frontiers | Frontiers in Remote Sensing

TYPE Original Research
PUBLISHED 31 January 2025
DOI 10.3389/frsen.2025.1498217

OPEN ACCESS

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RECEIVED 18 September 2024
ACCEPTED 06 January 2025
PUBLISHED 31 January 2025

CITATION
Zenonos A, Li S, Brandt M, Sciare J and Ciais P (2025) AI-powered estimation of tree covered area and number of trees over the Mediterranean island of Cyprus.
Front. Remote Sens. 6:1498217.
doi: 10.3389/frsen.2025.1498217

AI-powered estimation of tree covered area and number of trees over the Mediterranean island of Cyprus

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Trees play a crucial role in mitigating climate change by absorbing CO_2 and providing biophysical cooling. The European Commission's climate policies underscore the importance of forest monitoring systems to achieve substantial greenhouse gas reductions by 2030. In Cyprus, an EU member state located in the Eastern Mediterranean, and a climate change hot-spot, increasingly impacted by forest fires and more arid conditions, the absence of a comprehensive tree monitoring system hinders effective carbon stock assessment and land-based mitigation strategies. The exact tree population inside and outside forests is currently unknown. Artificial Intelligence is a powerful tool that can enable the development of tree monitoring systems by applying machine learning models to high-resolution image data. This study presents a deep learning neural network model applied to high resolution (10 cm) airborne images collected during the year 2019, to generate segmented tree crowns and the number of individual trees over selected areas of Cyprus, including a large national forest park, a forest park in the capital city, and a small urban area, encompassing a total studied area of $107km^2$. The model, previously applied in Denmark and Finland was completely re-tuned using local annotations to account for Cyprus's specific conditions and achieved an overall accuracy of 90% and 93% to estimate the area covered by tree crowns and the number of trees, respectively. The results are regressed against coarser resolution tree cover maps to predict the area covered by tree crowns at a national level. The accuracy of the tree cover maps created by this study is compared to those of existing global tree cover maps, such as the Copernicus products. This work lays the foundation for establishing a tree-level inventory for Cyprus using airborne remote-sensing.

KEYWORDS

tree segmentation, deep learning, remote sensing, image analysis, individual trees

1 Introduction

In the face of climate change, rapid implementation of mitigation and adaptation measures has become a major priority. The Eastern Mediterranean and Middle East region stands out as a climate change hot-spot (Cramer et al., 2018; Giorgi, 2006; Lelieveld et al., 2012; Zittis and Hadjinicolaou, 2017). In this region, the island of Cyprus, object of this study, has already experienced a higher warming rate than the global mean, with extreme heat and drought in summer (Zittis et al., 2019). One of the main mitigation measures is afforestation and reforestation since new trees absorb CO_2 and sequester carbon, while providing biophysical cooling through transpiration and shading. Reforestation also limits the loss of biodiversity in the case of natural forest restoration. In addition, trees emit volatile organic compounds causing the formation of clouds which can potentially cool the Earth's surface (Guenther et al., 2006). Within the scope of the 2021 (Parliament and Council, 2021) European climate law and the European Green Deal, the European Commission aims to reduce greenhouse gas emissions by at least 55% by 2030 including a sink of 400 MtCO_2 per year in the forest sector. Simultaneously, it is planned to invest in reforestation and planting trees in urban areas, with 3 billion new trees to be planted by 2030. To monitor their forest carbon stocks, a growing number of EU countries are aiming to complement existing national inventories by using remote-sensing data and models. The Cyprus Republic has no national inventory with a network of periodically sampled forest plots, and has neither established a tree monitoring system based on remote sensing. Moreover, forests in Cyprus have been recently impacted by forest fires, which requires protection of remaining trees and adds to the need of monitoring trees and forests. Such a gap leaves the country with highly uncertain information regarding the distribution of trees within and outside of forests, hindering efforts to accurately assess Cyprus's carbon balance and develop effective land-based mitigation strategies, to achieve national carbon neutrality objectives. The present study fills this critical information gap by developing a proof of concept for monitoring individual trees in Cyprus based on airborne remote sensing data. Specifically we developed a new methodology to estimate tree cover and to count trees over two large forest parks and one urban area. The specific condition of Cyprus is that it has few forests and many trees outside forests, included in urban areas and croplands. In this context, using coarse or moderate remote sensing images would not achieve a high accuracy (Turner et al., 2015; Hansen et al., 2013). In this study, we show the potential of high resolution airborne images and deep-learning models for monitoring the area of individual tree crowns and counting trees, over three contrasted areas with trees inside and outside forests. To reach this goal, we modified and adapted the deep-learning model of Li et al. (2023) that uses aerial images and LiDAR data to segment trees for estimating individual tree crown areas and heights. Similarly, a recent study developed a semi-supervised deep learning method to segment urban tree canopies from high-resolution remote sensing images across a number of cities in Brazil (Guo et al., 2023). In Cyprus, many urban areas lack dense forests, which limits the use of other models like the TreeDetector (Gong et al., 2024). LIDAR data have become popular for image segmentation tasks (Zhou et al., 2020) and can be applied to forestry. For example, Sun et al. (2022) used LIDAR-derived height maps and the YOLO-v4 deep learning network (Bochkovskiy et al., 2020) for tree crown segmentation, overcoming limitations of aerial imagery, such as sensitivity to capture angles (Yin et al., 2020) and uncertainties in solar radiation intensity (Zhang et al., 2022). Another study proposed a method combining high-resolution imagery and Canopy-Height-Model data for individual tree detection and canopy segmentation,

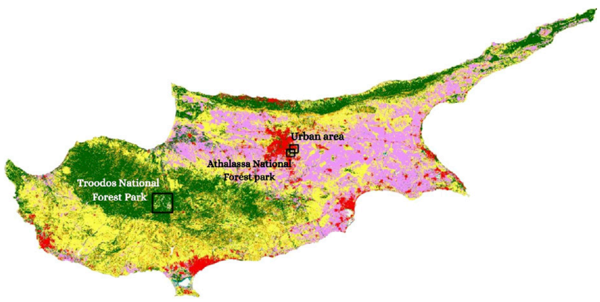

FIGURE 1
Land use map of Cyprus taken from ESA WorldCover Viewer ESA (2024). The location of the three study areas is pointed on the map.

demonstrating high accuracy and robustness (Zhang et al., 2024). Despite the benefits of LIDAR data, their high cost makes them less feasible. Given the lack of comprehensive LiDAR survey over Cyprus and the availability of very high-resolution aerial images (10 cm), we chose to adapt the model of Li et al. (2023) by training it only with airborne images.

The model was modified and optimized to produce an airborne tree inventory for an area of about 107km^2 in Cyprus, covering three different landscape types, a large national forest park in the Troodos mountains, a small forest park and a small urban area in the capital city (Nicosia). The main task is the estimation of the area covered by tree crowns and the number of trees in the three different landscapes. The model was applied to high-resolution airborne orthophotos with a 10 cm spatial resolution. Considering that Cyprus has a totally different type of landscape compared to Denmark, where the model was initially trained on, we used a supervised transfer learning strategy: the model was first pre-trained on the Denmark annotations and then fine-tuned by integrating some local annotations made in Cyprus. The main differences between the two countries that requires re-tuning of the model are the small size of the three studied areas in Cyprus, the prevalence of sparse forests located in mountains, with smaller trees, and the existence of many trees outside forests. Finally, we derived an improved estimate of the area covered by trees on the whole island by training a random forest to regress the CLC + Backbone (Copernicus, 2020) tree cover product, a comprehensive land cover mapping tool that categorizes land into 11 classes (based on a pixel-by-pixel analysis using a multi-temporal series of Sentinel-2 imagery, providing wall-to-wall coverage with a spatial resolution of 10 m), against our high resolution individual tree crown cover areas over the three landscapes studied. Our analysis lays the foundation for the establishment of the first national tree inventory for Cyprus and maps the precise number of trees and area covered by trees over two significant forest parks.

