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A Digital Twin Approach to Integrating Silviculture into Harvester Simulator Training

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Abstract

Forest machine simulators have been an integral part of forest machine training for several decades. However, the primary focus of this training has been on developing technical machine operation skills, while less emphasis has been placed on environmental and silvicultural competencies.

In this paper, we introduce new teaching modules that extend training beyond purely technical machine control, enabling the simultaneous development of operational skills and silvicultural decision-making. This is achieved through the use of digital twins of forest stands.

We present the methodologies used to capture individual tree data and terrain topography from drone-based inventories and to convert these data into a format compatible with a harvester simulator. We then demonstrate three new teaching modules in which trainees learn climate-smart management of forest edges, selection cutting in uneven-aged stands, and harvesting on erosion-prone steep slopes. In addition, we show how harvester operations can be supported by auxiliary data layers visualized through the onboard harvester computer.

We argue that digital twinning of forest sites can elevate harvester simulator training to a new level by integrating environmental and silvicultural considerations into machine operation. Furthermore, it provides an efficient testbed for evaluating which types of map layers most effectively support tree selection, operator training, and the management of information overload in operational settings.

Keywords: Extended Reality, forest operation, forest visualisation, simulator training

1. INTRODUCTION

Increasingly strong and versatile expectations are imposed to forest sector by society. Forests play a major role in the fight against climate change and biodiversity loss. Their ecosystem services contribute to our health and well-being through water regulation and provision of drinking water, provision of food, medicines and materials, risk reduction and control of natural disasters, soil stabilisation and erosion control. Moreover, forests are a place for recreation, relaxation and learning as well as an important part of human livelihoods and well-being, while at the same time providing decent work and income to people (European Commission 2021).

The mindset how we approach forest management operations are also subject to significant change. Forest stands are not anymore considered as homogenous treatment units expressed with mean values rather forest management decision making should also take into account the degree of forest heterogeneity affected by the variation of soil properties, topography and natural disturbances. This approach is strongly emphasized also in the new Closer-to-nature forest management principle proposed as the one of the key concepts of the new EU strategy (Larsen et al. 2022). The new concepts emphasize especially two objectives: Increase of structural complexity; and promotion of natural forest dynamics (European Commission 2023).

Forest harvesting in boreal ecosystems is increasingly shifting from stand-level optimization toward more refined, tree-by-tree decision-making. Precision harvesting encompasses the tools and methodologies that enable forest managers and machine operators to implement precision forestry principles in everyday practice. Modern forest machines are equipped with an information system that integrate GNSS positioning, machine control systems, and mapping platforms as an integral component of the wood supply information flow. In recent years, a rapidly expanding array of data layers has emerged, offering valuable support for tasks such as tree selection (Mao et al. 2025), biodiversity conservation (Niemi et al. 2026), soil and water protection (Salmivaara et al. 2020; Ågren et al. 2021; Hoffmann et al. 2022; Abdi and Uusitalo 2026), and the efficient planning of logging trail networks (Abdi et al. 2022b).

Since adoption of GIS in Forestry in 1980's, visualization has been seen as a powerful tool to assess forest practitioners in decision making (Orland 1994). Three different approaches or use cases were distinguished in the pioneering works (Orland et al. 2001; Uusitalo and Orland 2001). First, accurate depiction of variation of forest landscape by diagrammatic and schematic visualisation were regarded as an efficient and easily comprehensible mean to augment managers in decision-making. Second, visually more realistic forest environment could be depicted with extensive libraries of digitally edited photographic images; and these types of visualization could then be utilized in assisting decision making in aesthetically valuable destinations (lakeshore, mountains, recreation areas, etc.). Third, linked with highly advanced dynamic planning models or systems, forest visualization could support decision makers to foresee how forest evolve thorough time. The pioneering forest visualization applications generated the forests in quite abstract level. Trees in each forest stand were derived from inventory-based mean stand parameters by imputing "surrogate trees" and placing them spatially randomly over the forest stand (Uusitalo and Orland 2001).

As time has passed and technology developed forest visualization concept has been enriched with new features and concepts. The development in photogrammetry, Lidar technology, Artificial Intelligence (AI) has potential to deliver very precise and photo-realistic environments (Murtiyoso et al. 2024) and the users augmentation can further be complemented with XR (Extended Reality) or multiple screens. The realism has gained a level that even visits in virtual forests has been reported to alleviate mental stress similarly to real forest environment (Mattila et al. 2020; Hejtmánek et al. 2022). Moreover, visualisation has been seen as

powerful tool to communicate environmental effects of climate change in forest environment (Huang et al. 2021).

The precision how virtual trees represent real forest is continuously improving. Trees in forest visualization application may be reality-based or design-based. In reality-based virtual forest trees with their exact height, diameter, tree species, location and even some quality features are derived from real forest (Iwaszczuk et al. 2023). In design-based forest visualization approach the main focus is on the physical assets of each tree. Virtual reality may be utilised for example as an efficient tool to describe outcomes of ecosystem modelling (Chandler et al. 2022). Recently, there has been many attempts also to combine reality-based and design-based approaches. Since even the most advanced scanning methods cannot detect perfectly all features of tree components (e.g. stem, branches, leaves) a virtual tree can be predicted by combining single tree parameters with allometric modelling techniques, such as quantitative structure modelling (Raumonen et al. 2013; Brede et al. 2022; Dalla Corte et al. 2022; Wang et al. 2022).

Terminology related to virtual forest is also enriching. While the earliest works widely used the terms forest visualization or virtual forest, there is now a growing trend to replace these words with the digital twin of forest (Wang et al. 2022; Murtiyoso et al. 2024; Tam et al. 2025). Digital twinning, being an important and emerging trend in many applications, is generally regarded to comprise not only visual components but also meaningful linkage between visual assets and physical assets behind the object (Rasheed et al. 2020; Batty 2018; Lapointe and Robert 2000). In forest visualisation context it means that digital twin forest does not only look like a forest, but it is an exact replica of real forest with exactly same topography and trees with right tree species, diameter, height and essential quality features; and which then enables tree data to be linked with relevant growth conditions and functions. In ideal case, all important components of forests, such as grassland, shrubs, bushes and small trees should be digitally scanned, modelled and constructed (Iwaszczuk et al. 2023).

