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Real-time monitoring of thinning intensity using harvester data and remote sensing-based single-tree maps

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ABSTRACT

Achieving the recommended basal area and stem density of remaining trees in cut-to-length thinning operations can be a challenging task for the harvester operator. In recent years, thinning intensities have often violated recommended limits in the Nordic countries, and operators have expressed their desire for decision support and reporting assistance in thinnings. Here, we introduce a new concept named R-TIM (Real-Time Thinning Intensity Monitor) for the real-time monitoring of thinning intensity. R-TIM leverages a remote sensing-based single-tree level digital twin of the stand, maintained up to date during harvesting through matching harvested trees with their counterparts in the map. The properties of standing tree stock are calculated from the digital twin and the properties of removed stock from harvester measurements. Using simulations and field data from a test site in southern Finland, our tree matching algorithm attained an accuracy of over 85% for mean crane-tip positioning errors of 1 m or less. In the same positioning error range, the mean error in R-TIM-reported basal area of standing stock was below 0.5 m²/ha. The crane-tip positioning error estimated in the real harvesting was 0.71 ± 0.03 m, which is representative of modern crane-tip positioning accuracy and signals the feasibility of R-TIM for operational use.

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Introduction

Thinning cuttings are a key component of rotation-based forest management, undertaken particularly to increase economic return and resilience of the remaining stand. In Finland and Sweden, a total of 700,000 to 800,000 ha of forests are annually subjected to thinning (Natural Resources Institute Finland 2024; Skogsstyrelsen 2026). In thinning operations, reasonable tree selection and thinning intensity (TI) are essential to achieving high financial income and sawlog yield (Natural Resources Institute Finland 2024), minimum growth loss (Vuokila 1981), good levels of carbon sequestration (Bianchi et al. 2024), and mitigating the risk of abiotic and biotic forest damage (Wallentin and Nilsson 2014).

Through selecting trees to remove, the harvester operator plays an essential role in thinnings (Kärhä et al. 2021; Pohjala et al. 2024, 2025). Stem density (stems/ha), stem size, and the species distribution may vary significantly within the site. In addition to forest certification requirements (Forest Stewardship Council, Programme for the Endorsement of Forest Certification), forest owners often present their wishes regarding stand treatment. Furthermore, new TI recommendations were recently launched in Finland, including more thinning schemes to choose from depending on site characteristics (Tapio 2025). Together, these aspects create a significant challenge for the harvester operator in achieving the targeted TI and desired quality of the remaining stand.

Indeed, in recent years in Finland (Metsätrens Magazine 2023) and Sweden (Hannrup et al. 2021), realized TIs have often been significantly higher than recommended, i.e. many sites have been harvested too heavily. Correspondingly, machine operators have voiced a strong need for assistance systems in monitoring and following TI during harvesting, especially early in their career (Ylimäki et al. 2012; Kauppinen et al. 2016; Kärhä et al. 2021, 2025; Kymäläinen et al. 2025). Basal area (m²/ha) and stem density (stems/ha) are the key parameters in controlling and monitoring TI, and many instructions and follow-ups are based on these indicators (Tapio 2025). Currently, harvester operators are responsible for monitoring and reporting these TI metrics via manual measurements, a time-consuming task which decreases operational efficiency and includes risk of subjective effects.

To provide decision support for operators in achieving the desired TI and to alleviate problems in TI reporting, several operator-assistance systems have been proposed in recent years. In Sweden, Skogforsk has developed the hprGallring system for automatic calculation and reporting of TI metrics (Hannrup et al. 2011, 2014, 2021; Möller et al. 2011, 2015). During harvesting, the system continuously displays basal area, stem density, and other relevant metrics for removed trees. In addition, using the harvester-measured properties of removed stock and data on typical thinnings, hprGallring produces an estimate of the corresponding quantities for remaining stock.

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The system uses measurements of felled stems recorded into harvested production report HPR (.hpr) files in the StanForD 2010 standard (Skogforsk 2014). More recently, national LiDAR-based forest inventory data has been tested in predicting the properties of remaining stock in Sweden, with promising results (Nilsson and Bengtsdahl 2023). In addition, approaches leveraging spatial statistical modeling and harvester data (Stendahl and Dahlin 2002), comparison of a pre-collected tree map and harvester measurements of removed trees (Lindroos et al. 2015), and approaches using solely harvester data (Tarvainen et al. 2025) have been proposed for estimating the properties of the remaining stand.

Forest machine manufacturers have also introduced tools for following TI during harvesting. John Deere's TimberMatic system (Metsätrans Magazine 2022; Deere 2023, 2025) provides a map layer, using national aerial LiDAR data in Finland, that shows an estimate of tree density compared to optimal growing density, with a color scale indicating parts of the stand where thinning should be targeted. Another map layer provides an estimate of remaining stock. Ponsse (Ponsse 2025a) has introduced the Thinning Density Assistant (TDA) proof-of-concept. In TDA, continuous LiDAR scanning of the forest is performed by scanners onboard the harvester. The collected data is used to build a tree map of the stand, and the system directly measures the density of remaining trees. In addition, TDA guides the harvester operator in achieving a suitable value for stem density by highlighting locations where thinning should be targeted in the stand. Nordic Forestry Automation (Nordic Forestry Automation 2025) has developed the NFA R1 retrofit system, which similarly leverages on-board LiDAR scanning for harvester operator support in thinning operations.

An alternative approach to monitoring TI during harvesting could be to create a digital twin of the forest before thinning, and then to update this virtual model of the stand as trees are harvested. In this concept, a single-tree level map with position, height, diameter at breast height (DBH), and possibly other attributes for each tree is created from a high-quality point cloud collected from the site before harvesting. The scanning could be optimized through choosing good measurement conditions, and processing of the point cloud into a tree map could be done "offline" with abundant computational power. In practice, this approach assumes a high-precision crane-tip positioning system, which is becoming mainstream in the Nordic countries (Komatsu 2023; Kärhä et al. 2025; Ponsse 2025b; Deere 2026). Once the thinning begins, a tree-matching algorithm is harnessed to remove each harvested stem from the digital twin, the correct tree inferred by comparing harvester measurements with the attributes of trees in the vicinity of the estimated crane-tip position. In this way, the digital twin is maintained up to date during the harvesting, enabling the direct, real-time computation of TI metrics with no further modeling involved. The concept would require no new instrumentation or sensors on the harvester.

At the core of such a TI monitoring system would be an algorithm for matching each harvester-measured stem with its counterpart in the pre-collected tree map. The problem of such tree matching is relevant to many forestry applications,

including the pairing of harvester-based stem measurements with remote sensing data to create ground-truth data for training aerial-based forest inventory methods (Lindroos et al. 2015). While methods for, e.g. matching groups of trees measured by harvester-mounted LiDAR to a global tree map have been introduced (Rossmann et al. 2009, 2010), no algorithms for doing single-tree matching via standard harvester measurements in real time have been proposed to date.

In this work, we introduce, assess and demonstrate the described novel approach to real-time-monitoring of TI in cut-to-length harvesting operations. We name this concept "R-TIM" (Real-Time Thinning Intensity Monitor). Through a case study based on simulations and real forest data, we:

- (1) Present the methodology of R-TIM and our tree matching algorithm.
- (2) Quantify the accuracy of the harvester crane-tip positioning system used in our case study.
- (3) Evaluate the accuracy of our tree matching algorithm for different levels of positioning error.
- (4) Demonstrate the R-TIM concept and estimate its usefulness in TI monitoring.
- (5) Discuss future development of R-TIM and its implications for forestry applications in Finland and beyond.

Materials and methods

Description of the R-TIM concept

R-TIM is a concept designed to help the harvester operator achieve desired TI and to support the reporting of TI through continuous computing of basal area and stem density during harvesting (Figure 1). Before harvesting, a high-resolution point cloud is collected from the site. This can be done using LiDAR, photogrammetry, or both. From this point cloud, a single tree-level map is formed. The tree map consists of the position and stem attributes (e.g. DBH, height, species) for each tree. In effect, the tree map constitutes a digital twin of the stand, which is maintained up to date during the harvesting operation.

Once the harvesting begins, the following loop comes into action. Every time a stem is harvested, its harvester-derived position (from the crane-tip position estimate upon the felling cut) and stem attributes, recorded directly by the harvester or estimated from these, are used to find the best-matching tree in the map. This tree is then removed from the map. The basal area and stem density are computed for both standing and removed stock. For standing stock, these metrics are computed from the tree map, and for removed stock, from the harvester measurements. The TI metrics are continuously reported to the operator. R-TIM does not, at this stage, involve optimizing tree selection during thinning.

