The potential of intra-annual density information for crossdating of short tree-ring series

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Abstract

The crossdating of tree-ring series is typically based on tree-ring width sequences, which is a crude abstraction of the growth signal stored in tree rings. In contrast, intra-annual wood density data allows a much more detailed comparison of wood growth processes and new measurement techniques scale well to measure large amounts of samples. Thus, chronologies of intra-annual densitometric curves can be built. Here, we investigate to what extent intra-annual wood density information can improve crossdating. We evaluate different approaches on a data set of Norway spruce trees (*Picea abies*) and compare the results to standard methods that are based on ring width or maximum density. Our results show that intra-annual densitometric data indeed increases crossdating success rate notably for short tree ring series that cover less than 25 years.

Keywords: crossdating, tree ring, wood density profile, intra-annual, microdensitometry, Picea abies

1. Introduction

Chronologies of tree-ring data are central to crossdate wood samples (Fritts, 1976; Savnik et al., 2000). This is possible, since the growth of trees is governed by environmental conditions that are encoded within tree rings of the respective years (Cook and Pederson, 2011). Therefore, such chronologies have been successfully used to reconstruct various environmental factors like temperature (Schweingruber et al., 1993; Allen et al., 2012), precipitation (Büntgen et al., 2011), soil phosphorus availability (Kohler et al., 2019), or even cosmogenic radiocarbon signatures (Büntgen et al., 2018).

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While tree-ring width is rather easy to assess, it was shown that the consideration of wood density enables even better correlations with climatic factors (Briffa et al., 1998; Allen et al., 2012; Drew et al., 2012). Accordingly, already in the 70th, density data was suggested for crossdating (Polge, 1970). While well working for specific density properties, e.g. based on maximum late wood density (Wang et al., 2010), the combination of different tree ring properties (width, density, etc.) seems to stabilize and improve predictions (Wood and Smith, 2015).

Tree rings usually encode environmental conditions in higher than annual resolution (Zhang, 2015), so the investigation of intra-annual wood density curves[2] allows a much more detailed comparison of wood growth processes (Allen et al., 2012; De Mil et al., 2016). Furthermore, intra-annual information can be key for correct crossdating of Mediterranean trees (Cherubini et al., 2013) and respective climate reconstruction (Campelo et al., 2013). Still, high (intra-annual) resolution is not yet used by current density-based crossdating methods and the tree ring is typically represented by a single value per year. This partially resulted from the high labor and time costs of measuring high resolution densitometric data for a large number of trees that are needed to build respective chronologies. This problem was solved in the last years via the introduction of efficient measurement instrumentations and tools that scale well for increasing sample sets. Examples are high-frequency (HF) densitometry (Schinker et al., 2003; Wassenberg et al., 2014) or X-ray computed tomography densitometry (De Mil et al., 2016; Jacquin et al., 2019).

Standard ring-width-based crossdating approaches work best for samples that cover extreme events with characteristic signals (pointer years) detectable within the respective tree-ring (Yamaguchi, 1994; Dimitrov et al., 2016). Since shorter samples have a lower probability to cover pointer years, tree-ring sequences of less than 25 years are hard to crossdate with current approaches (Wigley et al., 1987; Mills, 1992). Here, the investigation and comparison of intra-annual density fluctuations (IADFs) (De Micco et al., 2016) might provide an option to overcome this problem.

To test the potential of intra-annual density information for crossdating of short tree-ring sequences, we build a high-resolution intra-annual densitometric chronology based on HF measurements of Norway spruce (*Picea abies*) trees from Southwest Germany. From this, we randomly extract samples to crossdate covering only 5 to 25 consecutive years before building respective chronologies. We compare the success rate with which the samples can be crossdated based on different tree-ring features. We consider full intra-annual density profiles, standard measures like ring width or maximum late wood density, as well as combinations. This enables an objective assessment if and how much intra-annual density information can improve crossdating.

