

UDC 630*5:623.746:582.445
DOI: 10.31548/forest/1.2023.39

UAV data collection parameters impact on accuracy of Scots pine stand mensuration

Roman Zadorozhniuk*

Postgraduate Student

National University of Life and Environmental Sciences of Ukraine
03041, 15 Heroiv Oborony, Kyiv, Ukraine
<https://orcid.org/0000-0001-6746-9733>

Abstract. A wide range of UAV systems used for forest research requires unified approaches to data collection. The research aims to determine the optimal parameters for UAV data collection to obtain accurate information about stands, considering the cost of resources for its collection. The process of collecting remote sensing data consisted of nine combinations divided into three levels of overlap and three levels of spatial resolution (survey altitude) and changing the degree of filtering of a dense point cloud during image processing. Individual tree detecting in the stand was performed using the R programming language and the ForestTools package. The results of the assessment of the dependence of the radius of tree crowns on their height were used to set the parameters of the variable filter function for finding local maxima for Scots pine stands. Errors in the identification of treetops were estimated using the *F-score*. The identified heights were compared with the field data of the ground survey. The proportion of classified digital elevation model DEM in the dense point cloud was reduced from the total area of the test site using images of 4.1 cm/pix spatial resolution (150 m survey altitude). The study presents the results of assessing the impact of spatial resolution of optical images collected from UAVs and their overlap on the results of measurements of stands parameters. It is determined that a photogrammetric survey with input images with a longitudinal overlap of less than 90% is not appropriate for the study of forest areas due to the impossibility of aligning all images. The results of the assessment of tree accounting in the stand showed that it is most appropriate to use images with a spatial resolution of up to 3.3 cm/pix (120 m survey altitude), otherwise, the proportion of missed treetops increases. Reducing the spatial resolution of remote sensing data leads to an increase in errors in determining the height of individual trees, and the average heights of the experimental plots had the same trend. Given the combination of the assessed

Suggested Citation:

Zadorozhniuk, R. (2023). UAV data collection parameters impact on accuracy of Scots pine stand mensuration. *Ukrainian Journal of Forest and Wood Science*, 14(1), 39-54. doi: 10.31548/forest/1.2023.39.

*Corresponding author



factors, it is not recommended to use images with a spatial resolution of more than 3.3 cm/pix for forestry research due to increased errors in the individual tree detection and tree height determination. The results obtained can be used to select data collection parameters for research on Scots pine stands to assess their growing stock and phytomass

Keywords: photogrammetry; canopy height model; individual tree detection; height determination; digital elevation model

Introduction

Remote sensing data is used in forestry to reduce the economic costs of operations and increase their efficiency (McRoberts & Tomppo, 2007). The availability of remote sensing data as an auxiliary material allows the performing of several tasks in forestry, eliminating the need to go to the field. However, there is always a need to estimate indicators of trees and stands for which field ground measurements are required. I. Korpela (2004) pointed out that field inventory data is essential for remote sensing and is used for training, calibration, and verification of results.

First of all, remote sensing data collection systems can be divided into the following categories by type of carrier: satellites, manned aircraft, unmanned aerial vehicles (fixed-wing or multi-rotor), and ground-based scanning systems (Pádua *et al.*, 2017). The use of different types of systems significantly increases the variability of data acquisition methods, and each of them has its advantages and disadvantages. J. White *et al.* (2016), V. Myroniuk *et al.* (2022) in their works, they noted that the use of satellite data in forestry is quite promising since such data cover large areas and can be widely used in forest inventory.

Data from unmanned aerial vehicles have several significant differences compared to satellite imagery: relative cheapness and accessibility, short data collection times, and the ability to obtain high-resolution data. A. Graham *et al.* (2020) described that the development

of computing technologies has led the use of *digital aerial photogrammetry*. *Structure-from-motion* technologies are used to reconstruct 3D scenes, including for forestry research and assessment parameters of forest stand (Westoby *et al.*, 2012).

