwood) and the other near the sapwood (outer heartwood). Samples were CT scanned before and after heat treatment, to estimate wood density and mass loss. Each board was virtually sliced into 1,000 CT images of 512×512 pixels each, with about 300- μm pixel size. Heat treatment was performed under nitrogen by conduction, by placing wood boards between two metallic heating plates in an oven. Before heat treatment, the boards were oven-dried at 103 °C for 48 h. Treatment application started and continued at 103 °C until mass stabilization, followed by 1 h at 170 °C and 2 h at 220 °C; the heating rate and gas flow were 1 °C·min⁻¹ and 120 mL·min⁻¹, respectively. Based on the average density values measured from CT scanning data before and after heat treatment, Hamada et al. (2016) reported a reduction of wood density after thermal modification, equal to about 7% of the initial mass of a board. The authors found important variation inside boards and no clear relationship between initial wood density and the thermo-degradation level. They nevertheless indicated that X-ray CT scanning appeared well-adapted to assess wood density variation and mass loss heterogeneity, in response to heat treatment application.

Meincken and du Plessis (2013) performed a study to visualize and quantify structural change caused by thermal degradation at the cellular level in Monterey pine (*Pinus radiata* D. Don) wood. Blocks of about $5 \times 5 \times 5 \text{ mm}^3$ containing early and latewood were cut from wood disks. Thermal degradation was obtained in a furnace by 15-min exposure to temperatures of 150, 200, 250, 275, 300, and 350 °C. The wood blocks were CT scanned (Table 1) in the same orientation, before and after degradation, at the CT Scanning Facility of Stellenbosch University (South Africa). The X-ray tube settings were 220-kV voltage and 200- μA intensity, and the side length of a voxel was 80 μm . Image reconstruction was performed with the system-supplied reconstruction software *Datos*. Degradation quantification was based on average wood density, volume and dimensional changes. The authors stated that exposure to elevated temperatures has a negative effect on most wood properties and that decreased cell wall density, sample and material volume will affect macroscopic, mechanical properties. The negative effect becomes more noticeable at temperatures exceeding 250 °C. Thus, CT scanning technology is a valuable tool to examine wood thermal degradation.

893

894 Wood degradation can also arise from fungi, especially saprotrophic basidiomycetes. Even
895 though other methods have relied on mechanical and physico-chemical properties of wood,
896 mass loss has traditionally been used to quantify the level of degradation, e.g. by Hamada et al.
897 (2016). In the case of the biodegradation of European beech wood by the white-rot fungus
898 *Phanerochaete chrysosporium*, Hervé et al. (2014) developed an X-ray CT scanning procedure for
899 fast, non-destructive and accurate measurement of the density variations of decaying wood.
900 From a European beech heartwood plank, they prepared 108 wood blocks (50 x 24 x 6 mm³),
901 free of knots and other defects, and autoclaved them twice (20 min, 120 °C, dry cycle). Fifty-four
902 blocks were placed in 90-mm Petri dishes containing a medium of malt (30 g·L⁻¹) plus agar (20
903 g·L⁻¹) in the presence of the fungus, and the other 54 blocks were installed similarly in the
904 absence of the fungus. Thereafter, the Petri dishes were sealed and incubated at 25 °C
905 temperature in the dark for 0, 15, 30, 60, or 150 days. For each of the nine combinations of the
906 presence/absence of the fungus and an incubation time, 12 wood blocks were analyzed. Wood
907 density for each block, in wet and dry states (after 24 h in oven at 103 °C for the dry state), was
908 estimated from CT scanning data (Table 1), and acquired with 80-kV voltage and 50-mA current
909 for the X-ray source. Slice thickness was 0.625 mm, each CT image had 512 x 512 pixels, and
910 pixel size was 0.1875 x 0.1875 mm². The loss of density for a given block was obtained by
911 subtraction between the two states. Hervé et al. (2014) reported that after 150 days of
912 incubation, the wood blocks had lost 13.07 ± 0.59% of their initial density. The authors found
913 that the density of wood samples colonized by the white-rot fungus was more variable than the
914 density of controls after 15 days of incubation. Based on their results, they indicated that CT
915 image processing and analysis is relevant for measuring the density variations between and
916 within wood samples during fungal biodegradation, i.e., spatially at the millimeter scale within
917 samples.

918

919 Li et al. (2016) examined fungal decay of plywood and medium density fiberboard (MDF), by
920 monitoring strength decrease (modulus of elasticity, MOE) and mass loss of specimens in a
921 laboratory test. The MOE was measured with a resonalyser, which is a non-destructive flexural
922 vibration method, and the internal structure and mass loss distribution were monitored by X-ray
923 CT scanning. Beam-shaped specimens (30 x 360 x panel thickness mm³) were prepared for each
924 of the types of plywood and MDF available on the market, and nine specimens from each type

were used for fungal decay testing. We refer to the original article for details about the conditioning of specimens in a control room, the inoculation of vermiculite with the fungus *Pleurotus ostreatus*, the removal of specimens after 6, 10 and 14 weeks during the inoculation period, and their re-conditioning before the second of two sessions of CT scanning (Table 1) at UGCT in Ghent (Belgium). The central 140-mm region of the specimens was CT scanned before and after fungal decay. The voxel side length in image reconstruction, performed with Octopus software (Vlassenbroeck et al. 2007), was about 80 μm . Li et al. (2016) reported a strong linear relationship between MOE decrease and the mass loss increase of plywood, which varies with wood species. Thus, the influence of mass loss on MOE decrease depends on the type of plywood. The authors also found that after 14 weeks of fungal contact, mass loss (1.5%) was much less important than MOE decrease (10%) for exterior MDF. A similar tendency was observed for plywood. They concluded that the resonalyser is a valuable technique to non-destructively monitor the MOE of plywood and MDF, and that X-ray CT scanning is an essential tool to visualize the interior structure and evaluate the local mass loss non-destructively.

El Hachem et al. (2018) characterized the micro-structural properties of Norway spruce wood by X-ray micro-tomography (Table 1), and evaluated the wooden hygrothermal transfer behavior. A reliable characterization of wood morphology was achieved thanks to voxels with 0.5- μm side length in CT image reconstruction. Heat and mass transfers were performed on the 3-D reconstructed geometry of wood, to highlight the effects of morphological disorder on the transport phenomena. Six wood specimens ($2 \times 2 \times 20 \text{ mm}^3$) were prepared and conditioned in a control room at 25 °C. Three of them were collected in early wood, and the three others, from the earlywood-latewood transition zone. The micro-CT scanning took place at the Centre Européen de Recherche et d'Enseignement des Géosciences de l'Environnement (CEREGE) in Aix-en-Provence, France. The settings were: 80 kV (tube voltage), 50 μA (tube current), and 5-7 μm (X-ray beam). The 3-D image reconstruction was performed with efX software, and automatic wood fiber extraction, with iMorph software (Brun et al. 2009). The hygrothermal behavior was simulated on the structure of a real specimen ($0.3 \times 0.3 \times 0.5 \text{ mm}^3$), using Cast3m software (CEA, <http://www-cast3m.cea.fr/>). Various wood micro-structural parameters were obtained at 0.5- μm voxel size. A new technique to individualize lumens and identify wood pits and parenchyma was also developed as part of the study. El Hachem et al. (2018) indicated that calculations on the real 3-D wood structure allowed the demonstration of an anisotropy effect

of the equivalent hygrothermal properties and that this is dependent on cell roughness and the presence of pits within the material. The authors highlighted the utility of micro-tomographic volumes for the morphological characterization of spruce wood and the calculation of its hygrothermal properties by simulation.