Forest machine simulators are definitely one of the most widely employed branches of forest visualization. The forest machine simulators have been an integral part of forest machine training for already many decades (Lapointe and Robert 2000; Ovaskainen 2005; Ranta 2009). The simulator environment has been shown to act similarly to real forest machines in most important respects and are thus an excellent tool to support forest machine trainee and skilled operators in their learning (Ovaskainen 2005). The best learning results will be achieved when simulator training is linked with theoretically based curriculum structure (Ranta 2009; Wenhold et al. 2020). The main motivation behind forest machine training is cost saving in machine operator training (Burk et al. 2024; Polowy and Rutkowski 2024; Tam et al. 2025), but forest machine simulators have shown to work also as a test-bed in comparing various working techniques (Ovaskainen et al. 2011).

The forest machine simulators commercially available today are equipped with the exact same seats, joysticks, and control systems as those found in real machines. The simulators typically use 3D graphics and physics engines to simulate the location and characteristics of trees, logging equipment, terrain conditions, and other objects in a predefined virtual environment.

A high level of immersion can be achieved through multiple displays or VR headsets. However, the default visualizations used in harvesting simulators often fail to represent the specific characteristics of individual forest stands. Typically, these environments are based on broad generalizations of tree species, terrain conditions, and soil types, and therefore do not capture the variability and complexity of real-world stands. As a result, while trainees can learn the technical aspects of tree processing, the integration of silvicultural knowledge into training remains limited.

In this paper, we introduce a novel harvester simulator concept that incorporates digital twins of six distinct forest stands. By integrating new teaching modules, the simulator advances training beyond purely

technical control, enabling the simultaneous development of operational skills and silvicultural decision-making. This approach represents a significant step toward more holistic and practice-oriented forestry education.

We provide a detailed description of the construction of the digital twins and the design of the associated teaching modules. We also demonstrate how digital twinning -based simulators can be used in demonstrating and testing new data layers that support harvester operators' daily operations. In addition, we discuss future directions for the development and broader application of digital twinning in forest environments.

2. MATERIALS AND METHODS

2.1 Forest inventories

We selected six forest stands that varied in tree species, age, thinning operations, soil types, and terrain conditions in southern Finland. We collected data using three sensors mounted on a GeoDrone X4L: a Sony RX1R (optic sensor), a MicaSense Altum (multispectral sensor), and a YellowScan Mapper LiDAR system. The Sony RX1R was used to capture very high-resolution images with a ground sampling distance (GSD) of approximately 1.5 cm/px, while the MicaSense Altum was used to acquire the multispectral bands (Blue, Green, Red, Red-edge, and Near-IR) with a slightly lower GSD of approximately 5 cm/px. The YellowScan Mapper was used to collect 3D cloud points with a high density of minimum 100 points per meter.

We collected field reference data from approximately 100 inventory plots (each approximately 100 m²), recording attributes for approximately 1,120 individual trees, including species identity, vitality class, diameter at breast height (DBH), and stem position. We measured tree positions using an RTK GNSS receiver at a positional accuracy of 10 cm. We manually annotated individual tree crowns by delineating instance segmentation masks, as required by the Mask-RCNN architecture (He et al. 2017a), over a five-channel composite comprising RGB, CHM, and NIR data at 0.10 m spatial resolution. To resolve ambiguous crown boundaries, we guided annotations simultaneously using RGB imagery, multispectral composites, and LiDAR-derived canopy profiles. We then extended labels beyond the inventory plots through visual interpretation, yielding approximately 9,000 annotated tree instances in total. We generated image chips of 256 × 256 pixels using a sliding window approach with a stride of 128 pixels (50% overlap), producing approximately 7,000 chips. We partitioned the dataset at the stand level to prevent spatial data leakage, allocating 70% for training, 10% for validation, and 20% for held-out testing.

2.2 Terrain characterisation

We performed ground point classification using the Standard Classification method in ArcGIS Pro, with the Latest detection algorithm. The reclassified points carrying class codes 0 and 1 to ground class 2, while systematically excluding points flagged as withheld or overlap to prevent point density artefacts and inter-flight calibration noise (Esri 2024). Model-key points were additionally classified to retain a morphologically representative ground subset for efficient downstream surface generation.

The forest ground surface, represented as a digital elevation model (DEM) for each corresponding tree list, was derived from publicly available LiDAR point clouds with a density of 5 points/m², obtained from the databases of the National Land Survey of Finland. The DEM was generated with a spatial resolution of 0.4 m by applying triangulated surface interpolation with a study area clip boundary enforced as a spatial

constraint to confine interpolation within the valid survey extent. The output was stored as a single-band 32-bit floating-point GeoTIFF.

2.3 Individual tree detection based on forest inventories

To achieve precise single-tree detection and segmentation, we implemented an instance segmentation framework based on the Mask R-CNN architecture (He et al. 2017b), optimized for multi-modal high-resolution data. Mask R-CNN extends Faster R-CNN by adding a branch for predicting segmentation masks in parallel with the existing branch for bounding box recognition. The architecture is composed of four primary stages corresponding to our workflow (Fig. 1). First, a backbone network (e.g., ResNet-50) extracts deep hierarchical features from the input multi-modal imagery. To address the inherent multi-scale nature of forest canopies and varying tree crown sizes, a Feature Pyramid Network (FPN) (Lin et al. 2016) was integrated (Fig. 1a-b). This allows the model to maintain high-level semantic information while preserving the fine-grained spatial details necessary for small-object detection. Second, the feature maps are processed by a Region Proposal Network (RPN). The RPN utilizes a sliding-window approach across the feature maps to generate candidate regions (anchors) that likely contain tree instances. To ensure spatial consistency, RoIAlign is employed to extract feature maps of a fixed size from each proposal. Unlike traditional RoIPool, RoIAlign avoids quantization of the ROI boundaries, which is critical for maintaining pixel-level accuracy in mask generation (Fig. 1c). Finally, the refined features are fed into two parallel branches. The first performs classification (e.g., Pine, Spruce, Birch) and bounding box regression. The second is a fully convolutional mask branch that predicts a binary mask for each instance (Fig. 1d).

