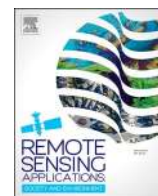




Contents lists available at ScienceDirect

Remote Sensing Applications: Society and Environment

journal homepage: www.elsevier.com/locate/rsase

Mapping large European aspens (*Populus tremula* L.) using national aerial imagery and a U-Net convolutional neural network

Anwarul Islam Chowdhury^{a,c,*}, Einari Heinaro^a, Topi Tanhuanpää^b,
Anis Ur Rahman^a, Samuli Junttila^{a,c}

^a School of Forest Sciences, University of Eastern Finland, Joensuu, 80101, Finland

^b Department of History and Geography, University of Eastern Finland, Joensuu, 80101, Finland

^c Department of Forest Science, University of Helsinki, Helsinki, 00010, Finland

ARTICLE INFO

Keywords:

Biodiversity
Keystone species
Deep learning
Semantic segmentation
U-Net

ABSTRACT

Biodiversity supports boreal forest stability, with European aspen (*Populus tremula* L.) enhancing it by providing crucial habitats and resources for dependent species. Despite existing aspen remote sensing methods, there is no efficient method for mapping it over large areas to support forest management and conservation. In this study, we developed a deep learning-based semantic segmentation model to segment aspen from openly available national aerial imagery, evaluated its accuracy using field data, and compared the segmentation performance between leaf-on and leaf-off conditions. The study was conducted in three areas in southern Finland: Helsinki, Lohja, and Evo. We employed a U-Net encoder-decoder architecture using four-band aerial imagery (RGB and NIR) with a spatial resolution of 0.5 m, captured during both seasonal conditions. Training data consisted of visually identified aspen locations from imagery between 2010 and 2023, covering 290 sites across Finland. We found notable differences in segmentation accuracy between leaf-on and leaf-off conditions and aspen size. The F1-score was higher in leaf-off (0.573) than leaf-on (0.494), with intersection over union (IoU) values of 0.280 and 0.256 for leaf-off and leaf-on, respectively. The diameter at breast height (DBH) of the segmented aspens was similar for both conditions. Moreover, segmentation accuracy improved for larger aspens, with F1-scores reaching 0.663 (leaf-off) and 0.551 (leaf-on) for aspens >20 cm DBH, and 0.710 (leaf-off) and 0.594 (leaf-on) for those >30 cm. The developed model reasonably locates aspen distribution and abundance, assisting forest managers to make informed management decisions.

1. Introduction

European aspen (*Populus tremula* L.; hereafter ‘aspen’) helps sustain biodiversity in conifer-dominated boreal forests subject to intensive management in Fennoscandia. Large aspens, in particular, support many species, and their continuous presence both alive and dead is vital for forest biodiversity (Tikkanen et al., 2006; Kivinen et al., 2020). Many species including willow tits (*Poecile montanus*; Baroni et al., 2021), woodpeckers and owls (Hardenbol et al., 2019; Tikkanen et al., 2006), flying squirrels (*Pteromys volans*; Remm et al., 2017), and tree-dwelling bats (Russo et al., 2023; Tillon et al., 2016; Michaelsen, 2016), rely on aspens for habitat. In addition, tree-dwelling bats prefer aspens for maternity roosts due to the greater warmth and shelter they provide compared to

* Corresponding author. School of Forest Sciences, University of Eastern Finland, Joensuu, 80101, Finland.

E-mail address: anwarul.islam.chowdhury@uef.fi (A.I. Chowdhury).

<https://doi.org/10.1016/j.rsase.2025.101755>

Received 25 June 2025; Received in revised form 2 October 2025; Accepted 13 October 2025

Available online 14 October 2025

2352-9385/© 2025 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

coniferous trees (Russo et al., 2023; Tillon et al., 2016; Michaelsen, 2016). Aspen's calcium-rich leaf litter helps elevate the pH of acidic soils, affecting nutrient cycling and ecosystem processes (Nikula et al., 2010), thus reinforcing its designation as a keystone species.

Aspen is an early-successional species that typically regenerates in open areas or forest gaps, reproducing sexually via seeds and mainly asexually via root suckers that form genetically identical clones (Kivinen et al., 2020; Latva-Karjanmaa et al., 2007). It typically occurs in small groups or stands within conifer-dominated forests and can grow across a range of site conditions (Rogers et al., 2020). Despite its ecological importance, the number of aspens has declined sharply in both pristine and managed boreal forests (Hardenbol et al., 2020; Hedenäs and Ericson, 2008). In managed forests, large aspens have often been removed, and natural recruitment remains low due to browsing, competition, and lack of disturbances. For example, Hardenbol et al. (2020) reported a 37 % decline in living aspens in Finland over 18 years. Latva-Karjanmaa et al. (2007) projected that in old-growth forests, only 10 % of mature aspens would survive beyond 90 years.

With aspen populations in decline and their ecological role critical, large-scale and accurate mapping is essential for conservation. One major barrier to aspen conservation is the lack of detailed spatial and temporal data (Kivinen et al., 2020). Its sparse, clustered distribution and low commercial value often lead to its grouping with other minor deciduous species in forest inventories, complicating identification and management (Kuzmin et al., 2021; Ørka et al., 2010). Recent advancements in remote sensing technologies, particularly LiDAR and high-resolution aerial imagery, offer new opportunities for accurate segmentation and mapping of aspen at broad scales (Tuominen et al., 2018). The remote sensing approach, gaining attention globally, has the potential to provide more accurate, consistent, and large-scale data on aspen distribution, which could greatly enhance forest management and conservation initiatives in boreal forests.

Aspen segmentation and mapping have been studied across Fennoscandia (Breidenbach et al., 2010; Erikson, 2004; Ørka et al., 2010), especially in Finland (e.g., Kuzmin et al., 2021; Säynäjoki et al., 2008; Toivonen et al., 2024; Tuominen et al., 2018; Viinikka et al., 2020). The accuracy of aspen segmentation is significantly influenced by the data sources and modeling techniques employed (Hardenbol et al., 2021; Kivinen et al., 2020; Kuzmin et al., 2021; Ørka et al., 2010; Toivonen et al., 2024). Traditional predictive models such as Random Forest (RF) and Support Vector Machine (SVM) have been extensively used for tree species classification including aspen, often yielding good accuracy (Kuzmin et al., 2021; Toivonen et al., 2024); for instance, SVM has demonstrated high precision in aspen classification tasks, reporting accuracies of up to 86 % (Kuzmin et al., 2021). However, these methods generally rely on manual feature extraction and accurate crown delineation, making them labor-intensive and prone to errors, especially in high-resolution imagery where background noise can reduce classification performance (Han et al., 2022; Dalponte et al., 2019). Additionally, tree-level classification often requires supplemental remote sensing data such as LiDAR to support accurate crown delineation.

While traditional models are effective, they have limitations in capturing complex crown structures. Deep learning approaches, particularly Convolutional Neural Networks (CNNs), have shown high potential in the segmentation and classification of tree crowns including aspen (Mäyrä et al., 2021). CNNs outperform traditional machine learning (ML) models by capturing complex spatial features, textures, and structural patterns in high-resolution imagery (Sothe et al., 2020; Chen et al., 2018; Audebert et al., 2018; Huang et al., 2018; Pešek et al., 2024). Mäyrä et al. (2021) reported a higher accuracy for aspen classification using 3D CNNs on LiDAR and hyperspectral data. Similarly, Junttila et al. (2024) reported an F1-score of 0.93 for forest canopy mortality segmentation in southeast Finland using U-Net with aerial imagery. Among CNN architectures, U-Net is particularly well-suited for crown segmentation because it performs pixel-level semantic segmentation, preserves both local and global image features, and maintains high accuracy even with limited annotated data (Ronneberger et al., 2015). These qualities make U-Net a promising choice for accurate and efficient crown segmentation, and several studies have used and recommended U-Net for tree segmentation and classification tasks (Mäyrä et al., 2021; Schiefer et al., 2020).

Several studies have employed different data sources for forest species segmentation and classification, especially focusing on aspen, such as unmanned aerial vehicle (UAV) aerial imagery (Hardenbol et al., 2021; Kuzmin et al., 2021; Tuominen et al., 2018), airborne laser scanning (ALS) (Ørka et al., 2010; Viinikka et al., 2020), satellite-based imagery (Troshin et al., 2025; Cook et al., 2024; Illarionova et al., 2024a) and combinations of multiple data types (e.g., Säynäjoki et al., 2008; Toivonen et al., 2024; Mäyrä et al., 2021). Among these, satellite-based imagery offers advantages such as broad spatial coverage and relatively low cost. However, its lower spatial resolution can hinder accurate species classification, and very-high-resolution satellite imagery often comes with a trade-off of low spectral resolution, which may further limit its ability to distinguish species. UAV aerial imagery, in contrast, has proven effective in classifying and mapping due to its high-resolution data, although the success varies depending on the data and methods applied. For instance, Hardenbol et al. (2021) reported high accuracy for aspen classification by combining multispectral UAV imagery with point clouds, while Tuominen et al. (2018) reported similarly strong performance using stereo-photogrammetric point clouds in combination with hyperspectral information. Moreover, UAV-based RGB and multispectral imagery have also shown impressive segmentation accuracy (Kuzmin et al., 2021). Combining UAV data with ALS or hyperspectral imagery can improve results, though inconsistently, for example, Toivonen et al. (2024) reported lower F1-scores. Although UAV-based approaches have demonstrated high accuracy for localized aspen segmentation, their high operational costs and limited spatial coverage limit their scalability and practical application in large-scale forest monitoring programs.

Aspen segmentation has proven more challenging than for species such as Scots pine (*Pinus sylvestris*) or Norway spruce (*Picea abies*) (Ørka et al., 2010; Kuzmin et al., 2021; Mäyrä et al., 2021; Breidenbach et al., 2010), though some studies (e.g., Viinikka et al., 2020) reported the opposite. Despite these mixed findings, there is clear potential to improve aspen segmentation using aerial imagery combined with U-Net deep learning. While challenges remain under both leaf-on and leaf-off conditions, no prior study has employed semantic segmentation to identify and localize aspens from remotely sensed data while comparing segmentation accuracy across seasonal conditions. Moreover, a scalable approach for large-area aspen mapping is still lacking, limiting its application in operational

forest management and biodiversity conservation.

Therefore, the main objective of this research is to develop a U-Net deep learning model to segment European aspen from openly available aerial imagery collected at the national scale and assess the segmentation accuracies of the developed model based on field data. We also aimed to compare the segmentation accuracy between leaf-on and leaf-off conditions.

This research makes the following contributions:

- Development of a U-Net deep learning model for European aspen segmentation using openly available, national-scale aerial imagery, enabling large-scale aspen mapping.
- Evaluation of segmentation accuracy under different leaf conditions (leaf-on vs. leaf-off), providing insights into the optimal timing for aspen monitoring.
- Assessment of the influence of aspen size, specifically diameter at breast height (DBH), on segmentation accuracy using independent field measurements from three study areas.

2. Data & methods

2.1. Study area

The study includes three testing areas in southern Finland: Helsinki central park (hereafter ‘Helsinki’) (60.2643°N, 24.9149°E), Lohja (60.3077°N, 24.0367°E), and Evo (61.2470°N, 25.0626°E) (Fig. 1). These sites were selected due to the availability of aerial imagery captured during both leaf-on (June–August) and leaf-off (October–May) conditions.

Helsinki presents a balanced integration of urban development and natural landscapes, including managed green spaces, urban forests, parks, and protected reserves. Dominant tree species include Norway spruce (*Picea abies* (L.) Karst), Scots pine (*Pinus sylvestris* L.), and Silver birch (*Betula pendula* Roth), with European aspen (*Populus tremula* L.) and willows (*Salix* spp.) thriving in wetlands (Tikkanen et al., 2006). The topography is generally flat, ranging from sea level to approximately 60 meters (m) above sea level (a.s.l.), with the Baltic Sea moderating the local microclimate. The region experiences a hemiboreal climate, featuring an average annual temperature of ~6.5 °C, a growing season of 180–200 days, and an annual precipitation of 653 mm (Karvinen et al., 2024).