2 Materials and methods

2.1 Description of the studied area

The Cyprus island (9,251 km^2) is located in the Mediterranean Sea and combines various ecosystems found across the basin. It has

TABLE 1 Estimated forest area occupied by different types - Table taken from National Forest Inventory report of 2019 (The republic of cyprus ministry of agriculture, rural development and environment. 2019).

	Area occupied by each type of forest (in hectares)
Coniferous	143,767.9
Broadleaves	3,958.4
Total	147,726.3

two prominent mountain ranges: the Troodos and the Kyrenia Mountains (also known as Pentadaktylos), with a central plain, the Mesaoria, lying between them. The peak of the range, Mount Olympus (also known as Mount Troodos), stands at an elevation of 1951 m. A significant portion of the island's arable land, more than one-third, is irrigated and is primarily concentrated in the Mesaoria Plain and surrounding regions of Paphos in the southwest. This facilitates agricultural activities and contributes to the productivity of these lands.

2.1.1 Cyprus forests

The total forest area of Cyprus is equal to 1,725.1 km^2 which corresponds to 18.65% of the total country area. The largest forests are located in the Troodos National Forest Park (see Figure 1) which corresponds to 5.3% of the total country forest land. Considering that the Cyprus climate is semi-arid, the official forest definition adopted by the Cyprus government is: "Forest comprises of land covered by forest trees which covers at least 0.3 ha, where the tree crown cover is at least 10 percent and the minimum tree height is of 5 m (at maturity)". (In agreement with the Forest National Law of 2012 (25 (I)/2012) and the Global Forest Resource assessment) (The republic of cyprus ministry of agriculture, rural development and environment. 2019).

2.1.2 National Forest Inventory data

The most recent National Forest Inventory (NFI) report was published in 2019 and was based on campaigns, where limited sampling and statistical methods were applied. The NFI data is re-evaluated every 10 years and so far, no remote sensing data have been used, to measure and report on the Cyprus forest resources.

According to the NFI report of 2019, there are two main types of trees in Cyprus, coniferous and broad-leaved. The most widespread forest types are composed of pinus brutia, pinus nigra, mixed pinus brutia, and riparian communities. The harvest rate was found to be about 9% of the increment, which is extremely low compared to Western and Central Europe, and was reported separately for coniferous and broad-leaved trees. The analysis for broad-leaved trees was based on previous NFI data of 2001–2011 while the analysis for the pinus brutia forests was based on permanent plots. The information used to estimate the forest reference area from the National Forest Inventory encompasses 81,575.42 ha of land that includes the Pinus brutia community within the state forest area. The tree covered area occupied by each forest type is presented in Table 1. This information does not refer to the tree crown area, and tree size has not been considered. Estimations in Table 1 result from a raw approximation based on the number of trees that have been surveyed from 1997 until 2013. Below is a short description of the three small areas analyzed for high resolution tree crown area in this study 1.

2.1.3 Troodos National Forest Park

The Troodos mountain range is the primary geological and topographical feature of the island, with natural forests providing habitats for various plant and animal species. Its central forest, encompassing its loftiest peaks is called Chionistra, in the heart of the range. In 1992, a major portion of this forest, around 91 square kilometers, was designated as a National Forest Park, aiming to preserve its unique biodiversity; and it has been integrated into the European network of "Natura 2000″ protected areas. The forests within the National Forest Park are predominantly natural, having regenerated without human intervention. Calabrian pine (Pinus brutia) is the prevailing tree species at lower heights, reaching up to 1,200 m, and on warm, south-facing slopes, up to 1,600 m. Smaller trees and shrubs occupy specific niches, influenced by altitude, geology, and moisture conditions. At higher elevations, from 1,200 to 1,500 m, black pine (Pinus nigra) dominates the forest species. Other hardwood species include foetid juniper (Juniperus foetiditssima), wild service tree (Sorbus aria), cotoneaster (Cotoneaster racemiflorus), barberry (Berberis cretica), and the endemic dwarf gorse (Genista sphacelata subsp. crudelis), among others. A significant number of black pine trees and junipers in this zone are exceptionally old, some exceeding 500 years, and a few reaching up to 1,000 years. These trees are strictly protected due to their high ecological and cultural value (Troodos, 2024).

2.1.4 Peri-urban forest park, Athalassa

This park (see map in Figure 1) is situated on the southeastern outskirts of the city of Nicosia, and covers 840 ha, serving as a "green paradise" with endemic and indigenous trees, shrubs, and grasses. Athalassa was designated a National Forest Park in 1990 in accordance with Forestry Legislation.

2.1.5 Urban area, Aglantzia

This area is a suburb of Nicosia, characterized by a mix of modern blocks of apartments and traditional houses. The maximum building height is 24 m adhering to urban planning regulations, and the building-plot ratio, according to the Department of Land and Survey of Cyprus, is equal to 1.60. Aglantzia has small parks and green spaces, such as the Pedagogical Academy National Forest Park. Our study domain includes a park with large trees of 0.25km^2 in area.

2.2 Data description and pre-processing

As an input, the model receives RGB and NIR orthophotos collected over Cyprus during 2019 with a 10-cm resolution by the Department of Land and Survey of Cyprus. The GeoTIFF images used here are of high-resolution (10 cm per pixel), derived from UAV (drone) flight data with Red, Green, Blue (RGB), and Near-Infrared (NIR) bands, and use the ESRI:102,319 - CGRS-1993-LTM coordinate reference system (Transverse Mercator, meters). The images were processed using the Inpho GmbH software, commonly used in photogrammetry. The combination of RGB and NIR bands makes the images suitable for both visual interpretation and vegetation analysis. We split the dataset into small images, each of $0.25km^2$ in size, that cover the Troodos, Athalassa and Aglantzia areas described above (428 images in total). The first step of the analysis was to produce specific training data by labeling trees in Cyprus. Since the model had already been pre-trained in Denmark, it was decided to use the method of transfer learning where the pre-trained model was fine-tuned using manually labeled tree crown data from Denmark and a new set of labels created for Cyprus (the size of the training set was determined by monitoring the performance of the model during the model training procedure aiming at a model loss of E–05 order - see Supplementary Appendix C). For the creation of the new Cyprus training dataset, trees from the each of the 3 studied areas have been labeled with 80% of labels in Troodos and 40% in Athalassa, and Aglantzia. As reference outputs, 6,000 individual tree crowns (mixed deciduous and coniferous) were delineated and labeled manually and further used together with 21,787 labels created for Denmark. This database was built through visual inspection of aerial images, without the aid of any semi-automatic assistance. The training areas were then created by considering rectangles, in which every tree has been delineated. The manual delineation of trees in Cyprus took approximately 2 months of computer-based processing and covered a variety of tree species and landscape types within urban and rural areas. This manual labeling was time-consuming but ensures that the reference database represents what the naked eye can see on an aerial image. No case separation was made for coniferous and broad-leaved trees. To distinguish neighboring tree crowns in dense forest areas, the spaces between adjacent crowns were included as input to the model, alongside the crown delineations. Note that this case of touching crowns is very rare in Cyprus due to the sparse distribution of trees, even in forests.

