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A temporal segmentation approach for dendrometers signal-to-noise discrimination

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Highlights

- Raw dendrometer time-series data are usually analyzed focusing just on specific periods
- New procedure to automatically filter dendrometer data
- Daily temporal features including stem shrinkage and swelling
- Rigorous accuracy assessment and method validation

Abstract

Automatic analysis of point dendrometer time series (DTS) registering radial stem variations of trees is of relevant interest to study tree water use and growth. Unfortunately, data from such sensors are often characterized by a large amount of noise that needs to be distinguished by sensors responses induced by biological processes (signal) and irregular fluctuations due to electrical disturbances, malfunctions, or external inputs (noise) such as stem flow, perturbation induced by animals, stem temperature and humidity variations. Although some algorithms have been developed to adjust jumps and correct peaks in DTS, it is nowadays challenging to extract biological signals after a large number of corrections and artifacts introduced during denoising processes. In this study, we present an alternative methodology consisting of the first attempt to automatically identify days in which the dendrometers are registering information related to the activity of the tree and relevant for a specific study (days-of-signal). Through (i) per-day temporal segmentation of different stem behaviors, (ii) daily temporal features extraction, and (iii) automatic days-of-signal and days-of-noise discrimination, we automatically analyzed 19 million DTS records acquired during three years by 12 dendrometers installed on xylem and bark at different stem heights from the collar, at the bottom and top-level, of *Pinus sylvestris* trees. To train and assess the performance of the model, we constructed a reference dataset by labelling 600 daily DTS into days-of-signal or days-of-noise. As a result of our model application, we detected 3,534 days-of-signal among the altogether 13,152 measurement days with a per sensor overall accuracy, calculated using the reference dataset, ranging between 100% and 82%. Finally, we showed the trend of stem shrinkage and swelling over the three years study period. The large accuracies obtained over the different sensors suggest that our method is versatile and generalizable.

Keywords: stem radial growth, time series, big data, scots pine, machine learning, artificial intelligence

1. Introduction

Stem radial changes in trees are of relevant interest in the field of forest ecophysiology and the use of the 'stem signals' as proxies of tree water use and growth pattern in response to environmental drivers has been continuously increasing in the last decade (Deslauriers et al., 2007a; Steppe et al., 2015). Stem radial variations are measured with dendrometers or gauges to monitor swelling and shrinkage at high resolution in time (minutes) and space (micrometers). In the past, dendrometer time series have been mainly used to obtain information about the seasonal pattern of stem radial/circumference increment (i.e. biomass allocation) or to assess the dependence of tree growth on environmental drivers or treatments (McLaughlin et al., 2003, Paoletti et al., 2019). These approaches are characterized by acquisitions at a low time resolution (i.e. daily or weekly interval data grouping) to measure the stem radial increments and model them at a seasonal level (McMahon et al., 2015). More advanced approaches exploit data acquired more frequently (from minute to hours) and apposite algorithms to (i) identify growth signals (Deslauriers et al., 2003, Bouriaud et al., 2005, van der Maaten et al., 2016, Knusel et al. 2021), (ii) define the seasonal pattern of tree water balance (Daudet et al., 2005; Dietrich et al. 2018) and (iii) carbon allocation in response to environmental drivers (Zweifel et al., 2010, Steppe et al., 2016), (iv) to study cold and drought acclimation strategy of trees (Cocozza et al., 2009, Giovannelli et al., 2007), (v) to analyze tree responses to climate change (Balducci et al., 2019, Giovannelli et al., 2022), (vi) to detect tree health declining in urban areas (Rocha et al., 2020, Giovannelli et al., 2021), (vii) to direct irrigation scheduling in woody crops (Tognetti et al., 2009, Li et al., 2020), and (viii) to drive timing of cambium collection for anatomical (Berta et al., 2010), and (ix) genomic analyses (Cruz-Garcia et al., 2019). Overall, the high-resolution analyses of the dendrometer data provide important details about the amplitude and duration of reversible stem radial changes related to tree water content (Offenthaler et al., 2001, Giovannelli et al., 2019) as well as irreversible changes related to stem growth patterns at a seasonal scale (De Swaef et al., 2015; Zweifel et al., 2016), and related to phenology and growth–climate relationships (Zweifel and Häsler, 2001, Deslauriers et al., 2003, Cocozza et al., 2016). Critically, the high time resolution of acquisitions foresees the production of wide and difficult-to-manage Dendrometer Time Series (DTS). In recent years parallel efforts were dedicated to the management and harmonization of DTS and their integration with proper modelling protocols (King et al., 2013; Van Der Maaten et al., 2018, Knüsel et al. 2021).