Crown development

Besides the characterization of internal wood properties and features, CT scanning technology has been shown to be instrumental in evaluating external characteristics of plants. In the *Other internal features* section (Knots and rameal traces) above, some of the studies touched on crown development via the measurement of branching-related traits from CT images; see e.g. Song et al. (2017) for pedunculate oak. Below, we discuss two studies conducted by the same research group at McGill University (Sainte-Anne-de-Bellevue, QC, Canada), who operates a helical high-resolution X-ray CT scanner. First, Dutilleul et al. (2008) studied the developing crowns (branching patterns and leaf canopies) of four pyramidal (non-miniature) cedars (*Thuja occidentalis* Fastigiata). So doing, the authors confirmed the concept of “repeated plant CT scanning” (Dutilleul et al. 2005), since each of the four experimental cedars were CT scanned (Table 1) three times at intervals of one month, i.e., in June, July, and August. Two key results were obtained: the 3-D modification of the Beer-Lambert law for light interception by leaf canopies, through the inclusion of the fractal dimension in the model, and the quantified increase of branching structural complexity (in July) before that of leaf volume (in August).

Recently, Dutilleul et al. (2015) demonstrated that for small-size trees, crown traits related to the structural geometry of branching pattern and space occupancy through phyllotaxis can be accurately evaluated in 3D, using CT scanning data. Their objectives were to (i) compare crown traits measured from CT scanning data between miniature conifers with needlelike versus scalelike leaves, covering a range of shade tolerance as wide as possible; (ii) test for statistical differences between mean values of the crown traits and a shade tolerance index depending on leaf type; and (iii) analyze correlations between crown traits and shade tolerance. Fifteen miniature conifers of different species (horticultural varieties of Canadian indigenous species) were the object of that study. They were classified in two groups according to their leaf type: 10 as needlelike and 5 as scalelike. Each of the 15 conifers was also assigned a shade tolerance index value between 1.0 and 5.0. The crowns of the 15 miniature conifers were CT scanned

(Table 1). The basic CT scanning settings were the same for all 15 trees: tube current (50 mA) and tube voltage (120 kV). The X-ray beam width (to be distinguished from the depth of voxels or the thickness of reconstructed CT images in this case; see below) was 1 mm for all but one tree, the widest one for which it was 2 mm. Three fields of view were used, depending on the width of the crown. They varied from 18 cm to 32 cm. Two zoom factors (1.2 and 1.5) were also applied to improve spatial resolution in the X-Y plane for six trees. Along the Z-axis, spatial resolution (depth of voxels) was 0.2, 0.3, or 0.4 mm, depending on the height of the tree. Every effort was also made to have same resolution, as much as possible, in all three dimensions (isotropic voxels). Between 400 and 600 CT images, each made of 512×512 pixels and associated CT numbers, were produced.

For all 15 miniature conifers, five crown traits were evaluated from the raw CT scanning data or the derived 2-D or 3-D images: the absolute leaf area in the vertical projection of the crown; the relative leaf area in the smallest disc including the vertical projection of the crown; total leaf volume, obtained from all leaf voxels (i.e., voxels with a CT number smaller than the branch threshold and greater than -980 HU to be distinguished from air); leaf volume-to-branch volume ratio; and the average leaf area displayed over four classes of azimuth $\times$ 20 solar elevation classes (every 4.5 degrees starting from 0), plus the 90-degree solar elevation. Fractal dimensions were estimated using 3-D images of skeletonized branching patterns, to avoid any bias introduced by the thickness of branches. Actually, two fractal dimensions, covering each a specific range of spatial scales, were estimated for each crown. Dutilleul et al. (2015) found statistically significant differences in mean values between the needlelike and scalelike groups of conifers for the shade tolerance index, both fractal dimensions, and the average leaf area displayed. Between-group differences in sign and strength of the correlations between traits were also observed. A contrasting physical attachment of the leaves to the branches could explain part of the between-group differences. These results, obtained for crowns of miniature conifers analyzed at a spatial resolution of 200 to 400 μm depending on the specimen thanks to CT scanning technology and advanced data processing, could be used for crown modeling of non-miniature indigenous species in situations where the leaf size-to-branch length ratio justifies it.

Discussion and conclusion

During the last few years, interest in CT scanning technology has considerably increased in forest research, as reflected by the large number of scientific publications in the field. That is not surprising, considering the possibilities of the technology for non-destructive assessment of both the tree-stem internal features and the branching and root-system patterns of small-size trees. Four main axes of research are distinguished, based on the assessment of 1) variation in wood density and delineation of annual growth and wood type, 2) wood moisture content and its distribution, 3) wood degradation, and 4) external features of small-size trees, such as branching geometry and canopy space occupancy.

Much progress has been made along the first axis of research. Swedish, French and Canadian research groups developed efficient algorithms to detect and delineate internal structures in wood logs or discs, and some of these algorithms were implemented as plug-ins in image analysis software. Some internal structures are more difficult to delineate than others. The density of the wood in which knots form, for instance, is often similar to that of wet sapwood (Nordmark 2005). This is why it is difficult to segment and measure knots within logs, but several methods using a CT scanner and companion algorithms for the data analysis and image processing were proposed and some appear very promising to solve the issue.

The estimation accuracy reached for most of the internal features, as reported by the authors, appears very good. Three-dimensional analysis of the data has begun to be performed for branch knots (Colin et al. 2010a; Duchateau et al. 2013; Krähenbühl et al. 2014; Song et al. 2017) and estimated wood densities (Dutilleul et al. 2014; Beaulieu et al. 2016). This is an interesting development because it is now possible to visualize defects and variation in wood properties within stems or logs better. Although newly developed algorithms can help provide an assessment of wood quality for an optimized manufacturing of forest products, they are also useful to better evaluate the impact of silvicultural practices such as thinning and stem pruning, for the development of high-quality wood supply. Better knowledge of fibre attributes is, indeed, important to optimize the wood-products value chain, especially in a context of changing demand on the wood market.

Wood is a hygroscopic material, i.e., it takes on moisture from the surrounding environment. It is doing this in an anisotropic way, as its moisture content does not vary evenly in all directions.