K. Stereńczak *et al.* (2020) described that to determine the individual trees attributes in a stand based on remote sensing data, it is necessary to detect them. A separate large group of works can be distinguished that are devoted to assessing the quality of individual tree detection using a wide range of methods (Duncanson *et al.*, 2014). During classical forestry surveys, the processes of accounting for the number of trees and determining their parameters can be separated: it is possible to determine the tree parameters without their continuous accounting on the site. It is impossible to determine the individual trees parameters based on digital aerial photogrammetry or LiDAR (Light Detection and Ranging) data without their detecting. Therefore, the identification of individual trees in a stand is an essential step in estimating their attributes (Mohan *et al.*, 2021). The number of tree parameters that can be estimated will depend on the applied detecting algorithms and the characteristics of the input remote sensing or scanning data (Guimarães *et al.*, 2020). The use of a local maximum filter is one of the simplest methods of tree detecting and measuring their height (Popescu & Wynne, 2004; Silva *et al.*, 2022).

K. Ma *et al.* (2022) found that the quality of individual trees detection in a stand is influenced by several factors: morphological features of the studied stands (tree crown shape, stand structure), selection of remote sensing data collection parameters, and remote sensing data processing parameters. Considering the morphological factor, it was found that the structure of forest stands significantly affects the quality of tree detection and delineation. The use of LiDAR data makes it possible to study the three-dimensional structure of forest stand under the canopy of the dominant trees, but the results of detection in the second or third tiers do not give satisfactory results (Ferraz *et al.*, 2012).

Methods of tree detection are constantly evolving to achieve better results, and the high accuracy of measuring the height of stands based on remote sensing data has been confirmed by several studies (Ota *et al.*, 2017; Guimarães *et al.*, 2020). The use of remote sensing methods is most promising in coniferous stands, as they are the most easily decipherable (Heurich, 2008). In Ukraine, where coniferous plantations occupy a significant share, the introduction of remote sensing methods is a very

promising direction. The height of Scots pine stands can be determined with sufficient accuracy based on photogrammetric survey data compared to classical measuring instruments (Bilous *et al.*, 2021).

Remote sensing data acquisition parameters affect the characteristics of the resulting dense point cloud, which affects the accuracy of tree attributes measuring and the possibility of their further application (Kameyama & Sugiura, 2021).

The research aimed to determine the optimal parameters for collecting data from UAVs to obtain sufficiently accurate information about forest stands.

Materials and Methods

The study was carried out in August 2020 on the territory of the Chernobyl Exclusion Zone, where plantations have been formed over the past decades without active (significant) anthropogenic intervention. The study was carried out on an 18.5-hectare polygon with eight circular sample plots. The experimental site was selected in such a way as to ensure the presence of the most contrasting stands in one remote sensing data collection (Table 1).

Table 1. Characteristics of the experimental stands

Sample plot, No	Area, m ²	Origin	Age, years	Number of trees in the site	Average diameter, cm	Average height, m	Site index
1	250	Artificial	58	46	18.3	20.8	I
2	100	Artificial	58	56	8.2	8.2	V
3	1000	Natural	50	30	11.5	7.3	V
4	250	Artificial	58	42	13.2	11.7	IV
5	100	Artificial	70	38	10.5	10	V
6	250	Artificial	58	59	16.8	21.7	I
7	100	Artificial	58	42	11.6	15.1	III
8	50	Artificial	58	62	4.6	5.4	Va

Source: compiled by the author

As a result of the dramatic change in habitat conditions, the experimental sites had different stands in terms of diameter, height, and number of trees per hectare. The size of the sample plots depends on the density of the trees and is set to ensure that there are at least 30 trees per plot. The spatial location of the trees in the sample plots were established using a *TruPulse 360B* laser-optical rangefinder and *MapSmart* software, with measurements of tree diameter at 1.3 m, height of model trees, tree species and live status. All trees that reached a height of 1.3 m without any minimum diameter restrictions were selected for the ground survey. For the assessment quality of individual tree detection, we used the trees occupying the highest position in the stand and their tops position on orthophoto maps. Heights were meas-

ured for 10 model trees in artificial stands and 17 in natural stands. The age of the stands was determined based on forest management materials (Mensuration description..., 2016), and for the natural stands, the age was determined by counting annual rings selected using a *Haglof* increment borer.