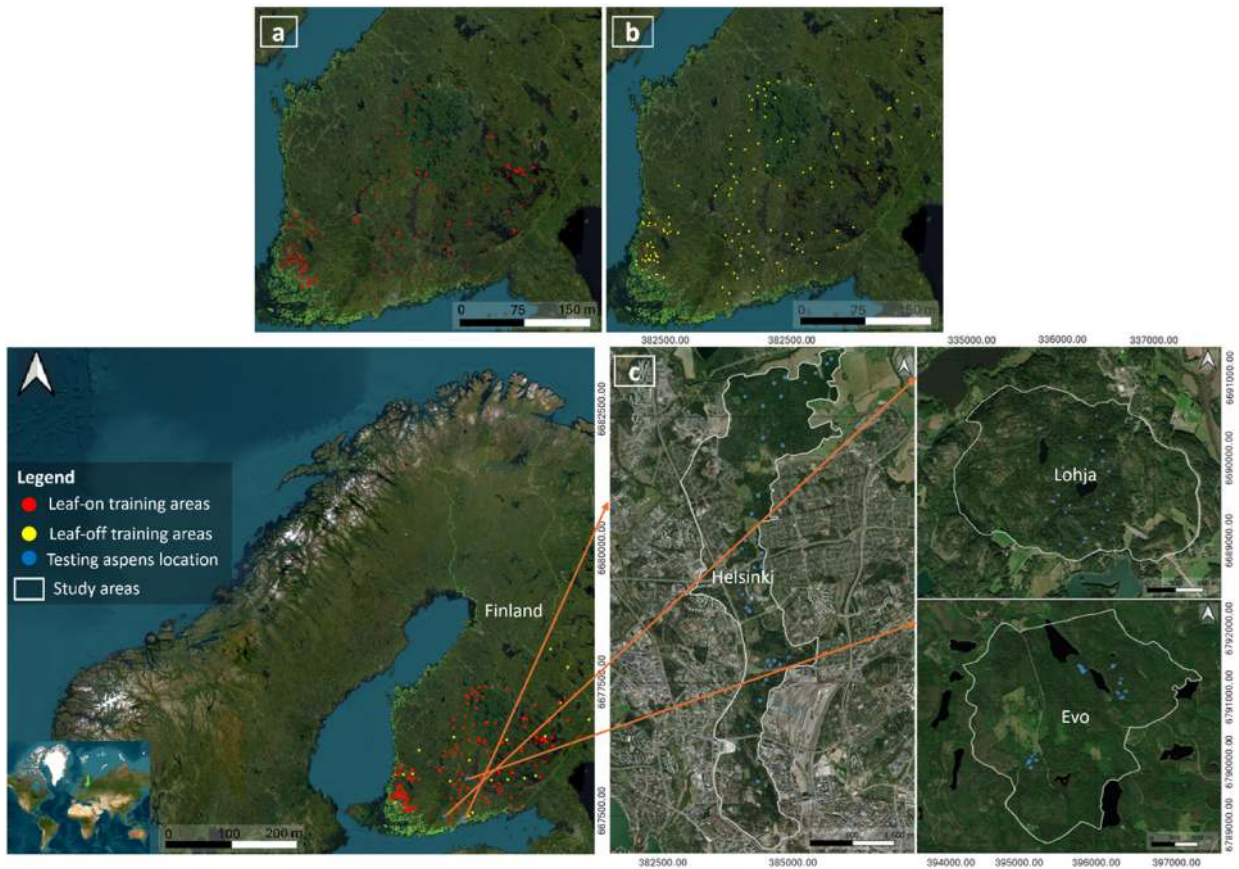


Fig. 1. Study area map: (a) Training areas during leaf-on conditions, marked in red; (b) Training areas during leaf-off conditions, marked in yellow; (c) Study areas with field data for aspens, highlighted in blue.

The Lohja site, located in the hemiboreal-southern boreal transition zone, is predominantly forested (61 %), with 19 % arable land and 1.3 % under protection or conservation programs (Pykälä, 2019). The landscape is a mosaic of forestry land, arable fields, inhabited areas, and frequent rock outcrops. Dominant tree species include Norway spruce (*P. abies* (L.) Karst), Scots pine (*P. sylvestris* L.), birches (*B. pendula* Roth and *B. pubescens* Ehrh.), European aspen (*P. tremula* L.), and other deciduous species. The climate features an average annual precipitation of 725 mm, mean July temperature of +17 °C, mean February temperature of −6.5 °C, and a 177-day growing season (Pykälä, 2004; Virtanen, 1995).

The Evo study area in Hämeenlinna municipality is characterized by a gradient of forest management, ranging from intensively managed to natural stands (Vauhkonen, 2018). The forest composition includes Downy birch (*B. pubescens*), Silver birch (*B. pendula*), Norway spruce (*P. abies*), Scots pine (*P. sylvestris*), and patchy European aspen (*P. tremula*) (Kuzmin et al., 2021). The terrain consists of gentle hills and depressions with elevations from 125 to 195 m a.s.l., underlain primarily by moraine and glaciofluvial deposits (Viinikka et al., 2020). The hemiboreal climate here has cold, snowy winters and mild summers, with an average annual temperature of 3.1 °C, a 160-day growing season, and approximately 670 mm of annual precipitation (Shorohova et al., 2024; Viinikka et al., 2020).

2.2. Aerial imagery in dataset preparation: training, validation, and testing

The training data were derived from visual observations of aspens in aerial imagery collected between 2010 and 2023 due to limited field data and the need for a large dataset to train a convolutional neural network. A total of 290 locations were manually selected for both leaf-on and leaf-off imagery, with area sizes ranging from 2 to 41 ha. Sites were chosen randomly, emphasizing diverse aspen distributions and sizes to ensure representation across forest types, imaging conditions, and image qualities for improved model robustness. The imagery, obtained from the National Land Survey of Finland (<https://paituli.csc.fi/download.html>, accessed 27 February 2025), was available under a CC-BY license. It included four spectral bands (red, green, blue, and near infrared) with a spatial resolution of 0.5 m. The imagery was orthorectified utilizing a 2-m digital elevation model (DEM), with pixel positional accuracy ranging from 0.5 to 2 m.

The annotation data consisted of aspen canopy segments manually outlined (i.e., polygons) within aerial imagery (Fig. 3). We aimed to segment each individual aspen, or groups of aspens where crowns overlapped, as single segments. Aspens were visually identified using RGB and false-color (NIR, red, green) imagery, occasionally supported by Google satellite imagery. As visual identification favors larger upper-canopy aspens, the training data primarily represent these individuals. Segmentation was performed in QGIS (v3.40.0) for both leaf-on and leaf-off imagery, depending on availability. A total of 20738 segments were outlined from imagery captured between 2010 and 2023 across Finland: 14011 for leaf-on and 6727 for leaf-off conditions (Table 1). Segments were reviewed by an additional expert to ensure accuracy. The dataset was split into training (90 %) and validation (10 %) sets, with the validation set used for hyperparameter tuning. We trained the model separately for both leaf-on and leaf-off imagery.

For testing, aerial imagery from 2019 to 2023 was collected for both leaf-on and leaf-off conditions, corresponding to available field-mapped aspen locations. Field data were obtained from three sites in southern Finland during inventories conducted between 2019 and 2023 (Table 2). All aspens with a DBH >5 cm were measured, and their locations within 9-m radius plots were recorded using a Trimble R10 RTK-GPS. In the imagery, each aspen or group of aspens was manually segmented to match field-mapped locations precisely. A total of 303 segments were outlined: 131 for leaf-on and 172 for leaf-off conditions (Table 3). The workflow is illustrated in Fig. 2.

Table 1

The number of aspen segments for the training and validating of the segmentation model.

Year	Number of segments		
	Leaf-on	Leaf-off	Total
2010	0	49	49
2011	16	44	60
2012	0	342	342
2013	0	40	40
2014	0	61	61
2015	95	0	95
2016	91	52	143
2017	75	329	404
2018	107	75	182
2019	274	454	728
2020	20	402	422
2021	785	185	970
2022	11959	107	12066
2023	589	4587	5176
Total	14011	6727	20738

Table 2

Aspen attributes (DBH in cm) statistics for testing datasets collected in the field. Stdv-standard deviation.

Statistic	Helsinki	Lohja	Evo	Total
Mean	33.71	23.48	38.72	32.98
Stdv	14.56	12.42	9.72	13.99
Range	5.10–78.60	5.00–51.00	16.20–55.00	5.00–78.60
Number of aspens (n)	115	75	99	289

Table 3

The number of aspen segments for testing the segmentation model. The number of aspens: Helsinki (n = 115), Lohja (n = 75), and Evo (n = 99).

Locations	Number of segments	
	Leaf-on	Leaf-off
Helsinki	68	104
Lohja	26	33
Evo	37	35
All	131	172

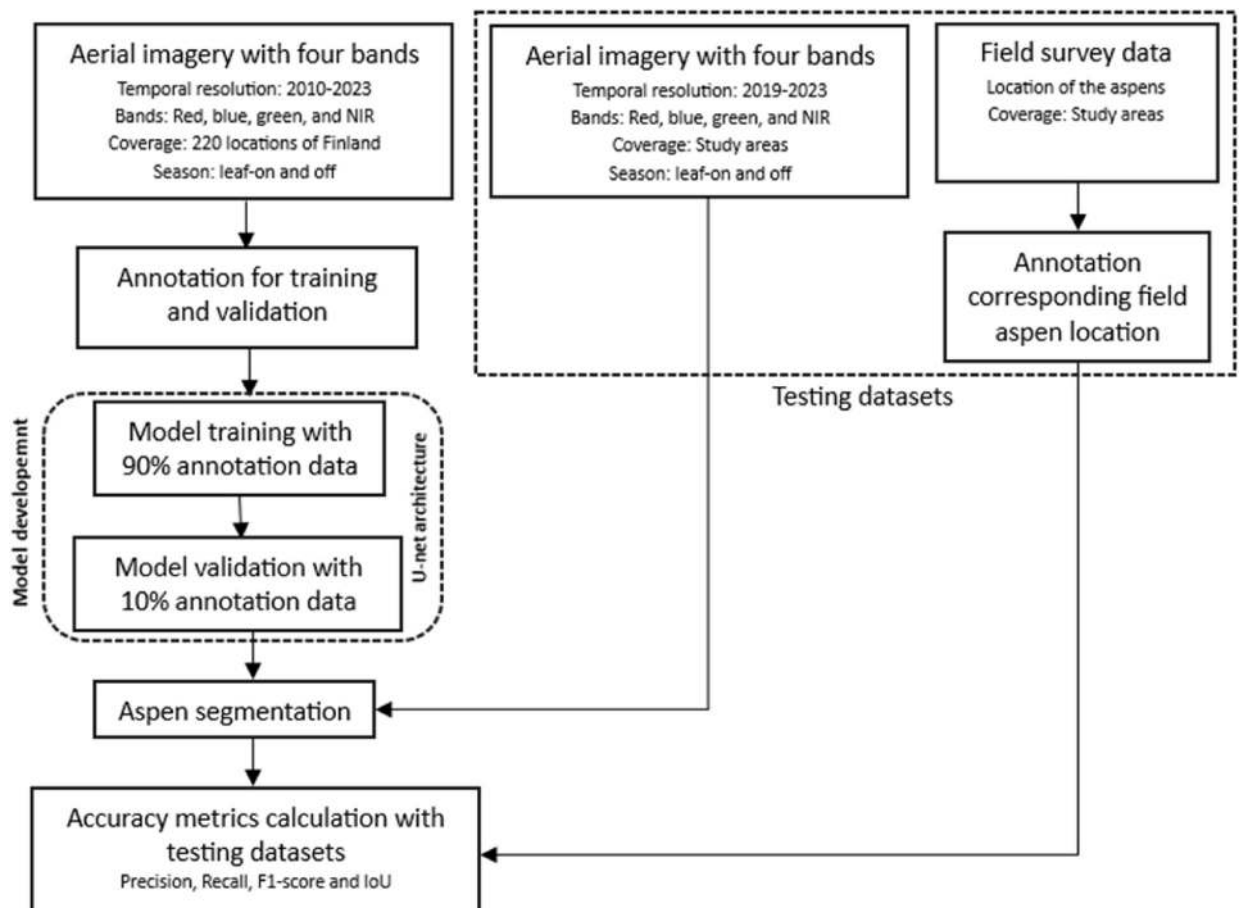


Fig. 2. Workflow of the main steps and analysis of aspen segmentations.