However, standard Mask R-CNN masks often suffer from over-smoothing, particularly at the irregular, high-frequency boundaries of tree crowns. To mitigate this, we integrated the PointRend (Point-based Rendering) module (Kirillov et al. 2019). PointRend treats image segmentation as a rendering problem, performing point-based feature sampling and iterative refinement to produce crisp boundaries. We evaluated the comparative performance of the baseline Mask R-CNN against the PointRend-enhanced version to quantify improvements in boundary delineation accuracy for complex forest structures.

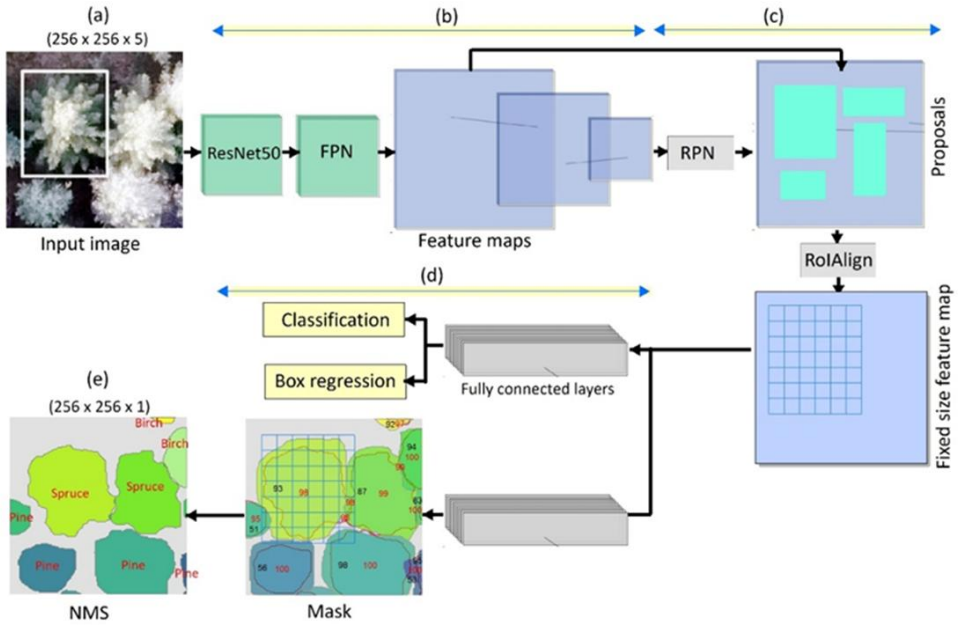


Figure 1. Mask R-CNN architecture for tree species instance segmentation. (a) Five-channel multi-modal input (256 x 256 x 5). (b) Feature extraction via ResNet-50 and Feature Pyramid Network (FPN) to generate multi-scale feature maps. (c) Region Proposal Network (RPN) identifying candidate objects and subsequent RoIAlign for feature normalization. (d) Parallel heads for bounding box regression, species classification, and mask prediction. (e) Final instance segmentation results after Non-Maximum Suppression (NMS).

The best-performing input configuration combined RGB, CHM, and NIR data incorporating PointRend for instance segmentation refinement, yielding an overall F1 score of 0.81 and mAP@0.5 of 0.67 across all detected trees. Per-species detection performance was higher for coniferous species (F1 = 0.85) than for broadleaf species (F1 = 0.67), consistent with the more geometrically distinct crown morphology of conifers in LiDAR and RGB imagery (Mao et al. 2025).

2.4 Conversion processes to achieve digital twinning-based harvester simulator environment

Individual trees, including their actual locations, species, and heights, were converted into the XML format required by the Ponsse harvest simulator. The tree list format includes the following parameters:

- Tree species (Scots pine, Norway spruce, silver/downy birch, or aspen)
- Tree height
- Tree location (x and y coordinates) relative to the stand's centre point
- Tree orientation (a random value between 0 and 360 degrees)

In addition, each tree list was accompanied by the precise coordinates of the stand's centre point, expressed in the WGS84 coordinate reference system. The DEMs were then further processed and refined for compatibility with the Ponsse forest simulator environment using the open-source software CloudCompare.

The Ponsse simulator represents each tree with its precise location. Trees are modelled using a combination of photorealistic trunks and individually rendered branches. The current version features photorealistic visualizations of the most important commercial tree species, including Scots pine, Norway spruce, silver and downy birch, aspen, and eucalyptus. Rotten standing trees and fallen wood can also be visualized when specified in the tree list. To enhance visual diversity, the simulator randomizes tree orientation, allowing greater variation despite relying on a limited set of original tree models.

Due to computational limitations, the level of realism is reduced compared to an actual forest environment. First, the number of branches represented in the simulator is significantly lower than in reality. Second, the lower portion of tree trunks does not include any branches. Third, the forest floor is depicted using relatively simple textures with limited variation. Fourth, no shrub layer is included unless it is explicitly defined in the tree list file. Additional ground features—such as ditches and roads—can be incorporated, but they must be manually created using the CloudCompare tool. Despite these limitations, the new version of the Ponsse simulator, which integrates real-world tree locations with terrain topography, represents a significant advancement. It introduces a new and compelling level of realism that has not previously been available in harvester simulator training.