[2]Within this work, we use the terms *curve* and *profile* synonymously.

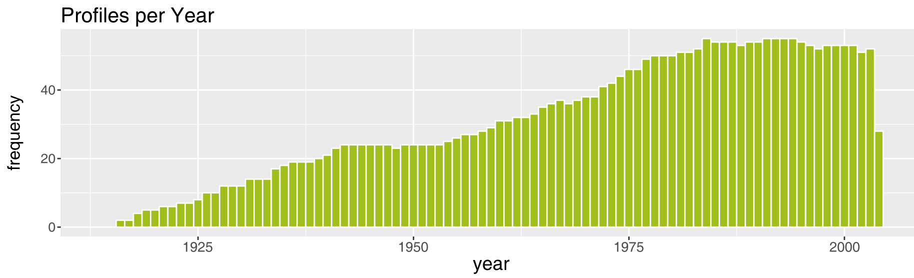

Figure 1: Number of available wood density profiles per calendar year within the data set.

2. Material and Methods

In the following, we introduce the data set used for our crossdating evaluations along with the respective measures and crossdating methods applied. Raw data and used R scripts are part of the supplementary material[3].

2.1. Intra-annual data aggregation

Measurement and post-processing. Our data set is based on 56 Norway spruce sample trees (*Picea abies*) felled for stem analyses in 2005 in the Eastern Swabian Alb in Germany at an average altitude of about 658 meters a.s.l. To measure intra-annual density information, we follow and refer to the protocol from (Bender et al., 2012). That is, for each sample tree, wood density profiles were measured along multiple directions of a stem disc (breast height) from pith to bark using high-frequency densitometry (Schinker et al., 2003; Wassenberg et al., 2014) excluding the first 5 years. Data was manually curated to remove measurement errors, transformed into units of gravimetric density (Wassenberg et al., 2014), and verified using conventional crossdating techniques.

This results in multiple densitometric curves for each calendar year y and tree t. A respective *ring width* $w(y,t)$ was determined as the mean over all radial measurements. To further reduce noise of individual wood density recordings (Bender et al., 2012; Stangler et al., 2016), measured profiles were synchronized using the `MICA`[4] curve alignment software (Mann et al., 2018). Subsequently, a single representative profile of average values was computed for each year. Each representative density profile was scaled to the average ring width of all measurements. A linear interpolation to 100 equidistant data points defines the final *density profile* $\rho(y,t)$ and its *maximum density* $\widehat{\rho}(y,t) = \max(\rho(y,t))$ for each year y and tree t used within this study.

[3] http://www.bioinf.uni-freiburg.de/Publications/Raden-crossdating-2019.supplement.zip

[4] Used `MICA` parameters: distFunc=3, distSample=500, distWarpScaling=0, maxWarpingFactor=2.5, maxRelXShift=0.1, minRelIntervalLength=0.05, minRelMinMaxDist=0.02, minRelSlopeHeight=0.02.

The final data set covers in total 2,843 tree-ring profiles spread over the calendar years 1916 to 2004 as visualized in Fig. 1. The average sequence length per tree is 50.9 years.

Separation into sample and chronology data. To simulate data to be crossdated, we randomly extracted samples uniformly from our data set. A *sample* s is defined by the tuple (t, y, k) and consists of the data of tree t for k consecutive calendar years starting in year y, i.e. the sequences of density profiles $(\rho(y,t),..,\rho(y{+}k{-}1,t))$, maximum densities $(\widehat{\rho}(y,t),..,\widehat{\rho}(y{+}k{-}1,t))$ and tree-ring widths $(w(y,t),..,w(y{+}k{-}1,t))$.

For sample length $k = 10$, we pick at random a *sample set* S of 50 samples to be crossdated from our data set, which contains 2,329 consecutive subsequences of length 10. Thus, S comprises about 18% of the data $(50 \cdot 10/2,843)$. Average cambial age of the tree-rings included in the sample data set is 34.4 years. While this generates a most simple artificial sample set for crossdating, it enables a detailed benchmarking of crossdating measures not biased by poor or missing sample data. Thus, results will depict the maximum crossdating performance that can be reached without further information. The remaining data (excluding S) provides the base for unbiased chronologies to crossdate the samples $s \in S$.