2.3 Model description

The deep-learning model of Li et al. (2023) to create maps of trees crown areas uses convolutional neural networks. Initially, it was developed to map trees in Denmark and further tested and validated in Finland and France (Li et al., 2023). Given the huge differences of trees and forest structure between Cyprus and Denmark, related to the dry climate of Cyprus which influences tree density, species and related crown shapes, as well as the presence of trees in mountains (not present in Denmark). The method used to re-tune the model for Cyprus is presented in the following section. We implemented tree counting and crown segmentation tasks simultaneously by using a multitask deep learning-based network (see Figure 2) derived from the U-Net architecture (Ronneberger et al., 2015), featuring two separate output branches dedicated to each task. The crown segmentation branch addressed a semantic segmentation challenge, where every pixel in an image was categorized either as part of an object (white) or as part of the background (black) (Wang, 2018). Therefore, the model outputs a binary mask (see Figure 3) showing tree areas with white pixels and non-tree areas with black pixels. The secondary branch estimates the overstory tree count by generating density maps through regression for a specific image. The ground truth density maps were created by applying normalized 2D Gaussian kernels (see Figure 2) on the delineated tree crowns (Zhang et al., 2016). The overall count of trees in an image of any dimension was determined by integrating the density map. Compared to counting by enumerating the segmented tree crowns, where several adjoining tree crowns might be incorrectly counted as one, the density estimation-based approach, according to the authors (Li et al., 2023), improves the overall counting bias.

2.4 Model configurations and training

The model architecture is a U-Net framework, widely employed in computer vision tasks. In line with the methodology proposed by Oktay (2018), the conventional U-Net was enhanced by integrating self-attention blocks to capture more relevant information during the down-sampling phase. Additionally, batch normalization was employed after each convolutional layer to enhance stability and accelerate the training procedure (Wang, 2018; Zhang et al., 2016). Most of the model parameters were shared between the two branches (segmentation and counting) with only those necessary for generating the ultimate output predictions being specific to each task. In the segmentation branch, a sigmoid activation function was employed in the final output layer to generate probabilities of a pixel to belong to a tree, ranging from 0 to 1. These probabilities were subsequently transformed into binary labels using a threshold of 0.5. According to Li et al. (2023), in the counting branch, a linear activation function is the best choice to preserve the values of the Gaussian kernel.

During each training epoch, random patches (tree crown labels) measuring 256×256 pixels were extracted from all accessible labeled images to create training and validation patches with a batch size of 8. These image patches were standardized, adjusting each instance and channel to have a mean of 0 and a standard deviation of 1, before being utilized as inputs to the network. The model was trained using the Adam optimizer for 2,500 epochs. Machine learning methods offer the opportunity to play with several parameters to improve the quality of the model. Several combinations of hyper-parameters (such as the optimizer, the number of epochs, etc.) were checked by inspecting the model performance, to find the most optimal one (see Supplementary Appendix A). The model was optimized by minimizing a loss function that was derived from the two branches and has been evaluated by monitoring closely the evolution of the loss function. The Tversky loss function (Salehi et al., 2017) was chosen as in Li et al. (2023). The model performed well for accurate estimate of tree counting (error of order 10^{-2}). Various data augmentation methods were implemented, such as random flipping, cropping, Gaussian blurring, and brightness adjustment, to augment the dataset (Shorten and Khoshgoftaar, 2019).

2.5 Model evaluation

For evaluation, we generated a new test dataset of 2,500 manually created tree crown labels, 2,000 labels in Troodos forest, and 500 labels of trees in Athalassa, and Aglantzia. There was no spatial overlap between this test data and the training data. There is unfortunately no accurate National Forest Inventory (NFI) sample data for Cyprus, as recent data based on permanent plots is lacking.

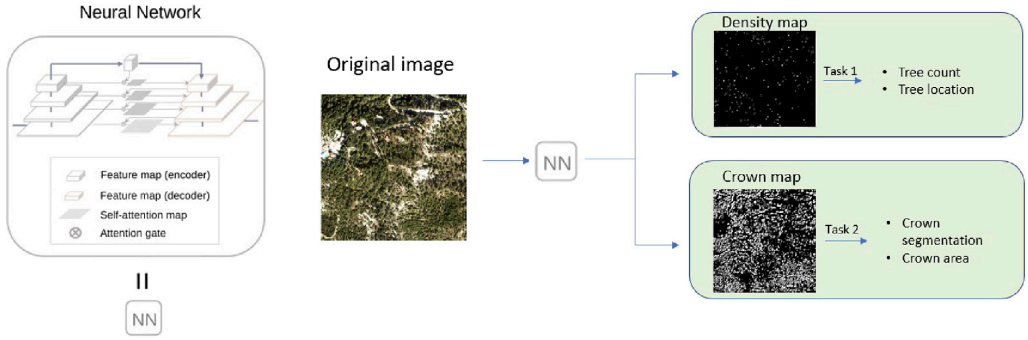

FIGURE 2
Graphical representation of the model - based on Figure 1 of Li et al., 2023, Li et al. (2023).

Consequently, the evaluation of the model was done by using only our new testing dataset. For the crown area segmentation task, the model output was evaluated by calculating the common area between predictions and labels (F1 score). For the tree counting task, three metrics were used (Chalmers and Adkins, 2020; Sigal and Chalmers, 2016): the relative mean error (Equation 1), the relative total error (Equation 2), and the coefficient of determination R^2 (Equation 3), a measure of how well the independent variable explains the variability of the dependent variable.

$$\text{Relative MAE} = \frac{\frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|}{\bar{y}} \tag{1}$$

$$\text{Relative total error RTE} = \frac{\left|\sum_{i=1}^{n}\frac{\hat{y}_i - y_i}{y_i}\right|}{\sum_{i=1}^{n} y_i} \tag{2}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{3}$$

where y_i, $\hat{y}_i$, and $\bar{y}$ denote the reference, prediction, and the mean reference value, respectively, and n denotes the total number of samples (tree crowns).

3 Results - estimation of tree crown area and tree counts

The evaluation metrics reported in the second column of Table 2, indicate an overall good agreement between manually created and predicted tree crown areas, as reflected by a relative total error of 7.21%. As a second step, we extended the test set by adding 500 labels of trees in urban areas and open dry fields (see Figure 4). By doing so, the model was evaluated with the same metrics against a test set of 2000 labels from forest trees and an additional 500 labels from trees in urban areas (see third column of Table 2), achieving a relative total error 14.81% for crown segmentation. Yet the model over-predicted tree counts for forest areas by 3.5%, for forest and non-forest areas by 9.5%. Overall, we found that the model failed to count trees accurately in dry open fields and overestimated them in such areas. This pattern indicates that the model is trained to count trees more efficiently in forest areas than in cities or open fields. The coefficient of determination for crown areas was found equal to 0.98 for forests and 0.92 for non-forests. Over the Troodos area, our calculations using high-resolution images make it possible to separate accurately individual tree crowns, avoiding the false accounting of space between trees. The tree cover density (TCD) defined as the total area covered by tree crowns divided by the total area, ranges from 8.57% to 40.15% per km^2 (see Figure 5A; Table 3). The number of trees per km^2 ranges from 6,028 to 17,780 trees, for a total of 927,562 trees (no species categorization). Over the Aglantzia area, which includes the majority of the Athalassa National Forest Park. Within the building-covered area (almost 850 ha), a total of 48,104 trees were counted, with a tree density of 38 trees per hectare (see Table 4). In the Athalassa Forest Park (750 ha), we counted 81,258 trees corresponding to 70 ha of tree-covered area (see Table 4) with density ranging from 2.24% to 13.72% per km^2. Considering that the small urban area accommodates a significant number of trees and is located next to the Athalassa forest park, it can be characterized as a relatively "green" urban area.