Through the analysis and comparison of CT images depending on time, space, or the experimental conditions, CT scanning technology offers the possibility of monitoring changes in moisture content. The second axis of research and development is developed along the advanced algorithms of image processing which were recently developed to analyze moisture content change during the water uptake or drying process (Johansson and Kitefew 2010; Watanabe et al. 2012; Longuetaud et al. 2016; Hansson et al. 2017). A challenge in the mapping of local fluctuations of moisture content comes from the shrinkage of drying wood, which begins when the moisture content reaches the fiber saturation point, or from swelling when dry wood absorbs water. The algorithms developed to compare CT images (either geometrically transformed or not, depending on the wood specimen moisture condition) can provide good assessment of moisture content change during the drying process, and be used to understand better how water uptake takes place and develop models to predict it.

Extensively used as outdoor building material, wood undergoes degradation due to a variety of biotic and abiotic factors, when not protected. This degradation can lead to mass loss and a deterioration of its physical and mechanical properties. Coupled with other non-destructive technologies, CT scanning allows the quantification and monitoring of the changes related to degradation (Hervé et al. 2014, Hamada et al. 2016, Li et al. 2016). Its use in wood degradation research is recent, but offers a high potential to improve our understanding of the basic physical and biological principles in action (El Hachem et al. 2018).

The fourth axis of forest research with a CT scanner that we reviewed concerns the modeling of branching geometry and canopy space occupancy of small-size trees. Less emphasis in the literature has been put on this axis, than on the other two. One reason is the limited size of the living trees that can be moved, in pots, to a CT scanning facility and pass, still in pots, through the gantry of a CT scanner, even “macro”. Another reason is the scarcity of the CT scanning equipment that can be brought on a forest stand, for scanning stems of living trees ‘on site’ (Onoe et al. 1984). Other technologies, such as terrestrial and aerial LiDAR, are more and more available and used to characterize the forest canopy and individual-tree crown structure. Nevertheless, CT scanning technology provides very fine information about the above-ground part of an individual plant, like a tree of the size of a human being, and the fractal dimension, as

measure of complexity of the branching pattern, as well as other canopy characteristics can be estimated very precisely from the constructed 3-D image (Dutilleul et al. 2015).

This review demonstrated that computed tomography (CT) scanning is a powerful technology that can help provide better understanding of tree development as well as optimize industrial processes of wood products. Recent studies showed, indeed, that the technology can deliver accurate and quick assessments of internal features of tree logs and detailed information concerning biological processes such as tree growth at various scales. The images constructed by CT scanning provide researchers with massive datasets that require appropriate algorithms for automatic or semi-automatic detection of the tree internal properties of interest and their graphical representation and quantitative analysis in 3D. There is no doubt that this technology will continue to contribute to the development of even more accurate models of tree growth because modern CT scanners can give access to data from a larger number of samples, more rapidly and at reasonable costs. This expansion is tied with that of plant phenotyping and phytometrics, the branch of statistics applied to the plant sciences.

References

- Andreu, J.-P., and Rinnhofer, A. 2003. Modeling of internal defects in logs for value optimization based on industrial CT scanning. *In* Proceedings of the 5th International Conference on Image Processing and Scanning of Wood. March 23-26, 2003, Bad Waltersdorf, Austria. pp 141–150.
- Antony, F., Schimleck, L.R., Daniels, R.F., Clark III, A., and Hall, D.B. 2010. Modeling the longitudinal variation in wood specific gravity of planted loblolly pine (*Pinus taeda*) in the United States. *Can. J. For. Res.* **40**: 2439–2451.
- Baumgartner, R., Brüchert, F., and Sauter, U. 2010. Knots in CT scans of Scots pine logs. *In* Proceedings of the Final Conference of COST Action E53: The Future of Quality Control for Wood & Wood Products, Edinburgh, UK, 4–7 May 2010. *Edited by* D.J. Ridley-Ellis and J.R. Moore. Forest Products Research Institute/Centre for Timber Engineering, Edinburgh Napier University, Edinburgh, UK. pp. 343–351.
- Beaulieu, J., Han, L., and Dutilleul, P. 2016. Using computed tomography scanning technology to extract virtual wood cores, derive wood density radial patterns, and test hypotheses about direction, core size, and year of growth. *Wood Fiber Sci.* **48**: 171–182.
- Berglund, A., Johansson, E., and Skog, J. 2014. Value optimized log rotation for strength-graded boards using computed tomography. *Eur. J. Wood Prod.* **72**: 635–642.
- Bill, J., Daly, A., Johnsen, O., and Dalen, K.S. 2012. DendroCT – dendrochronology without damage. *Dendrochronologia* **30**: 223–230.
- Boukadida, H., Longuetaud, F., Colin, F., Freyburger, C., Constant, T., Leban, J.-M., and Mothe, F. 2012. PithExtract: A robust algorithm for pith detection in computer tomography images of wood – Application to 125 logs from 17 tree species. *Comput. Electron. Agric.* **85**: 90–98.
- Brännström, M. 2005. Establishing a model for the dry density of heartwood of Norway spruce by parameters industrially measurable on green logs. Master's thesis, Luleå University of Technology, Division of Wood Technology, Skellefteå, Sweden.
- Brun, E., Vicente, J., Topin, F., Occelli, R., and Clifton, M.J. 2009. Microstructure and transport properties of cellular materials: Representative volume element. *Adv. Eng. Mater.* **10**: 805–810.
- Bucur, V. 2003. Techniques for high resolution imaging of wood structure: a review. *Meas. Sci. Technol.* **14**: R91–R98.

- Colin, F., Mothe, F., Freyburger, C., Morisset, J.-B., Leban, J.-M., and Fontaine, F. 2010a. Tracking
rameal traces in sessile oak trunks with X-ray computer tomography: biological bases,
preliminary results and perspectives. *Trees–Struct. Funct.* **24**: 953–967.
- Colin, F., Ducouso, A., and Fontaine, F. 2010b. Epicormics in 13-year-old *Quercus petraea*: small
effect of provenance and large influence of branches and growth unit limits. *Ann. For. Sci.* **67**:
312. doi:10.1051/forest/2009118.
- Couceiro, J.M., and Elustondo, D. 2015. Implementation of computer aided tool for non-
destructive X-ray measurement of moisture content distribution in wood. *Pro Ligno* **11**: 330–
336.
- Danvind, J., and Synnergren, P. 2001. Method for measuring shrinkage behavior of drying wood
using digital speckle photography and X-ray computerized tomography. *In Proceedings of the*
7th International IUFRO Wood Drying Conference, July 9-13, 2001, Tsukuba, Japan. pp. 276–
281.
- Defo, M., Goodison, A., and Uy, N. 2009. A method to map within-tree distribution of fibre
properties using SilviScan-3 data. *Forest. Chron.* **85**: 409–414.
- De Mil, T., Vannoppen, A., Beeckman, H., Van Acker, J., and Van den Bulcke, J. 2016. A field-to-
desktop toolchain for X-ray CT densitometry enables tree ring analysis. *Ann. Bot.* **117**: 1187–
1196. doi:10.1093/aob/mcw063.
- De Ridder, M., Van den Bulcke, J., Vansteenkiste, J., Van Loo, D., Dierick, M., Masschaele, B., De
Witte, Y., Mannes, D., Lehmann, E., Beeckman, H., Van Hoorebeke, L., and Van Acker, J. 2011.
High-resolution proxies for wood density variations in *Terminalia superba*. *Ann. Bot.* **107**:
293–302.
- Dierick, M., Masschaele, B., and Van Hoorebeke, L. 2004. Octopus, a fast and user-friendly
tomographic reconstruction package developed in LabView®. *Meas. Sci. Tech.* **15**: 1366–
1370.
- Dierick, M., Van Loo, D., Masschaele, B., Van den Bulcke, J., Van Acker, J., Cnudde, V., and Van
Hoorebeke, L. 2014. Recent micro-CT scanner developments at UGCT. *Nucl. Instrum.*
Methods Phys. Res. Section B **324**: 35–40.
- Duchateau, E., Longuetaud, F., Mothe, F., Ung, C.-H., Auty, D., and Achim, A. 2013. Modelling
knot morphology as a function of external tree and branch attributes. *Can. J. For. Res.* **43**:
266–277.