Due to the limited size of the data set, we can only pick a small sample set to keep the chronology information stable. To counter a possible non-uniform distribution of samples within the time range of the chronology, we repeated sampling and benchmarking 5 times for $k = 10$ and report averaged statistics for the random sets of samples $S_1,..,S_5$ crossdated via respective chronologies.

To get samples of length $k = 5$, we split the samples of length 10 into non-overlapping individual samples. For length $k = 15$, 20 and 25, sample set sizes are smaller (33, 25 and 21, resp.) to ensure that respective chronologies are based on a similar amount of data. This enables a better comparison of crossdating results for different sample lengths. To compensate for the smaller sample sets for length 15, 20 and 25, repetition was based on 7, 10 and 12 sets, respectively. That way, we crossdate at least 250 samples per sample length.

Master chronology generation. The whole chronology data set of intra-annual wood density profile data $\rho(y,t)$ (excluding the sample data) defines the *profile-set chronology* C_ρ. That is for each year y, $C_\rho(y)$ provides the set of density profiles $\rho(y,t)$ of all trees t, which is illustrated in Fig. 2. Based on that, we compile a *ring-width chronology* C_w, which provides a mean ring width for each year. To reduce outlier artifacts, we compute Tukey's biweight robust mean estimation[5] (Beaton and Tukey, 1974) of all ring widths $w(y,t)$ for each year y following Bunn (2008). The *maximum-density chronology* $C_{\widehat{\rho}}$ is created analogously.

[5]We follow Affymetrix http://tools.thermofisher.com/content/sfs/brochures/sadd_whitepaper.pdf using $\epsilon = 0.0001$ and $c = 9$.

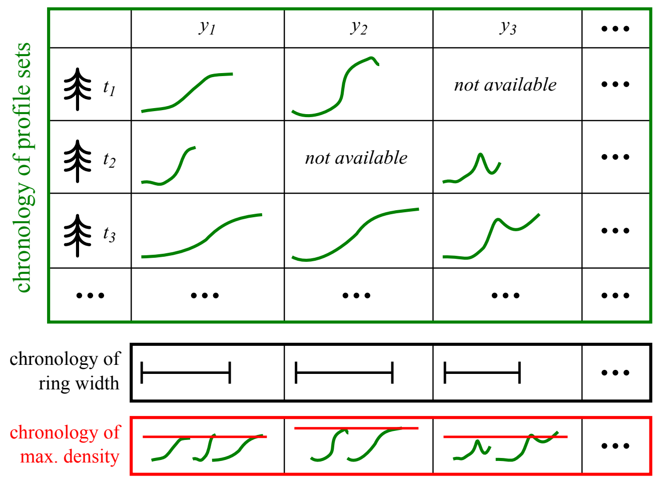

Figure 2: Illustration of the different chronologies used within this work. All chronologies are build from the sets of intra-annual wood density profiles (green lines) of individual trees t available for each year y. This data set already defines the chronology of profile sets C_ρ (green box). The chronology of ring width C_w (black box) provides the mean profile length per year, while the averaged maximum densities are covered by the chronology of maximum density $C_{\widehat{\rho}}$ (red box).

2.2. Crossdating and evaluation

Given a distance function $d(s, C, y')$ that evaluates the similarity of a sample $s = (t, y, k)$ (data of tree t for calendar years $y..(y+k-1)$) and the subchronology $C(y')..C(y'+k-1))$. To crossdate s using a given chronology C, we have to identify the year y^* such that the distance $d(s, C, y^*)$ is minimized, i.e. we are searching for $y^* = \arg\min_{y'} (d(s, C, y'))$. Thus, if y^* equals the sample's y, a correct crossdating was done.