Tree matching algorithm

To maintain an up-to-date digital twin of the stand being thinned, R-TIM requires an algorithm for automatically matching a felled tree to its counterpart in the tree map.

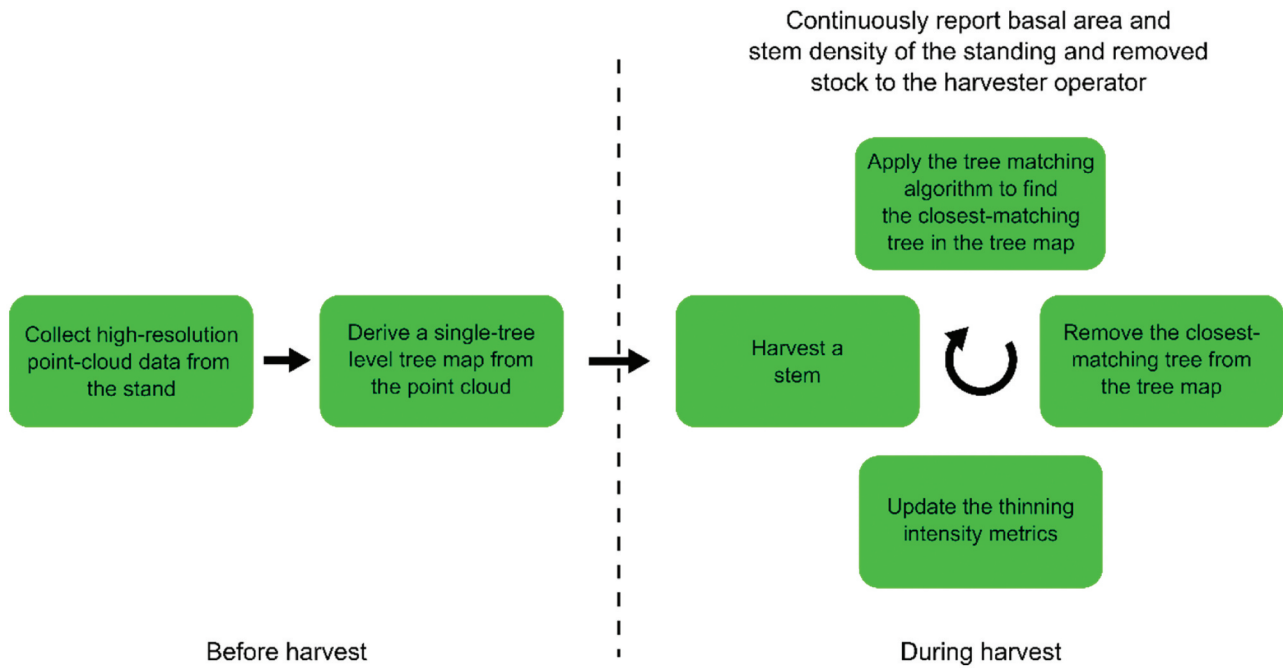


Figure 1. Schematic diagram of the R-TIM concept for real-time monitoring of thinning intensity during cut-to-length thinning operations for reporting purposes and operator decision support.

After experimenting with different approaches to matching HPR stems with trees in a LiDAR-based single-tree map, we ended up with the following algorithm.

For each harvested stem:

- (1) Given the stump position estimate $P_{\text{estimated}}$, consider all trees in the tree map within distance R_{max} from $P_{\text{estimated}}$. Order this set of trees by distance from $P_{\text{estimated}}$.
- (2) Find all trees within this set whose tree map DBH and the harvester-based DBH differ by at most ΔDBH m.
- (3) Out of these, find all trees whose tree map height and the harvester-based tree height differ by at most Δh m.
- (4) Out of these, find all trees of the same species as the harvested stem.
- (5) Out of the remaining set, designate the tree at the shortest distance from $P_{\text{estimated}}$ as the matching tree.

The algorithm can be tuned using the parameters R_{max} , ΔDBH , and Δh , and optimal values of these parameters are expected to vary depending on site, tree map, and mean crane-tip positioning error. If enforcing the distance, DBH, height, or species requirement (steps 1 to 4) results in no remaining candidate trees, the algorithm reports that no match could be found. Any of steps 2, 3, and 4 can be omitted when using the algorithm, which means that the algorithm can be tailored to use only the

stem properties available in the map. Throughout the present study, step 4 is omitted, as the data used here does not include tree species. The definition of the three parameters of the matching algorithm, and the definition of another key parameter in our simulation approach introduced below (ϵ), are summarized in Table 1.

Test site and harvesting operation

We performed a case study of R-TIM using harvester and remote-sensing data from a real first thinning, with simulations built on top of these. The site of our case study, harvested in October 2024, was in Evo, southern Finland (61°13'N, 25°07' E; ETRS89). The site was densely grown with mixed tree species. In the harvesting, five strips were created to thin the site (Figure 2). The first four strips were approximately 80 m in length, whereas the fifth strip was 50 m in length. According to our LiDAR-based tree maps, the mean DBH in strips 1, 2, and 3, which our work focuses on, was 15 cm to 17 cm. Stem density was approximately 800 stems/ha to 1300 stems/ha or 1300 stems/ha to 2000 stems/ha, depending on tree map, with basal area varying between 21 m²/ha and 29 m²/ha or 33 m²/ha and 42 m²/ha, respectively (Table 2). The harvester was a Ponsse Scorpion with an 11-m boom reach, equipped with the Active Crane high-precision positioning system.

Table 1. Summary of the key variables of the tree matching algorithm and the harvesting simulations.

Variable	Description
R_{max} (m)	Maximum allowed distance from the estimated crane-tip position for candidate tree matches.
ΔDBH (m)	Maximum allowed deviation in DBH from the harvester-measured DBH for candidate tree matches.
Δh (m)	Maximum allowed deviation in height from the harvester-measured height for candidate tree matches.
ϵ (m)	Simulated mean crane-tip positioning error in the easting-northing plane.

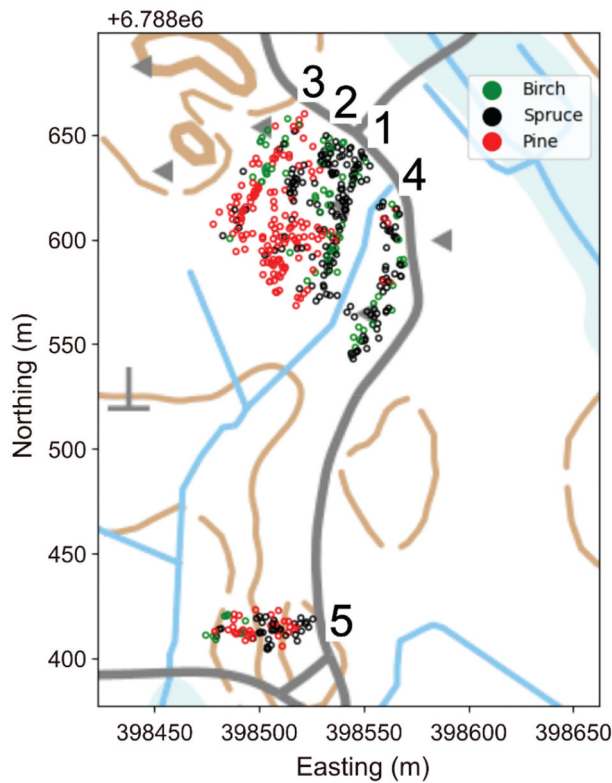


Figure 2. Map view of our case study test site, with the harvesting strips numbered. The colored dots indicate stems harvested and recorded into the HPR file. The background map is the topographic raster map distributed by the National Land Survey of Finland (2023).

Collecting the field data

Ground-based LiDAR

A ground-based LiDAR point cloud was collected prior to harvesting using the Faro Orbis mobile laser scanner (MLS). Faro Orbis features a scanning range of 120 m, a point cloud rate of 640,000 points/s (single return per pulse), and a $360^\circ \times 290^\circ$ field of view. The scanner uses GeoSLAM's simultaneous localization and mapping (SLAM) algorithm for real-time, fully automatic operation. Post-processing into LAS files (.las) was done using FARO Connect.

Harvester data

The HPR data was collected from the harvester computer after the thinning. For each stem, the data included DBH, tree species, and the crane-tip positioning result as EUREF-FIN

latitude, longitude readings. There were a total of 495 stems in the HPR file. The stem positions were projected into planar ETRS-TM35FIN easting, northing coordinates through an exact coordinate conversion.