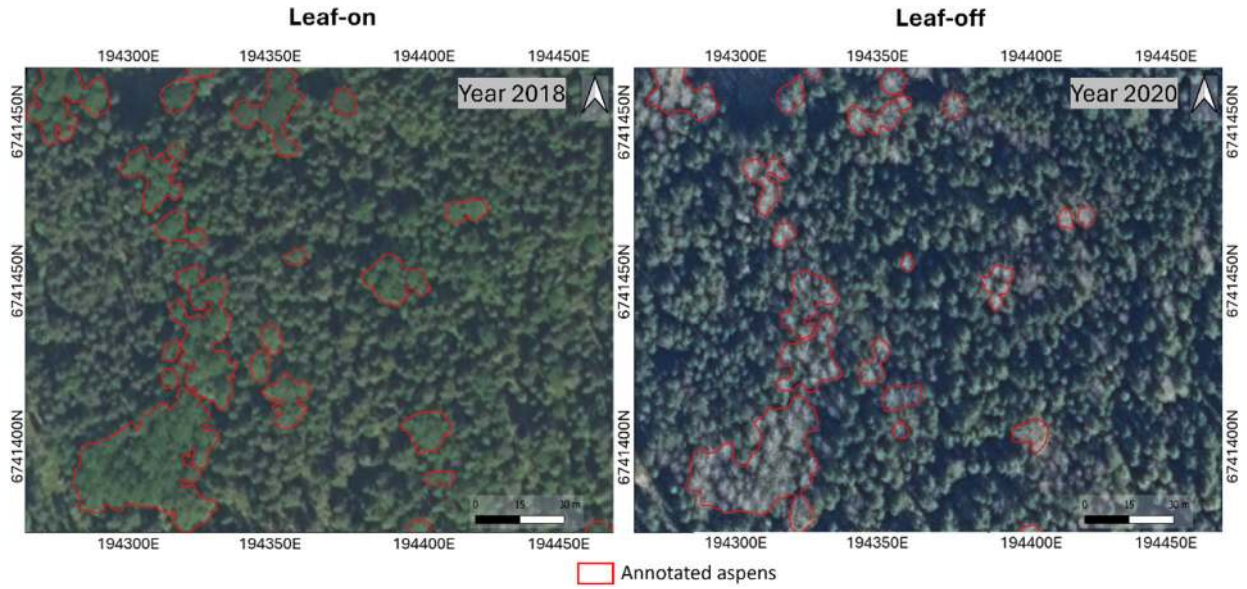


Fig. 3. Example of aspen annotations in both leaf-on and leaf-off imagery used for training and validation datasets.

2.3. Aspen segmentation model

In this study, we designed a fully convolutional neural network for semantic segmentation of aspens in aerial imagery, building on the U-Net encoder–decoder framework (Ronneberger et al., 2015). Our approach introduced four key modifications over the conventional U-Nets: Mobile Residual Blocks (M_ResB), an Atrous Spatial Pyramid Pooling (ASPP) module, refined decoder upsampling blocks combining transposed convolutions (Trans_CONV2D) and Conv2D layers, and an output layer using tanh activation tailored for the segmentation task. The encoder extracts hierarchical, multi-scale features while reducing spatial dimensions (Badrinarayanan et al., 2017), and the decoder reconstructs high-resolution feature maps through transposed convolutions, integrating skip connections to merge low- and high-level features for accurate reconstruction (Zelioli et al., 2024).

Within the encoder, the model incorporates three distinct types of blocks (Fig. 4a). First, 2D Convolutional blocks (CONV2D) adjust feature depth with 1×1 kernels, batch normalization, and ReLU activation, preserving spatial dimensions (Krizhevsky et al., 2017; Lanjewar and Gurav, 2022; Schiefer et al., 2020). Second, Mobile Residual Blocks (M_ResB) perform feature extraction using a combination of layers. These blocks start with a convolutional layer that maps the input to a higher-dimensional feature space, followed by a depth-wise separable convolution layer that extracts features individually for each channel of the intermediate representation (Fu et al., 2024) as shown in Fig. 4b. A final pointwise convolutional layer with 1×1 kernels reduces the dimensionality of the high-dimensional mapping to a lower dimensional space (Junttila et al., 2024). Additionally, skip connections between input and output improve the gradient flow for more efficient training. Overall, these Residual Mobile Blocks (M_ResB) inspired by MobileNets (Carvalho et al., 2022) provide computational efficiency while maintaining comparable performance levels. Third, the Atrous Spatial Pyramid Pooling (ASPP) block, illustrated in Fig. 4c, employs atrous convolutions with dilation rates of 2, 4, and 8 to capture multi-scale features, and concatenates the resulting outputs depth-wise to enhance contextual representation (Chen et al., 2018; Sunandini et al., 2023; Torres et al., 2020).

The decoder reconstructs high-resolution feature maps while gradually upsampling (Zhao and Fogler, 2023). The process begins with a Trans_Conv2D block, which upsamples the feature maps to $256 \times 256 \times 128$, followed by a Conv2D operation to refine the depth to 64 channels. Within each transposed convolution block, a transposed convolution layer is paired with batch normalization and subsequently activated with a rectified linear unit (ReLU; Junttila et al., 2024; Krizhevsky et al., 2017). To preserve fine-grained spatial information, CONCAT merges decoder outputs with corresponding encoder features. A second Trans_CONV2D increases resolution to $512 \times 512 \times 32$, followed by Conv2D producing a single-channel segmentation map ($512 \times 512 \times 1$). At the output layer, the tanh activation function is applied to constrain the segmentation map values between -1 and 1 (Sun et al., 2022). The resulting map is binarized using a threshold of -0.5 , and transformed into polygons via contour extraction as postprocessing.

Images were channel-wise normalized, and training data were augmented with random rotations, brightness/contrast adjustments, multiplicative noise, and gamma variations using Albumentations library (Illarionova et al., 2022). All the experimental evaluations were performed using Tensorflow (Abadi et al., 2016) with Python. The proposed network was trained for 100 epochs utilizing Adam optimizer (Kingma and Ba, 2014) with an initial learning rate of 2×10^{-4} and momentum update parameters as $\beta_1 = 0.9$ and $\beta_2 = 0.999$. We used mean-squared error as loss function with a batch size of 8. The learning rate was gradually decreased by a factor of 0.7 whenever the validation metrics showed no further improvement.

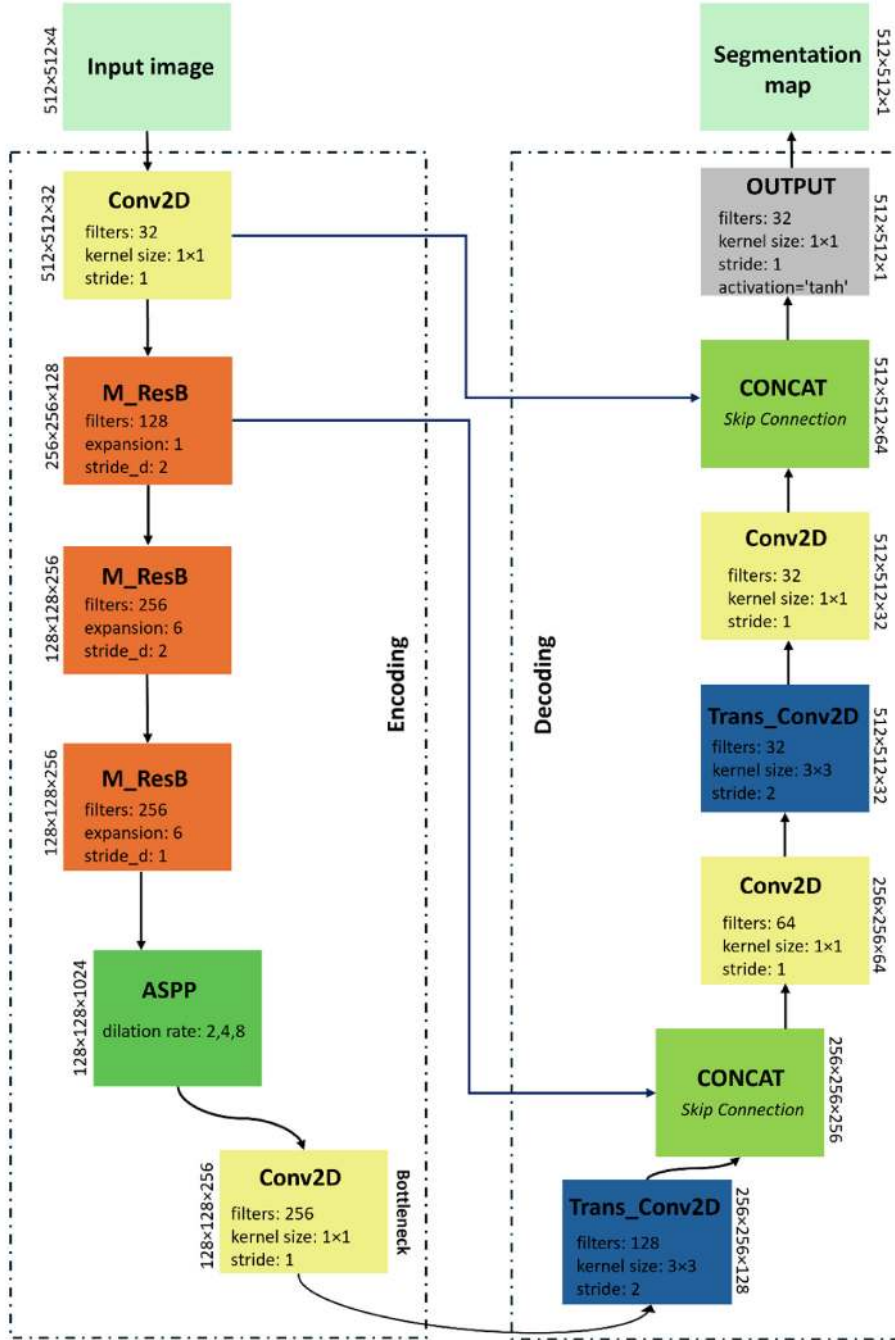


Fig. 4a. Aspen segmentation U-Net model architecture. The model processes $512 \times 512 \times 4$ images using an encoder-decoder structure. The encoder extracts hierarchical features using a series of CONV2D layers and Mobile Residual Blocks (M_ResB) illustrated in Fig. 4b. At the bottleneck, an Atrous Spatial Pyramid Pooling (ASPP) module shown in Fig. 4c captures multi-scale context. The decoder upsamples features using Trans-CONV2D layers and merges them with corresponding encoder outputs via CONCAT layers to preserve spatial detail. A final 1×1 convolution with tanh activation produces the segmentation map. All convolutions use “same” padding to maintain spatial resolution throughout.