- 1160 Duda, R.O., and Hart, P.E. 1972. Use of the Hough transformation to detect lines and curves in
1161 pictures. Commun. ACM **15**: 1–15.
- 1162 Dutilleul, P., Lontoc-Roy, M., and Prasher, S. O. 2005. Branching out with a CT scanner. Trends
1163 Plant Sci. **10**: 411–412.
- 1164 Dutilleul, P., Han, L., and Smith, D. L. 2008. Plant light interception can be explained via
1165 computed tomography scanning: demonstration with pyramidal cedar (*Thuja occidentalis*,
1166 *Fastigiata*). Ann. Bot. **101**: 19–23.
- 1167 Dutilleul, P., Han, L., and Beaulieu, J. 2014. How do trees grow? Response from the graphical and
1168 quantitative analyses of computed tomography scanning data collected on stem sections.
1169 Comment les arbres poussent-ils? Réponse des analyses graphique et quantitative de
1170 données de tomodensitométrie pour des sections de la tige. C. R. Biol. **337**: 391–398.
- 1171 Dutilleul, P., Han, L., Valladares, F., and Messier, C. 2015. Crown traits of coniferous trees and
1172 their relation to shade tolerance can differ with leaf type: A biophysical demonstration using
1173 computed tomography scanning data. Frontiers Plant Sci. **6**: 172.
1174 doi:10.3389/fpls.2015.00172.
- 1175 El Hachem, C., Abahri, K., Vincente, J., Bennacer, R., and Belarbi, R. 2018. Hygromorphic
1176 characterization of softwood under high resolution X-ray tomography for hygrothermal
1177 simulation. Heat and Mass Transfer **54**: 2671–2769. doi.org/10.1007/s00231-018-2311-9.
- 1178 Espinoza, G.R., Hernández, R., Condal, A., Verret, D., and Beauregard, R. 2005. Exploration of the
1179 physical properties of internal characteristics of sugar maple logs and relationships with CT
1180 images. Wood Fiber Sci. **37**: 591–604.
- 1181 Evans, R., Gartside, G., and Downes, G. 1995. Present and prospective use of Silviscan for wood
1182 microstructure analysis. Appita J. **95**: 91–96.
- 1183 Fredriksson, M., Cool, J., Duchesne, I., and Belley, D. 2017. Knot detection in computed
1184 tomography images of partially dried jack pine (*Pinus banksiana*) and white spruce (*Picea*
1185 *glauca*) logs from a Nelder type plantation. Can. J. For. Res. **47**: 910–915.
- 1186 Freyburger, C., Longuetaud, F., Mothe, F., Constant, T., and Leban, J.-M. 2009. Measuring wood
1187 density by means of X-ray computer tomography. Ann. For. Sci. **66**: 804–812.
- 1188 Fromm, J.H. 2013. Xylem development in trees: from cambial divisions to mature wood cells. In
1189 Cellular Aspects of Wood Formation. Edited by J.H. Fromm. Springer-Verlag, Berlin
1190 Heidelberg, Germany. pp. 3–40.

- 1191 Fromm, J.H., Sautter, I., Matthies, D., Kremer, J., Schumacher, P., and Ganter, C. 2001. Xylem
1192 water content and wood density in spruce and oak trees detected by high-resolution
1193 computed tomography. *Plant Physiol.* **127**: 416–425.
- 1194 Grönlund, A., Björklund, L., Grundberg, S., and Berggren, G. 1995. Manual för furustambank.
1195 Technical Report 19, Luleå University of Technology, Division of Wood Technology,
1196 Skellefteå, Sweden. In Swedish.
- 1197 Grundberg, S. 1994. Scanning for internal defects in logs. Licentiate thesis, Luleå University of
1198 Technology, Division of Wood Technology, Skellefteå, Sweden.
- 1199 Grundberg, S., and Grönlund, A. 1992. Log scanning - extraction of knot geometry. *In*
1200 *Proceedings of the 1st International Seminar/Workshop on Scanning Technology and Image*
1201 *Processing on Wood*, Skellefteå, Sweden, 30 August-1 September 1992. Luleå University of
1202 Technology, Luleå, Sweden.
- 1203 Grundberg, S., and Grönlund, A. 1999. Validation of a virtual sawmill. *In* *An X-ray Log Scanner – A*
1204 *Tool for Control of the Sawmill Process*. Doctoral thesis, Luleå University of Technology,
1205 Division of Wood Technology, Skellefteå, Sweden.
- 1206 Hamada, J., Pétrissans, A., Mothe, F., Ruelle, J., Pétrissans, M., and Gérardin, P. 2016. Variations
1207 in the natural density of European oak wood affect thermal degradation during thermal
1208 modification. *Ann. For. Sci.* **73**: 277–286.
- 1209 Han, L., Dutilleul, P., Prasher, S.O., Beaulieu, C., and Smith, D.L. 2009. Assessment of density
1210 effects of the common scab-inducing pathogen on the seed and peripheral organs of potato
1211 during growth using computed tomography scanning data. *Trans. ASABE* **52**: 305–311.
- 1212 Han, L., Dutilleul, P., Prasher, S.O., Beaulieu, C., and Smith, D.L. 2008. Assessment of common
1213 scab-inducing pathogen effects on potato underground organs via computed tomography
1214 scanning. *Phytopathology* **98**: 1118–1125.
- 1215 Hansson, L. 2007. Microwave treatment of wood. Ph.D. thesis, Luleå University of Technology,
1216 Division of Wood Technology, Skellefteå, Sweden.
- 1217 Hansson, L., and Cherepanova, E. 2012. Determination of wood moisture properties using a CT-
1218 scanner in a controlled low-temperature environment. *Wood Mater. Sci. Eng.* **7**: 87–92.
- 1219 Hansson, L., Couceiro, J., and Fjellner, B.-A. 2017. Estimation of shrinkage coefficients in radial
1220 and tangential directions from CT images. *Wood Mater. Sci. Eng.* **12**: 251–256.
- 1221 Helama, S., Vartiainen, M., Kolström, T., Peltola, H., and Meriläinen, J. 2008. X-ray
1222 microdensitometry applied to subfossil tree-rings: growth characteristics of ancient pines