Post-harvest stump position measurements

To assess the accuracy of the harvester crane-tip positioning system, we returned to the site in November 2024 to measure post-harvest stump positions using manual real-time kinematic (RTK) global navigation satellite system (GNSS) measurements. These reference measurements were carried out using Emlid Reach RS2+ and Trimble R2 receivers.

Our original goal was to measure the position, top-surface diameter, and tree species of all harvester-created stumps at the site. However, this turned out unfeasible, because some of the visible stumps originated from the pre-clearing and manual post-harvest chainsaw work performed at the site, and some stumps created by the harvester were hidden under logging residue, which meant that some visible stumps did not correspond to any record in the HPR file, and vice versa. Accordingly, the objective was reformulated to measure a representative sample of stumps likely to be present in the HPR file. Possible inclusion of non-HPR stumps was later mitigated by manually pairing the post-harvest RTK GNSS reference stump measurements with HPR stump records and accepting only credible matches.

The Reach and R2 receivers were both operated in RTK mode with an elevation mask of 10° , a PDOP limit of 6.0, and simultaneous tracking of GPS, GLONASS, Galileo, QZSS, and BeiDou constellations. The receiver output rate was 1 Hz. For Reach, a fixed RTK solution was typically obtained after a few tens of seconds at most, after which stump positions were recorded while the fix was maintained, usually requiring only a few seconds per stump. For R2, at least 60 s of positioning was collected for each stump.

Strip 1 was measured using R2 only, strips 2 and 3 using both R2 and Reach (with a single, unique positioning result collected per stump), and strips 4 and 5 using Reach only. A total of 168 stumps were measured using R2 and 249 stumps using Reach. Before filtering, the mean lateral RMS was 22 cm for R2 and 9.3 cm for Reach. The R2 measurements were logged directly in ETRS-TM35FIN, whereas the Reach measurements were logged as EUREF-FIN latitude and longitude and converted to ETRS-TM35FIN using an exact coordinate conversion.

Table 2. Stand properties from the two pre-harvest tree maps created from the same Faro Orbis LiDAR data through two different approaches (tree map A, tree map B; see text for details). The corresponding quantities computed for removed stock from harvester data (HPR) from the thinning are also given. The tree map-based stand properties and HPR-based properties for removed stock are given for the three harvesting strips that this study focuses on.

Strip	Species distribution HPR	Min, mean, max DBH (mm)			Stem density (stems/ha)			Basal area (m ² /ha)		
		Tree map A	Tree map B	HPR	Tree map A	Tree map B	HPR	Tree map A	Tree map B	HPR
1	11.6% spruce, 62.3% pine, 26.1% birch	80, 170, 323	33, 163, 509	56, 115, 207	831	1344	431	21.0	32.7	4.9
2	49.4% spruce, 40.4% pine, 10.1% birch	37, 158, 394	22, 154, 580	60, 125, 306	894	1613	556	19.6	36.5	7.8
3	44.4% spruce, 43.5% pine, 12.1% birch	53, 162, 571	25, 150, 540	61, 119, 267	1250	2038	775	29.4	42.1	9.5

Producing tree maps from the point clouds

Two different approaches were used to create a single-tree map from the Faro Orbis point cloud. We name the two resulting maps “tree map A” and “tree map B.” Tree map A was produced using an automated terrestrial laser scanning stem segmentation approach applied to the Faro Orbis point cloud in LiDAR360 (GreenValley International). The workflow identified individual tree stems and derived DBH, height, and position for each tree. Quality control was performed by excluding stems with uncertain DBH estimates and trees with DBH values exceeding 60 cm.

Tree map B, on the contrary, was generated semi-automatically. First, we applied the Cloth Simulation Filter (CSF) algorithm (Zhang et al. 2016) to normalize the original point cloud’s height with respect to the ground. Then, we employed 3DFin to detect individual candidate stems through verticality analysis and clustering (Laino et al. 2024). Missing stems were manually cropped from the original point cloud and added to the automatically generated stem map. Furthermore, we manually split merged trees and removed protruding branches or misclassified point blobs utilizing CloudCompare (Girardeau-Montaut 2024). Despite being manually corrected, the resulting stem point cloud was noisy, which could affect diameter estimation. To alleviate this problem, we denoised the point cloud using the Maximum Consistency with Minimum Distance (MCMD) method with a neighborhood size of 50 points (Nurunnabi et al. 2015).

For each stem, we extracted 10 cm thick slices at 1.3 m height to fit circles as described in Prendes et al. (2021). These circles served to estimate stem diameter and position. Whenever slices had less than 50 points, we increased the slicing height by 10 cm until we found enough points. In case no valid slice was found upwards, we repeated the process

slicing the stem downwards. When no valid slice was found at any height, we considered the average side length of the bounding box enclosing the stem point cloud as the diameter. In such cases, the center coordinates of the fitted circle were obtained as the average x, y coordinates of the stem points. These diameters were deemed unreliable.

For each fitted circle, we cropped a cylinder with identical radius plus 0.5 m around its center from the original, height-normalized point cloud. Next, we voxelized the cylinder point cloud with a voxel size of 5 cm. We then estimated tree height by computing the 99th percentile of the cylinder point cloud z dimension. As in the case of tree map A, the resulting tree map consisted of DBH, height, and position for each detected tree. To remove uncertain trees, we filtered the map by removing all stems with no valid slice found, sector occupancy < 30% (Laino et al. 2024), number of inner points > 30 (Laino et al. 2024), or DBH > 60 cm. For a view of the two tree maps and examples of differences between the two, see Figure 3.

Evaluating the accuracy of the harvester crane-tip positioning system

To identify reliable pairs of post-harvest stump position reference measurements (R2, Reach) and the corresponding HPR stump positions, we took the following approach. First, the R2 and Reach data were filtered to remove unreliable positioning results. This meant only including positions with a fix solution and lateral RMS at most 10 cm. After this process, a total of 193 Reach and 78 R2 stump positions remained.

We then plotted the manual RTK GNSS stump positions along with tree species and stump diameter in the easting, northing plane in same plot with the HPR stump positions, species, and stem DBHs. Using these plots, we manually

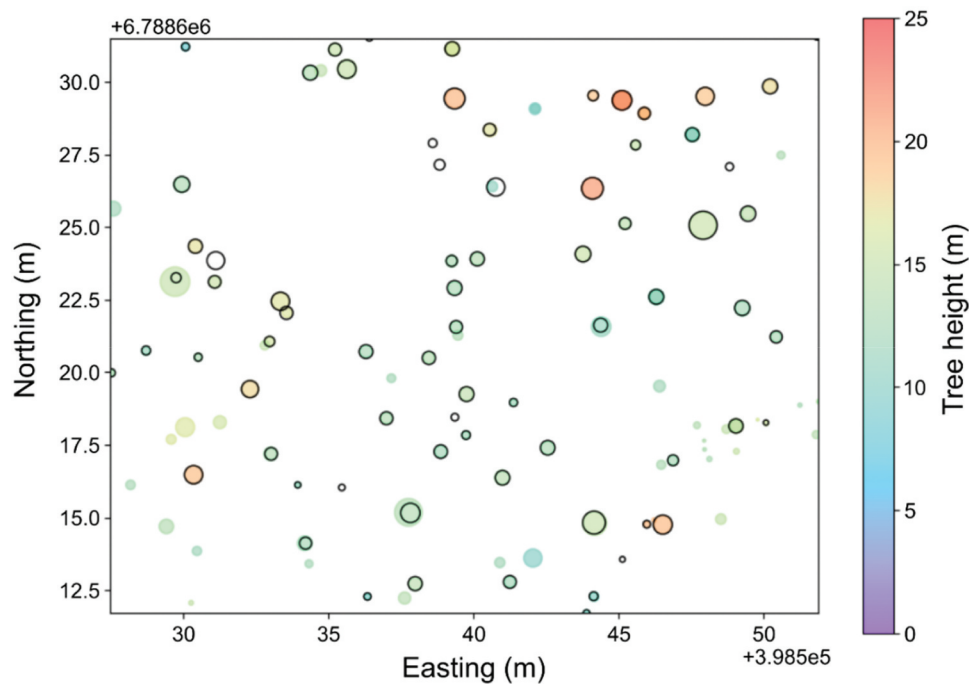


Figure 3. Close-up visualization of tree map A (black circles) and tree map B (filled circles). Symbol size indicates DBH for both maps. Color indicates height for tree map B.

assessed the neighborhood of each manual stump measurement (For an example, see Figure S1 in the Supplementary Material). If an HPR stump whose position, species, and stem DBH indicated a likely match to the manual measurement in question was found, the two were designated a pair. If no credible match was found, the manual measurement was discarded. This process resulted in a total of 173 HPR stem to post-measured stump pairs, of which 124 were positioned using Reach and 49 using R2.