A *Phantom 4 Pro* UAV was used for remote sensing, equipped with a 1 “CMO” camera with a 20-megapixel matrix. The input data for remote sensing are a series of UAV images obtained at different shooting altitude and overlaps. Flight planning and surveying of the test polygon were performed using *Pix4Dcapture* software. An estimate of the time spent on collecting remote sensing data, and quantitative and qualitative characteristics of the input image series is given in Table 2.

Table 2. Quantitative characteristics and timing of UAV data collection

Combination number	Survey altitude, m	Longitudinal (transverse) overlap, %.	Record time, min:sec	The number of pictures, pcs.	UAV flight distance, m	Picture resolution, cm/pix
1	80	90(81)	21:06	513	4296	2.18
2	80	80(72)	11:01	209	3529	2.18
3	80	70(63)	06:52	129	2805	2.18
4	120	90(81)	15:24	329	4282	3.27
5	120	80(72)	08:14	125	2929	3.27
6	120	70(63)	07:01	95	3107	3.27
7	150	90(81)	12:07	233	3771	4.09
8	150	80(72)	07:30	102	2868	4.09
9	150	70(63)	07:00	82	2871	4.09

Source: compiled by the author

Photogrammetric image processing was performed using specialized *Metashape* software. During the processing of each of the individual series of images, iterations of their alignment and the creation of a dense point cloud were performed using identical processing parameters. For each iteration, two dense point clouds were built: one with an aggressive degree of filtering and one with a soft degree. Next, the ground points of the dense cloud were classified, based on which a digital elevation model (DEM) was built, and a digital surface model (DSM) was created based on all cloud points. The original raster materials were exported in the metric coordinate system with a spatial resolution of 15 cm/pix. Visual analysis and aggregation with ground data were performed in the QGIS (Quantum GIS) geographic information system, where the canopy height model (CHM) was calculated using formula (1):

$$CHM = DSM - DEM \quad (1)$$

At the first stage of the study, the quality of terrain classification of the dense point cloud used to create the DEM was assessed. To do this, the proportion of the terrain classified to the total area of the polygon was determined. The area of classified terrain was defined as the sum of pixels of the DEM generated without interpolation.

Individual tree detection using algorithms in the R programming language with the use of the local maximum search function implemented in the {ForestTools} package (Plowright, 2020). This function uses a local maximum search filter, which is necessary to limit the search radius between potential treetops. This filter can be set to a fixed search radius or given a variable radius function. The advantage of the variable radius filter is that after identifying the treetop, it takes the height value as

an independent variable and determines the potential radius of the tree crown (Popescu & Wynne, 2004). Considering that the experimental polygon contains sample plots with different stand parameters, a variable radius filter was applied.

The crown radius of Scots pine was determined from the collected remote sensing data using UAVs. Based on the formed array of 380 Scots pines, a logarithmic dependence of the crown radius of trees on their height within the experimental polygon was established (formula 2). The computed confidence interval at the level of 2.5% for parameters of the established regression was used to describe the lower level dependence of the crown radius to tree height. Thus, the variable search radius filter was assigned the expression of the established confidence interval for parameters of level 2.5% (formula 3).

$$rF = 0,369 \cdot \ln(h) + 0,421, \quad (2)$$

$$rF(2,5\%) = 0,297 \cdot \ln(h) + 0,221, \quad (3)$$

where rF is the established search radius (tree crown radius), m; $rF_{(2,5\%)}$ is the lower confidence interval of the model parameters; h is the height of the tree, m.