To evaluate the *success rate* of a crossdating methods, we measure how often the original year y of a given sample $s = (t, y, k)$ is recovered, i.e. $y = y^*$.

We also assess crossdating reliability in terms of rank statistics. Here, the rank $r(s, C, d)$ provides the index of the sample's year y within the list of all putative start years in C in ascending order for a given distance function d. Thus, a rank of 1 corresponds to a correctly crossdated sample. For evaluation, we accumulate rank statistics per sample set and report averaged values over all sets. In the following, we introduce the distance functions used within this study.

Crossdating based on ring width and maximum density. The *maximum-density distance* $d_{\widehat{\rho}}(s, C_{\widehat{\rho}}, y')$ of a sample $s = (t, y, k)$ to a maximum-density subchronology of $C_{\widehat{\rho}}$ starting in year y' is computed based on the (negated[6]) Pearson

[6] Negation of test results is needed for distance minimization.

correlation coefficient of the respective maximum-density series of length k.

To compute the respective *ring-width distance* $d_w(s, C_w, y')$ based on a ring-width chronology C_w, we follow (Bleicher, 2014; Nechita, 2014) and use the (negated[6]) modified t-test[7] based on *Hollstein Wuchswert* normalizations of the respective ring-width sequences of length k. The Hollstein Wuchswert of a year y for tree t is defined as $\log(w(y,t)/w(y-1,t))$ and provides a normalized signal of growth changes of subsequent years (Hollstein, 1980). Other measures like correlation coefficients of the raw ring-width sequences or %-Gleichläufigkeit (Schweingruber, 1989) showed inferior crossdating success rate compared to t-tests on Hollstein Wuchswert (data not shown).

Crossdating based on intra-annual wood density. The *profile distance* $d(a, b)$ of two density profiles a and b of equal lengths is computed as the average point-wise difference of the slopes of the profiles' z-values[8]. The use of z-values (normalization) allows us to ignore multiplicative or additive differences between profiles and is computed by substracting from each value the mean of a profile followed by a division with its standard deviation. We assess the slope difference since we want to measure the shape similarity of the two profiles. Slopes are derived via a linear model using a window of 5 data points. Similar distance measures based on raw profiles or z-values only provided inferior results (data not shown).

The *profile-set distance* $d_\rho(s, C_\rho, y')$ based on a profile-set chronology C_ρ is the sum of the minimal profile distance (over all profiles in C_ρ) per year, i.e. $\sum_{i=0}^{k-1} \min_{x \in C_\rho(y'+i)} d(x, \rho(y+i, t))$.

3. Results and Discussion

To evaluate the crossdating success rate achieved for the different chronologies and distance measures, we assess the percentage of correctly crossdated samples visualized in Fig. 3. Furthermore, we compiled rank statistics of samples' correct years within the overall distance distribution and collected respective median, mean and variance values. Results are shown in Tab. 1 and discussed in the following.

3.1. Crossdating based on ring-width and maximum density

Our results reproduce that it is not possible to reliably crossdate very short wood samples based on ring-width information only. For sample length $k = 20$, the crossdating success rate is only about 68% and drops to 28% and even 7% for length 10 and 5, respectively. This is in good agreement with the literature, where sample lengths of 25 or above are recommended for reliable t-test statistics (Hedderich and Sachs, 2018). High mean and variance values of the respective rank statistics (see Tab. 1) show that the correct crossdating often is not among

[7] $t_{score} = cor \cdot \sqrt{k-2}/(1-cor^2)$, where *cor* denotes the Pearson correlation.
[8] Also known as *z-score* or *standard score*.