The first step of DTS analysis is the detection of outliers (values out of the range of the others), shifts (rapid changes in the average distribution of values), or jumps (one-point duration spikes) frequently present in DTS due to electronic failures, mechanical disturbances, calibration issues, or software acquisition bugs. Then, the DTS is adjusted through data cleaning and gap-filling procedures (De Swaef et al., 2015; Deslauriers et al., 2007b) and, finally, DTS is split and compared over different months, growing seasons, or years, to identify tree responses to variations of environmental conditions (Zweifel and Sterck, 2018; Kannenberg et al., 2019). However, daily monitoring of changes in tree water content requires precise and high-frequency DTS, with up to 1 observation per minute. In these cases, it is often complicated to distinguish between sensor responses induced by biological processes of interest – from now on "signal" - and fluctuations noncoding for biological processes or out of interest due to rainwater, fog, humidity absorption by the bark, stemflow, or mechanical movements due to animal perturbations or temperature variations – from now on referred as "noise". For these reasons, the common procedure is to select portions of the DTS where the signal-to-noise ratio is large, namely when the intensity/magnitude of the signal consistently prevails over the noise. This often means a manual, time-consuming uncertain, and, most critically, subjective checking of the DTS which, in turn, implies losing a lot of data and information that may be relevant. Moreover, subjective checking of DTS makes the procedure hardly repeatable and it can lead to contrasting results with the same datasets. Critically, automatically identifying which portion of the DTS should be removed is challenging, and several studies aim to standardize the processing of dendrometer data, to clean multiannual DTS, remove outliers, and correct erroneous shifts and jumps (Knüsel et al. 2021, Sugam et al., 2020).

For example, the dendrometeR and the dendRoAnalyst R packages (Maaten et al. 2016; Aryal et al. 2020) allow handling and pre-cleaning of data, erosion of artefacts, identification of data gaps within records, and allow dealing with the possibility of changes in temporal resolution. In addition, those packages allow analyzing DTS using the most common analytics methods, including the daily approaches to calculate or extract single values per day, and the stem-cycle approaches to separate high-resolution dendrometer records into distinct phases of contraction, expansion, and stem-radius increment. In turn, such procedures often result in DTS from which it is complicated to extract representative information on a daily scale, mainly due to a large number of corrections and artefacts introduced during the process which may hide the signal of the original variable of interest. Also, the reparation of DTS performed by such procedures often implies subjective choices, which can affect the results and thus the conclusions of the research. Seriously, such approaches repair DTS also acquired by sensors that are not working correctly, thus providing data that do not include any relevant information but that is just the result of several corrections and adjustments steps.

To fill these gaps, in this study, we propose an alternative procedure based on a reframing of the way mentioned issues are usually addressed. Instead of adjusting the DTS, we aim to automatically identify days in which the sensors record data that are considered signals and useful according to the aim of the research. Herein, we considered days-of-signal those in which the sensors registered the change in stem radius typical of sunny days during the season of stem radial growth. The procedure is articulated in three main steps: temporal segmentation (section 3.1), daily temporal feature extraction (section 3.2), and days-of-signal automatic identification (section 3.3). To remove redundant or out-of-interest information by DTS, we exploited Random Forests (Breiman, 2001), which has a powerful predictive performance (Hawryło et al., 2020), it is mostly unaffected by overfitting (Vaglio et al., 2021, Cavalli et al., 2022, 2023) and can accommodate non-normal responses and nonlinear relationships (Hermosilla et al., 2022, Francini et al., 2023). The approach was tested over 12 installed dendrometers which acquired data every minute for the period between 2010-01-01 and 2012-12-31, for a total of about 19 million records.