3.1 Correlation between tree cover density (TCD) and number of trees

The relationship between tree cover density and the number of trees within an area allows us to better understand the structure of forests that include sparse trees. The correlation between these two variables for the Troodos National Forest Park, Aglantzia urban area, and Athalassa Forest Park is shown in Figures 6B, D, F, respectively.

For the Troodos Park, a correlation coefficient of 0.93 was found between tree cover density and the number of trees, as shown in Figure 6B. In other words, as tree cover density increases, there is a tendency for the number of trees to increase as well. The $1km^2$ sub-areas with the largest TCD contains trees with the largest size of tree crown, equal to $23m^2$. Over the Troodos Park, for a given number of trees (e.g., 3,000 per area) there is a large range of TCD. The area with minimum TCD (8%–10%) contains trees with an average crown size equal to $10m^2$. This area has the potential to grow up to TCD of about 20% with an average tree crown size of $20m^2$ (as shown in Figure 6B). This information can be used in future studies

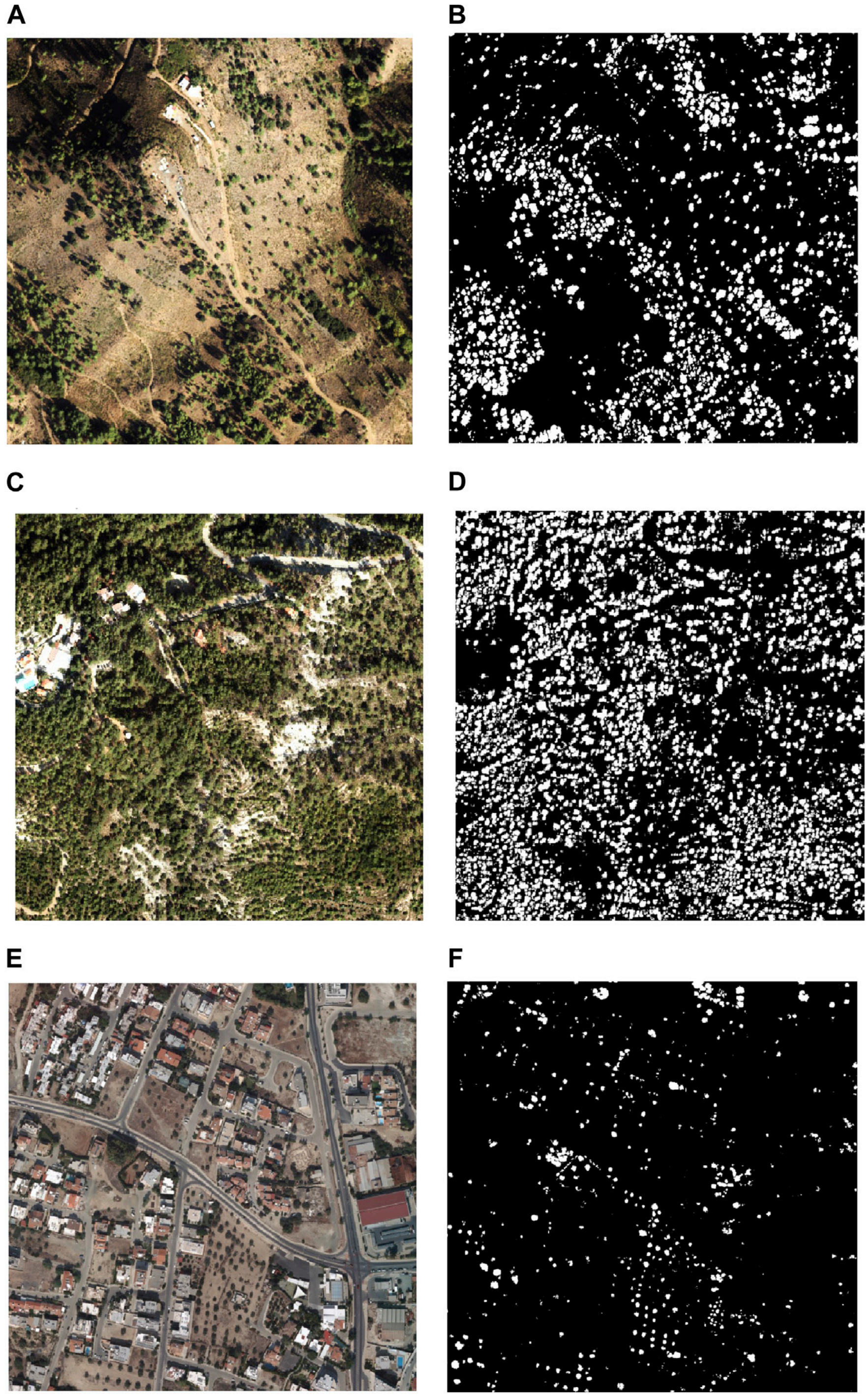

FIGURE 3
Three images of different landscapes that have been considered by the model together with the corresponding picture of tree masks that has been created by the model as crown segmentation output. **(A)** Athalassa forest park, **(C)** Troodos forest park, **(E)** Urban area). Each image covers an area of 0.25km^2. **(A)** Image with low tree cover density. **(B)** Tree masked image with low density. **(C)** Image with high tree cover density. **(D)** Tree masked image with high density. **(E)** Image of an urban area (Aglantzia area). **(F)** Tree masked image of the urban area.

to predict the potential growth of this area (e.g., in terms of carbon stock). The positive correlation suggests that the Troodos forest is quite homogeneous with a fairly constant crown area per tree. In specific areas where the above relationship does not apply, tree crown areas are different from the rest of the forest. This is consistent with the NFI data in Section 2.1.2 which indicates that the Troodos forest park encompasses a diverse array of tree species with different typical crown areas. Alternatively, the diversity of crown sizes within these areas can also be explained by a mix of large or mature trees next to smaller or younger ones. In Figure 6B, there are a few outliers that correspond to areas that accommodate a large number of trees with small tree crown sizes. We found that these

TABLE 2 Evaluation metrics of the model.

Predictions	Tree in forest areas (2000 annotations)	Trees inside and outside Forest areas (2,500 annotations)
rMAE	15.01%	20.8%
Relative total error	7.21%	14.81%
Reference count (labeled trees)	2041	2,525
Predicted count (predicted trees)	2,112	2,771

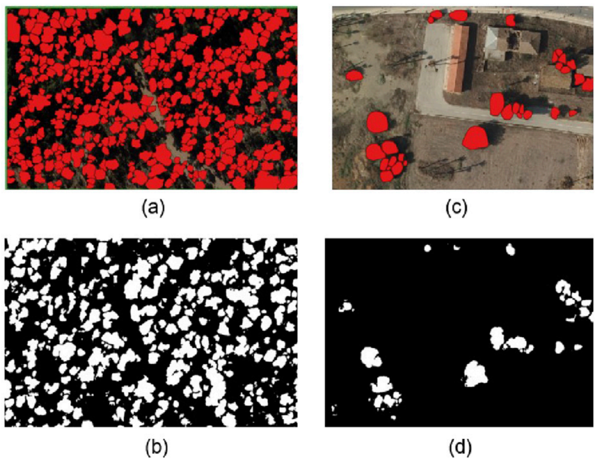

FIGURE 4
Examples of a dense forest area [image **(A)**] and a dry field [image **(C)**] that the model has been tested on, where all the trees were manually labeled with red masks. The corresponding binary masks of tree crowns are shown in images **(B, D)**. The relative Mean Absolute Error (considering the total tree count based on density estimation for the two areas) for images (**A, C**) respectively, was found equal to 2% and 12.85%. The relative total error was found equal to 0.93% and 57.36%, respectively. Based on the relative error of the prediction for each image, it can be seen that the model counts trees more efficiently in dense forest areas due to its original design.

outliers correspond to planted areas with many young trees at the Amiantos mines (see Supplementary Figure S8 in the Appendix section), within the Troodos forest park. This area has been planted in the context of a reforestation campaign of the Department of Forests between 2009 and 2014.