2.5 Additional data layers of forest structural features

Individual tree detection (ITD) procedures are widely recognized for their strong potential to support harvester operators in identifying forest structural features that are essential for balancing ecological, economic, and social objectives. Using ITD, specific tree types can be accurately identified for protection, monitoring, or removal. To support the detection and removal of trees prone to wind damage, we developed a data layer that highlights dominant trees—defined as those at least 15% taller than their immediate neighbours.

All selected stands had undergone at least one prior thinning operation, meaning an existing OLT network was present in each stand. These trails constitute the primary machine access infrastructure and are beneficial inputs for the simulator to teach trainees on how OLT map layers can be utilised in thinning operation. We delineated OLT networks using the RAUNet semantic segmentation model (Abdi et al. 2022b; Abdi and Uusitalo 2026), applied to a three-channel input raster comprising the digital surface model (DSM), canopy height model (CHM), and DEM, all derived from the LiDAR data at 0.4 m spatial resolution. The model was applied directly to the study site data without retraining, producing a binary segmentation mask classifying each pixel as trail or non-trail. The resulting raster was subsequently converted to vector format using, following centreline thinning to enable direct integration into the simulation environment.

3. THE NEW TEACHING MODULES WITH DIGITAL TWIN -BASED HARVEST SIMULATOR ENVIRONMENT

3.1 Climate-smart management of forest edges

Background: Climate change will induce multiple risks to forests and forestry. Warming is expected to be higher in northern Europe than close to equators, and larger in winter than summer. The most important risks include wind damages, bark beetle outbreaks and wood decay by Heterobasidion root rot (Venäläinen et al. 2020). Due to longer periods of heat, spruces and firs can also be exposed to drought (Pretzsch et al. 2015; Rukh et al. 2020). Climate-Smart Forestry is an emerging concept that helps forest manager to comprehend multiple and complex phenomenon that climate change is bringing to our forests. It should enable both forests and society to transform, adapt to and mitigate climate-induced changes (Bowditch et al. 2020; Santopuoli et al. 2021). In general, mixed forest and diversity in constructional and functional forest structure should be favored. Wind damage probability of a tree is affected by tree species, size and shape; local wind conditions and intensity of storms (Suvanto et al. 2018; Gardiner 2021).

Bark beetle (Blomqvist et al. 2018; Müller et al. 2022)

General description of the practise:
Your task is to carry out thinning operations at the forest edge in a climate-adaptive manner. The exercise takes place in a 40–50-year-old mixed spruce–pine forest stand. The adjacent stand was clear-cut a few years earlier. (In practice, thinning should ideally be conducted a few years prior to clear-cutting to allow the remaining stand to adapt to changing conditions.)

Instructions for trainees:
Aim to create a mixed forest structure composed of the most vigorous trees. Mixed forests improve soil stability, as different tree species have complementary root systems. Pine trees typically develop a deep taproot, while spruce root systems are shallower and more spread across the upper soil layers. Deciduous trees generally have the most robust root systems. As a result, mixed stands tend to be more resistant to wind damage.

Tree size and shape are also important considerations. Spruce trees develop the widest crowns and are therefore usually the most susceptible to windthrow. Remove the tallest trees, as they are more prone to wind damage than shorter ones. Pay attention to crown length and shape, and remove suppressed or stagnated trees. There is a strong correlation between crown size and root system development.

Tree positioning within the stand is equally important. Retain pines and birches closest to the forest edge, while larger spruces can be left further inside the edge zone. Preserve undergrowth trees in the edge zone to support wildlife and provide additional wind protection.

Plan logging trails so that they are not directly perpendicular to the forest edge, in order to avoid creating a wind tunnel effect within the stand. Remove large spruces adjacent to logging trails to reduce root damage to remaining trees. If the nearest trees are spruces, the logging trail may be widened if necessary.

Practise tasks:

Task 1a (Fig.2a):

Select and harvest trees within the edge zone following climate-smart forest management principles. The harvester starts at the far edge of the stand. Thinning is carried out by establishing a logging trail in front of the machine. All trees within the trail are removed, along with approximately one-third of the trees between trails. The trees to be removed have been pre-selected by the instructor and are marked with white-orange striped indicators.

Task 1b (Fig2b): This task is identical to Task 1a, except that the pre-selected trees are not marked.

Task 1c (Fig2c): This task follows the same principles as Tasks 1a and 1b but is conducted in a completely new forest area.

b)



a)



c)



Figure 2. Screenshots from the starting positions of Tasks 1a, 1b, and 1c. In 3D training sessions, trainees can observe and assess trees in a way that closely resembles real harvester operation. They can also evaluate tree height and crown structure by adjusting their viewpoint toward the tops of the trees.

3.2 Climate-smart selection cutting to achieve uneven-aged structure

Background:

Forest management can broadly be divided into two contrasting approaches: (1) selecting individual trees for harvesting while maintaining a continuously closed canopy (commonly referred to as Continuous Cover Forestry, CCF), or (2) harvesting all trees within a given area at the same time (Rotation Forestry, RF). These approaches are closely linked to the age and diameter distribution of trees within a stand. RF is characterized by even-aged stand structures, typically resulting from regeneration through clear-cutting, often followed by single-species planting and intermediate thinning from below. In contrast, CCF promotes uneven-aged stand structures. This structure is maintained through selection cuttings, where trees are removed either individually (single-tree selection) or in small groups (patch cutting).

Uneven-aged forest management is often considered difficult to implement in Fennoscandian boreal forests, largely due to the prevalence of three primary commercial tree species, only one of which—Norway spruce—can tolerate shade. As a result, pine and birch species regenerate poorly beneath the canopy of larger trees. Historically, uneven-aged management was prohibited in Finland, and although societal pressure to expand continuous cover forestry (CCF) practices has increased, their adoption remains limited across much of Scandinavia. In this context, it is crucial to ensure that new harvester operators are properly trained to implement selection cuttings that support the development of uneven-aged stand structures.