2. Materials

2.1. Study area

The study area is located in Hyytiälä, University of Helsinki's Station for Measuring Forest Ecosystem-Atmosphere Relations (SMEAR II). The area is located within the southern boreal zone in southern Finland (61°50′50″N, 24°17′41″E, 180 m a.s.l.). The studied forest stand is an even-aged homogeneous ~ 60- year-old Scots pine (*Pinus sylvestris* L.) stand (Vesala et al., 1998), grown after prescribed burning and sowing in 1961. In 2012, the dominant height of the stand was 19.6 m and the mean stem diameter at breast height was about 17.5 cm (Back et al., 2012). The mean annual (1991-2020) precipitation and air temperatures were 690 mm and +4.1 °C, respectively. February is typically the coldest month (mean −6.7 °C) and July is the warmest (mean +16.2 °C).

2.2. Dendrometer data

The procedure was tested on 12 DTS of sensors installed on three *Pinus sylvestris* trees. The dataset was constituted by data recorded with four sensors per tree. Stem radial variations were measured every minute for the period between 2010-01-01 and 2012-12-31 using two linear variable displacement transducers (point-dendrometers) (LVDT; model AX/5.0/S; Solartron Inc., West Sussex, UK) installed at 1.5 m (b=base) and 12.5 m (t=top) from the collar in tree 1, at 2.5 m and 10.5 m in tree 2, and 2 m and 10 m in tree 3. A detailed description of the point-dendrometers and sensor installation is provided by Sevanto et al. (2005) and Chan et al. (2016). A first dendrometer was installed on a screw that was inserted approximately 10 mm through the outer and inner bark into the superficial part of the existing xylem to measure changes in the xylem diameter, not measuring the growth of the stem (Sevanto et al., 2005). A second dendrometer was mounted on the bark to measure the radius changes including growth, and changes in the thickness of the phloem and bark.

2.3. Reference data

To train, validate, and assess the performance of our algorithm we constructed a reference dataset of 600 daily DTS by selecting – through simple random sampling - 50 days for each of the 12 DTS. As a result, an average of 67 days was selected for each month, with most days (95) selected in March and the fewest days (56) selected in August. The 600 daily DTS were analyzed by a group of three experts to identify days-of-signal and to label the remaining ones as days-of-noise. In this study, the experts' classification of days-of-signal was based on the confirmation of the presence of all the three following stem cycle phases: (1) the contraction – the phase between the maximum in the early morning and daily minimum in the middle of the day, (2) the expansion – phase from the daily minimum to the following morning maximum at the end of the day, and (3) the stem radius increment – phase from the time the stem radius exceeds the morning maximum of the previous day until the next maximum. Based on this classification, the dendro-signals related to freeze-thaw cycles were included among days-of-noise. It is postulated that freeze-thaw cycles are induced by apoplastic ice nucleation at low temperatures (Lintunen et al., 2015, Lindfors et al., 2019) and their occurrence is independent of the hour of the day (asynchronism between daily phase and phase cycle).

A cross-check methodology was implemented similar to that presented by Francini et al., (2022a, 2022b). All 600 days were analyzed independently and labeled by the three photointerpreters. For the daily DTS on which photointerpreters initially disagreed on the label (i.e. signal or noise), the photointerpreters discussed their respective labels while viewing the same imagery and came to a common conclusion. Thus, in the final reference dataset, any disagreement between the three experts was present for any of the 600 daily DTS.

3. Methods

The proposed workflow aims to (i) remove out-of-interest or useless information by DTS and (ii) provide relevant and meaningful features for the remaining data. It was implemented in R 4.0 (R Core team 2017) and is divided into three main steps. The first step is temporal segmentation, in which we identify 5 vertices for each day by defining the four segments that better summarize the time series (section 3.1, Fig. 1-B). The second step is feature extraction, in which we calculate a set of metrics describing the behavior of the segments for each daily DTS (section 3.2, Fig. 1-C). In the third one, we use Random Forests and daily metrics as predictors to classify between days-of-noise and days-of-signals and to assess the importance of the metrics (section 3.3, Fig.1-D). In the fourth and last step, we assess (i) the performance of the classification model, (ii) the model generalizability, i.e., the capability of the model to be applied over data acquired from different sensors than that used for training the model, and (iii) the relationship between the amount of available training data and the accuracy of the model (section 3.4).