For the Athalassa National Forest Park, the situation is slightly different. The correlation between TCD and the number of trees across $1km^2$ sub-areas is equal to 0.94 (see Figure 6D), possibly indicating either similar diversity of the tree species in this area with the Troodos forest or trees with similar maturity. This is consistent with the fact that the majority of the Athalassa forest park primarily consists of artificially planted trees for recreation and environmental conservation purposes.

For the urban area, which includes buildings, a large number of trees has been found. Despite the fact that a very small area has been considered as a sample, it was found that there is a strong positive correlation between TCD and tree numbers, equal to 0.99 (seen Figure 6F). This is a surprising result given the expected wide variety of trees (and related maturity) encountered within the city.

According to Figure 6D, the maximum tree cover density of a $1km^2$ sub-area in Athalassa forest park is equal to 14%, corresponding to almost 14,000 trees, with an average tree crown size equal to $10.5m^2$. Such an area with tree cover density equal to 14% can accommodate between 8,000 and 10,000 trees in the Troodos forest (Figure 6B), corresponding to an average tree

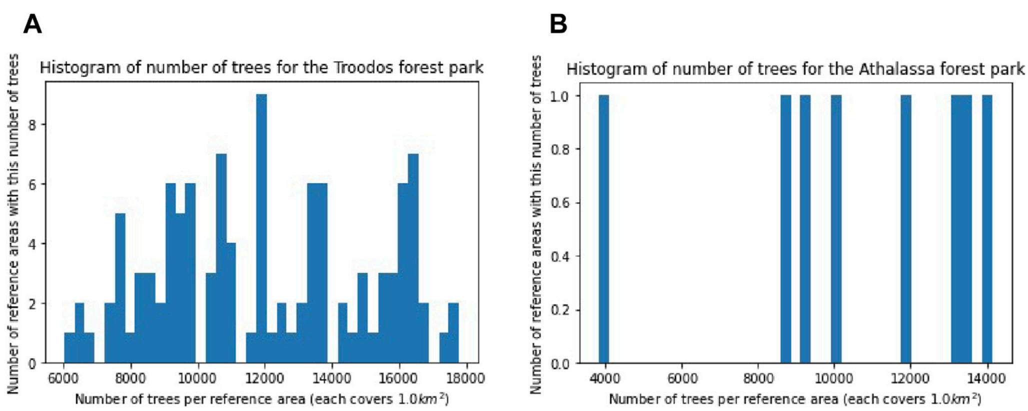

FIGURE 5
Histogram of the number of trees (*X*-axis) for Troodos forest park and Athalassa forest park (Frequency corresponds to the number of reference area images (covering 1.0km^2) that possess this number of trees). **(A)** Troodos forest park. **(B)** Athalassa forest park.

TABLE 3 Tree covered area, number of trees, and tree cover density range among 91 images in Troodos forest park. The tree covered area and the TCD have been calculated per reference area that covers $1.0km^2$

Variable	Estimated value	Range of quantity	Value	Tree covered density	Value
Total tree covered area	$16.38km^2$	Range of tree covered area	$0.085km^2$ to $0.4km^2$	Minimum TCD	8.57%
Tree counts	927,562	Range of tree counts	6,028 to 17,780	Maximum TCD	40.15%

TABLE 4 Tree covered area, number of trees and tree cover density (per $1km^2$) over the Athalassa National forest park and the small urban area.

Studied area	Tree covered area	Number of trees	Min TCD	Max TCD
Athalassa forest park (total area 750 ha)	70 ha	81,258	2.24%	13.72%
Small urban area (total area 850 ha)	38 ha	48,104	1.60%	7.86%

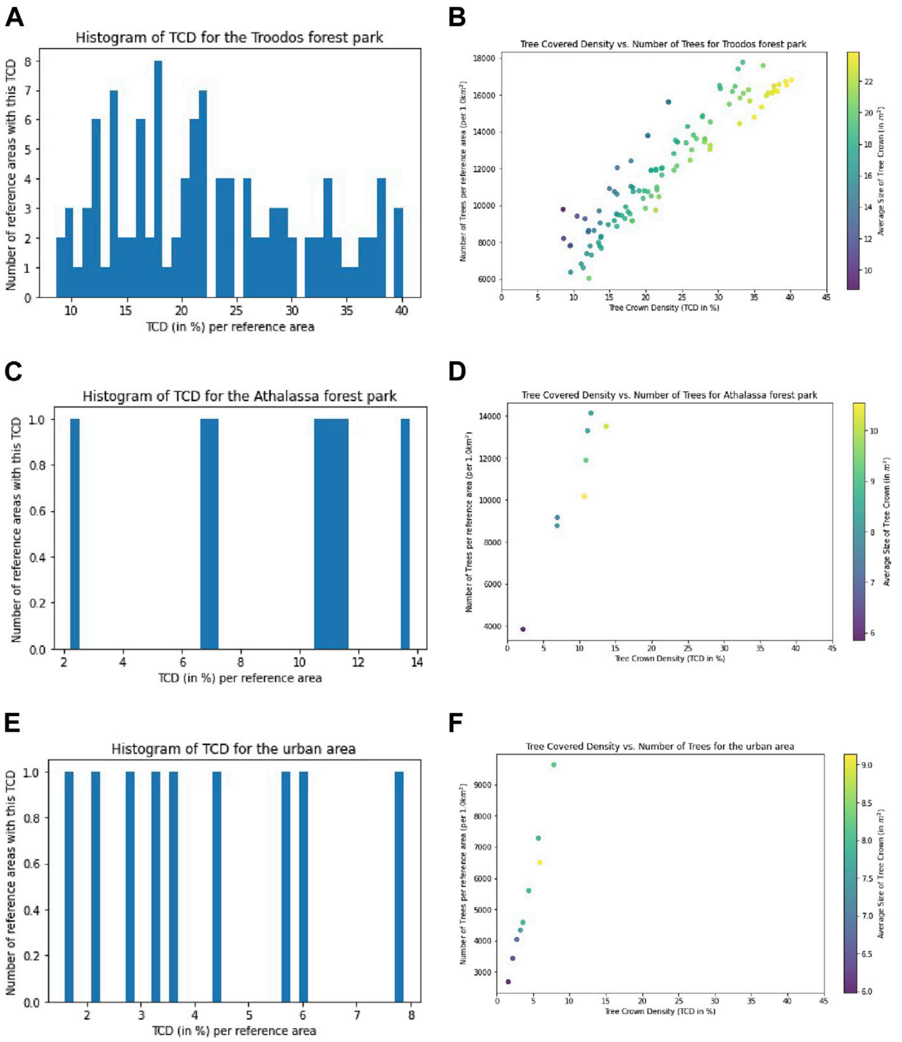

FIGURE 6
Histogram of the tree covered density and Scatter plot of Tree Cover Density (TCD) vs. Number of trees per reference area (size $1.0km^2$) for Troodos forest park **(A, B)**, Athalassa forest park **(C, D)** and the small urban area **(E, F)**. The color scale defines the average size of the tree crown in the reference area. **(A)** Tree covered density for Troodos. **(B)** TCD vs. Number of trees for Troodos. **(C)** Tree covered density for Athalassa. **(D)** TCD vs. Number of trees for Athalassa. **(E)** Tree covered density for urban area. **(F)** TCD vs. Number of trees for urban area.