In boreal forest uneven-aged management, removed tees are selected primarily from mature diameter classes, removing surplus trees to maintain a balanced, multi-storied structure through single-tree or small group selection. When the objective is to promote regeneration and growth of shade-intolerant species (e.g., pine), a substantial number of overstory trees should be removed to create sufficiently large canopy gaps. In contrast, shade-tolerant species (e.g., spruce) can respond positively to much smaller openings. Regardless of the approach, priority should be given to removing damaged, diseased, or poorly formed trees.

Small understory spruces and firs often respond poorly to the sudden removal of overstory trees. Release cuttings rapidly alter their growing environment, exposing them to warmer, drier, and brighter conditions. This rapid exposure can cause photoinhibition, leading to reduced chlorophyll content, lower potassium concentrations, and diminished branch growth, while increasing foliage damage and altering shoot morphology. These effects are typically more pronounced on moist sites (Tucker et al. 1987; Gnojek 1992; Saarinen 1996).

Instructions for trainees:
Your task is to apply partial cutting in a 40–50-year-old mixed spruce–pine stand that has so far been managed under even-aged RF principles. Despite this, the stand already exhibits some horizontal and vertical variation in tree diameters and heights. This operation can therefore be considered a transition cutting aimed at moving the stand toward a more uneven-aged structure in line with continuous cover forestry (CCF) principles.

First, clear the planned logging trail in front of your machine. Fell trees in the direction of the trail rather than into the surrounding dense forest. Before cutting each tree, determine suitable locations for log piles, placing them only in already managed areas—not within untouched forest.

Begin by removing spruce to improve visibility within the working area. Then focus on harvesting suppressed or stagnant trees and finally remove the tallest individuals. Ensure that the remaining trees have sufficient space for future growth.

Create larger canopy openings when aiming to promote the growth of individual pine trees. Protect suppressed but vigorous spruces by retaining some overstory trees to provide partial shade.

Practise tasks:

Task 2a (Fig.3a): The first task focuses on practicing tree felling in dense forest conditions. Begin by removing the large spruce on the left, close to the machine. Use a tree that will also be removed as a “prop” and target tree, directing the felling toward the pine located in the middle of the planned trail. As the tree falls, it will prune some branches from the pine; in this case, this is acceptable because the prop tree will be removed in the next phase. A yellow pole is provided to help guide the direction of felling, as it is aligned with both the spruce being removed and the prop/target tree.

Task 2b (Fig3b): In the next task, the trainee should apply partial cutting principles by removing all trees from the logging trail and thinning the surrounding stand to meet the target density, following the previously described order of operations. Directional felling techniques practiced in Task 2a should be used throughout.

Inspectors have marked suppressed but vigorous spruces in red and the overstory trees providing them with shade in blue. These trees should be retained, leaving both the suppressed individuals and their shading trees undisturbed to support the development of the most promising specimens for future growth.

Task 2c and 2d (Fig3c and 3d): These tasks involve the same forest site and objectives as Task 2b. The only difference is that unlike in Task 2b, the trainee is not supported by any predefined indicators. Task 2d is carried out in darkness using artificial illumination, which makes it considerably more challenging than Task 2c, which is performed in daylight.

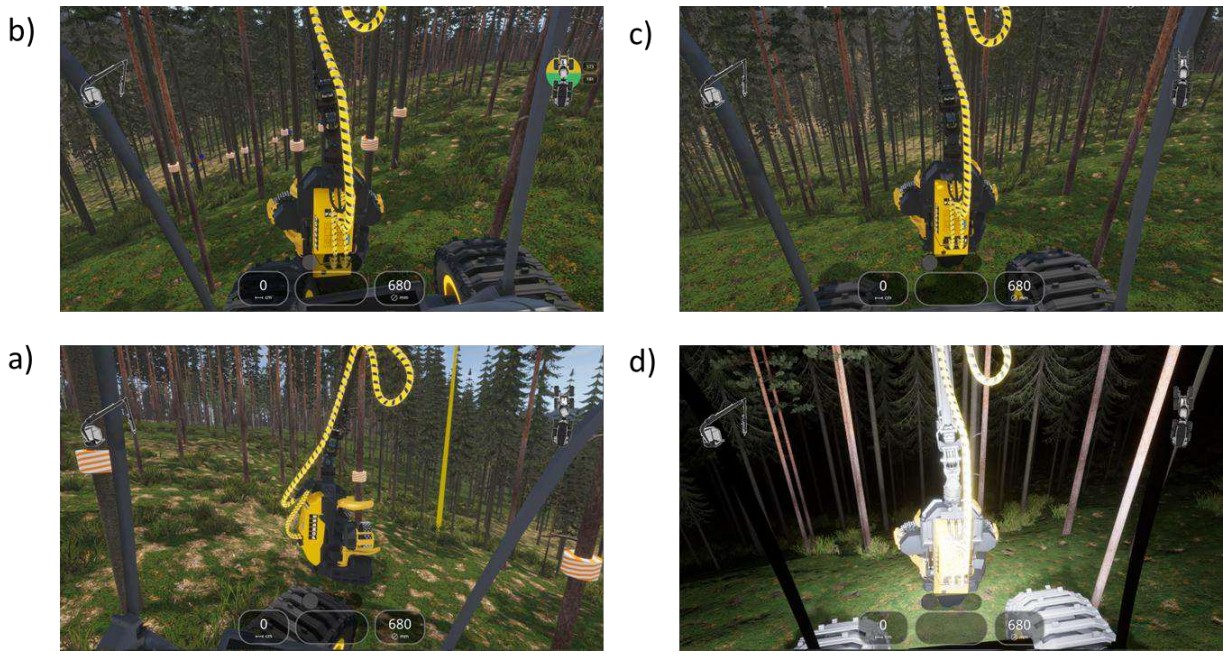


Figure 3. Screenshots from the starting positions of Tasks 2a, 2b, 2c and 2c. Task 2a focuses on practising tree felling by utilising a “prop” or target tree. Tasks 2b, 2c and 2d are carried out in the same forest but with (2b) or without (2c, 2d) predefined indicators. The tasks can be executed in daylight (2b, 2c) or in darkness (2d).