3.1. Temporal segmentation

To increase the signal-to-noise ratio and filter out redundant and meaningless information we propose a temporal segmentation procedure based on a revisitation of the Sliding Window And Bottom-up (SWAB) procedure, for which functions and detailed representation of the algorithm are provided in Keogh et al. (2000), table 4. For each one-day time window (Fig. 1-A), we created the finest possible approximation of the DTS by merging all pairs of adjacent points. In this way, the DTS is represented as a set of N-1 segments, where N = 1440 is the number of minutes - and thus points or vertices - per day. Second, the cost - in terms of Root Mean Square Error (RMSE) - of merging each pair of adjacent segments is calculated and the pair with the lower cost is merged, i.e., the vertex between that pair of segments is removed. After that, the process is repeated until some pre-defined conditions are met. Keogh et al. (2000) suggested that the segmentation process should be repeated until the number of segments does not exceed a threshold (maximum number of segments) or the RMSE does not exceed a threshold (maximum RMSE). However, depending on the sensor, the RMSE can change a lot, and defining a general maximum RMSE is challenging. Plus, DTS with a different number of segments makes it challenging to compare segments and temporal features (section 3.2) across different days. For these reasons, we used just the number of segments = *4* as the stopping criteria. Thus, for each daily DTS, we identified among the initial 1440 daily points the five vertices defining the *4* segments that better summarize the daily DTS, i.e., that minimize the RMSE (Fig. 1-B). Although we tested several different values, *4* was the number of segments (Fig. 1B) that better describes the daily variation of DTS, resulting in the best compromise between not losing too much information and the need for daily TS approximation and relevant features extraction (Fig. 1B)

Segment 1 refers to the night, with the increase of stem radius in the first part of the day. Segment 2 refers to the morning, with a slow decrease in stem radius. Segment 3 refers to the period around midday. Finally, segment 4 refers to the evening, with the slow increase of stem radius typical of the last part of the day.

3.2. Temporal features extraction

To characterize the daily behaviour of variables we calculated a set of three metrics for each of the 4 segments (Fig. 1C): (i) the magnitude (a change on the y-axis), (ii) the duration (a change on the x-axis), and (iii) the RMSE (Root Mean Square Error). As a result, we obtained 12 temporal features per day. More information on temporal features calculation can be found in Hermosilla et al. (2015), where a similar approach was applied to time series of remote sensing images.

3.3. Signal to Noise discrimination model

To automatically classify daily DTS into signal or noise (section 3.2), we used the temporal features as input predictors for the Random Forests algorithm (Breiman, 2001), an ensemble of decision trees that learns through a supervised approach and produces multiple models that are aggregated through bootstrapping. Using Random Forests, the training dataset is randomly divided to train N models "trees" which are then aggregated to build the "forest". Random Forests requires a set of hyperparameters set a priori, among which are the number of trees and the number of variables to be used by each tree. Although the tuning of these hyperparameters can partially improve the performance of Random Forests (Vaglio et al., 2021, Hawrylo et al., 2020), we used default values:

100 as the number of trees in the forest and 3 as the number of variables considered by each tree. The model was then trained using all available reference data (600 days) and applied to the whole data (1,096 days for 12 TS) to automatically discriminate between days-of-signal and days-of-noise.

The 12 daily temporal features were also studied to define their contribution to increasing the accuracy of the model and discriminating between days-of-signal and days-of-noise. To do it, we used the reference dataset and RF to calculate the variables' importance in terms of the Gini Index (GI) which indicates for each variable the probability that a sample is classified correctly when that variable is randomly selected during Random Forests splitting. The greater the GI of a specific variable the greater the contribution of that variable to increase the performance of the model.