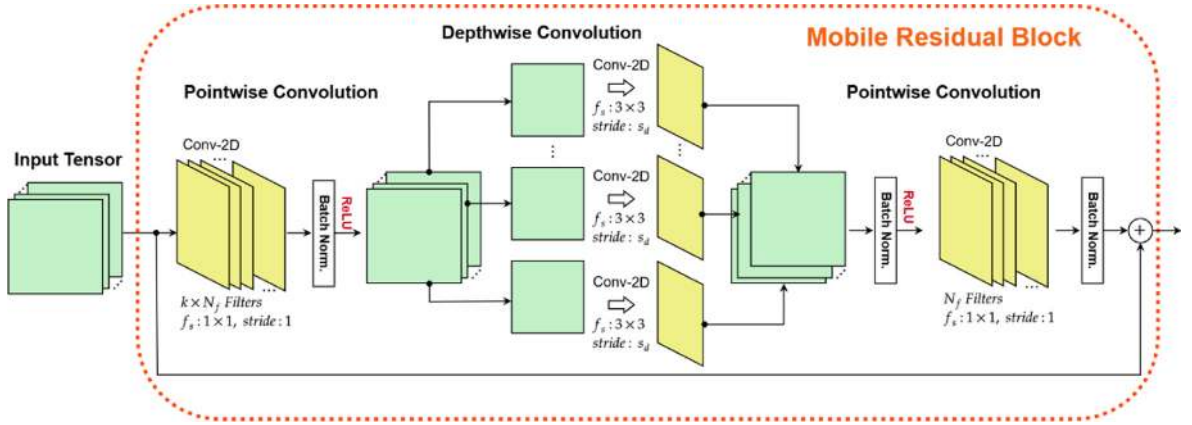


Fig. 4b. Mobile Residual Block (M_ResB) of the proposed U-Net architecture (Fig. 4a) is presented, where N_f is the number of filters, f_s is filter size, k is the expansion factor, and s_d is the stride number. N_f , k , and s_d are varied for the blocks and specified in Fig. 4a. Each M_ResB includes a 1×1 pointwise convolution for channel expansion, a 3×3 depthwise separable convolution (with block-specific stride), and a final 1×1 projection convolution.

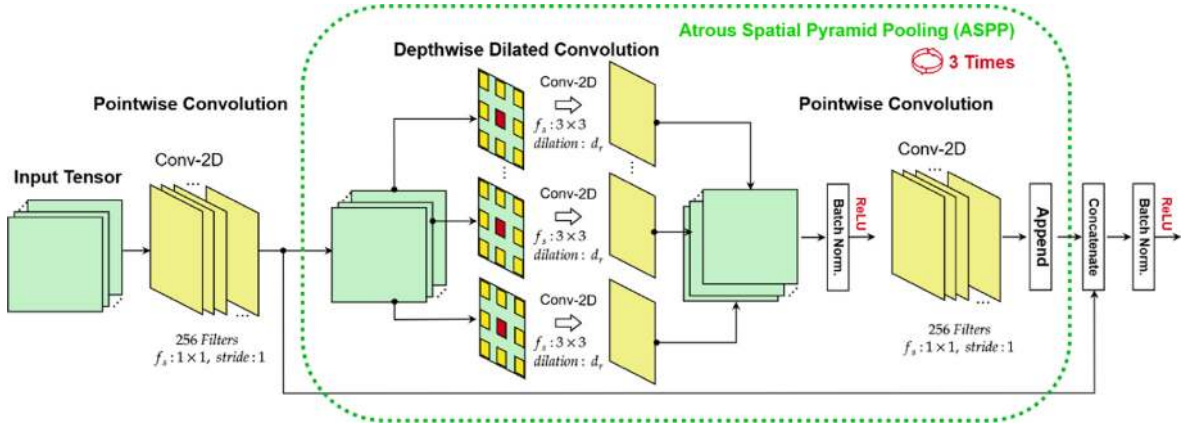


Fig. 4c. Atrous Spatial Pyramid Pooling (ASPP) of the proposed U-Net architecture (Fig. 4a) is presented, where the dilation rate is expressed by d_r and f_s is filter size. The ASPP consists of multiple 3×3 depthwise convolutions and one 1×1 convolution with 256 filters. The dilation rate d_r : 2, 4, and 8 is varied for each iteration as specified in Fig. 4a. Outputs are concatenated along the channel dimension.

2.4. Assessing the trained model's performance

To evaluate the model, the predicted segments were compared with field measurements and manually annotated segments from the testing dataset. Performance metrics such as precision (Eq. (1)), recall (Eq. (2)), and F1-score (Eq. (3)) were computed based on field-measured aspens, while intersection over union (IoU) (Eq. (4)) was calculated using the manually annotated segments. True positives (TP) were defined as model-derived aspen segments that overlapped with field-measured aspen locations, while false positives (FP) were model segments without any overlapping with field observations. Field-measured aspens without a spatial match from the model were identified as false negatives (FN). Spatial join tools in QGIS (version 3.40.0) facilitated the matching process.

$$\text{precision} = \frac{TP}{TP + FP} \quad \text{Eq. 1}$$

$$\text{recall} = \frac{TP}{TP + FN} \quad \text{Eq. 2}$$

$$\text{F1-score} = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \quad \text{Eq. 3}$$

$$\text{IoU} = \frac{\text{Area}(S_{\text{model}} \cap S_{\text{manual}})}{\text{Area}(S_{\text{model}} \cup S_{\text{manual}})} \quad \text{Eq. 4}$$

The model performance was measured using several evaluation metrics: precision, recall, F1-score, and IoU. Precision represents the proportion of model-predicted aspen segments that correctly correspond to manually annotated ground-truth segments. Recall indicates the fraction of annotated aspen segments that were successfully matched with the model's predictions. The F1-score provides a balanced metric by combining precision and recall through their harmonic mean. Finally, IoU quantifies the extent of spatial overlap between the model-segmented and manually labeled segments. DBH statistics were calculated by spatially matching each segmented aspen polygon to the nearest aspen field measurement.

To generate the aspen cover map ($16 \times 16 \text{ m}^2$ resolution), we calculated the percentage of aspen within each pixel using data from the forest mask and aspen cover. The forest mask data was provided by the Finnish Forest Centre (*Metsäkeskus* in Finnish).

3. Results

3.1. Aspen segmentation accuracy was higher for leaf-off imagery

There are notable differences in aspen segmentation accuracy between leaf-on and leaf-off conditions. The F1-score was higher in leaf-off (0.573) than in leaf-on (0.494), and IoU showed a similar trend (0.280 vs. 0.256; [Table 4](#)). Precision, however, was higher in leaf-on (0.907) than in leaf-off (0.879), whereas recall was higher in leaf-off (0.426) than in leaf-on (0.339).

Performance also varied across study sites. In Helsinki, leaf-off conditions showed moderate precision (0.848) and recall (0.583), leading to an F1-score of 0.691, while leaf-on precision was 0.781, and recall decreased sharply (0.217) (see [Table 4](#)). Lohja consistently achieved high precision in both conditions (1.000 in leaf-on and 0.875 in leaf-off), but recall was modest (0.360 in leaf-on and 0.467 in leaf-off), with better overall balance during leaf-off. Evo displayed the highest precision (1.000 in leaf-off and 0.939 in leaf-on), but recall was particularly low, especially in leaf-off conditions (0.212), contributing to reduced F1-scores and IoU.

The model segmentation performance under leaf-on and leaf-off conditions is illustrated in [Fig. 5](#). Panel (a) shows aspens that were correctly segmented (true positives), demonstrating the model's ability to accurately identify trees under varying foliage conditions. Panel (b) highlights misclassifications, including false positives, where non-aspen areas were incorrectly labeled, and false negatives, where aspens were missed. Panel (c) highlights incorrect segmentations, showing where the model struggled.

Aspen segmentation under both leaf-on and leaf-off conditions yielded comparable results, with minor variations in the mean DBH across locations. In the leaf-off condition, the mean DBH across all locations was 42.12 ± 8.98 cm, closely aligning with the leaf-on segmentations ([Table 5](#)). The mean DBH values were 42.85 ± 8.98 cm for Helsinki, 38.81 ± 9.51 cm for Lohja, and 45.07 ± 5.64 cm for Evo. As in the leaf-on condition, larger aspens were predominantly segmented in Evo. In leaf-on condition, the overall mean DBH across all locations was 42.06 cm (± 8.23 cm), with Helsinki showing a mean DBH of 42.90 cm (± 6.09 cm), Lohja 35.71 cm (± 9.78 cm), and Evo 44.99 cm (± 6.50 cm) (see [Table 5](#)). Overall, DBH exhibited a slightly wider range and greater standard deviation in the leaf-off condition compared to leaf-on.

3.2. Improved model performance with larger aspens

The model performs better in segmenting larger aspens, as evidenced by improved segmentation metrics when focusing on trees with DBH greater than 20 cm in both leaf-on and leaf-off conditions. For aspens larger than 20 cm, the F1-score increased to 0.663 in leaf-off (up from 0.573 for all aspens) and to 0.551 in leaf-on (up from 0.494), while the Intersection over Union (IoU) also improved slightly in both conditions. Location-specific results showed similar trends: in Helsinki, the leaf-off F1-score increased from 0.691 to 0.722, and leaf-on from 0.340 to 0.424; in Lohja, scores reached 0.757 during leaf-off and 0.667 in leaf-on. Evo exhibited high precision (0.938–1.000) but low recall, particularly in leaf-off (0.241), which led to lower F1-scores ([Table 6](#)).

Moreover, the model performance further improves for aspens larger than 30 cm in DBH, particularly in leaf-off conditions. For aspens >30 cm, the F1-score reached 0.710 in leaf-off and 0.594 in leaf-on, both exceeding the scores for all aspens (0.573 and 0.494) and aspens >20 cm (0.663 and 0.551). IoU increased significantly to 0.323 in both leaf-on and leaf-off conditions, surpassing values observed for smaller aspens. Precision remained consistent across size categories, while recall showed marked improvement for aspens >30 cm, especially during leaf-off (0.606). Location-specific results reinforce this trend: in Helsinki, the F1-score for aspens >30 cm increased to 0.736 in leaf-off and 0.452 in leaf-on; in Lohja, leaf-off F1-score improved to 0.903 with an outstanding recall of 0.933, and leaf-on scores improved to 0.783. Evo's precision remained high (0.938–1.000), but its low recall in leaf-off (0.280) caused lower F1-scores (see [Table 6](#)). Overall, the segmentation accuracy improved by 12–16 % (F1-score) for aspens >20 cm DBH and by 20–24 % for those >30 cm when smaller trees were excluded. Corresponding IoU gains were 5–14 % and 15–26 %, respectively.

Table 4
Summary of the segmentation model performances.