3.3 Harvesting in erosion risk steep slopes

Background:

Harvesting operations on steep slopes require particular care, as poorly planned or executed activities can negatively affect the water quality of downslope water bodies. Special attention is needed in forests with fine-grained soils, where water infiltration rates are significantly lower than in coarse-grained soils. The use of heavy machinery on fine-grained soils can lead to several adverse effects. Soil compaction caused by machinery further reduces infiltration capacity, increasing surface runoff and the risk of transporting sediments and nutrients into nearby water bodies (Startsev and McNabb 2000; Cambi et al. 2015; Toivio et al. 2017).

The timing of operations is also critical. Harvesting should be avoided during wet conditions, such as in the spring or immediately following heavy rainfall, when soils are most vulnerable to compaction and erosion. It is important to note that the upper sections of steep slopes tend to dry faster than the middle and lower sections. Careful planning of logging trails is essential. Trails should not be aligned directly downhill; instead, they should be oriented obliquely across the slope and incorporate gentle turns to reduce water flow velocity. Additionally, sufficiently wide buffer zones should be maintained between harvesting areas and adjacent water bodies to protect water quality (Sutherland 2003; Wei et al. 2022).

Instructions for trainees:
Your task is to carry out a conventional below-thinning operation in a 40–50-year-old mixed spruce–pine stand. The operation area is located on a relatively steep slope that eventually ends at a small river at the bottom of the valley. The lower slope soil may be nearly or fully saturated, creating special operational challenges. Climate change is also reflected in harvesting operations on slopes, increasing the risk of erosion.

During operations, the topsoil should be kept as undisturbed as possible to avoid unnecessary erosion and sediment transport. The downhill wheel track is particularly susceptible to damage; therefore, logging residues should be placed in the lower track to protect the soil. Unnecessary wheel movement should be avoided, and differential locks should be used proactively when operating on slopes. To facilitate operations, piles should be placed on the upslope side, allowing the forwarder to load them safely without damaging the soil surface.

Tree species along the extraction trail are also important. The trail should be wide enough to prevent root damage. Where possible, shallow-rooted trees adjacent to the trail should be removed, as they are most vulnerable to root damage. A mixed-stand structure should be maintained on slopes to ensure that root systems are as widespread as possible, thereby improving soil stability and resistance to erosion.

The positioning and alignment of logging trails are also of utmost importance. Trails should be planned in accordance with topographic contour lines. Long dry periods can dry out the soil surface, causing trails that run perpendicular to the slope to function as channels during rainfall. If heavy rain occurs after such a dry period, water may flow excessively along these channels, resulting in severe erosion on the slope. When designing the trail network, the entire harvesting chain must be considered to ensure that the forwarder can operate safely and economically along the route.

Practise tasks:

Task 3a (Fig.4a): In the first exercise, you will be working in an area where no trees remain in the logging trails, as they have been removed during a previous operation. The trees to be removed have been pre-selected by the instructor and are marked with white-orange striped indicators. Focus on using proper techniques in steep terrain. Ensure that your base machine is correctly positioned in relation to the intended felling direction. Be aware that side slopes can reduce the crane's rotation capacity. When positioning the harvester head for the felling cut, take care to avoid dulling the saw chain. Exercise extra caution when extending the boom to reach the farthest trees. Avoid damaging trees when positioning the harvester head and directing your felling.

Task 3b (Fig4b): This task is identical to Task 3a, except that the pre-selected trees are not marked.

Task 3c (Fig4c): This task is identical to Task 3b, except that no old logging trail is visible in the forest. You should plan an appropriate route for the logging trail, establish the trail with suitable width, and thin the forest using proper technique.

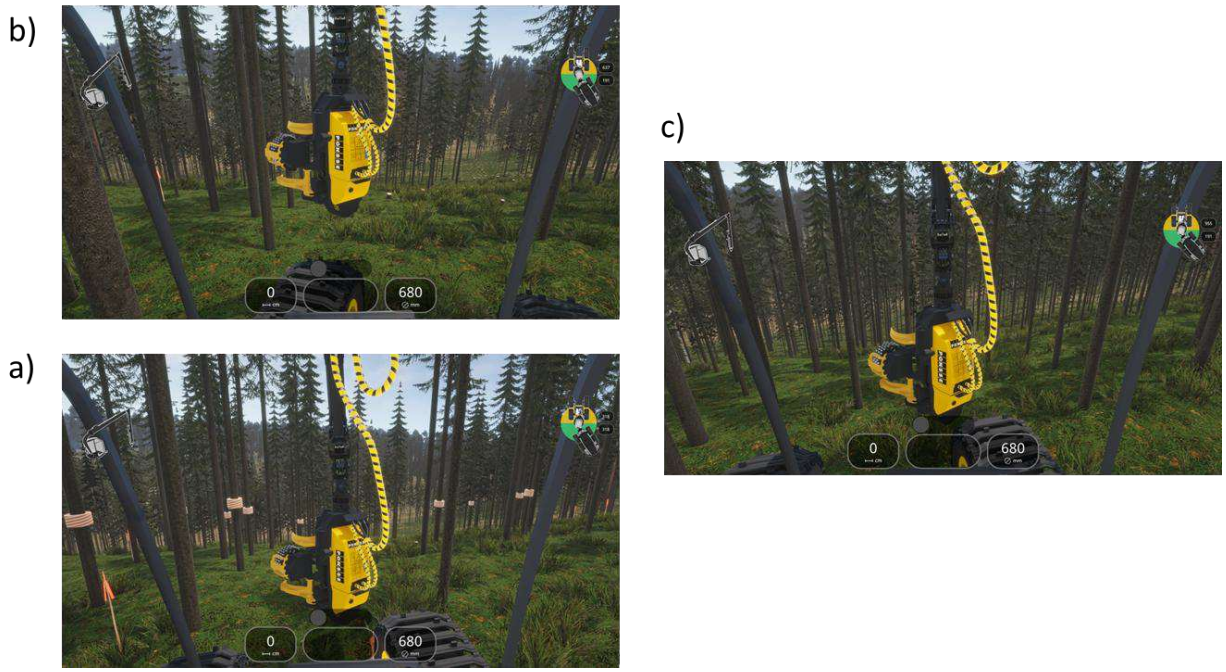


Figure 4. Screenshots from the starting positions of Tasks 3a, 3b and 3c. In task 3a and 3b are where no trees remain in the logging trails, as they have been removed during a previous operation. The difference between 3a and 3b is that pre-selected trees by the instructor has been (3a) or has not been (3b) marked. In task 3c, no old logging trail is visible in the forest which mean that you should plan an appropriate route for the logging trail, establish the trail with suitable width, and thin the forest using proper technique.