crown size between $14m^2$ and $16m^2$, respectively. In other words, for the same TCD, the Troodos forest has two times less trees but each with almost double crown size compared to Athalassa Park. Assuming these two forests are similar (in terms of abundance of tree species), such difference can indicate a different level of maturity for the two forests (with older trees in Troodos having larger crowns). Other features can also explain this difference such as the location of the forest park (in the mountains for Troodos and a flat terrain for Athalassa), and the limited amount of rainfall over the Athalassa area (compared to Troodos). For the urban area, it can be observed in Figure 6F that it contains a reference area of $1.0km^2$ with a surprisingly high tree cover density, almost equal to 10%, and many trees in it, almost 10,000 trees. A careful visual check of this reference area shows that it includes a green park with large trees, located in the urban area.

3.2 A power law for closed forests

A well-known empirical law in closed forests, referred to as self-thinning, is a linear heuristic relationship between log-transformed tree density and individual tree crown size in a forest stand that reaches its maximum density (Farrior et al., 2016). Essentially, trees compete for resources and space, so that a given area can only accommodate either a few large trees or many small trees. This principle is well-established in dense forests (i.e., with high TCD) where trees compete for access to sunlight. It is therefore, very interesting to examine the law for non-closed (i.e., with low TCD) forests such as the Troodos forest park and the small Athalassa forest park, where trees do not compete for light but rather for water or nutrients. The self-thinning exponent for these two forests is calculated as the linear regression slope between the logarithm of the average area covered by a tree crown against the logarithm of the number of trees. For the Troodos Forest Park, the self-thinning exponent equals −0.45, indicating that as the average individual tree size increases, the number of trees decrease quickly, with a strong relationship between the two (see Supplementary Appendix E). This steeper slope suggests a higher level of competition among tree species for resources such as water and nutrients. It also implies a more pronounced hierarchical canopy structure, with larger, dominant trees more effectively competing for resources and a decrease in the number of smaller trees. Additionally, the maximum tree cover density in a reference area of Troodos was found to be approximately 45%, indicating that Troodos is a sparse forest. This observation is particularly interesting because the forest law considered here has not been previously applied to sparse forests. For the Athalassa forest park, the self-thinning exponent equals −1.17, which indicates a moderate to strong negative relationship between tree density and individual tree size within this small city forest park (see Supplementary Appendix E). This indicates that trees in the area compete strongly for resources and they form a relatively uniform canopy. Since the park consists of mainly man-made vegetation we could suggest that a lot (possibly too many) trees were planted per area in Athalassa compared to Troodos forest park (see slopes of Figures 6B, C. The self-thinning exponent carries significant implications for forest management practices. For example, it can help in making decisions related to thinning treatments, spacing of trees, and stand density management to optimize timber production, biodiversity conservation, or other management objectives.

3.3 Estimation of the total area covered by tree crowns over Cyprus using our results and CLC + Backbone product map for tree cover

Because it was not possible to get access to all the photos available for Cyprus, we established a transfer function between our very high resolution dataset and a coarser resolution dataset, available for the whole island. When considering different coarse resolution tree cover datasets in Cyprus, such as the Global Forest Watch (GFW), the European Forest Institute (EFI) Maps, the CORINE Land Cover (CLC), we decided to use the CORINE CLC + Backbone product with 10 m resolution for the year 2018 to derive a moderate resolution estimation of the total tree covered area over Cyprus (Copernicus, 2020). The CLC + Backbone raster product provides comprehensive land-cover mapping, distinguishing 11 different land cover types, one of which is the tree cover. It uses pixel-based, multi-temporal Sentinel-2 imagery to create a continuous 10 m resolution map. When overlapping land cover types occur within a single pixel (such as a combination of vegetation and sealed surfaces), the product assigns one dominant class, generally using a majority rule where the class covering more than 50% of the pixel is selected. In the case of tree cover, the pixels of tree cover class are classified into two forest type classes, coniferous and broad-leaved.

The reason behind the choice of CLC+ is the quality of the prediction, which for Cyprus is almost 90% and its open access. The main differences between CLC + Backbone and our methodology and data sample are essentially i) the type of the sensors (CLC+: satellite images of Sentinel-2, our study: aerial images - orthophotos), ii) the resolution (CLC+: 10 m/pixel, Our study: 10 cm/pixel), iii) the size of the reference area (CLC+: all Cyprus, our study: $107km^2$), and iv) the definition of tree cover (CLC+: categorizes each pixel to a land category and then to a forest type, our study: segments each tree without the space between them set as a condition the existence of the visible shadow of the tree to avoid including shrubs). The CLC + Backbone product forest type tree cover map was used in combination with our results to estimate the total tree covered area of Cyprus (occupied and non-occupied parts). Firstly, the tree covered area of our very-high-resolution dataset has been calculated over 428 images of 0.25 km^2. The lowest recorded tree cover density was 1.81% in an open, arid field with sparse tree coverage, while the highest tree cover density reached 44.94% in Troodos forest. As a first step, we resampled the CLC + data to match the resolution of our images ($10cm/pixel$) and re-projected it to the same coordinate system. After that, we cut the map into small parts with the same dimensions of our original data ($0.25km^2$). As a next step, we calculated the percentage of each image that is forested (includes trees of any type). Now, for our studied areas we have the area covered by tree crowns per reference image area and we combine this information with the forested percentage. At this step we have a dataset of 106 images of $0.25km^2$ for which we have the size of the area covered by tree crowns (output of our model) and the percentage of the image classified as forested in CLC+.

For the prediction of the size of the area covered by tree crowns per reference area, we used a Random Forest regression method, having as a feature value the forested percentage of CLC+ and as a target value the area covered by tree crowns from our very high resolution images. Using the area that is covered by our dataset of high-resolution images as a test set, we found that the performance of the model was good with Mean Absolute Error (MAE) equal to 0.0068, Mean Squared Error (MSE) equal to 9.125e-05 and R-squared (R^2): 0.82. The data in Figure 7) show