Season	Location	Precision	Recall	F1-score	IoU
Leaf-on	Helsinki	0.781	0.217	0.340	0.122
	Lohja	1.000	0.360	0.529	0.486
	Evo	0.939	0.465	0.622	0.411
	All	0.907	0.339	0.494	0.256
Leaf-off	Helsinki	0.848	0.583	0.691	0.378
	Lohja	0.875	0.467	0.609	0.492
	Evo	1.000	0.212	0.350	0.066
	All	0.879	0.426	0.573	0.280

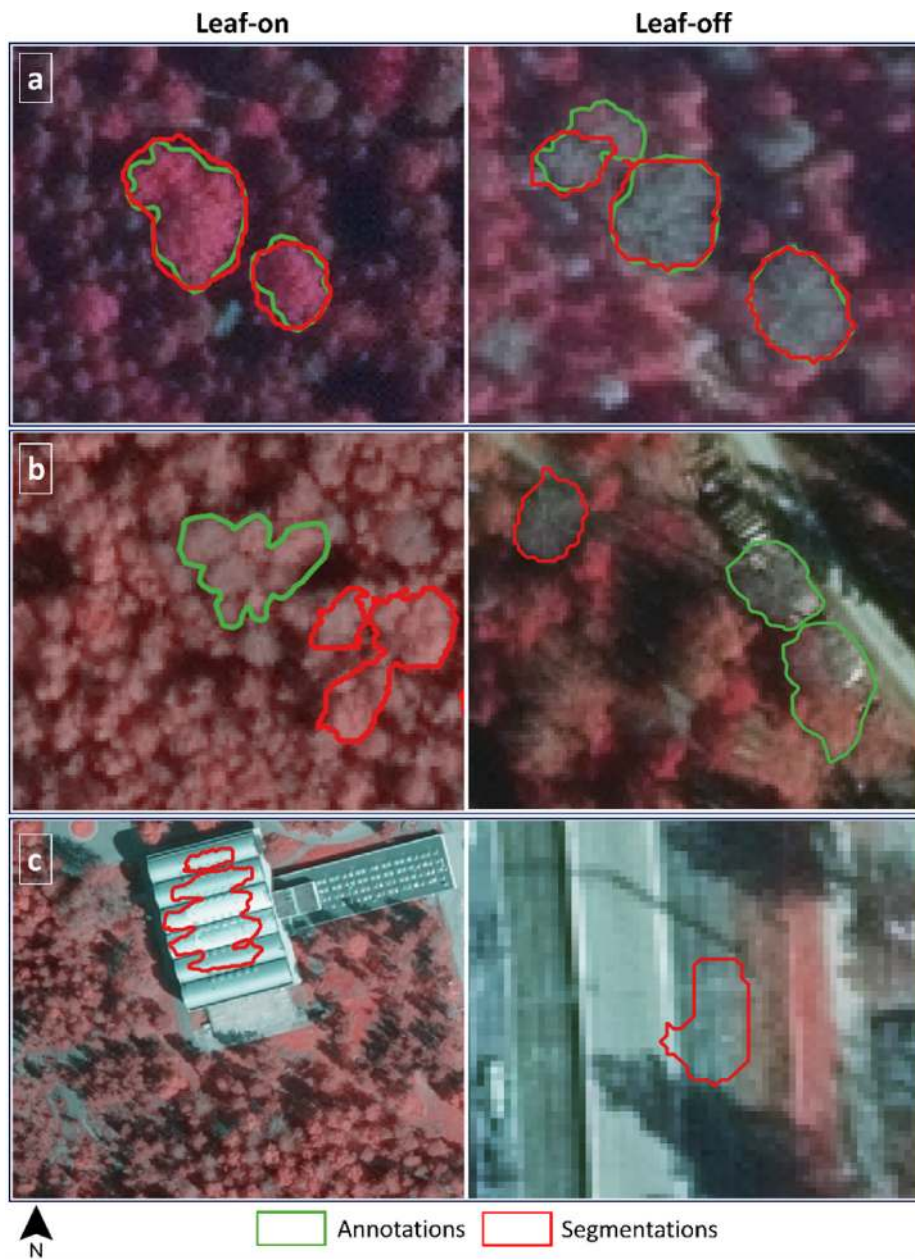


Fig. 5. Model segmentation results under leaf-on and leaf-off conditions. Panels show (a) true positives, (b) false positives and false negatives, and (c) incorrect segmentations. Visualization uses false-color imagery (NIR, red, and green).

Table 5

Segmented aspen DBH (cm) statistics for leaf-on and leaf-off conditions. Stdv-standard deviation.

Season	Location	Mean	Stdv	Range
Leaf-on	Helsinki	42.90	6.09	24.20–49.90
	Lohja	35.71	9.78	21–51
	Evo	44.99	6.50	33.60–55
	All	42.06	8.23	21–55
Leaf-off	Helsinki	42.85	8.98	23.30–62.70
	Lohja	38.81	9.51	22–51
	Evo	45.07	5.64	40–55
	All	42.12	8.98	22–62.70

Table 6

Summary of the segmentation model performance in larger aspens.

Aspen	Season	Location	Precision	Recall	F1-score	IoU
Aspens >20 cm DBH	Leaf-on	Helsinki	0.778	0.292	0.424	0.150
		Lohja	1.000	0.500	0.667	0.548
		Evo	0.938	0.517	0.667	0.418
		All	0.884	0.400	0.551	0.292
	Leaf-off	Helsinki	0.830	0.641	0.722	0.402
		Lohja	0.875	0.667	0.757	0.527
		Evo	1.000	0.241	0.389	0.067
		All	0.857	0.541	0.663	0.293
	Leaf-on	Helsinki	0.778	0.318	0.452	0.165
		Lohja	1.000	0.643	0.783	0.591
		Evo	0.938	0.556	0.698	0.467
		All	0.884	0.447	0.594	0.323
Aspens >30 cm DBH	Leaf-off	Helsinki	0.830	0.661	0.736	0.410
		Lohja	0.875	0.933	0.903	0.603
		Evo	1.000	0.280	0.438	0.084
		All	0.857	0.606	0.710	0.323

4. Discussion

The study focused on developing and evaluating a U-Net deep learning model for segmenting aspens from aerial imagery. Specifically, it assessed segmentation accuracy under varying seasonal conditions (leaf-on and leaf-off) and examined how aspen size influences segmentation performance. The results showed that the efficiency of the segmentation model varied with the season and the size of the aspens, with lower segmentation accuracy observed during the leaf-on condition and for smaller aspens.

4.1. Model performance differences of aspen segmentation

Our model achieved F1-scores of 0.494–0.573 under leaf-on and leaf-off conditions, consistent with [Säynäjoki et al. \(2008\)](#), who used aerial imagery and laser scanning data in eastern Finland. Several studies using Random Forest (RF) and Support Vector Machine (SVM) have reported higher segmentation accuracy for aspen. For instance, [Troshin et al. \(2025\)](#) achieved 95.03 % accuracy using RF with Sentinel-2 imagery; [Viinikka et al. \(2020\)](#) reported F1-scores of 0.77–0.91 using RF and SVM with airborne hyperspectral and LiDAR data; [Kuzmin et al. \(2021\)](#) achieved 84 % F1-score with UAV RGB imagery and SVM; [Hardenbol et al. \(2021\)](#) reported 97 % user's accuracy (UA) and 96 % producer's accuracy (PA) using multispectral drone imagery and linear discriminant analysis (LDA); and [Cook et al. \(2024\)](#) found an F1-score of 0.93 for quaking aspen classification in the western United States. In contrast, [Toivonen et al. \(2024\)](#) obtained lower F1-scores (0.21–0.44) with aerial imagery and ALS data. In comparison with the U-Net model accuracy, traditional ML models, RF and SVM, performed poorly when tested using the same dataset (see supplementary data). We observed F1-scores of 0.098–0.140 for RF (regionally up to 0.163) ([Table S2](#)) and 0.081–0.128 for SVM (regionally up to 0.156) ([Table S3](#)). The outputs from these models were generally noisy and lacked spatial coherence. Their limited performance can be attributed to the computational burden of extracting features from millions of pixels and the inherent difficulty of capturing spatial context. These challenges became particularly pronounced when working with high-resolution imagery (0.5 m) and a large training dataset.

Deep learning approaches, particularly CNNs, address these limitations by integrating spectral-spatial feature learning and pixel-wise segmentation in a single end-to-end framework. Previous studies have demonstrated the effectiveness of CNNs for tree crown and forest classification: [Mäyrä et al. \(2021\)](#) achieved F1-scores up to 0.91 for aspen using 3D-CNNs with hyperspectral and LiDAR, surpassing RF, SVM, and gradient boosting. Similarly, [Sothe et al. \(2020\)](#) found CNNs to be 22–26 % more accurate than RF and SVM with hyperspectral bands, while [Natesan et al. \(2019\)](#) achieved F1-scores of 0.80 for *Pinus* species using UAV-based CNNs. A UAV-based U-Net model achieved even higher performance, with F-scores of 0.93 for species classification ([Schieffer et al., 2020](#)). Expanding beyond crown delineation, [Pyo et al. \(2022\)](#) demonstrated U-Net's broader applicability, reporting an F1-score of 0.97 for forest/non-forest classification. In this study, we applied U-Net directly to large-scale, high resolution (0.5 m) imagery under both leaf-on and leaf-off conditions. U-Net successfully captured spatial context and hierarchical features, enabling the delineation of complex crown shapes and overlapping canopies ([Schieffer et al., 2020](#)). However, differences in accuracy likely reflect variations in target tree size (many high-accuracy studies focused on aspens >15–20 cm DBH, whereas we included >5 cm), data type (hyperspectral/LiDAR vs. RGBNIR aerial imagery), and segmentation scale (plot level vs. individual/group). Importantly, our approach relied on openly available, national-scale imagery rather than expensive, spatially limited datasets, making it a practical and scalable solution for large-area aspen mapping.

Segmentation accuracy in our study was higher under leaf-off conditions (F1-score = 0.573) than leaf-on (F1-score = 0.494), likely due to reduced foliage density exposing structural features such as branch architecture and bark texture. Such exposure enhances spectral and spatial distinctiveness, reduces background noise especially in the NIR band and enables the model to better capture fine structural and spectral patterns. These results align with [Ørka et al. \(2010\)](#), [Kim et al. \(2009\)](#), [Reitberger et al. \(2008\)](#), and [Heurich \(2006\)](#), who reported improved accuracy using leaf-off imagery. For instance, [Reitberger et al. \(2008\)](#) and [Heurich \(2006\)](#) found accuracies of 96–97 % in leaf-off conditions compared to 81–85 % in leaf-on for tree species classification. Seasonal timing is also

critical: in Finland, [Hovi et al. \(2016\)](#) and [Villikka et al. \(2012\)](#) showed that early spring, when aspens are leafless, but birches have flushed, offers optimal separability due to phenological differences. Our results, aligned with this, show improved segmentation during this window (see [Fig. 6](#)). However, large intraspecific variation can sometimes limit this advantage ([Lisein et al., 2015](#)). Late spring and summer, when both species are in full foliage, reduce spectral contrast despite the continued usefulness of red edge and NIR bands ([Viinikka et al., 2020](#)).

Aspen segmentation remains more challenging than identifying pine, spruce, or other deciduous species. Studies consistently support this, with [Tuominen et al. \(2018\)](#) and [Kuzmin et al. \(2021\)](#) reporting F1-scores 10–20 % lower for aspen, and [Breidenbach et al. \(2010\)](#) finding relative RMSEs of 39 % for pine, 40 % for spruce, 101 % for birch, and 222 % for aspen. Unlike conifers with distinctive needle-like foliage and forms, aspens resemble other deciduous species in structure and appearance ([Hardenbol et al., 2021](#); [Simpson, 2010](#)), and seasonal leaf color changes can cause misidentification. Aspens often grow in mixed stands, especially dense forests, further