3.4. Performance assessment

Overfitting is an issue of models that are too specific, thus able to reproduce closely the training data used but weak to generalize outside the calibration examples. In these cases, the accuracy of models consistently decreases when they are applied over data different than that used for training. To avoid overfitting, one of the most useful methods is k-fold cross-validation (k-fold CV) which splits the training set into K number of subsets, called folds. When k is equal to the number of samples in the reference dataset (in our case 600) this method is called Leave-One-Out LOO. For comparison purposes, and to double-check the robustness of our accuracy estimates, we used both LOO CV, with k = 600, and k-fold CV, with k = 12, or the number of different dendrometers sensors in our data. Using LOO CV, our model was iteratively fitted k=600 times. Each time, the model was trained on data from 600−k (599 samples) of the folds, and the performance was evaluated on the remaining kth-fold. Therefore, our model was iteratively fitted k=12 times. Each time, the model was trained using data acquired from 11 sensors (550 samples), and the performance was evaluated on data acquired from the remaining sensor (50 samples). This procedure aimed to verify if the calibrated model can be transferred to other sensors.

Finally, to test how the size of the training dataset affects the accuracy of the discrimination process, we trained and validated the model by gradually decreasing the ratio between the training dataset and the validation dataset and by applying a Repeated Cross Validation procedure (rCV). For 100 times, we randomly selected 90% of the data as training and we validated the resulting model on the remaining 10% of data. Then, we repeated this procedure by gradually decreasing the training/validation ratio using a 5% step: 85% for training and 15% for validation, then 80% for training and 20% for validation, and so on until the training data is 10% and the validation is 90%. For each training/validation ratio, the following three steps were repeated 100 times: (i) the training data is randomly selected, (ii) the model is trained, and (iii) the accuracy is assessed using the validation data.

For all the three mentioned methods – LOOCV, k-fold CV, and rCV - the performance parameters we calculated are (i) overall accuracy (OA), i.e. the percentage of cases correctly classified, (ii) omissions, i.e. the percentage of days-of-signal that were incorrectly classified as days-of-noise, (iii) commissions, i.e. the percentage of days-of-noise that were incorrectly classified as days-of-signal, and (iv) true skill statistic (TSS, Allouche et al., 2006), i.e. the sum of sensitivity and specificity minus 1. Where, in our study, the sensitivity reflected the ratio of days-of-signal correctly classified as days-of-signal and the specificity reflected the ratio of days-of-noise correctly classified as days-of-noise (Togashi et al., 2022).

4. Results

First, we show four examples of segmented days in Fig. 2, where graphs A and B describe days-of-signal defined by the first segment that shows the night with low transpiration, the second segment that shows the daily phase of increasing transpiration, the third segment that shows high transpiration, and the fourth segment that shows decreasing transpiration. Graphs C and D (Fig. 2) are days-of-noise, where the 4 segments do not define phases typical for a representative day in a vegetative season. Such days-of-noise could occur in peculiar weather conditions, such as high relative humidity.

Most of the RMSEs ranged between 0 and 5 with very small differences between segments but large differences between sensors (Fig. 3).

The LOO CV performance assessment of the Random Forests model resulted in OA = 89.8%, TSS = 79.3%, omissions = 10.4%, and commissions = 4.7%. Similarly, the k-fold CV performance assessment (k = 12) confirmed large accuracies and supported the robustness of our results: OA = 87.3%, TSS = 73.8%, omissions=12.1%, and commissions=5.7%. Using LOO CV, the OA assumed values were consistently different for different sensors, ranging between 100% for the dendrometer on the stem at the top of tree "2" (stem 2t) and 82% (stem 2b and xylem 1t) (Table 1). Using k-fold CV, the lowest accuracy was still registered for the xylem 1t sensor (OA = 66%, TSS = 39%). Finally, using the rCV and by gradually decreasing the ratio between training and validation data we checked the relation between the amount of training data and obtained accuracy (Fig. 4). Although, as expected, model performance decreases together with the amount of training data used, all the accuracy parameters maintained satisfactory values (OA = 82%, TSS = 61%, omissions = 15%, and commissions = 9%) also using just 10% of data for training (60 samples of our reference dataset) and the remaining 90% for validation (540 reference samples).