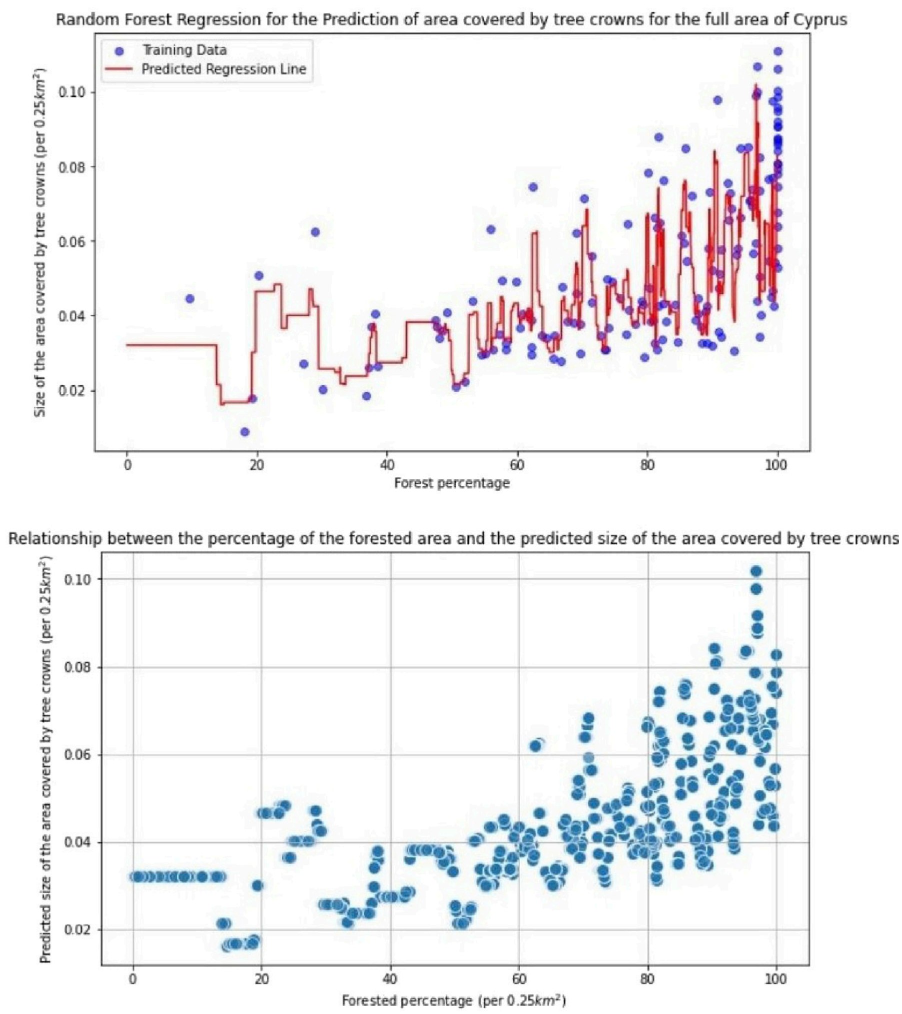

FIGURE 7
Prediction of the area covered by tree crowns in Cyprus by using the Random Forest regression.

that the model prediction is more efficient for areas with a moderate tree cover value compared to the rest of the data but also achieves the accurate prediction of tree cover in dense forest areas.

The RF results applied to the whole island indicate that in Cyprus, $1381 km^2$ are covered by tree crowns, which corresponds to almost 15% of the total country area. According to Figure 8, when a very small part of a reference area is covered by tree crowns, the CLC + Backbone failed to identify it as being tree-covered. On the other hand, when a reference area includes a large fraction of tree crowns, the CLC + overestimated the tree cover. For instance, when we considered the Troodos forest park as a case study, we found that according to CLC+, $32.71 km^2$ are covered by trees compared only to $16.38 km^2$ in our very high resolution data. Thus, CLC + over-estimates tree cover by 100 per cent.

4 Discussion

We used airborne remote sensing images alongside deep learning neural network models to estimate both area covered by tree crowns and the number of trees over three small study areas in Cyprus. This approach was selected based on the best available methods for creating tree inventories at the time of the study. The high-resolution (10 cm) aerial images enabled us to segment even small trees located outside forest areas, providing insights into urban tree resources, which have not been accounted for in any tree inventory conducted in the Mediterranean region. Simultaneously, deep learning models allow for fast and efficient analysis and prediction.

A test set was created to evaluate the model's performance, covering all landscape types. The size of the test and training sets was determined based on the acceptable loss threshold we established, as well as the quality of the prediction we aimed to achieve. For other applications, such as the segmentation of larger objects (e.g., buildings), a smaller test set may suffice to achieve acceptable model performance.

The overall prediction quality of the model was excellent in forest areas and remained acceptable for trees outside of forests. In the original study by Li et al. (2023), the relative total error for non-forest trees was approximately 20%, indicating that our model can effectively count trees in urban areas. To validate this, a test case was designed for a small urban area that includes a forest park within the capital city of Cyprus. Our results revealed a significant number of trees in the urban area, demonstrating that the model is suitable for estimating tree resources across various landscapes. Based on these findings, the model will be

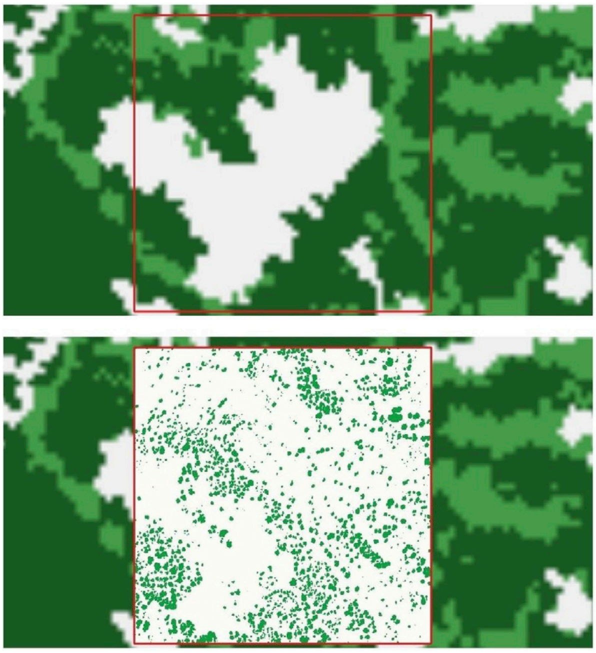

FIGURE 8
Comparison between the tree masks created by our model and the CLC + Backbone map of forest type tree cover with resolution 10 m/pixel.

applied in a subsequent study to create Cyprus's first national airborne tree inventory and calculate for the first time the total biomass and carbon stock of trees at a national scale.

When combining our results with coarser resolution maps of tree cover and forest types, we found that tree canopy can be predicted at a national level by using a small sample of very high-resolution images as a reference. This combination improves the quality of the information derived from lower-resolution maps and highlights the advantages of using high-resolution images and state-of-the-art models. As illustrated in Figure 8, coarser-resolution (10 m) maps such as CLC + tend to overestimate tree cover in dense forest regions while underestimating it in urban areas with smaller trees. In the case of Troodos Forest Park, we found that CLC + Backbone overestimated tree canopy size by 100%, underscoring the importance of high-resolution data for developing tree inventories and the advantages of using advanced methods like CNN models for segmenting individual tree crowns. Our results can be compared with other freely accessible tree cover maps, such as the Copernicus Tree Cover Density map, as shown in Figure 9, and observe that our findings reveal the true structure of the tree canopy, identifying small trees that low-resolution maps fail to capture. Our observations highlight the importance and the urgent need for high quality national inventories that lie on up-to-date data of high resolution to illustrate the realistic image of tree resources in a country.

5 Summary and conclusions

This study addressed for the first time the quantification of the number of trees and the extent of tree cover within the largest forested region of Cyprus (the Troodos National Forest Park), employing tree segmentation and density mapping techniques. The model developed by Li et al., 2023 was used here by applying minor modifications to become compatible with the Cypriot landscape. It must be highlighted that this is the first time that a state-of-art model has been applied to segment and count trees over an Eastern Mediterranean region, Cyprus, making our results to be of high importance. Until now, there are no accurate estimates of the total number of trees in Cyprus and no national airborne inventory has been created. Therefore, the model can offer us the opportunity, having available data for the full country area of Cyprus, to create the first national airborne tree inventory.