Once the pairs had been formed, the error of the harvester crane-tip positioning system was estimated by considering the manually measured positions as the reference positions. The mean positioning error and standard error of the mean were computed separately for the sets of Reach and R2 measurements as well as the pooled measurements.

Analyzing the tree matching algorithm

Since the tree matching algorithm is a core component of R-TIM, we analyzed the algorithm in detail before implementing

the full R-TIM concept in simulated harvesting. The goal was to study how optimal algorithm parameter values and the accuracy of tree matching depend on crane-tip positioning error. In addition, we wanted to assess how useful each stem feature beyond position available in our tree maps (DBH, height) was in achieving successful matches. To accomplish this, we first divided the northern part of tree map A into a training and test dataset. Moreover, to gauge how sensitive matching performance is on stand properties, we formed another test set from tree map B. These spatial train-test splits of the two tree maps are visualized in Figure 4. For a more detailed comparison of the datasets, stand properties for the two test sets are summarized in Table 2, and DBH and height distributions for all three datasets are presented in Figure 5.

Then, using a grid search (Bischi et al. 2021) with $R_{\max} = 0.1, 0.5, 1.0, 2.0, 3.0, 5.0, 10.0, 15.0, 20.0, 50.0$ m, $\Delta DBH = 0.01, 0.02, 0.03, 0.05, 0.10, 0.20$ m, and $\Delta h = 1.0, 2.0, 3.0, 5.0, 7.0$ m for each value of mean lateral positioning error ε in 0.01, 0.025, 0.05, 0.10, 0.25, 0.50, 0.71, 0.75, 1.0, 1.5, 2.0, 2.5, 3.0, 4.0, 5.0 m, for each combination of tree attributes leveraged in the

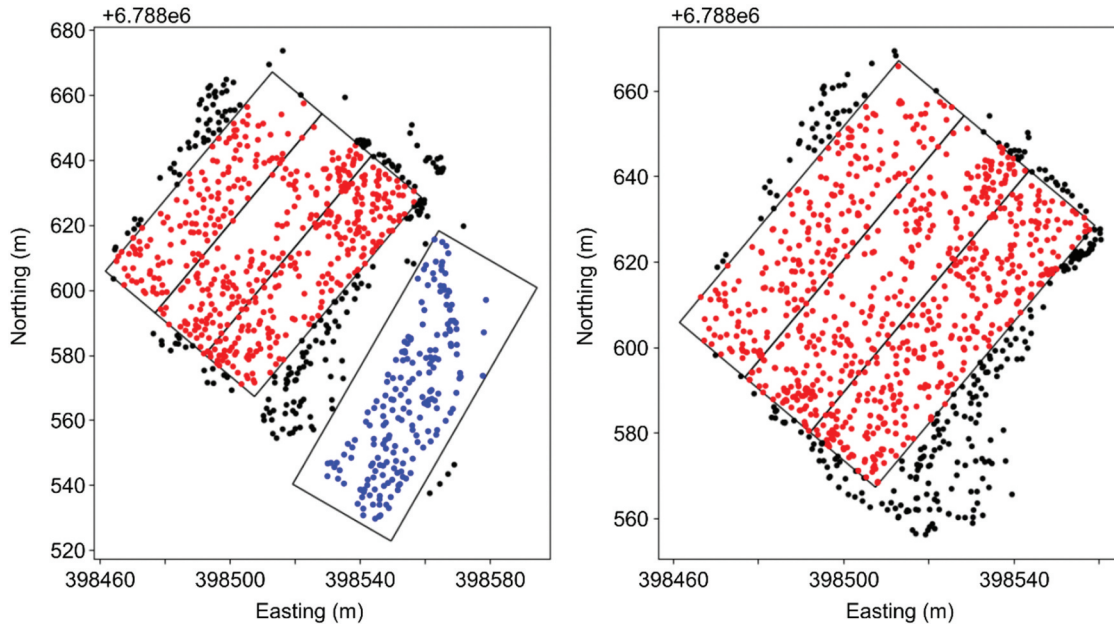


Figure 4. The train-test split of tree map A for optimizing and evaluating the tree matching algorithm. The test data is in red, the training data is in blue (left). The test data of tree map B, shown in red, for evaluating the matching algorithm (right).

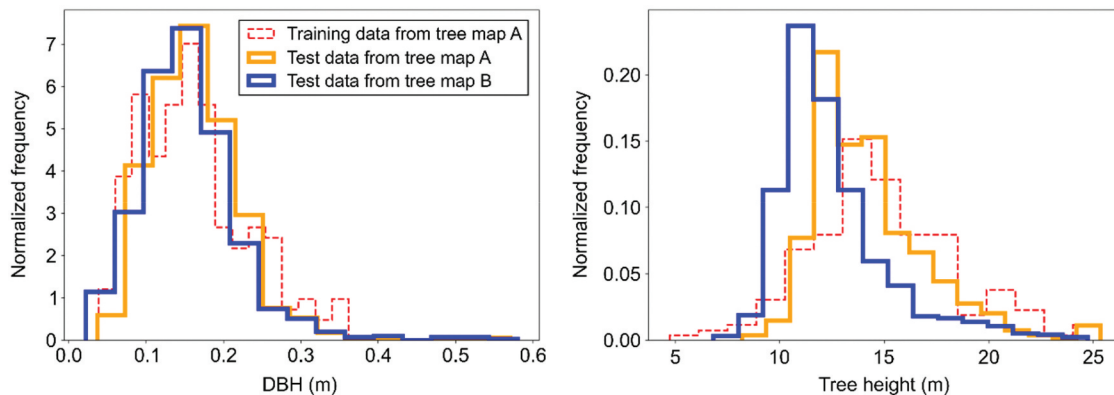


Figure 5. DBH (left) and height (right) distribution of the tree map A training and test datasets and the tree map B test set.

matching (position; position and DBH; position and height; position, height, and DBH), we found the optimal matching algorithm parameters on the training data. The values of ϵ include 0.71 m, which was the empirically found crane-tip positioning error as described below. We performed the optimization by running a “uniform harvesting simulation” for each case. The principles of this simulation were the following.

Before starting the simulation, two copies were made of the tree map: the “ground-truth” copy and the “R-TIM” copy. In our simulation, the ground-truth (GT) tree map was taken to be the true description of the stand, comprising all stems and their true position, height, and DBH values. This tree map was used to generate the simulated harvester data. In this generation process, the crane-tip position was simulated, at the time of felling the stem, by adding a 2D normally distributed random error to the true position of the tree. The DBH and height of the tree were read directly from the tree map.

The R-TIM tree map is the digital twin that the harvester updates during harvesting. In our simulation, this represents the map created prior to harvesting. To simulate the deviation of tree attributes in such a tree map from the GT, we added a uniformly random error to the DBH and height value of each tree in the R-TIM tree map before the harvesting. For stem positions in the R-TIM map, we used the GT positions. In the simulation, when the harvester felled a stem, the harvester data was used to find the best-matching tree in the R-TIM tree map. This “uniform harvesting simulation” is described formally in the Supplementary Material.

The grid search was repeated a total of 100 times, due to stochasticity in creating the simulated errors. The optimal parameter values, i.e. values that gave the highest mean accuracy, were saved from each repetition. At each value of ϵ , the mean of these for each parameter was taken as the optimal value.

After optimizing the parameters on the training set (tree map A), the matching algorithm was evaluated on the two test sets (tree map A, tree map B) by performing a uniform harvesting simulation using the optimized parameters. In these evaluations, each case was repeated a total of 100 times due to stochasticity.

Demonstrating R-TIM

To demonstrate the full R-TIM concept, we performed the following set of simulations. We defined three harvesting strips into the northern part of tree map A. These strips exactly match the test data region of tree maps A and B (Figure 4), and they resemble the strips 1, 2, and 3 used in the actual harvesting (Figure 2). For each strip, we performed an “R-TIM simulation” as follows (Figure 6).