The analysis of the importance (in terms of GI) of the temporal features (Fig. 5) revealed that the contributions of segments 2 and 4 in increasing the accuracy of the model were consistently greater than those of the other segments, with the magnitude providing the greatest contribution. Temporal features GIs of segment 3 were generally very small. The RMSE contribution was the smallest in all segments with GIs values ranging around 8%.

Among the 13,152 days, 3,534 days were detected as days-of-signal (Fig. 6) with a very unbalanced distribution among the different sensors (Fig. 7). While the dendrometer in the xylem at the top of the tree "3" ("xylem 3t") registered just 45 days-of-signal, the dendrometer installed in the xylem at the bottom of the tree "1" ("xylem 1b") registered 549 days-of-signal among the 1095 days in the three years TS. For this sensor, we show in Fig. 8 the trend over time of segment 2 and segment 4 magnitudes – corresponding to shrinkage and swelling, respectively. The shrinkage and swelling trends over the three years of the analysis shown in Fig. 8 reflect the expected behavior over time due to trees' phenology. Finally, in Fig. 9 we show the output of the signal (blue dots) to noise (red dots) discrimination process applied over some examples of DTS.

5. Discussion

Plant sensors are of high interest as ‘phenotyping’ tools that need to be capable of high-throughput screening of a huge number of plants (Fiorani and Schurr, 2013). Herein we introduced a new procedure for DTS analysis by application of a temporal segmentation algorithm and a machine learning approach to automatically discriminate between days-of-signal and days-of-noise. Accordingly, 9,618 days-of-noise were discarded among the 13,152 days in the TS. This method consistently differs from the usual ones, which aim to adjust and repair DTS instead of removing out-of-interest information as we did.

The construction of the 600 days reference dataset we used required about three days of manual work, one for each of the three photointerpreters. The resulting model was then applied to classify 13,152 days - that is all the data we had – saving a relevant amount of time and manual work. Also, the same model may be applied over even more days, further increasing the advantage of automation. On the other hand, decreasing the ratio between the amount of training data and the amount of data over which to apply the model might negatively affect the accuracy (Raz et al., 2017, McGiff et al., 2019), but – depending on the dataset – the accuracy decrease is expected to be very minimal (Han and Kim 2021). Accordingly, in this study, we progressively decreased the ratio between training and validation data and we showed that the amount of training data required by our model can be as small as 60 samples, or 10% of the data for training and 90% for validation.

The sensor's overall accuracies – estimated using a reference dataset of 600 days – were up to 100% and never smaller than 82% using LOO CV. Furthermore, the number of commissions was half the number of omissions (5% and 10% respectively), which means that most (about 95%) of the days-of-signal selected using our model included relevant information suitable to perform additional analysis, such as investigating the relationships between daily dendrometers variation and weather conditions (e.g. temperature, precipitation). While the LOO performance assessment procedure is suitable when you have a small set of reference data as we have (600 samples), the calculated accuracy is an estimate, and slightly different results may be obtained by using different assessment procedures, such as the k-fold CV (Bengio and Grandvalet 2004). On the other hand, the expected differences in the accuracy estimates are subtle (Zhang and Yang 2015). Accordingly, even if using k-fold CV our model was calibrated on a selected subset of sensors and validated with the remaining ones, the differences with the accuracy parameters estimated using LOO were minimal – OA, TSS, omissions, and commissions decreased respectively by 2.5%, 4.5%, 1.7%, and 1%. These results suggest that the herein proposed model can be applied to sensors different from those used for calibration and it shows that the amount of training data can be very small while maintaining good model performance. On the other hand, for some sensors, the accuracy can be consistently small, in particular considering the TSS performance parameters. For instance, the stem 1t sensor revealed large OA (92% using LOO CV and 90% using k-fold CV) but low TSS (29% using LOO CV and 21% using k-fold CV). Those results point out the need of having an exhaustive reference dataset, representing all sensors and including enough of both days-of-signal and days-of-noise. Indeed, the percentage of days-of-signal in the reference days for the stem 1t sensor was very low (6%), complicating both model training and performance assessment exercises.