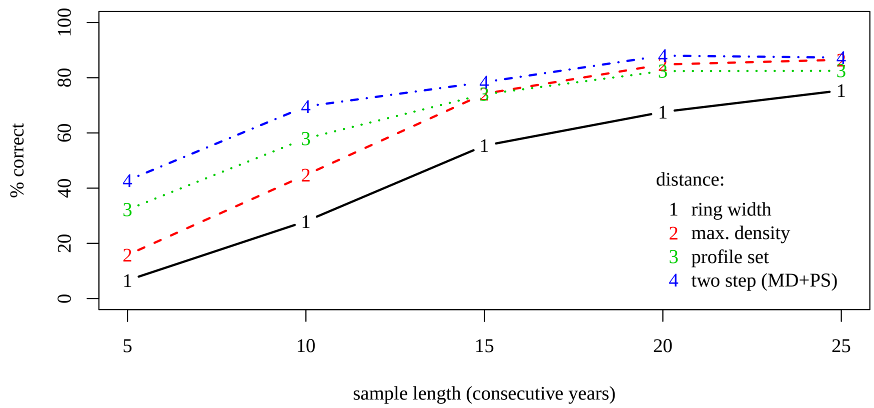

Figure 3: Success rate in percent of correctly crossdated samples for different sample lengths and optimized distance measures. Visualized values are detailed in Tab. 1.

crossdating approach	k	% correct (rank=1)	rank of sample year median	mean	variance
ring width	5	6.6	14.2	20.4	392
	10	28.0	3.3	8.7	148
	15	55.4	1.4	4.3	60
	20	67.6	1	3.4	45
	25	75.4	1	3	43
max. density	5	15.8	5.8	13.1	300
	10	44.8	2	5.1	66
	15	73.2	1	2.2	23
	20	84.8	1	1.6	5
	25	86.5	1	1.7	6
profile set	5	32.2	3.5	11.3	318
	10	58.0	1.2	7.9	260
	15	74.0	1	5.2	160
	20	82.4	1	4.7	173
	25	82.5	1	4.5	145
two-step approach (1) max. dens (2) prof. set for top-20	5	42.8	not available		
	10	69.6			
	15	78.4			
	20	88.0			
	25	87.3			

Table 1: Crossdating success rate and rank statistics for different distance measures and sample lengths (k). The values are averages for the respective sample sets per length.

the top-ranked crossdatings. Within the following, the ring-width-based results define the 'gold standard' to which we will compare to.

First, we tested the simplest approach based on maximum intra-annual wood density as a basis for crossdating. While computationally as easy to use as ring-width data (one data point per year within the chronology), a tree ring's maximum density enables a much better crossdating success rate when compared to its width. On average, we observe about 10-15% higher success rate over all sample lengths. This is in good agreement with our expectations, since it has been shown that wood density much better correlates with climatic conditions like temperature (Allen et al., 2012). These first results already point to the high potential of intra-annual wood density for crossdating of short samples.

3.2. Crossdating based on intra-annual wood density

Next, we investigated the potential of intra-annual wood density profiles for crossdating. The profile-set chronology shows superior results compared to all other methods tested so far. It significantly superseeds maximum density and provides about 15-30% higher crossdating success rate compared to ring width for $k \leq 20$. The improvement is most prominent for short sample lengths.

When compared to maximum-density-based crossdating, profile-set chronologies show only better performance for very short sample lengths of 5 and 10. For length 15 to 25 the performance is approximately the same.

Note, neither ring-width nor maximum-density information is used within the distance computation, since the latter is based on slopes of length-normalized z-values. This suggests that the intra-annual shape of wood density profiles indeed well represents the calendar-year-specific growth information. In contrast, we observe inferior results (data not shown) when using a distance measure based on absolute density values and non-z-normalized profiles, which would provide some notion of mean-density distance.

3.3. Crossdating using a combined approach

While the profile-set chronologies show the best success rate among the tested approaches, they do not scale well computationally. In contrast to the other approaches, computing the distance does not only consider a single (mean) data point from the chronology per year but now the full set of available tree-specific profiles is investigated. This dramatically slows down crossdating. Furthermore, extending the chronology data will immediately result in a respective runtime increase, which is unfavorable.