- 1223 from the southern boreal forest zone in Finland at intra-annual to centennial time-scales.
 1224 Veget. Hist. Archaeobot. **17**: 675–686.
- 1225 Hervé, V., Mothe, F., Freyburger, C., Gelhaye, E., and Frey-Klett, P. 2014. Density mapping of
 1226 decaying wood using X-ray computed tomography. Int. Biodeterior. Biodegradation **86**: 358–
 1227 363.
- 1228 Jacquin, P., Longuetaud, F., Leban, J.-M., and Mothe, F. 2017. X-ray microdensitometry of wood:
 1229 a review of existing principles and devices. Dendrochronologia **42**: 42–50.
- 1230 Jacquin, P., Mothe, F., Longuetaud, F., Billard, A., Kerfriden, B., and Leban, J.-M. 2019. CarDen: A
 1231 software for fast measurement of wood density on increment cores by CT scanning. Comput.
 1232 Electron. Agric. **156**: 606–617.
- 1233 Jessome, A.P. 1977. Strength and related properties of woods grown in Canada. Environ. Can.,
 1234 Can. For. Serv., East. For. Prod. Lab., Ottawa, Canada. For. Tech. Rep. 21.
- 1235 Johansson, J., and Kifetew, G. 2010. CT-scanning and modelling of the capillary water uptake in
 1236 aspen, oak and pine. Eur. J. Wood Wood Prod. **68**: 77–85.
- 1237 Johansson, E., Johansson, D., Skog, J., and Fredriksson, M. 2013. Automated knot detection for
 1238 high speed computed tomography on *Pinus sylvestris* L. and *Picea abies* (L.) Karst. Using
 1239 ellipse fitting in concentric surfaces. Comput. Electron. Agric. **96**: 238–245.
- 1240 Jozsa, L.A., and Middleton, G.R. 1994. A discussion of wood quality attributes and their practical
 1241 implications. Forintek Canada Corporation, Vancouver, Canada. Spec. Publ. No. SP-34.
- 1242 Kalender, W.A. 2000. Computed tomography: fundamentals, system technology, image quality,
 1243 applications. Publicis MCD Verlag, Munich, Germany. 220 p.
- 1244 Katsevich, A. 2004. An improved exact filtered backprojection algorithm for spiral computed
 1245 tomography. Adv. Appl. Math. **32**: 681–697.
- 1246 Ketcham, R.A., and Carlson, W.D. 2001. Acquisition, optimization and interpretation of X-ray
 1247 computed tomographic imagery: applications to the geosciences. Comput. Geosci. **27**: 381–
 1248 400.
- 1249
- 1250 Krähenbühl, A., Kerautret, B., Debled-Rennesson, I., Mothe, F., and Longuetaud, F. 2014. Knot
 1251 segmentation in 3D CT images of wet wood. Pattern Recogn. **47**: 3852–3869.
- 1252 Lazarescu, C., Watanabe, K., and Avramidis, S. 2010. Density and moisture profile evolution
 1253 during timber drying by CT scanning measurements. Drying Technol. **28**: 460–467.

- 1254 Leban, J.-M., Hervé, J.-C., Bontemps, J.-D., Longuetaud, F., Mothe, F., and Jacquin, P. 2016.
 1255 Measurement of the annual biomass increment of the French forests – XYLOMAPDENS
 1256 project. Presentation at The 8th International Conference “Modelling Wood Quality, Supply
 1257 and Value Chain Networks” of IUFRO Working Parties 5.01.04 and 3.02.04, 12-17 June 2016,
 1258 Baie-St-Paul, Canada.
- 1259 Li, W., Van den Bulcke, J., De Windt, I., Van Loo, D., Dierick, M., Brabant, L., and Van Acker, J.
 1260 2013. Combining electrical resistance and 3-D X-ray computed tomography for moisture
 1261 distribution measurements in wood products exposed in dynamic moisture conditions. *Build.*
 1262 *Environ.* **67**: 250–259.
- 1263 Li, W., Van den Bulcke, J., De Windt, I., Defoirdt, N., Dhaene, J., Dierick, M., Sol, H., and Van
 1264 Acker, J. 2016. Relating MOE decrease and mass loss due to fungal decay in plywood and
 1265 MDF using resonalyser and X-ray CT scanning. *Int. Biodeter. Biodegradation* **110**: 113–120.
- 1266 Lindgren, L.O. 1991a. Medical CAT-scanning: X-ray absorption coefficients, CT-numbers and
 1267 their relation to wood density. *Wood Sci. Technol.* **25**: 341–349.
- 1268 Lindgren, L.O. 1991b. The accuracy of medical CAT-scan images for non-destructive density
 1269 measurements in small volume elements within solid wood. *Wood Sci. Technol.* **25**: 425–432.
- 1270 Lindgren, L.O. 1992. Medical CT-scanners for non-destructive wood density and moisture
 1271 content measurements. Doctoral thesis, Luleå University of Technology, Division of Wood
 1272 Technology, Skellefteå, Sweden.
- 1273 Longuetaud, F., Leban, J.-M., Mothe, F., Kerrien, E., and Berger, M.-O. 2004. Automatic
 1274 detection of pith on CT images of spruce logs. *Comput. Electron. Agric.* **44**: 107–119.
- 1275 Longuetaud, F., Mothe, F., Fournier, M., Dlouha, J., Santenoise, P., and Deleuze, C. 2016. Within-
 1276 stem maps of wood density and water content for characterization of species: a case study
 1277 on three hardwood and two softwood species. *Ann. For. Sci.* **73**: 601–614.
- 1278 Longuetaud, F., Mothe, F., Kerautret, B., Krähenbühl, A., Hory, L., Leban, J.-M., and Debled-
 1279 Rennesson, I. 2012. Automatic knot detection and measurements from X-ray CT images of
 1280 wood: a review and validation of an improved algorithm on softwood samples. *Comput.*
 1281 *Electron. Agric.* **85**: 77–89.
- 1282 Longuetaud, F., Mothe, F., and Leban, J.-M. 2007. Automatic detection of the
 1283 heartwood/sapwood boundary within Norway spruce (*Picea abies* (L.) Karst.) logs by means
 1284 of CT images. *Comput. Electron. Agric.* **58**: 100–111.