3.4 Auxiliary data layers supporting daily operations

Background: Harvester information systems are of increasing importance in operators' daily work. Advances in remote sensing technologies, computing power, and artificial intelligence have enabled the integration of increasingly sophisticated map layers into harvester mapping systems. However, there are significant

differences in how actively operators utilize these supportive layers (Kymäläinen et al. 2025). Incorporating their use as an integral part of simulator training could foster a new generation of operators who recognize their value and effectively integrate them into operational workflows. At present, there is also a lack of clear understanding regarding how different map layers should be presented to best support operator performance.

Nowadays, forest machine operators are typically responsible for planning logging trails within the context of harvesting operations. This process is supported by a built-in mapping system in harvesters, which are integrated with Global Navigation Satellite System (GNSS) technology to assists in trail routing. Managed forest often includes some additional infrastructure that may influence trail network design. Ignoring old logging trail network in previously managed forests may lead to unintentional overexploitation of growing trees. This challenge can be successfully tackled with a map layer that visualizes old logging trails, hereafter referred to as OLT-layer. These layers can be derived using high-density open-source LiDAR data (Abdi et al. 2022a; Abdi and Uusitalo 2026). Such solutions are no longer limited to research demonstrations but have been broadly adopted for practical applications in Finland.

Practice tasks: We demonstrate here two map layers integrated into the digital twin–based harvester simulator environment (Figure 5). The first layer comprises the locations of the tallest trees, hereafter referred to as the *excessively tall trees* map. These trees are not veteran trees originating from a previous forest succession period; rather, they are overgrown trees that are somewhat taller or broader than the dominant cohort trees within the stand.

The second layer is the OLT layer, which visualizes the locations of old logging trails. Harvester operator trainees are instructed to drive the harvester along old logging trails that can be visually identified in the forest. The OLT layer supports trainees' decision-making in this task.

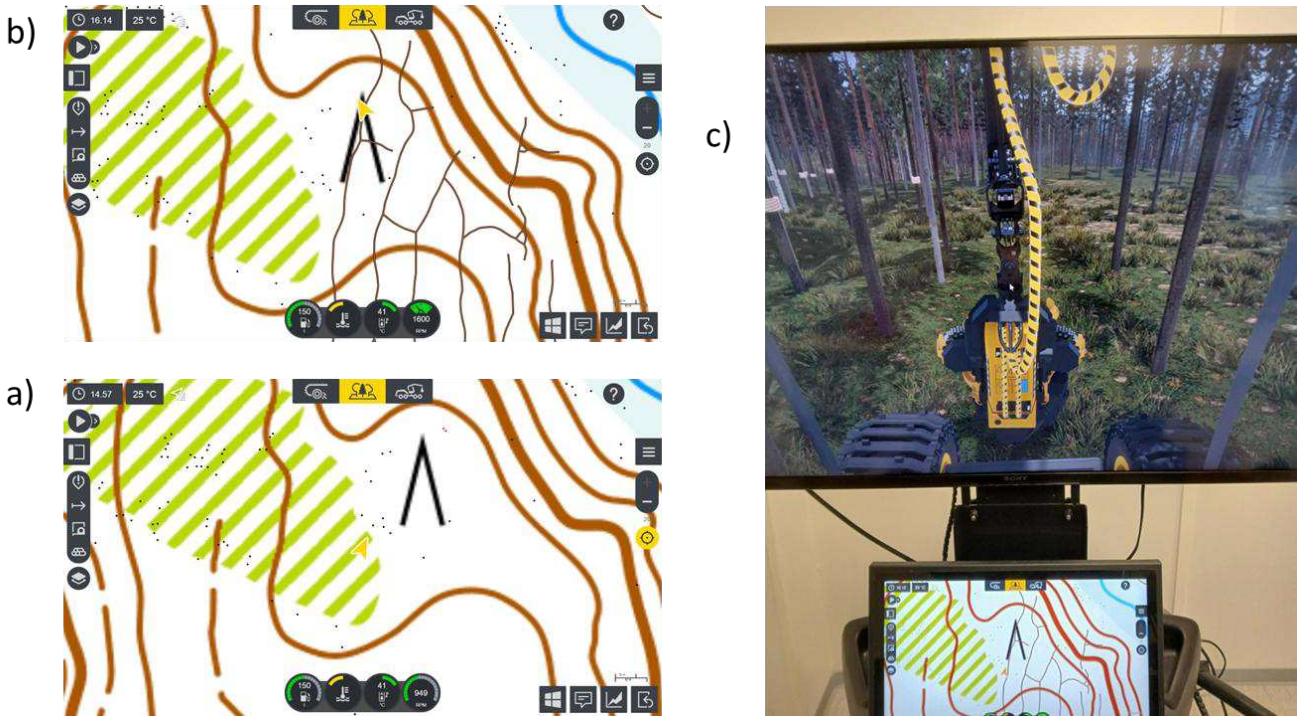


Figure 5. The Ponsse simulator and the Ponsse Opti 5G measuring device, which is identical to the computer used in a real forestry machine, include an integrated map application. The simulator environment comprises two computers: the first is used to run the simulated world and display it on screen, while the second is dedicated to harvester control and the visualization of supportive map layers (Figure 5c). The use

of supportive map layers in decision-making forms an integral part of trainee education. In the supportive map interface, the harvester's position is indicated by a yellow arrow, excessively tall trees by black dots, and old logging trails by brown polylines. The layers also display topographic contour lines as thick brown polylines and areas of high soil moisture as green stripes. Figure 5a demonstrates a training exercise in which the excessively tall trees map is utilized, whereas Figure 5b presents a case in which both the excessively tall trees map and the OLT layer are used to support training.