We set down a rectangle of 7 m by 20 m at the start of the strip. This we call the “thinning window.” The central 4.5 m region of the 20 m width of the thinning window describes the strip road opened by the harvester (“central region”), and the two 7.75 m wide sections on each side describe the areas from which trees are thinned (“outer region”). The thinning window is moved in steps of 7 m along the strip to follow the simulated movement of the harvester. Furthermore, at each position of the thinning window, we set down a rectangle 20 m in width,

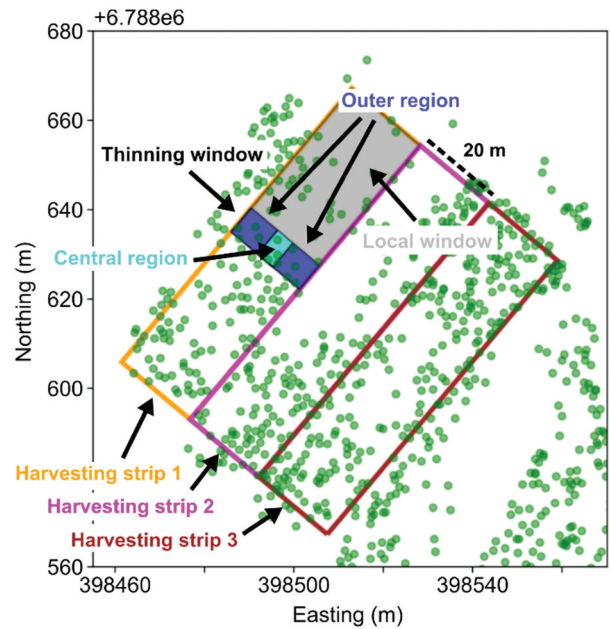


Figure 6. The “R-TIM simulation” setup. The central region and the outer region form the thinning window. In the simulation, the window is moved in steps from the beginning to the end of the harvesting strip. At each step, all trees are first harvested from the central region. Then, all trees with DBH < 11 cm or DBH > 24 cm are harvested from the outer region. Thinning intensity metrics are continuously computed in the local window from the simulated harvester data and the ground-truth and R-TIM tree maps.

reaching from the thinning window foremost edge to the beginning of the strip. During harvesting, R-TIM reports TI metrics in this “local window.” A formal description of this “R-TIM simulation” and the computation of all TI metrics is given in the Supplementary Material. The simulation was performed using $\epsilon = 0.71$ m, which corresponds to the empirically found crane-tip positioning error.

Reliability of TI metrics

As tree matching accuracy was found to strongly depend on mean crane-tip positioning error ϵ , it was of interest to study how the accuracy of R-TIM-based TI metrics depend on ϵ . The goal was to estimate whether modern crane-tip positioning accuracy is enough to enable R-TIM to produce reliable estimates of TI metrics. To achieve this, we made 100 repetitions of the R-TIM simulation at each value of ϵ used in the tree matching analysis (Sec. “Analyzing the tree matching algorithm”) again due to stochasticity. For each repetition, we computed the mean and maximum absolute difference between R-TIM and GT basal area over the full simulation. These were then averaged over the repetitions, and the standard error was computed for the means, yielding the deviation of basal area between R-TIM and GT as a function of ϵ . In addition, the corresponding relative deviations were computed.

Results

Harvester crane-tip positioning accuracy

The error distributions of harvester-measured stump positions differed somewhat depending on whether Reach or R2 was

used as the reference (Figure 7). The mean of the positioning error was 0.61 ± 0.03 m for Reach-measured stumps and 0.95 ± 0.08 m for R2-measured stumps. When the Reach and R2 measurements were pooled, the mean of the positioning error was 0.71 ± 0.03 m. The mean error vector was $(0.13 \pm 0.04, 0.14 \pm 0.05)$ m, i.e. there is a slight bias into the northeast.

Tree matching algorithm analysis

For all combinations of tree attributes leveraged in the matching, the optimal values of $R_{\max}$, ΔDBH , and Δh reflected the deviation between harvester-based and corresponding tree map-based tree properties. The higher ε , the higher the optimal $R_{\max}$. Optimal choices of ΔDBH and Δh were close to the simulated discrepancy between the harvester measurements and R-TIM tree map attributes. Candidate matches in the R-TIM tree map should, therefore, optimally consist of trees within the actual range of deviations between harvester measurements and tree map attributes. To illustrate these optimization results, an example is presented in Figure S2 of the Supplementary Material.

Matching accuracy on the test data of tree map A is somewhat lower than on the training data (Figure 8), possibly reflecting slight overfitting or differences in tree attribute distributions between the two datasets, in particular height (Figure 5). Large differences are seen in performance between different combinations of features used in the matching. DBH appears to be more useful than height in matching, possibly because height appears to differ more strongly than DBH between the training and test set. Using all available features, accuracy on the tree map A test set stays well above 85% up to $\varepsilon = 1$ m. On tree map B, matching accuracy is significantly lower than on tree map A. This was to be expected, as the parameters were optimized on the training data of tree map A, and tree map B has a different spatial structure and attribute distribution (Table 2, Figure 5).

R-TIM demonstration

In the R-TIM demonstration (Figure 9), the final basal area and stem density for all three strips, both for GT and R-TIM, settle

to values less than the nationally recommended target values (Tapio 2025) computed for a pine-birch mixture (strips 1 and 2) or pine-spruce mixture (strip 3) and interest rate of 3% using mean tree height from the GT tree map. The reason for this is likely two-fold. First, the spatial ordering of trees is not considered in the simulation, in that thinning would be focused on dense clusters of trees. Instead, thinning is conducted purely according to DBH limits. Second, the three strips had fairly low GT tree map basal area (21.0, 19.6, 29.4 m²/ha, respectively) and stem density (831, 894, 1250 stems/ha, respectively, Table 2) at the time of starting the simulation. This is largely because of the difficulty of estimating DBHs from the point cloud and the subsequent discarding of many trees when filtering the tree map (Sec. “Producing tree maps from the point clouds”). Moreover, the real-life strips contained large open areas, which were captured into the tree map (Figure 4). We emphasize that this demonstration represents how R-TIM would report TI metrics continuously during thinning, for the given stand and tree map, in a scenario of performing tree selection solely based on DBH. In Figure 10, we present the time series for key TI metrics, also for removed stock, as computed in the R-TIM demonstration.

Reliability analysis

Both the maximum and mean deviation of R-TIM-reported standing stock basal area with respect to the ground truth follow a nearly linear trend as a function of ε (Figure 11). When $\varepsilon < 1$ m, the mean deviation between R-TIM and GT is less than 0.5 m²/ha or 5%. In this range of positioning error, the maximum difference is approximately 2 m²/ha or 15% to 20%.

Discussion

Crane-tip positioning error and R-TIM

The empirically found crane-tip positioning error of 0.71 ± 0.03 m is in fair agreement with earlier studies on high-precision crane-tip positioning systems, which have found errors of approximately 0.5 m (Skogforsk 2025; Ylä-Pöntinen et al. 2025). The error found here is slightly higher, possibly

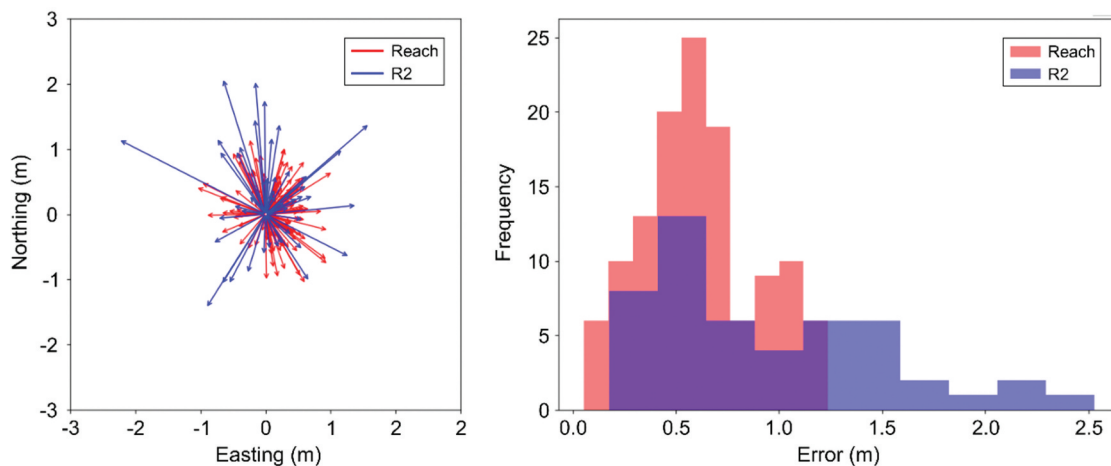


Figure 7. Harvester crane-tip positioning errors with respect to the manual RTK GNSS reference measurements, presented as vectors from manual to HPR positions (left) and histograms of error magnitudes (right). Errors when considering R2 the reference tend to be larger than in the case of Reach.