Segments predicted using our approach summarise the daily behaviour of dendrometers' signal, by removing redundant information and thus increasing the signal-to-noise ratio. Due to the different positions of the 12 dendrometers (i.e. over the bark, xylem, and at 1.5 and 15 m from the ground), they had very different absolute values, daily ranges, noise sources, characteristics, and amounts. We stress that to obtain accurate results with different sensors, proper reference data acquired for different DTS are needed. To this aim, also the number of segments used by the temporal segmentation approach may need to be adjusted to match the daily trend of different traits. Similarly, also the amount of discarded data can be decreased if needed by decreasing the number of days considered as days-of-noise in the reference data.

The 12 temporal features (section 3.1 and Fig. 1-C) were used to discriminate between days-of-signal and days-of-noise (OA = 90%) and for summarising the daily trend by removing redundant information and by extracting the daily features of greatest interest, such as the stem shrinkage and the swelling. The temporal features were also studied to define their capability (in terms of GI) in discriminating between days-of-signal and days-of-noise and thus increasing the accuracy of the model. The GIs of the second and fourth temporal segments' magnitudes (namely, the change of dendrometer values on the y-axis) were considerably greater than other temporal features' due to the relevance of the presence of shrinkage and swelling of the stem in the daily time series to be considered as day-of-signal. These results also agree with the days-of-signal definition given in this study. The GIs of the third segment temporal features were generally small, pointing out that this segment does not particularly affect the noise-signal classification process. On the other hand, temporal features related to the third segment may be of great interest to several research purposes. For example, the duration of the third segment defines the time between the end of the shrinkage phase in the morning and the start of the swelling phase in the evening, and thus provides important information on the sensitivity of the tree to the environment. Indeed, during that daytime, the thermal and water conditions change by causing swelling after the shrinkage of the stem. In turn, in further investigations, additional features of the presented and analyzed 12 temporal features may be tested and studied such as the slope (the magnitude/duration ratio) or the daily range of values.

The RMSE importance was very small in all segments with values ranging around 8%. As per the temporal features of the third segment, the small GI values of RMSE indicated little contribution in detecting days-of-signal but it might be important in future research. On the other hand, the RMSE can be considered a per-segment measure of the reliability of the segmentation process output: a small RMSE of a specific segment indicates that the segment fits very well with the data - a minimum loss of intra-segment variability - while a large RMSE indicates a high intra-segment variability, possibly implying a loss of relevant information and/or a not state-of-the-art segment fitting. The high reliability of the RMSE was confirmed by the high variability of values between different sensors, although they showed similar values between different segments of the same sensor. Indeed, if a sensor is working properly, it is expected that the RMSE is low in all segments. In summary, temporal features calculated over days with large values of RMSE may be considered less reliable than those of days characterized by small RMSE values.

The temporal segmentation method, daily features extraction, and the Random Forests application steps allowed for discarding noisy data that may alter the validity of the results. This procedure is usually performed through a time-consuming and, most questionable, subjective visual inspection of the whole DTS. Manually - possibly subjectively - selecting a specific portion of the DTS can compromise the scientific validity of the confirmation of an eventual hypothesis that, instead, should be verified objectively and considering the whole data. Automatic routines, such as that presented in this study, permit to a priori define criteria and definitions for selecting or discarding data and, consequently, overcome mentioned issues. The procedure we demonstrated in this study is a useful tools for identifying days-of-signal, that in this study were days in which the contraction, the expansion, and the stem radius increment were registered by the sensor, according to the user definition and thus to the study aim.

Future research should aim to investigate the relationships between environmental variables and tree functional traits considering long DTS and exploiting the temporal features our procedure provides. Exploiting the potential of the procedure we proposed in this paper, correlations between temperature/humidity and the daily trend of tree diameters can be studied considering the whole time series obtaining results more significant from a scientific point of view compared to results obtained manually selecting a specific DTS portions.