As a first step to mitigate this problem we test a heuristic hierarchical procedure, in the following named *two-step approach*. It combines the fast but less accurate maximum-density (MD) distance with the more accurate but slower profile-set-based (PS) method. This is based on the observation of low median and mean rank statistics from Tab. 1 for the MD approach. That is, the respective year of most samples is among the top-ranked candidates but maximum-density comparison is too coarse for the final crossdating. Therefore, we want to reevaluate the top MD predictions using the more reliable but also computationally more demanding PS method.

In (Step 1), we first identify for a sample the top-20 candidate years based on the MD chronology. In (Step 2), these 20 candidates are subsequently reevaluated based on the respective PS distances, which defines their final ranking and thus crossdating (rank=1 candidate). However, the original year of the scored sample might be missed by (Step 1), and is thus not within the final list of the reevaluated top-20 years. Therefore, no rank statistics can be provided in Tab. 1.

Since our data set covers 89 years, the top-20 two-step approach speeds up computation by a factor of about three to four compared to the exhaustive profile-set evaluation. Furthermore, it even further improves prediction and provides the best crossdatings for all tested sample lengths. The improvement is most notably for very short samples of lengths 5 or 10 as depicted in Fig. 3.

4. Conclusions

Ring width provides an easy to assess and reliable metric to crossdate wood samples. Thus, ring-width sequences are widely used and multi-millennia chronologies for various tree species have been built. Since tree growth is not well reflected by ring width alone, the use of intra-annual wood density information was proposed to provide improved crossdating success rate (Polge, 1970). It was hypothesized that the use of density-based chronologies can provide better climate reconstructions since density was observed to correlate better with climatic factors like temperature (Allen et al., 2012).

Within this work, we tested the potential of intra-annual wood density chronologies and measures for crossdating. Since ring-width-based crossdating is often already very accurate for long samples, especially when characteristic pointer years are covered, we focus in our intra-annual-data-based study on very short samples that are so far hard to annotate. For the evaluation and comparison of methods, we constructed a densitometric data set for Norway spruce trees using HF densitometry. From this data set, short samples (covering 5 to 25 consecutive years) were extracted to test the crossdating reliability of different approaches. While such perfect samples reflect an artificial situation for crossdating, it provides benchmark results not biased by poor or missing data. Thus, we can assess an upper bound of a method's potential without additional constraints or heuristics.

We observe improved success rates when using the maximum density per year, which is in accordance with results from the literature (Polge, 1970). Furthermore, we tested the potential of crossdating based on detailed comparison of densitometric curves taking the whole profile shape into account. We observe superior results when identifying the most similar density profile of any tree in the chronology per year. These results could be even improved, when combined in a hierarchical two-step heuristic that (re)evaluates only high-ranked maximum-density crossdating candidates. This two-step procedure provides an average crossdating success rate of 73% (over all samples) compared to only 47% for ring-width-based crossdatings.

Intra-annual densitometric curves are compared based on a shape (slope) estimate of respective z-value curves, which makes it independent of absolute density values. Due to that it would be possible to combine densitometric data from different sources and experiments (e.g. also using X-ray based series as produced by `xRing` (Campelo et al., 2019)) to generate chronologies for cross-dating.

While superior in quality, the two-step approach is still much slower than standard methods, since it compares each sample against respective data of all individual trees from the chronology for the tested candidate years. This could be countered by clustering methods to (a) define classes of similar densitometric curves per year and (b) compute for each class a representative profile. The latter could be done similar to the described preprocessing of radial measurements of individual trees. That way, one could reduce the computational complexity while still representing the spectrum of intra-annual density profiles per year. For instance, for *Pinus pinaster*, a relation of tree age and the abundance of intra-annual density fluctuations (IADFs) was shown (Campelo et al., 2013). We observe a similar relationship of cambial age of a tree ring and the shape of its wood density profile by visual inspection (data not shown), which we expect to be well covered by the suggested clustering.

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