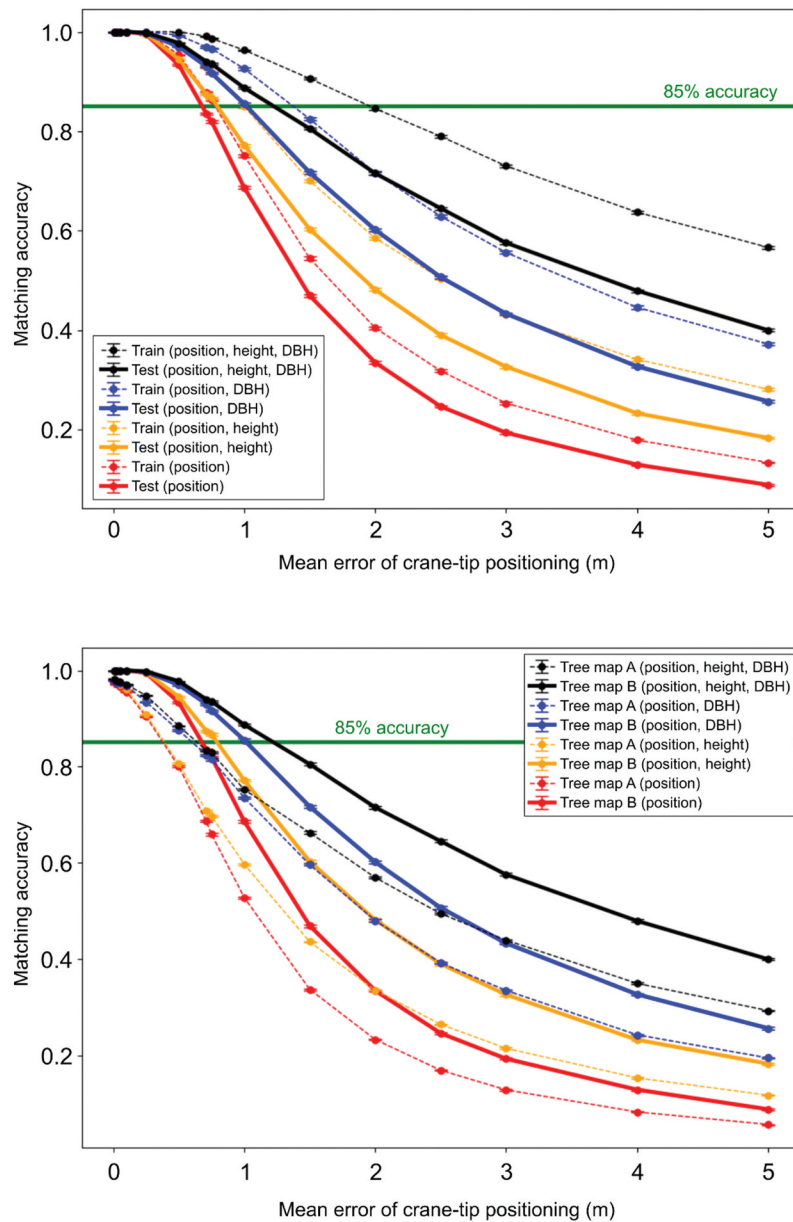


Figure 8. Tree matching accuracy as a function of simulated mean crane-tip positioning error (ϵ). Results on tree map A (top), and results on tree map A and tree map B (bottom). The error bar is the standard error of the mean over simulation repetitions performed due to stochasticity. The matching algorithm parameters were optimized on tree map A training data before evaluation on the two test sets (tree map A, tree map B). With positioning errors < 1 m, accuracy on the tree map A test set stays above 85% (green horizontal line).

due to relatively dense stand structure (although the produced tree maps were fairly sparse, Table 2). Another explanation could have been the switching of the geodetic datum of harvester-based stump coordinates away from EUREF-FIN during harvesting due to RTK positioning failing, but this appears a negligible effect given that the GNSS logs indicate the coordinates being logged in EUREF-FIN for 99% of the time.

The estimate 0.71 ± 0.03 m includes both the R2 (0.95 ± 0.08 m) and Reach (0.61 ± 0.03 m) measurements. The higher error obtained when using R2 as the reference may be explained by receiver-dependent behavior in obstructed environments. R2 uses an advanced Trimble Maxwell 6 GNSS chip, high-precision multiple-correlator pseudorange measurements, unfiltered and unsmoothed pseudorange data for low multipath error, Trimble EVEREST multipath signal rejection,

and Trimble Floodlight satellite shadow reduction for difficult GNSS environments (Trimble 2026). The Reach RS2+ is specified as a multi-band RTK GNSS receiver with a multi-feed antenna with multipath rejection (Emlid 2026). Thus, the two receivers use different hardware and signal-processing approaches in obstructed GNSS environments. Under dense canopy, both receivers may record observations contaminated by multipath signals, contributing to positioning error (Danskin et al. 2009), and the two different strategies for rejecting multipath signals may have led to the observed difference (0.95 m vs. 0.61 m). This would imply that the true crane-tip positioning error is lower than 0.71 ± 0.03 m. In support of this explanation, spatial analysis revealed that the larger mean and wider distribution of errors when using R2 measurements does not appear to be due to stand structure.

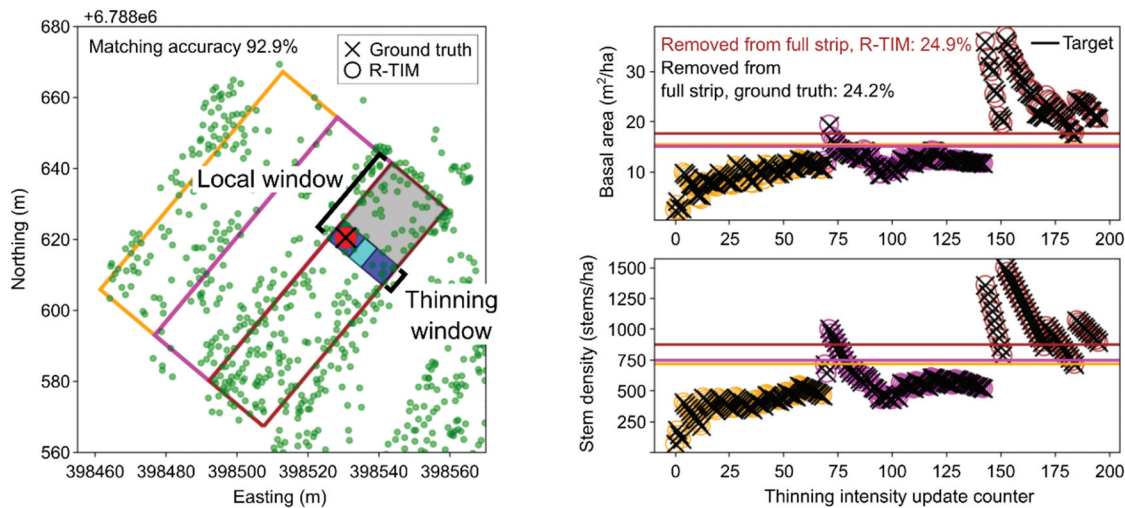


Figure 9. Snapshot of the “R-TIM simulation” visualization. On the left, the thinning window and local window are shown on top of the ground-truth tree map (green dots). The cross (x) shows which tree is harvested, and the red dot shows the location of the tree that R-TIM believes is being harvested. Matching accuracy is reported from the start of the entire simulation. On the right, continuously updated thinning intensity metrics in the local window are shown, color-coded by harvesting strip. The crosses (x) are ground truth, the hollow circles are R-TIM results. Target values for basal area and stem density were obtained from the national forest management recommendations in Finland (Tapio 2025) and are shown as horizontal lines (color-coded by harvesting strip).

In our R-TIM simulations, with mean crane-tip positioning errors less than 1 m, the basal area estimates stay, on average, within $0.5 \text{ m}^2/\text{ha}$ of the true value, and tree matching accuracy stays above 85%. These results suggest that R-TIM can provide reliable TI metrics when used in modern cut-to-length harvesters with high-precision crane-tip positioning systems together with accurate tree maps, thereby addressing the pressing need for decision and reporting support in first thinnings in the Nordic countries.

Benefits of R-TIM with respect to alternative solutions

R-TIM is based on a single-tree map collected prior to harvesting. This makes it possible to choose good conditions for collecting the necessary point-cloud data and using abundant computing resources for turning this into a tree map. After harvesting begins, the only new data collected are the harvester-based stump position estimates and stem measurements. Together, these aspects make R-TIM robust to operating conditions. In addition, no new instrumentation is required on the harvester. These are benefits with respect to approaches utilizing LiDAR scanners on board the harvester (e.g. The TDA and NFA R1 concepts).