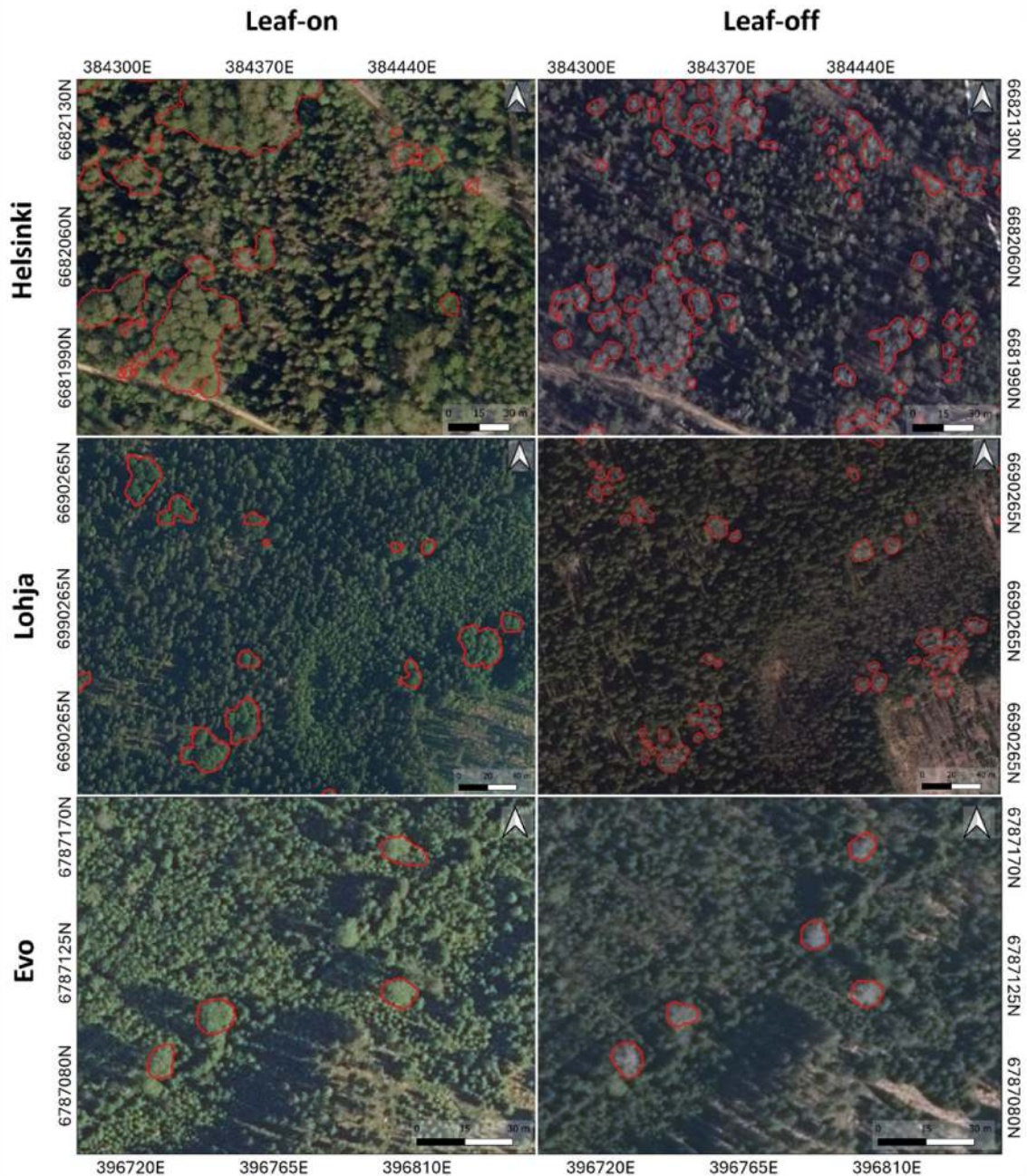


Fig. 6. Final model output illustrating aspen segmentation at a consistent location, where the model outlines both individual aspens and groups in aerial imagery captured during leaf-on and leaf-off conditions.

complicating segmentation (Clair et al., 2013; Rogers et al., 2020). Remote sensing struggles with their less distinctive spectral signatures (Chernenkova et al., 2021; Hardenbol et al., 2021), though structural traits like broader crowns, larger branches, and coarser canopy texture can help distinguish them.

4.2. Model results for larger aspens

Our results indicate that larger aspens (>30 cm DBH) were segmented with higher probability (overall F1-score up to 0.710; regional F1-score up to 0.903) than smaller ones, consistent with previous findings. Many studies deliberately excluded smaller aspens (e.g., <15 cm Mäyrä et al., 2021; <20 cm Kuzmin et al., 2021; <25 cm Hardenbol et al., 2021) to ensure crown visibility in aerial imagery and improve segmentation of mature trees. Sänäjoki et al. (2008) reported that larger aspens were segmented more successfully, with overall accuracy reaching 57 % (ranging from 27 % to 100 % across plots). For aspens with DBH ≥ 15 cm, accuracy increased to 81 % (43–100 % per plot), and for those with DBH ≥ 25 cm, it rose to 96 %, with nearly all large trees successfully identified. Similarly, Toivonen et al. (2024) found that aspens >22 cm DBH increased F1-scores by up to 23 % at the tree level and 13 % at the plot level, while Dalponte et al. (2014) reported higher classification accuracy for larger trees in boreal forests using hyperspectral data. Our segmentation accuracy increased by 12–16 % in F1-score when focused on larger aspens (>20 cm DBH), and by 20–24 % when considering only aspens >30 cm DBH, indicating improved performance with the exclusion of smaller aspens. This trend is mirrored in overall accuracy, highlighting that segmentation performance consistently improves as smaller aspens are excluded. The improved segmentation of larger aspens likely reflects their more distinct crowns, greater structural definition, and stronger spectral signals, which enhance visibility in remote sensing, whereas smaller aspens often blend into the canopy or are obscured by undergrowth.

Our model also exhibited sensitivity to aspens with similar DBH in both leaf-on and leaf-off conditions. This is likely due to the correlation between DBH and crown attributes, as trees of similar size often share comparable crown dimensions, shapes, and textures, which can appear visually similar in aerial imagery. Consequently, such similarities may reduce separability in dense or mixed species

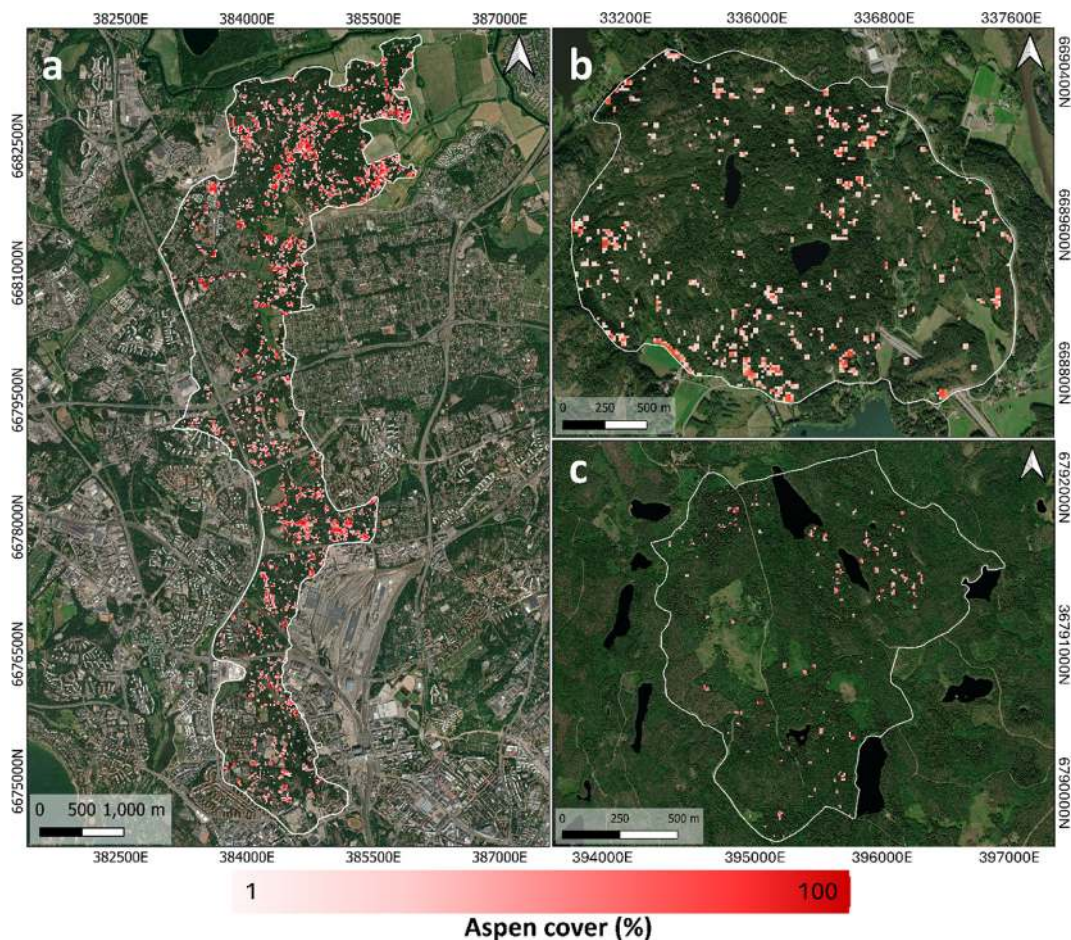


Fig. 7. Aspen cover estimation using the best model (leaf-off) for the study areas: a) Helsinki, b) Lohja, and c) Evo. Each grid cell measures 16×16 m², with coordinates presented in the ETRS89-TM35FIN reference system.

stands, leading to occasional misclassification or omission. Timing of aerial imagery acquisition further influenced segmentation performances. At the Evo site, we observed a lower recall (0.212) during the leaf-off condition (Table 4). This reduction is primarily due to the timing of image acquisition, which occurred during a transitional phenological stage when leaves were already beginning to sprout. While most aspens did not have leaves, some already had them leading to differences in the spectral properties of the aspen canopies among the Evo leaf-off dataset. This intermediate state reduced the visual contrast between aspens and surrounding conifers, making them more difficult for segmentation. Since Evo's forest composition is comparable to other sites, we attribute this performance drop mainly to acquisition timing rather than differences in species mix. Therefore, we recommend capturing leaf-off imagery during full defoliation and leaf-on imagery during peak foliage for better segmentation accuracy.

Despite these challenges, our models achieved reasonable accuracy in mapping aspen distribution (Fig. 7), marking a significant advancement over traditional inventory methods that often underrepresent scattered aspen populations. These remote sensing-based maps provide forest managers with valuable tools for sustainable management and conservation of key species for biodiversity, ensuring that both dense stands and isolated individuals are adequately represented in planning (Rogers et al., 2020; Viinikka et al., 2020).

Several factors could further enhance segmentation accuracy. First, we used aerial imagery at 0.5 m resolution; adopting higher-resolution imagery (e.g., 0.2 m) could enhance segmentation precision. Second, while our four spectral bands (RGB and NIR) provided a solid basis for segmentation, hyperspectral data could further improve the accuracy by capturing finer spectral differences. However, the added cost, complexity, and processing demands of hyperspectral imagery may reduce scalability for large-area monitoring. Third, model architecture could be optimized. Alternatives such as HRNet, which preserves high-resolution features throughout the network, or architectures that integrate diverse convolutional blocks, may improve feature extraction and segmentation accuracy. At the same time, persistent misclassification among spectrally or structurally similar classes represents an important limitation. One promising strategy would be to adopt multi-stage pipelines that first isolate broad land-cover types (e.g., forests vs. non-forests) before performing detailed class recognition, as outlined in recent studies using high-resolution remote sensing data (Illarionova et al., 2024b). Finally, the inclusion of attention layers, along with the expansion of training data from diverse forest ecosystems and fine-tuning the model to account for these variations, could also lead to significant improvements in model accuracy.

5. Conclusion

Mapping aspen distribution supports effective forest management by helping managers make informed, sustainable decisions based on its ecological significance. This study aimed to develop and evaluate a deep learning model, specifically a U-Net convolutional neural network, to segment aspens using both leaf-on and leaf-off aerial imagery and to compare them. Additionally, it examined how factors like aspen size influence segmentation performance. The results showed that the accuracy of aspen segmentation varies notably between leaf-on and leaf-off conditions. Both the F1-score and IoU were higher in leaf-off conditions than in leaf-on conditions. Furthermore, the model segmentation accuracy improved considerably for larger aspens, as shown by the F1-score and IoU. In particular, the model performed best with aspens larger than 30 cm in DBH. Overall, our model can aid in forest management by providing insights into the abundance and distribution of aspens.