- 1285 Longuetaud, F., Mothe, F., Santenoise, P., Diop, N., Dlouha, J., Fournier, M., and Deleuze, C.
 1286 2017. Patterns of within-stem variations in wood specific gravity and water content for five
 1287 temperate tree species. *Ann. For. Sci.* **74**: 64. doi:org/10.1007/s13595-017-0657-7.
- 1288 Manceur, A.M., Beaulieu, J., Han, L., and Dutilleul, P. 2012. A multidimensional statistical model
 1289 for wood data analysis, with density estimated from CT scanning data as an example. *Can. J.*
 1290 *For. Res.* **42**: 1038–1049.
- 1291 Mansfield, S.D., Parish, R., Goodie, J.W., Kang, K.-Y., and Ott, P. 2007. The effects of crown ratio
 1292 on the transition from juvenile to mature wood production in lodgepole pine in western
 1293 Canada. *Can. J. For. Res.* **37**: 1450–1459.
- 1294 Mauriat, M., Le Provost, G., Rozenberg, P., Delzon, S., Breda, N., Clair, B., Coutand, C., Domec, J.-
 1295 C., Fourcaud, T., Grima-Pettenati, J., Herrera, R., Leplé, J.-C., Richet, N., Trontin, J.-F., and
 1296 Plomion, C. 2014. Wood formation in trees. *In Tree Biotechnology. Edited by K.G. Ramawat,*
 1297 *J.-M. Mérillon, and M.R. Ahuja.* CRC Press, Boston, USA. pp. 56–111.
- 1298 Meincken, M., and du Plessis, A. 2013. Visualising and quantifying thermal degradation of wood
 1299 by computed tomography. *Eur. J. Wood Prod.* **71**: 387–389
- 1300 Molteberg, D., and Høibø, O. 2007. Modelling of wood density and fibre dimensions in mature
 1301 Norway spruce. *Can. J. For. Res.* **37**: 1373–1389.
- 1302 Myronenko, A., and Song, X. 2010. Intensity-based image registration by minimizing residual
 1303 complexity. *IEEE Trans. Med. Imaging* **29**: 1882–1891.
- 1304 Nordmark, U. 2005. Value recovery and production control in the forestry-wood chain using
 1305 simulation technique. Doctoral thesis, Luleå University of Technology, Division of Wood
 1306 Technology, Skellefteå, Sweden.
- 1307 Oja, J. 2000. Evaluation of knot parameters measured automatically in CT-images of Norway
 1308 spruce (*Picea abies* (L.) Karst.). *Holz Roh Werkst.* **58**: 375–379.
- 1309 Onoe, M., Tsao, J.W., Yamada, H., Nakamura, H., Kogure, J., Kawamura, H., and Yoshimatsu, M.
 1310 1984. Computed tomography for measuring the annual rings of a live tree. *Nucl. Instrum.*
 1311 *Methods* **221**: 213–220.
- 1312 Osborne, N.L., Høibø, Ø.A., and Maguire, D.A. 2016. Estimating the density of coast Douglas-fir
 1313 wood samples at different moisture contents using medical X-ray computed tomography.
 1314 *Comput. Electron. Agric.* **127**: 50–55.

- 1315 Pan, B., Qian, K., Xie, H., and Asundi, A. 2009. Two-dimensional digital image correlation for in-
 1316 plane displacement and strain measurement: a review. *Meas. Sci. Technol.* **20**: 062001.
 1317 doi:10.1088/0957-0233/20/6/062001.
- 1318 Panshin, A.J., and de Zeeuw, C. 1980. Textbook of wood technology. 4th ed. McGraw-Hill, New
 1319 York, USA, 722 p.
- 1320 Pernestål, K., Jonsson, B., and Larsson, B. 1995. A simple model for density of annual rings.
 1321 *Wood Sci. Technol.* **29**: 441–449.
- 1322 Plomion, C., Le Provost, G., and Stokes, A. 2001. Wood formation in trees. *Plant Physiol.* **127**:
 1323 1513–1523.
- 1324 Plourde, B.T., Boukili, V.K., and Chazdon, R.L. 2015. Radial changes in wood specific gravity of
 1325 tropical trees: inter- and intraspecific variation during secondary succession. *Funct. Ecol.* **29**:
 1326 111–120.
- 1327 Pont, D., Brownlie, R.K., and Grace, J.C. 2007. Disc image-processing software for three-
 1328 dimensional mapping of stem ring width and compression wood. *New Zealand J. For. Sci.* **37**:
 1329 168–185.
- 1330 Rais, A., Ursella, E., Vicario, E., and Giudiceandrea, F. 2017. The use of the first industrial X-ray CT
 1331 scanner increases the lumber recovery value: case study on visually strength-graded Douglas-
 1332 fir timber. *Ann. For. Sci.* **74**: 28. doi:10.1007/s13595-017-0630-5.
- 1333 Roussel, J.R., Mothe, F., Krähenbühl, A., Kerautret, B., Debled-Rennesson, I., and Longuetaud, F.
 1334 2014. Automatic knot segmentation in CT images of wet softwood logs using a tangential
 1335 approach. *Comput. Electron. Agric.* **104**: 46–56.
- 1336 Sandberg, K., and Salin, J.-G. 2012. Liquid water absorption in dried Norway spruce timber
 1337 measured with CT scanning and viewed as a percolation process. *Wood Sci. Technol.* **46**:
 1338 207–219.
- 1339 Schneider, C.A., Rasband, W.S., and Eliceiri, K.W. 2012. NIH image to ImageJ: 25 years of image
 1340 analysis. *Nat. Methods* **9**: 671–675.
- 1341 Shchupakivskyy, R., Clauser, L., Linke, N., and Pfriem, A. 2014. Application of high-frequency
 1342 densitometry to detect changes in early- and latewood density of oak (*Quercus robur* L.) due
 1343 to thermal modification. *Eur. J. Wood Prod.* **72**: 5–10.
- 1344 Song, J., Brendel, O., Bodénès, C., Plomion, C., Kremer, A., and Colin, F. 2017. X-ray computed
 1345 tomography to decipher the genetic architecture of tree branching traits: oak as a case study.
 1346 *Tree Genet. Genomes* **13**: 1–15.