Moreover, TI metrics are computed directly from the digital twin and the harvester data with no need for further modeling. These, in turn, are benefits with respect to approaches utilizing further computations or modeling in constructing properties of the remaining stand (hprGalling, Tarvainen et al. 2025). Methods relying on estimating remaining stock properties from trees felled when creating new strip roads are applicable only in first thinnings (Tarvainen et al. 2025). We also note that the same high-resolution point-cloud collected for R-TIM can be used for several other purposes, such as detecting tree damage (e.g. stem breakage due to snow and wind), identifying no-go areas with high nature values, or assessing the risk and cost of entering with machinery.

Practical considerations and limitations

Based on our results, the R-TIM concept is a promising approach to assisting harvester operators in monitoring key TI metrics and complying with target TI at the harvesting site. Our present results are, however, conditional to the simulation setup, including the simulated errors between harvester-based and tree map-based tree attributes and positions.

Moreover, in real use, the reliability of R-TIM-based TI metrics for standing stock and thinning percentage is strongly dependent on the fidelity of the pre-collected tree map (Table S1, Supplementary Material). Improving the accuracy of these metrics can be achieved “off-line” by increasing the quality of point-cloud data collection. However, while assumed in our simulations, acquiring a pre-harvest tree map with exactly one entry for each real stem in the forest is currently not possible for most types of stands in Finland, nor in many cases outside of Finland. This is an important constraint of the R-TIM concept and must be considered when developing the concept toward operational use.

A further limitation in applying R-TIM is that high-fidelity tree maps will, at least in the near future, likely require MLS (as used in the present work) to obtain sufficiently dense and accurate data for creating useful pre-harvest tree maps, with aerial laser scanning (ALS) resulting in too many missed trees for most stand types. Collecting MLS data is, as of today, time-consuming and costly, which are disadvantages with respect to TI monitoring approaches utilizing harvester-mounted MLS (TDA, NFA R1) or only standard harvester data (hprGalling, Tarvainen et al. 2025). Future progress in LiDAR technology and analysis methods will likely alleviate this problem.

In the current implementation of the tree matching algorithm, no action is taken if no candidates remain after DBH and height filtering. An alternative option would be to add the harvested tree to the pre-harvest map to increase the

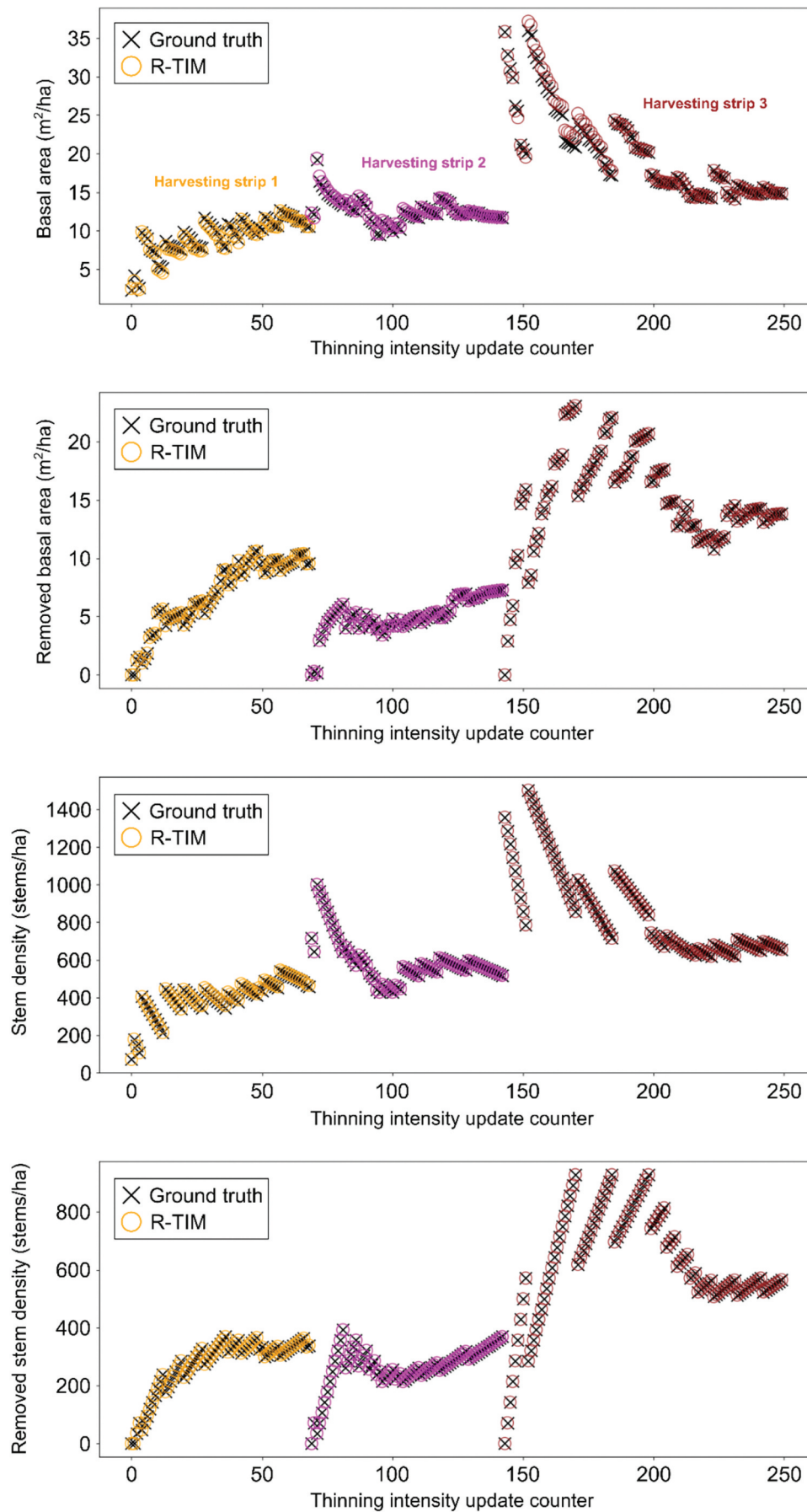


Figure 10. Key thinning intensity metrics computed in the local window, i.e. from the start of the strip up to the harvester position, during the R-TIM simulation.