CRediT authorship contribution statement

Anwarul Islam Chowdhury: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Einari Heinaro:** Writing – review & editing, Validation, Supervision, Software. **Topi Tanhuanpää:** Writing – review & editing, Supervision. **Anis Ur Rahman:** Writing – review & editing. **Samuli Junttila:** Writing – review & editing, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

Ethical statement

We hereby declare that:

- All authors have given their consent to submit this manuscript to *Remote Sensing Applications: Society and Environment*.
- This manuscript is not currently under consideration for publication elsewhere, nor will it be submitted to another journal until a final decision has been made.
- The content of this work is entirely original. Any ideas, text, or data derived from other sources have been properly acknowledged through appropriate citation or quotation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This study was funded by the University of Eastern Finland. SJ received support from the European Union (ERC-2023-STG, Grant Agreement No. 101116404). The views and conclusions presented in this work are solely those of the author(s) and do not necessarily represent those of the European Union or the European Research Council Executive Agency. Neither the EU nor the funding body is liable for any use that may be made of the information contained herein. The authors would like to express their gratitude to Niina Palokunnas, Rosa Loikkanen, and Kasper Holm for their assistance with data annotation. They are also grateful to Mete Ahishali for his insightful suggestions and support. The authors would like to express sincere gratitude to CSC – IT Center for Science, Finland, for providing access to the supercomputer. Additionally, the authors appreciate the valuable feedback from the anonymous reviewers, which contributed to improving the manuscript.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.rsase.2025.101755>.

Data availability

Data will be made available on request.

References

- Abadi, M., Agarwal, A., Barham, P., Brevdo, E., Chen, Z., Citro, C., Corrado, G.S., Davis, A., Dean, J., Devin, M., Ghemawat, S., Goodfellow, I., Harp, A., Irving, G., Isard, M., Jia, Y., Jozefowicz, R., Kaiser, L., Kudlur, M., Levenberg, J., Mane, D., Monga, R., Moore, S., Murray, D., Olah, C., Schuster, M., Shlens, J., Steiner, B., Sutskever, I., Talwar, K., Tucker, P., Vanhoucke, V., Vasudevan, V., Viegas, F., Vinyals, O., Warden, P., Wattenberg, M., Wicke, M., Yu, Y., Zheng, X., 2016. TensorFlow: large-scale machine learning on heterogeneous distributed systems. <https://doi.org/10.48550/arXiv.1603.04467>.
- Audebert, N., Le Saux, B., Lefèvre, S., 2018. Beyond RGB: very high resolution urban remote sensing with multimodal deep networks. *ISPRS J. Photogrammetry Remote Sens.* 140, 20–32. <https://doi.org/10.1016/j.isprsjprs.2017.11.011>.
- Badrinarayanan, V., Kendall, A., Cipolla, R., 2017. SegNet: a deep convolutional encoder-decoder architecture for image segmentation. *IEEE Trans. Pattern Anal. Mach. Intell.* 39, 2481–2495. <https://doi.org/10.1109/TPAMI.2016.2644615>.
- Baroni, D., Masoero, G., Korpimäki, E., Morosinotto, C., Laaksonen, T., 2021. Habitat choice of a secondary cavity user indicates higher avoidance of disturbed habitat during breeding than during food-hoarding. *For. Ecol. Manag.* 483, 118925. <https://doi.org/10.1016/j.foreco.2021.118925>.
- Breidenbach, J., Næsset, E., Lien, V., Gobakken, T., Solberg, S., 2010. Prediction of species specific forest inventory attributes using a nonparametric semi-individual tree crown approach based on fused airborne laser scanning and multispectral data. *Remote Sens. Environ.* 114, 911–924. <https://doi.org/10.1016/j.rse.2009.12.004>.
- Carvalho, M.D.A., Marcato, J., Martins, J.A.C., Zamboni, P., Costa, C.S., Siqueira, H.L., Araújo, M.S., Gonçalves, D.N., Furuya, D.E.G., Osco, L.P., Ramos, A.P.M., Li, J., De Castro, A.A., Gonçalves, W.N., 2022. A deep learning-based Mobile application for tree species mapping in RGB images. *Int. J. Appl. Earth Obs. Geoinf.* 114, 103045. <https://doi.org/10.1016/j.jag.2022.103045>.
- Chen, L.-C., Papandreou, G., Kokkinos, I., Murphy, K., Yuille, A.L., 2018. DeepLab: semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected CRFs. *IEEE Trans. Pattern Anal. Mach. Intell.* 40, 834–848. <https://doi.org/10.1109/TPAMI.2017.2699184>.
- Chernenkova, T., Kotlov, I., Belyaeva, N., Suslova, E., 2021. Spatiotemporal modeling of coniferous forests dynamics along the southern edge of their range in the central Russian plain. *Remote Sens.* 13, 1886. <https://doi.org/10.3390/rs13101886>.
- Clair, S.B.St, Cavard, X., Bergeron, Y., 2013. The role of facilitation and competition in the development and resilience of aspen forests. *For. Ecol. Manag.* 299, 91–99. <https://doi.org/10.1016/j.foreco.2013.02.026>.
- Cook, M., Chapman, T., Hart, S., Paudel, A., Balch, J., 2024. Mapping quaking aspen using seasonal Sentinel-1 and Sentinel-2 composite imagery across the southern rockies, USA. *Remote Sens.* 16, 1619. <https://doi.org/10.3390/rs16091619>.
- Dalponte, M., Frizzera, L., Gianelle, D., 2019. Individual tree crown delineation and tree species classification with hyperspectral and LiDAR data. *PeerJ* 6, e6227. <https://doi.org/10.7717/peerj.6227>.
- Dalponte, M., Ørka, H.O., Ene, L.T., Gobakken, T., Næsset, E., 2014. Tree crown delineation and tree species classification in boreal forests using hyperspectral and ALS data. *Remote Sens. Environ.* 140, 306–317. <https://doi.org/10.1016/j.rse.2013.09.006>.
- Erikson, M., 2004. Species classification of individually segmented tree crowns in high-resolution aerial images using radiometric and morphologic image measures. *Remote Sens. Environ.* 91, 469–477. <https://doi.org/10.1016/j.rse.2004.04.006>.
- Fu, M., Lu, C., Mao, Y., Zhang, X., Wu, Y., Luo, H., Liu, Z., Li, W., Ou, G., 2024. An efficient and accurate deep learning method for tree species classification that integrates depthwise separable convolution and dilated convolution using hyperspectral data. *Int. J. Digit. Earth* 17, 2307999. <https://doi.org/10.1080/17538947.2024.2307999>.
- Han, Z., Hu, W., Peng, S., Lin, H., Zhang, J., Zhou, J., Wang, P., Dian, Y., 2022. Detection of standing dead trees after pine wilt disease outbreak with airborne remote sensing imagery by multi-scale spatial attention deep learning and Gaussian Kernel approach. *Remote Sens.* 14, 3075. <https://doi.org/10.3390/rs14133075>.
- Hardenbol, A.A., Junninen, K., Kouki, J., 2020. A key tree species for forest biodiversity, European aspen (*Populus tremula*), is rapidly declining in boreal old-growth forest reserves. *For. Ecol. Manag.* 462, 118009. <https://doi.org/10.1016/j.foreco.2020.118009>.
- Hardenbol, A., Kuzmin, A., Korhonen, L., Korpelainen, P., Kumpula, T., Maltamo, M., Kouki, J., 2021. Detection of aspen in conifer-dominated boreal forests with seasonal multispectral drone image point clouds. *Silva Fenn.* 55. <https://doi.org/10.14214/sf.10515>.
- Hardenbol, A.A., Pakkala, T., Kouki, J., 2019. Persistence of a keystone microhabitat in boreal forests: cavities of Eurasian three-toed Woodpeckers (*Picoides tridactylus*). *For. Ecol. Manag.* 450, 117530. <https://doi.org/10.1016/j.foreco.2019.117530>.
- Hedenäs, H., Ericson, L., 2008. Species occurrences at stand level cannot be understood without considering the landscape context: cyanolichens on aspen in boreal Sweden. *Biol. Conserv.* 141, 710–718. <https://doi.org/10.1016/j.biocon.2007.12.019>.
- Heurich, M., 2006. Evaluation and Development of Methods for the Automatic Determination of Forest Structures Using Data from Aerial Sensors (Phd Thesis). Technische Universität München.
- Hovi, A., Korhonen, L., Vauhkonen, J., Korpela, I., 2016. LiDAR waveform features for tree species classification and their sensitivity to tree- and acquisition related parameters. *Remote Sens. Environ.* 173, 224–237. <https://doi.org/10.1016/j.rse.2015.08.019>.
- Huang, H., Kalogerakis, E., Chaudhuri, S., Ceylan, D., Kim, V.G., Yumer, E., 2018. Learning local shape descriptors from part correspondences with multiview convolutional networks. *ACM Trans. Graph.* 37, 1–14. <https://doi.org/10.1145/3137609>.