4 DISCUSSION

Harvester simulators have been an integral part of forest operator training for several decades, and their usefulness in supporting operator training has been demonstrated in numerous studies (Lapointe and Robert 2000; Ovaskainen 2005; Ranta 2009; Wenhold et al. 2020; Burk et al. 2023; Polowy and Rutkowski 2024; Tam et al. 2025). However, all previous studies examining the effectiveness of simulator training have focused mainly on mastering the technical skills required for harvester maneuvering.

In past few years, we have witnessed how recent strategic policy guidelines and growing public awareness of the ecological aspects of forest management have changed the operational environment of harvester operators. Harvesting operations are increasingly guided by detailed instructions and regulations that operators must incorporate into their tree-level and stand-level decision-making processes. This creates a growing need to further develop and update operator training.

In this work, we present a novel system that elevates harvester simulator training to a completely new level by integrating environmental and silvicultural aspects as an integral part of harvester maneuvering. This work should be regarded as a conceptual study. Its primary aim is to demonstrate and discuss novel concepts and emerging approaches rather than to empirically validate training effectiveness. The usefulness of the proposed approach remains to be assessed in future research.

Although our study environments and technological solutions have taken significant steps from previously documented concepts (Burk et al. 2023; Polowy and Rutkowski 2024), the virtual forest environment is still not perfect in relation to the real world. Due to computational limitations, the simulated harvester environment contains a reduced number of tree branches. In addition, the amount of undergrowth vegetation is lower than in a real forest environment, which makes the working environment easier to navigate and operate in. Furthermore, the harvester simulator terrain lacks detailed micro-scale information on surface roughness such as stones, pits, roots, terrain softness. From a learning perspective, however, these characteristics may also be considered beneficial. By reducing real-world complexity, trainees can initially focus on the most important aspects of the task, and once these have been mastered, they can progress to more realistic environments. In this approach, the most challenging operating conditions are encountered with real harvesters rather than within the simulation environment.

Over the past year, the potential of forest visualization in forestry has been repeatedly emphasized. The motivations for forest visualization are manifold (Murtiyoso et al. 2024). Traditionally, one of its primary purposes has been to support communication of forest management alternatives to stakeholders (Holm and Schweier 2024; Murtiyoso et al. 2024; Kushwaha et al. 2026; Rammer et al. 2026). Recent advances in GIS data and computer graphics have made this task considerably easier.

In addition, forest visualization has been recognized as an effective tool for improving forest planning processes and facilitating information sharing among the many groups involved in harvesting operations, including forest owners, planners, timber buyers and sellers, and logging operators (Holm and Schweier

2024; Murtiyoso et al. 2024; Kushwaha et al. 2026). (Hyyppä et al. 2024) demonstrated the feasibility of visualizing large-scale forest digital twins with realistic representations of mature forest stands. Nevertheless, the limited inclusion of small trees in these digital twins raises questions regarding their applicability across different phases of forest planning. Forest digital twinning has also been recognized as having significant potential for improving the modelling of forest ecosystem functions, such as biodiversity, greenhouse gas emissions, and carbon sequestration, as well as for enhancing communication of these processes among researchers and stakeholders (Silva et al. 2023). Despite recent demonstrations, forest visualization has largely remained a field of high expectations, where researchers have successfully demonstrated its potential, but only a limited number of solutions have been integrated into real-world forestry operations.

Among the proposed applications of forest visualization, educational use has emerged as the area with the clearest practical potential. In addition to training forest machine operators, visualization tools have been shown to support education in tree selection for thinning operations, tree bucking, and planting operations. (Wang et al. 2009; Fabrika et al. 2018; Wang et al. 2022). As shown in our training modules, tree selection is an increasingly demanding process that requires balancing ecological, economic, and social objectives. Decision-makers must not only assess the current state of a stand but also anticipate future growth responses and stand development. This area of training has already been addressed for some time through the use of Marteloscopes in many European countries (Thormann et al. 2019; Soucy et al. 2016). Marteloscopes are forest stands in which each tree is thoroughly inventoried (including exact coordinates, species, diameter, height, crown characteristics, vitality, and more), allowing trainees to compare their own tree selection decisions against an “ideal selection” defined by a panel of experts. Because the training procedures are implemented using computer-based applications, Marteloscopes can be regarded as semi-graphical solutions. As technology continues to develop, the Marteloscope concept can readily be extended into fully graphical training environments (Kushwaha et al. 2026).

In visualization-driven training systems, the challenge is not limited to combining computer graphics and forestry expertise. Equally important is how information is structured and presented in supportive systems so that operators receive the necessary information without being overwhelmed by excessive cognitive load. While we consider digital-twin-based harvesting simulator environments essential for future training—particularly due to their realistic representation of trees and their spatial configurations—equally important are the learning processes enabled by supporting information systems, such as maps visualizing old logging trails or over-dimensioned trees. We strongly believe this represents the direction in which trainee education is evolving. In addition, digital twin environments provide an effective testbed for evaluating which types of map layers most effectively support tree selection, operator training, and the management of information overload for operators.

Statements and Declarations

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Competing interests

The authors declare no competing interests.

Availability of data and material

The single tree predictions cannot be shared with third parties without permission from landowners.

Code availability

This work does not include any special software. The simulator itself is a commercial product by Ponsse Plc

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Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the author(s) used ChatGPT 4.0 in order to polish some part of the text. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication

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