- 1347 Song, T., and Usenius, A. 2007. InnoSim – A simulation model of wood conversion chain.
 1348 Conference Proceedings, COST Action E44 Conference on Wood Processing Strategy,
 1349 Helsinki, Finland. pp. 95–108.
- 1350 Sorzano, C.O.S., Thévenaz, P., and Unser, M. 2005. Elastic registration of biological images using
 1351 vector-spline regularization. *IEEE Trans. Biomed. Eng.* **52**: 652–663.
- 1352 Stängle, S.M., Brüchert, F., Heikkilä, A., Usenius, T., Usenius, a., and Sauter, U.H. 2015.
 1353 Potentially increased sawmill yield from hardwoods using X-ray computed tomography for
 1354 knot detection. *Ann. For. Sci.* **72**: 57–65.
- 1355 Steffenrem, A., Kvaalen, H., Høibø, O.A., Edvardsen, Ø.M., and Skrøppa, T. 2009. Genetic
 1356 variation of wood quality traits and relationships with growth in *Picea abies*. *Scand. J. For.*
 1357 *Res.* **24**: 15–27.
- 1358 Steffenrem, A., Kvaalen, H., Sigmund Dalen, K., and Høibø, O.A. 2014. A high-throughput X-ray-
 1359 based method for measurements of relative wood density from unprepared increment cores
 1360 from *Picea abies*. *Scand. J. For. Res.* **29**: 506–514.
- 1361 Tian, X., Cown, D.J., and McConchie, D.L. 1995. Modelling of *Pinus radiata* wood properties. Part
 1362 2: basic density. *New Zealand J. For. Sci.* **25**: 214–230.
- 1363 Van den Bulcke, J., Wernersson, E.L.G., Dierick, M., Van Loo, D., Masschaele, B., Brabant, L.,
 1364 Boone, M.N., Van Hoorebeke, L., Haneca, K., Brun, A., Luengo Hendriks, C.L., and Van Acker,
 1365 J. 2014. 3D tree-ring analysis using helical X-ray tomography. *Dendrochronologia* **32**: 39–46.
- 1366 Vlassenbroeck, J., Dierick, M., Masschaele, B., Cnudde, V., Van Hoorebeke, L., and Jacobs, P.
 1367 2007. Software tools for quantification of X-ray microtomography at the UGCT. *Nucl.*
 1368 *Instrum. Methods Phys. Res. Section A* **580**: 442–445.
- 1369 Watanabe, K., Lazarescu, C., Shida, S., and Avramidis, S. 2012. A novel method of measuring
 1370 moisture content distribution in timber during drying using CT scanning and image
 1371 processing techniques. *Drying Technol.* **30**: 256–262.
- 1372 Wei, Q., Lebon, B., and La Roque, A. 2011. On the use of X-ray computed tomography for
 1373 determining wood properties: a review. *Can. J. For. Res.* **41**: 2120–2140.
- 1374 Williamson, G.B., and Wiemann, M.C. 2010. Measuring wood specific gravity... Correctly. *Am. J.*
 1375 *Bot.* **97**: 519–524.
- 1376 Wimmer, R., Downes, G.M., and Evans, R. 2002. High-resolution analysis of radial growth and
 1377 wood density in *Eucalyptus nitens*, grown under different irrigation regimes. *Ann. For. Sci.* **59**:
 1378 519–524.

- 1379 Woodcock, D., and Shier, A. 2002. Wood specific gravity and its radial variations: the many ways
1380 to make a tree. *Trees* **16**: 437–443.
- 1381 Zobel, B.J., and Sprague, J.R. 1998. Juvenile wood in forest trees. Springer-Verlag, Berlin
1382 Heidelberg, Germany. Springer Series in Wood Science. 300 p.
- 1383 Zobel, B.J., and Talbert, J. 1984. Applied forest tree improvement. Wiley, New York, USA. 505 p.
- 1384 Zobel, B.J., and van Buijtenen, J.P. 1989. Wood variation: its causes and control. Springer-Verlag,
1385 Berlin Heidelberg, Germany. Springer Series in Wood Science. 363 p.

Draft

Table 1. Recent studies on the assessment of forest tree traits using the computer tomography scanning technology

Trait	Species	CT scanner type and model, and manufacturer	Reference
Wood density and radial growth	European silver fir, Caucasian fir, Field maple, Sycamore, Silver birch, European hornbeam, Mediterranean cypress, European beech, European larch, European ash, Norway spruce, Austrian pine, Scots pine, Poplar, European aspen, Sweet cherry, Douglas-fir, Pedunculate oak, Black locus, Mountain ash, Wild service tree, Western redcedar, European small-leaved linden	Medical <i>BrightSpeed Excel</i> CT scanner by GE Healthcare	Jacquin et al. 2019
	Pedunculate oak, European beech, Sycamore, European silver fir, Douglas-fir	Medical <i>BrightSpeed Excel</i> CT scanner by GE Healthcare	Longuetaud et al. 2016 Longuetaud et al. 2017
	Norway spruce	Medical <i>SOMATOM Emotion</i> single-slice CT scanner by Siemens	Steffenrem et al. 2009
	Norway spruce	Medical <i>SOMATOM Emotion</i> single-slice CT scanner by Siemens	Steffenrem et al. 2014
	White spruce	Medical <i>Xvision</i> high-resolution X-ray CT scanner by Toshiba	Manceur et al. 2012
	White spruce	Medical <i>Xvision</i> high-resolution X-ray CT scanner by Toshiba	Dutilleul et al. 2014
	White spruce	Medical <i>Xvision</i> high-resolution X-ray CT scanner by Toshiba	Beaulieu et al. 2016
	Pedunculate oak	Medical <i>SOMATOM Emotion</i> single-slice CT scanner by Siemens Industrial Micro-focus CT scanner XT H 225 LC by Nikon	Bill et al. 2012

	Douglas-fir	Medical <i>Aquilion</i> CT scanner by Toshiba	Osborne et al. 2016
	Scots pine, Pedunculate oak, Teak	<i>Nanowood</i> high-resolution micro-CT scanner by University of Ghent and XRE NV (Ghent, Belgium)	De Mil et al. 2016
Pith, sapwood and heartwood delineation	Norway spruce	<i>Invision</i> CTX 2500 CT scanner by GE Security	Andreu and Rinnhofer 2003
	Norway spruce	Medical <i>SOMATOM AR.T</i> CT scanner by Siemens	Longuetaud et al. 2004
	Norway spruce	Medical <i>SOMATOM AR.T</i> CT scanner by Siemens	Longuetaud et al. 2007
Knots and rameal traces	Norway spruce	Medical <i>SOMATOM AR.T</i> CT scanner by Siemens	Oja 2000
	European silver fir, Norway spruce	Medical <i>BrightSpeed Excel</i> CT Scanner by GE Healthcare	Longuetaud et al. 2012
	Scots pine, Norway spruce	Medical <i>SOMATOM AR.T</i> CT scanner by Siemens	Johansson et al. 2013
	Douglas-fir, European silver fir, European larch, Norway spruce, Scots pine	Medical <i>BrightSpeed Excel</i> CT Scanner by GE Healthcare	Roussel et al. 2014
	Norway spruce	Medical <i>SOMATOM AR.T</i> CT scanner by Siemens	Berglund et al. 2014
	European beech	Industrial high-speed <i>CT Log</i> CT scanner by Microtec	Stängle et al. 2015
	Jack pine, White spruce	Medical <i>SOMATOM Sensation</i> CT scanner by Siemens	Fredriksson et al. 2017
	Pedunculate oak	Medical <i>BrightSpeed Excel</i> CT scanner by GE Healthcare	Song et al. 2017
	Douglas-fir	Industrial high-speed <i>CT Log</i> CT scanner by Microtec	Rais et al. 2017
Water content and distribution	Pedunculate oak, Norway spruce	Medical <i>SOMATOM Plus</i> CT scanner by Siemens	Fromm et al. 2001
	Aspen, Pedunculate oak, Scots pine	Medical <i>SOMATOM AR.T</i> CT scanner by Siemens	Johansson and Kitefew 2010
	Norway spruce	Medical <i>SOMATOM AR.T</i> CT scanner by Siemens	Sandberg and Salin 2012