To set up our model, a high-resolution orthophoto dataset was used to create manual annotations to define accurate tree areas and train our model efficiently. It was found that the Troodos forest area contains as many as 927,562 trees (no species categorization) with a total tree-covered area equal to $16.38km^2$. Considering that Troodos forest park has a size of about $91km^2$, trees cover almost 18% of the area while the remaining area is the background space between trees. The accurate segmentation of trees, accounting for space between them is one of the main features of our model since every previous tree inventory over Cyprus has utilized satellite images of much lower resolution compared to ours. Hence, our model results can provide the real number of trees in Troodos and have the potential to be extended to the entire country easily, thereby creating the first national airborne tree inventory for Cyprus.

As a case study, we extended the application of our model to an urban area which includes a small forest park in the suburb of Nicosia. This is the first time that a study counted trees and evaluated the tree coverage in an urban area of Cyprus. A significant number of trees were found in this urban area, with approximately 130,000 trees in $16km^2$ and a total tree-covered area of 108 ha. It is worth noting here that trees in urban areas have not been considered so far by any previous study or National Forest Inventory.

Our model results were further processed by employing some additional statistical tests such as the correlation between the tree cover density and the number of trees measured for each image of reference area. The existence of areas with the same tree cover density but different numbers of trees at Troodos Forest Park, despite the strong correlation between the two variables, highlights the presence of tree species diversity in the area and provides insight into the nature of the ecosystem. For the Athalassa forest park (in Nicosia), there is also a strong correlation between tree cover density and the number of trees but with a rather different slope compared to the Troodos forest, suggesting a rather different type of forest while the strong correlation also suggests a quite homogeneous forest with trees in this area having similar size and age. Interestingly, for the small urban area, the correlation is again very strong with a slope similar to the forest park next to Nicosia. Therefore, our analysis highlights the significance of monitoring the number of trees and not only the tree-covered area, which is the parameter that is mainly studied worldwide. The correlation between tree cover density and the number of trees holds important implications for forest management and conservation efforts. Some of the aspects that can be considered, to develop a more sophisticated analysis are biodiversity, carbon stock, and the ecosystem in general. Consequently, it will be beneficiary to refine our study and examine other parameters such as climate, soil characteristics, and other environmental factors.

Due to the high purchasing cost of aerial images, we restricted our study to a small portion of the Troodos Mountains area while the CLC + backbone product map was used to scale up our model results and derive a raw estimation of the total tree covered area of

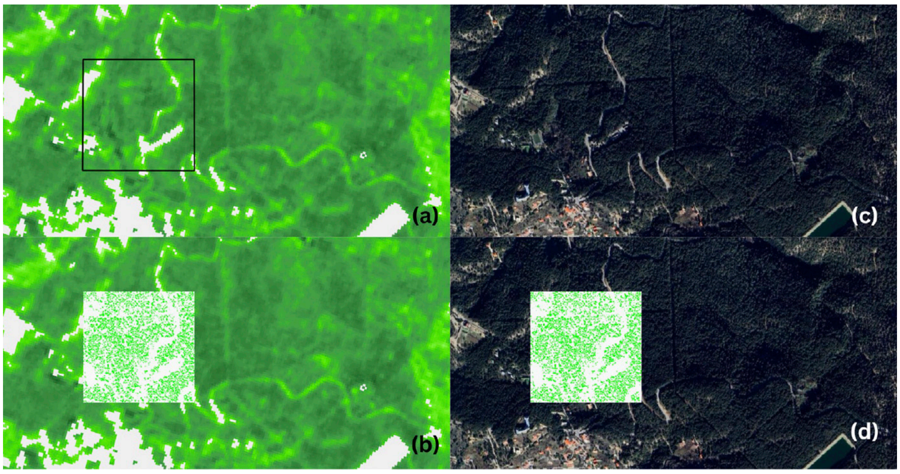

FIGURE 9
Comparison between our results, Copernicus TCD dataset, and Google satellite. Image **(A)** Copernicus TCD data image that includes the reference area that we used for estimating the total tree covered area of Cyprus. Image **(B)** Image of the same area including the tree masks that have been created by our model for the area in the rectangular. Images **(C, D)** Image taken by Google satellite for the same area and the tree-masked image that has been created by our model.

Cyprus. In 2019, the total tree-covered area of Cyprus was estimated to be approximately 138,100 ha. Using the Troodos Forest Park as a case study, we found that the CLC + Backbone overestimated the tree canopy size by 100%. This result underscores the key advantage of our analysis—the use of high-resolution images. These images, with a resolution finer than 1 m/pixel, allow us to accurately account for gaps between trees, large shrubs, and other green objects that are not detectable in lower-resolution imagery. Overall, our results indicate that Cyprus holds a significant amount of tree-covered area which contributes to carbon stock. Our analysis emphasizes how important it is to look at both tree cover density and the number of trees. Knowing how these two factors interact can help in making smart choices in forest management and conservation efforts. It should be noted that the images were collected in 2019. Consequently, the variation in tree cover must be considered to make an accurate evaluation of the tree resources of Cyprus today. Our proposed strategy can be used in the future to evaluate how the tree-covered area changed through the years by using deep learning models and high-resolution orthophotos.

Thanks to the development of this model, we can realistically aim at the creation of the first national airborne tree inventory of Cyprus by applying the model to high-resolution images that cover the full area of the island. Such an inventory can contribute to the monitoring of the carbon emissions level to assess the development of strategies for the achievement of carbon neutrality, especially in the context of the Land Use, Land-Use Change and Forestry (LULUCF) initiative.

Data availability statement

A part of the dataset generated for this study and all the developed tree cover maps can be found on Zenodo470 under the paper title (https://zenodo.org/records/13987821?preview=1&token=471eyJhbGciOiJIUzUxMiJ9.eyJpZCI6ImM3NzZjZTNiLTc4ODQtNDJjNy05MzM4LTY5NTQ2YThhZmU5472_zKT4fCa12KmLRSTEt2fkpdtb8R9pD-jpTFpGvziA9GlicCkgMflJlpy1Il3HEjZPq-BO05k6oCdY Frontiers 12 Zenonos et al. Running Title The maps can also be accessed online in the following links: https://annzen.github.io/Athalassa_Forest_park_tree_map/index_Athalassa.html, https://annzen.github.io/Troodos_Forest_park_tree_map. All the generated dataset can be provided upon request to the correspondence author.

Author contributions

AZ: Conceptualization, Formal Analysis, Investigation, Resources, Software, Validation, Visualization, Writing–original draft, Writing–review and editing. SL: Data curation, Methodology, Writing–review and editing. MB: Writing–review and editing. JS: Funding acquisition, Supervision, Writing–review and editing. PC: Resources, Supervision, Writing–review and editing.

Funding

The author(s) declare that financial support was received for the research, authorship, and/or publication of this article. This project has received funding from the European Union's Horizon Europe research and innovation program under Grant Agreement N° 101071247 (Edu4Climate – European Higher Education Institutions Network for Climate and Atmospheric Sciences).

Acknowledgments

PC acknowledges support from the German-French BMBF ANR project AI4FOREST.

Conflict of interest

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/frsen.2025.1498217/full#supplementary-material

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