6. Conclusions

Dendrometers are known to produce time-series data including a large amount of noise. In this study, we present the first attempt to automatically identify days in which the dendrometers are registering information that is of interest depending on the purpose of the study (days-of-signal). This methodology should be in our opinion preferred to methods that correct peaks and jumps, which – due to a large amount of noise often present in DTS – can alter the original DTS signal. The proposed approach automatically detects shrinkage-swelling cycles within stem radius variations, allowing to investigate relationships between tree functional traits and environmental variables and to interpret the adaptation and mitigation potential of trees under current and future climate change conditions.

Today the availability of this kind of tool promises the expansion of such technologies into plant - species-specific - biology and physiology when high temporal frequency (sub-hour monitoring), real-time data transmission and massive monitoring points at low cost are required. These assumptions create new opportunities in terms of future development of *in-situ* earth observation systems to increase the quality and sustainability of forest management through a better understanding of the relationship between tree growth and climate variables.

By a daily temporal segmentation, temporal features extraction, and days-of-signal days-of-noise discrimination, we automatically analyzed 12 DTS over three years with one observation per minute for a total of about 19 million data records. We obtained a dataset reporting for each day and each sensor the output of the segmentation process (i.e. the detected vertices) and a set of 12 relevant temporal features - including those related to stem shrinkage and swelling. Using Random Forests, we detected 3,534 days-of-signal among the 13,152 with a per-sensor overall accuracy ranging between 100% and 82%. Considering the remaining days-of-signal, we were able to show the trend of shrinkage and swelling over the three years study period. Future research may exploit the herein presented method to investigate relationships between tree functional traits and environmental variables and to intepret the adaptation and mitigation potential of trees under current and future climate change conditions.

Data availability statement

Codes needed for implementing the temporal segmentation approach and calculating the metrics are provided on Zenodo (https://zenodo.org/record/7116133#.YzLjnXZBzb0) together with a brief documentation to help execute the codes.

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Table and Figures' captions

Table 1. Per sensor overall accuracy (OA) and true skill statistic (TSS) obtained using both LOOCV and KFCV performance assessment procedures. Values are represented per tree (1, 2, and 3) by considering the dendrometers installed on the bark and xylem at the bottom ("b") and top ("t") level of the stem.

Fig. 1. Proposed workflow: the original time series (A), temporal segmentation (B), feature extraction (C), and signal-to-noise discrimination (D). Temporal features calculated for the detected days-of-signal can be then used to further analysis and to verify any scientific hypothesis related to DTS analysis.

Fig. 2. Examples of temporal segmentation outputs. Panels A and B show days-of-signal while panels C and D show days-of-noise. The TS refers to the dendrometer installed at 1.5 meters on the stem of the first pine.

Fig. 3. Box plots of segments RMSE per sensor. Values are represented per tree (1, 2, and 3) by considering the dendrometers installed in the stem and xylem at the base ("b") and top ("t") level of the stem. S=segment, S1= night with low transpiration, S2=morning with increasing transpiration, S3=day with high transpiration, and segment, S4=the evening with decreasing transpiration.

Fig. 4. Relation between accuracy (y-axes) and percentage of data used for training and validation (x-axes). The average and the standard deviation resulting from the repeated Cross Validation procedure (section 3.4) are shown for each training/validation percentage combination and for each parameter of performance assessed: Overall Accuracy (OA), True Skill Statistic (TSS), omission, and commission errors.

Fig. 5. Temporal features importance in each temporal segment in terms of Gini Index. The greater the GI of a specific variable the greater the contribution of that variable to increase the performance of the model.

Fig. 6. Distribution over time of the detected days-of-signal (black dashed lines) per sensor. Values are represented per tree (1, 2, and 3) by considering the dendrometers installed and xylem at the bottom ("b") and top ("t") level of the stem.

Fig. 7. Distribution of the 3,534 detected days-of-signal per sensor. Values are represented per tree (1, 2, and 3) by considering the dendrometers installed and xylem at the bottom ("b") and top ("t") level of the stem.

Fig 8. Segment 2 (shrinkage in the morning) and segment 4 (swelling in the evening) magnitude trends over time in the xylem 1b sensor.

Fig 9. Examples of DTS and the results of the signal (blue dots) and noise (red dots) automatic discrimination process.