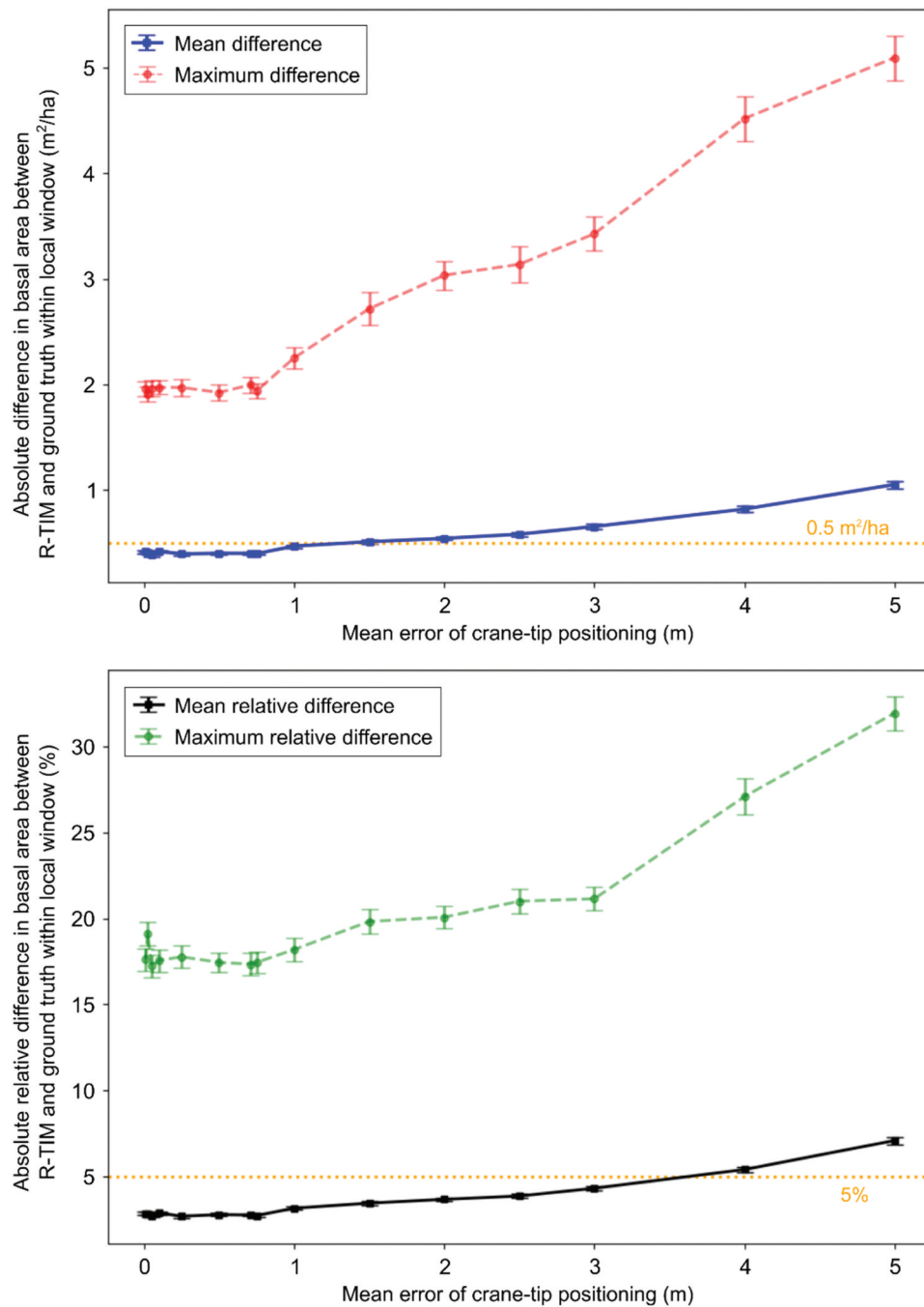


Figure 11. Mean and maximum deviation of R-TIM-reported basal area of standing stock from the ground truth in the “R-TIM simulation” (top). The corresponding quantities for the relative deviation (bottom). These quantities were computed in the local window, i.e. from the start of the strip up to the harvester position, over each separate simulation. The error bar is the standard error of the mean over simulation repetitions performed due to stochasticity. With positioning errors < 1 m, the mean basal area deviation is below 0.5 m²/ha and the mean relative basal area deviation is well below 5% (orange dotted lines).

accuracy of the thinning percentage estimate. This action would be beneficial if the tree really was missing from the map, but detrimental if the tree was already in the map but escaped detection by the matching algorithm. In the ideal case that all trees are included in the pre-harvest map, when DBH and height filtering result in no candidates, taking the tree closest to the harvester-based stump position as the matching tree could be the best option. This ideal case of 100% of trees being represented in the pre-harvest map was assumed in our simulations, but our matching algorithm

functioned on the former, more generally applicable principle.

In scenarios where reliable tree matching can be achieved, such as with very low mean positioning error, there is the prospect of using on-line learning to determine the deviations between tree map-based and harvester-based stem properties. These deviations could then be corrected during harvesting to increase accuracy of the tree map. This process would be similar to using field measurements to calibrate models linking remote-sensing measurements to tree attributes. The

correction of tree map attributes might not require more than a handful of reliably matched trees (Jääskeläinen et al. 2024).

As only matches of high confidence were considered when forming the pairs of manual and HPR stump positions, there is a possible bias in the pairing procedure toward spatially close-lying pairs, which might lead to underestimating the harvester-based stump positioning error. To attain a less biased sample of harvester and GT measurements, the stems to be harvested should be, e.g. marked and numbered and their order of felling recorded during future harvesting tests. We note also that the harvester stump positioning errors determined here and in corresponding previous assessments (Skogforsk 2025; Ylä-Pöntinen et al. 2025) include error due to the harvester reporting the crane-tip position and not the center of the harvesting head for each stump. This error source may be diminished through future developments. The error vectors of crane-tip positioning in our results (Figure 7) are slightly biased into the north-eastern sector of the plane, possibly due to this effect.

Our tree matching algorithm is based on absolute criteria for the allowed position, DBH, and height deviation between the harvester measurements and tree map. This choice was made primarily for robustness, transparency, and ease of implementation. Conveniently, it can be assumed that the approximate deviations between harvester measurements and tree map are known beforehand from existing field work, which makes it possible to set these parameters close to their optimal values (Sec. “Tree matching algorithm analysis”). In our results, height was less useful in the matching than DBH (Figure 8). Height distributions of the training and test data appeared to differ more than the corresponding DBH distributions (Figure 5). Furthermore, matching accuracy on the test set of tree map A was clearly higher than on tree map B, which differed in both spatial and tree properties from tree map A. These observations highlight the importance of setting the parameters to reflect the true attribute deviations between harvester-based and tree map attributes.

Broader implications for forestry applications

By providing continuous, spatially explicit feedback on TI and remaining stand structure, R-TIM could support operators in maintaining target thinning levels across heterogeneous stands, potentially reducing over- and under-thinning. In this sense, the system is not intended to replace operator expertise, but instead to complement it by making key stand-level indicators visible during decision-making. Moreover, subjective and sample-based manual reporting could be replaced by a more accurate, continuous, and automated R-TIM system.

R-TIM also has potential value as a training and learning tool. A digital twin that is updated in real time during harvesting could be used in operator training environments or simulators to illustrate how individual tree-selection decisions accumulate into stand-level outcomes. Such feedback could help operators better understand the longer-term silvicultural consequences of thinning choices and improve consistency across operators with different experience levels.

More broadly, the concept aligns with ongoing developments in digital silviculture and forest digital twins (Döllner et al. 2023; Qiu et al. 2023). If integrated with stand-level planning tools and optimization models, R-TIM could serve as a link between pre-harvesting planning and on-site operational execution, enabling comparisons between planned and realized thinning outcomes. In the longer term, such integration could support adaptive planning, post-harvest evaluation, and data-driven refinement of thinning guidelines, thereby extending the impact of R-TIM beyond real-time monitoring toward more holistic decision-support across the forest management workflow.

Future development of R-TIM

In our R-TIM simulations, trees were selected for removal purely based on DBH. This simple removal criterion was chosen at this first stage of validating the R-TIM concept. To make the simulation more realistic, the spatial ordering of trees should be considered by focusing thinning on dense parts of the stand and performing less thinning in sparse parts. In addition, instead of a rectangle (Figure 6), a curved thinning window should be simulated to better correspond to the harvester boom reach.

Future work should also include practical validation of R-TIM in field tests using only real harvester data. This would require integrating the method into the harvester measurement feed or the HPR data creation process to obtain the required real-time harvester measurements. The practical value of R-TIM will ultimately be determined by how useful harvester operators perceive such a system. Therefore, a user feedback study is an essential part of future work.

Other strategies could be considered for tree matching in future developments. For example, probabilistic or Bayesian approaches could replace hard thresholds with likelihood-based ranking of candidate trees, explicitly accounting for uncertainty in crane-tip positioning and tree attribute estimates. Such methods could better handle ambiguous situations by assigning confidence levels to matches or by propagating matching uncertainty into the reported TI metrics.

Machine learning-based matching approaches represent another potential direction, especially if larger datasets of reliably matched harvester and tree-map stems become available. Supervised or metric-learning methods could learn stand-specific relationships between spatial proximity and tree attributes and might improve matching performance in dense or structurally complex stands. However, the need for labeled training data, model transparency, and predictable behavior in operator-assistance systems currently limits the practical adoption of such approaches.

From an operational perspective, real-time computational constraints are important. The current rule-based algorithm is lightweight, deterministic, and well suited for real-time execution within existing harvester computing environments. While more advanced probabilistic or learning-based methods are not inherently incompatible with real-time use, their

deployment would require careful evaluation of latency, robustness, and system integration. In this sense, the present matching algorithm should be seen as a pragmatic first-order solution, with uncertainty-aware or learning-based extensions forming a natural avenue for future research.

Conclusions

In this work, we introduce, assess, and demonstrate the R-TIM concept for real-time monitoring of thinning intensity in cut-to-length harvesting operations for operator decision support and reporting purposes. R-TIM is based on updating a pre-collected, point cloud-based single-tree map of the stand during harvesting via an algorithm that matches harvester measurements with the corresponding stems in the map. Evaluation of the concept using a case study of simulations and real forest data indicates that when mean crane-tip positioning error stays below 1 m, tree matching and basal area monitoring are performed at better than 85% and 0.5 m²/ha accuracy, respectively. In our field tests, we find a mean error of 0.71 ± 0.03 m for harvester crane-tip-based stump positioning, broadly in line with earlier studies. The major challenge in successfully implementing R-TIM in practice is the creation of high-fidelity tree maps. Regardless, R-TIM is a promising approach to assisting machine operators in reaching desired thinning intensities and providing automated thinning reports in cut-to-length harvesting. Field validation using real harvester data over varied forest types and integration into the harvester processing pipeline constitute the core of future development of R-TIM.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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