- Illarionova, S., Shadrin, D., Ignatiev, V., Shayakhmetov, S., Trekin, A., Oseledets, I., 2022. Estimation of the canopy height model from multispectral satellite imagery with convolutional neural networks. *IEEE Access* 10, 34116–34132. <https://doi.org/10.1109/ACCESS.2022.3161568>.
- Illarionova, S., Tregubova, P., Shukhratov, I., Shadrin, D., Efimov, A., Burnaev, E., 2024a. Advancing forest carbon stocks' mapping using a hierarchical approach with machine learning and satellite imagery. *Sci. Rep.* 14, 21032. <https://doi.org/10.1038/s41598-024-71133-8>.
- Illarionova, S., Tregubova, P., Shukhratov, I., Shadrin, D., Kedrov, A., Burnaev, E., 2024b. Remote sensing data fusion approach for estimating forest degradation: a case study of boreal forests damaged by *Polygraphus proximus*. *Front. Environ. Sci.* 12, 1412870. <https://doi.org/10.3389/fenvs.2024.1412870>.
- Junttila, S., Blomqvist, M., Laukkanen, V., Heinara, E., Polvivaara, A., O'Sullivan, H., Yrttimaa, T., Vastaranta, M., Peltola, H., 2024. Significant increase in forest canopy mortality in boreal forests in Southeast Finland. *For. Ecol. Manag.* 565, 122020. <https://doi.org/10.1016/j.foreco.2024.122020>.
- Karvinen, E., Backman, L., Järvi, L., Kulmala, L., 2024. Soil respiration across a variety of tree-covered urban green spaces in Helsinki, Finland. *SOIL* 10, 381–406. <https://doi.org/10.5194/soil-10-381-2024>.
- Kim, S., McGaughey, R.J., Andersen, H.-E., Schreuder, G., 2009. Tree species differentiation using intensity data derived from leaf-on and leaf-off airborne laser scanner data. *Remote Sens. Environ.* 113, 1575–1586. <https://doi.org/10.1016/j.rse.2009.03.017>.
- Kingma, D.P., Ba, J., 2014. Adam: a method for stochastic optimization. <https://doi.org/10.48550/arXiv.1412.6980>.
- Kivinen, S., Koivisto, E., Keski-Saari, S., Poikolainen, L., Tanhuanpää, T., Kuzmin, A., Viinikka, A., Heikkinen, R.K., Pykälä, J., Virkkala, R., Vihervaara, P., Kumpula, T., 2020. A keystone species, European aspen (*Populus tremula* L.), in boreal forests: ecological role, knowledge needs and mapping using remote sensing. *For. Ecol. Manag.* 462, 118008. <https://doi.org/10.1016/j.foreco.2020.118008>.
- Krizhevsky, A., Sutskever, I., Hinton, G.E., 2017. ImageNet classification with deep convolutional neural networks. *Commun. ACM* 60, 84–90. <https://doi.org/10.1145/3065386>.
- Kuzmin, A., Korhonen, L., Kivinen, S., Hurskainen, P., Korpelainen, P., Tanhuanpää, T., Maltamo, M., Vihervaara, P., Kumpula, T., 2021. Detection of European Aspen (*Populus tremula* L.) based on an unmanned aerial vehicle approach in boreal forests. *Remote Sens.* 13, 1723. <https://doi.org/10.3390/rs13091723>.
- Lanjewar, M.G., Gurav, O.L., 2022. Convolutional Neural Networks based classifications of soil images. *Multimed. Tool. Appl.* 81, 10313–10336. <https://doi.org/10.1007/s11042-022-12200-y>.
- Latva-Karjanmaa, T., Penttilä, R., Siitonen, J., 2007. The demographic structure of European aspen (*Populus tremula*) populations in managed and old-growth boreal forests in eastern Finland. *Can. J. For. Res.* 37, 1070–1081. <https://doi.org/10.1139/X06-289>.
- Lisein, J., Michez, A., Claessens, H., Lejeune, P., 2015. Discrimination of deciduous tree species from time series of unmanned aerial System imagery. *PLoS One* 10, e0141006. <https://doi.org/10.1371/journal.pone.0141006>.
- Mäyrä, J., Keski-Saari, S., Kivinen, S., Tanhuanpää, T., Hurskainen, P., Kullberg, P., Poikolainen, L., Viinikka, A., Tuominen, S., Kumpula, T., Vihervaara, P., 2021. Tree species classification from airborne hyperspectral and LiDAR data using 3D convolutional neural networks. *Remote Sens. Environ.* 256, 112322. <https://doi.org/10.1016/j.rse.2021.112322>.
- Michaelsen, T.C., 2016. Aspen *Populus tremula* is a key habitat for tree-dwelling bats in boreonemoral and south boreal woodlands in Norway. *Scand. J. For. Res.* 31, 477–483. <https://doi.org/10.1080/02827581.2015.1133844>.
- Natesan, S., Armenakis, C., Vepakomma, U., 2019. RESNET-based tree species classification using uav images. *Int. Arch. Photogram. Rem. Sens. Spatial Inf. Sci. XLII-2/W13*, 475–481. <https://doi.org/10.5194/isprs-archives-XLII-2-W13-475-2019>.
- Nikula, S., Vapaavuori, E., Manninen, S., 2010. Urbanization-related changes in European aspen (*Populus tremula* L.): leaf traits and litter decomposition. *Environ. Pollut.* 158, 2132–2142. <https://doi.org/10.1016/j.envpol.2010.02.025>.
- Ørka, H.O., Næsset, E., Bollandsås, O.M., 2010. Effects of different sensors and leaf-on and leaf-off canopy conditions on echo distributions and individual tree properties derived from airborne laser scanning. *Remote Sens. Environ.* 114, 1445–1461. <https://doi.org/10.1016/j.rse.2010.01.024>.
- Pešek, O., Brodský, L., Halounová, L., Landa, M., Bouček, T., 2024. Convolutional neural networks for urban green areas semantic segmentation on Sentinel-2 data. *Remote Sens. Appl.: Soc. Environ.* 36, 101238. <https://doi.org/10.1016/j.rsase.2024.101238>.
- Pykälä, J., 2019. Habitat loss and deterioration explain the disappearance of populations of threatened vascular plants, bryophytes and lichens in a hemiboreal landscape. *Glob. Ecol. Conserv.* 18, e00610. <https://doi.org/10.1016/j.gecco.2019.e00610>.
- Pykälä, J., 2004. Effects of new forestry practices on rare epiphytic macrolichens. *Conserv. Biol.* 18, 831–838. <https://doi.org/10.1111/j.1523-1739.2004.00210.x>.
- Pyo, J., Han, K., Cho, Y., Kim, D., Jin, D., 2022. Generalization of U-Net semantic segmentation for Forest change detection in South Korea using airborne imagery. *Forests* 13, 2170. <https://doi.org/10.3390/f13122170>.
- Reitberger, J., Krzystek, P., Stilla, U., 2008. Analysis of full waveform LIDAR data for the classification of deciduous and coniferous trees. *Int. J. Rem. Sens.* 29, 1407–1431. <https://doi.org/10.1080/01431160701736448>.
- Remm, J., Hanski, I.K., Tuominen, S., Selonen, V., 2017. Multilevel landscape utilization of the Siberian flying squirrel: scale effects on species habitat use. *Ecol. Evol.* 7, 8303–8315. <https://doi.org/10.1002/eece3.3359>.
- Rogers, P.C., Pinno, B.D., Šebesta, J., Albrechtsen, B.R., Li, G., Ivanova, N., Kusbach, A., Kuuluvainen, T., Landhäusser, S.M., Liu, H., Myking, T., Pulkkinen, P., Wen, Z., Kulakowski, D., 2020. A global view of aspen: conservation science for widespread keystone systems. *Glob. Ecol. Conserv.* 21, e00828. <https://doi.org/10.1016/j.gecco.2019.e00828>.
- Ronneberger, O., Fischer, P., Brox, T., 2015. U-Net: Convolutional networks for biomedical image segmentation. In: Navab, N., Hornegger, J., Wells, W.M., Frangi, A. F. (Eds.), *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015, Lecture Notes in Computer Science*. Springer International Publishing, Cham, pp. 234–241. https://doi.org/10.1007/978-3-319-24574-4_28.
- Russo, D., Mäenurm, A., Martinoli, A., Zotti, M., Cistrone, L., 2023. Forest islands in farmland provide vital roost trees year-round for giant and common noctule bats: management implications. *For. Ecol. Manag.* 540, 121053. <https://doi.org/10.1016/j.foreco.2023.121053>.
- Säynäjäki, R., Packalen, P., Maltamo, M., Vehmas, M., Eerikainen, K., 2008. Detection of aspens using high resolution aerial laser scanning data and digital aerial images. *Sensors* 8, 5037–5054. <https://doi.org/10.3390/s8085037>.
- Schiefer, F., Kattenborn, T., Frick, A., Frey, J., Schall, P., Koch, B., Schmidtlein, S., 2020. Mapping forest tree species in high resolution UAV-based RGB-imagery by means of convolutional neural networks. *ISPRS J. Photogrammetry Remote Sens.* 170, 205–215. <https://doi.org/10.1016/j.isprsjprs.2020.10.015>.
- Shorohova, E., Lindberg, H., Kuuluvainen, T., Vanha-Majamaa, I., 2024. Deadwood enrichment in Fennoscandian spruce forests – new results from the EVO experiment. *For. Ecol. Manag.* 564, 122013. <https://doi.org/10.1016/j.foreco.2024.122013>.
- Simpson, M.G., 2010. Evolution and diversity of woody and seed plants. In: *Plant Systematics*. Elsevier, pp. 129–162. <https://doi.org/10.1016/B978-0-12-374380-0.050005-1>.
- Sun, C., Huang, C., Zhang, H., Chen, B., An, F., Wang, L., Yun, T., 2022. Individual tree crown segmentation and crown width extraction from a heightmap derived from aerial laser scanning data using a deep learning framework. *Front. Plant Sci.* 13, 914974. <https://doi.org/10.3389/fpls.2022.914974>.
- Sunandini, G., Sivanpillai, R., Sowmya, V., Sajith Variyar, V.V., 2023. Significance of Atrous Spatial Pyramid Pooling (ASPP) in Deeplabv3+ for water body segmentation. In: 2023 10th International Conference on Signal Processing and Integrated Networks (SPIN). Presented at the 2023 10th International Conference on Signal Processing and Integrated Networks (SPIN). IEEE, Noida, India, pp. 744–749. <https://doi.org/10.1109/SPIN57001.2023.10116882>.
- Sothe, C., De Almeida, C.M., Schimalski, M.B., La Rosa, L.E.C., Castro, J.D.B., Feitosa, R.Q., Dalponte, M., Lima, C.L., Liesenberg, V., Miyoshi, G.T., Tommaselli, A.M. G., 2020. Comparative performance of convolutional neural network, weighted and conventional support vector machine and random forest for classifying tree species using hyperspectral and photogrammetric data. *GIScience Remote Sens.* 57, 369–394. <https://doi.org/10.1080/15481603.2020.1712102>.
- Tikkanen, O., Martikainen, P., Hyvärinen, E., Junninen, K., Kouki, J., 2006. Red-listed boreal forest species of Finland: associations with forest structure, tree species, and decaying wood. *Ann. zool. Fennici* 43.
- Tillon, L., Bresso, K., Aulagnier, S., 2016. Tree selection by roosting bats in a European temperate lowland sub-atlantic forest. *Mammalia* 80. <https://doi.org/10.1515/mammalia-2014-0095>.
- Toivonen, J., Kangas, A., Maltamo, M., Kukkonen, M., Packalen, P., 2024. Mapping large European aspen (*Populus tremula* L.) in Finland using airborne lidar and image data. *Can. J. For. Res.* 54, 762–773. <https://doi.org/10.1139/cjfr-2023-0271>.

- Torres, D.L., Feitosa, R.Q., La Rosa, L.E.C., Happ, P.N., Marcato, J., Goncalves, W.N., Martins, J., Liesenberg, V., 2020. Semantic segmentation of endangered tree species in Brazilian savanna using Deeplabv3+ variants. In: 2020 IEEE Latin American GRSS & ISPRS Remote Sensing Conference (LAGIRS). Presented at the 2020 IEEE Latin American GRSS & ISPRS Remote Sensing Conference (LAGIRS). IEEE, Santiago, Chile, pp. 515–520. <https://doi.org/10.1109/LAGIRS48042.2020.9165625>.
- Troshin, D., Fayzulin, M., Mirin, D., 2025. Spatial and temporal classification and prediction of aspen probability in boreal forests using machine learning algorithms. *Environ. Monit. Assess.* 197 (5), 527. <https://doi.org/10.1007/s10661-025-13985-9>.
- Tuominen, S., Näsi, R., Honkavaara, E., Balazs, A., Hakala, T., Viljanen, N., Pölönen, I., Saari, H., Ojanen, H., 2018. Assessment of classifiers and remote sensing features of hyperspectral imagery and stereo-photogrammetric point clouds for recognition of tree species in a Forest area of high species diversity. *Remote Sens.* 10, 714. <https://doi.org/10.3390/rs10050714>.
- Vauhkonen, J., 2018. Predicting the provisioning potential of forest ecosystem services using airborne laser scanning data and forest resource maps. *For. Ecosyst.* 5, 24. <https://doi.org/10.1186/s40663-018-0143-1>.
- Viinikka, A., Hurskainen, P., Keski-Saari, S., Kivinen, S., Tanhuanpää, T., Mäyrä, J., Poikolainen, L., Vihervaara, P., Kumpula, T., 2020. Detecting European aspen (*Populus tremula* L.) in boreal forests using airborne hyperspectral and airborne laser scanning data. *Remote Sens.* 12, 2610. <https://doi.org/10.3390/rs12162610>.
- Villikka, M., Packalén, P., Maltamo, M., 2012. The suitability of leaf-off airborne laser scanning data in an area-based forest inventory of coniferous and deciduous trees. *Silva Fenn.* 46. <https://doi.org/10.14214/sf.68>.
- Virtanen, V., 1995. Floristic composition and habitat ecology of stream bryophytes in Lohja parish, southern Finland. In: *Annales Botanici Fennici*. Finnish Zoological and Botanical Publishing Board, pp. 179–192. www.jstor.org/stable/23726319.
- Zelioli, L., Farahnakian, Fahimeh, Farahnakian, Farshad, Middleton, M., Heikkonen, J., 2024. Enhancing peatland classification using Sentinel-1 and Sentinel-2 fusion with encoder-decoder Architecture. In: 2024 27th International Conference on Information Fusion (FUSION). Presented at the 2024 27th International Conference on Information Fusion (FUSION). IEEE, Venice, Italy, pp. 1–7. <https://doi.org/10.23919/FUSION59988.2024.10706276>.
- Zhao, Y., Fogler, M.M., 2023. Shape prediction on the basis of spectrum using neural networks. *Phys. Rev. Res.* 5, 013110. <https://doi.org/10.1103/PhysRevResearch.5.013110>.