	Pedunculate oak, European beech, Sycamore, European silver fir, Douglas-fir	Medical <i>BrightSpeed Excel</i> CT scanner by GE Healthcare	Longuetaud et al. 2016 Longuetaud et al. 2017
	Poplar, Scots pine, European birch	<i>HECTOR</i> high-resolution CT scanner by UGCT and XRE	Li et al. 2013
Moisture monitoring during drying	Pacific silver fir	Customized <i>ACTIS 1000/3000 CT/DR</i> CT scanner by Bio-Imaging Research Inc.	Watanabe et al. 2012
	Scots pine	Medical <i>SOMATOM Emotion</i> CT scanner by Siemens and a climate chamber by Valutec	Hansson and Cherepanova 2012
	Norway spruce	Medical <i>SOMATOM Emotion</i> CT scanner by Siemens and drying kiln	Couceiro and Elustondo 2015
	Scots pine, Norway spruce	Medical <i>SOMATOM Emotion Duo</i> CT scanner by Siemens	Hansson et al. 2017
Wood degradation	European beech	Medical <i>BrightSpeed Excel 4</i> CT Scanner by GE Healthcare	Hervé et al. 2014
	Sessile oak	Medical <i>BrightSpeed Excel 4</i> CT Scanner by GE Healthcare	Hamada et al. 2016
	Monterey pine	<i>Phoenix V/TomeX L240</i> CT scanner by General Electric	Meincken and du Plessis 2013
	Poplar, European beech, Oukoumé	<i>HECTOR</i> high-resolution CT scanner by UGCT and XRE	Li et al. 2016
	Norway spruce	<i>MicroXCT-400</i> tomograph by Zeiss-Xradia	El Hachem et al. 2018
Crown development	Eastern white-cedar	Medical <i>Xvision</i> high-resolution X-ray CT scanner by Toshiba	Dutilleul et al. 2008
	15 miniature conifer species	Medical <i>Xvision</i> high-resolution X-ray CT scanner by Toshiba	Dutilleul et al. 2015

Figure legends

Fig. 1. Three-dimensional illustration of conifer wood showing the structure of softwood xylem, and the annual ring formation. Adapted from Jozsa and Middleton (1994).

Fig. 2. Map of means in the x–y plane (perpendicular to the stem), computed from wood density estimates obtained from 25 CT images constructed along the Z-axis (stem axis), for a stem section of a white spruce (*Picea glauca* (Moench) Voss). The bark was digitally removed from the CT images and thus excluded from the computations. Different colors are used in accordance to the values mapped, from lowest value (dark blue) to highest value (red) with light blue, green, yellow and orange in this order in-between, for intermediate values (see values reported on the vertical axis). From Dutilleul et al. 2014. How do trees grow? Response from the graphical and quantitative analyses of computed tomography scanning data collected on stem sections. C. R. Biologies 337 (2014) 391–398 (Fig. 2a). Copyright © 2014 Elsevier Masson SAS. All Rights Reserved.

Fig. 3. . From left to right, one of the 428 gray-tone CT images (thickness: 0.4 mm; light gray is used to represent denser voxels, and dark gray represents lighter voxels) constructed for the crown of the miniature coniferous tree (*Picea abies* Tompa); the branch part delineated from the corresponding 512 × 512 matrix of CT numbers, colored in brown; and the leaf part obtained by subtraction (excluding air) and colored in green. From Dutilleul et al. 2015. Crown traits of coniferous trees and their relation to shade tolerance can differ with leaf type: a biophysical demonstration using computed tomography scanning data. Frontiers in Plant science 6: 17. 13 p. (Fig. 3a). Copyright © 2015 Frontiers Media S.A. All Rights Reserved.

Fig. 4. View of a computed tomography (CT) scanning session at the CT Scanning Laboratory for agricultural and environmental research on Macdonald Campus of McGill University, for a pyramidal cedar (*Thuja occidentalis*, Fastigiata) (Dutilleul et al., 2008).

Fig. 1. Three-dimensional illustration of conifer wood showing the structure of softwood xylem, and the annual ring formation. Adapted from Jozsa and Middleton (1994).

Draft

Fig. 2. Map of means in the x–y plane (perpendicular to the stem), computed from wood density estimates obtained from 25 CT images constructed along the Z-axis (stem axis), for a stem section of a white spruce (*Picea glauca* (Moench) Voss). The bark was digitally removed from the CT images and thus excluded from the computations. Different colors are used in accordance to the values mapped, from lowest value (dark blue) to highest value (red) with light blue, green, yellow and orange in this order in-between, for intermediate values (see values reported on the vertical axis). From Dutilleul et al. 2014. How do trees grow? Response from the graphical and quantitative analyses of computed tomography scanning data collected on stem sections. C. R. Biologies 337 (2014) 391–398 (Fig. 2a). Copyright © 2014 Elsevier Masson SAS. All Rights Reserved.

Fig. 3. From left to right, one of the 428 gray-tone CT images (thickness: 0.4 mm; light gray is used to represent denser voxels, and dark gray represents lighter voxels) constructed for the crown of the miniature coniferous tree (*Picea abies* Tompa); the branch part delineated from the corresponding 512×512 matrix of CT numbers, colored in brown; and the leaf part obtained by subtraction (excluding air) and colored in green. From Dutilleul et al. 2015. Crown traits of coniferous trees and their relation to shade tolerance can differ with leaf type: a biophysical demonstration using computed tomography scanning data. *Frontiers in Plant science* 6: 17. 13 p. (Fig. 3a). Copyright © 2015 Frontiers Media S.A. All Rights Reserved.

Fig. 4. View of a computed tomography (CT) scanning session at the CT Scanning Laboratory for agricultural and environmental research on Macdonald Campus of McGill University, for a pyramidal cedar (*Thuja occidentalis*, Fastigiata) (Dutilleul et al., 2008).

Supplementary material

Video (Helical CT Scan)

Draft

Three-dimensional illustration of conifer wood showing the structure of softwood xylem, and the annual ring formation. Adapted from Jozsa and Middleton (1994).

Map of means in the x-y plane (perpendicular to the stem), computed from wood density estimates obtained from 25 CT images constructed along the Z-axis (stem axis), for a stem section of a white spruce (*Picea glauca* (Moench) Voss). The bark was digitally removed from the CT images and thus excluded from the computations. Different colors are used in accordance to the values mapped, from lowest value (dark blue) to highest value (red) with light blue, green, yellow and orange in this order in-between, for intermediate values (see values reported on the vertical axis). From Dutilleul et al. 2014. How do trees grow? Response from the graphical and quantitative analyses of computed tomography scanning data collected on stem sections. *C. R. Biologies* 337 (2014) 391–398 (Fig. 2a). Copyright © 2014 Elsevier Masson SAS. All Rights Reserved.

1693x1270mm (72 x 72 DPI)

View of a computed tomography (CT) scanning session at the CT Scanning Laboratory for agricultural and environmental research on Macdonald Campus of McGill University, for a pyramidal cedar (*Thuja occidentalis*, *Fastigiata*) (Dutilleul et al., 2008).

284x213mm (230 x 230 DPI)