The *CHM* smoothing was performed to test whether it is possible to achieve better tree detection results by avoiding the identification of false tops caused by tree branches (Mohan *et al.*, 2017). The detection was performed with and without smoothing the image using a 5x5 pixel Gaussian filter. The {rLiDAR} package in the R programming language was used to smooth *CHM* rasters.

In a geographic information system, the detected tops are compared with ground-measured data and an orthophoto map of the sample plots (Fig. 1).

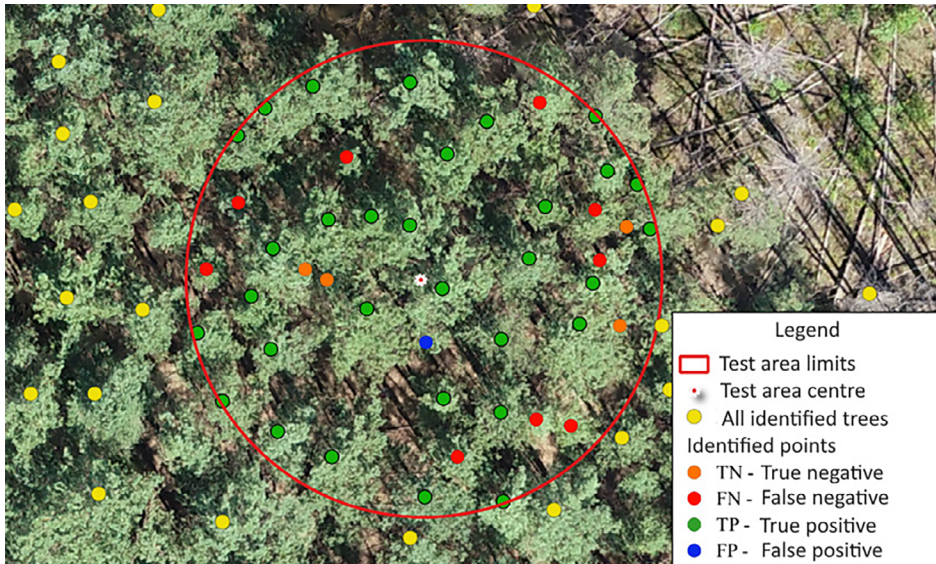


Figure 1. A confusion matrix of tree detection quality assessment in sample plot No. 1
Source: compiled by the author

The quality of individual tree detecting was assessed using confusion matrix. Twelve iterations of detecting were compared, the identified treetops were assigned the TP status, and

the missed ones were assigned the FN status. Falsely identified tops during the comparison of each iteration were assigned the FP status (Table 3).

Table 3. Confusion matrix indicators and individual tree detecting accuracy values

CHM type	Number of treetop	TP	FP	FN	Recall	Precision	F-score	FNR	FDR
a80	246	172	23	74	0.70	0.88	0.78	0.30	0.12
a80SMTH	246	165	10	81	0.67	0.94	0.78	0.33	0.06
m80	246	168	24	78	0.68	0.88	0.77	0.32	0.13
m80SMTH	246	164	12	82	0.67	0.93	0.78	0.33	0.07
a120	246	166	23	80	0.67	0.88	0.76	0.33	0.12
a120SMTH	246	155	10	91	0.63	0.94	0.75	0.37	0.06
m120	246	178	40	68	0.72	0.82	0.77	0.28	0.18
m120SMTH	246	168	28	78	0.68	0.86	0.76	0.32	0.14
a150	246	135	9	111	0.55	0.94	0.69	0.45	0.06
a150SMTH	246	129	6	117	0.52	0.96	0.68	0.48	0.04
m150	246	138	9	108	0.56	0.94	0.70	0.44	0.06
m150SMTH	246	133	7	113	0.54	0.95	0.69	0.46	0.05

Note: “80, 120, 150” = shooting height, “a, m” = dense cloud filtering parameters (aggressive, soft), SMTH = CHM raster was smoothing

Source: compiled by the author

The accuracy indicator of tree detecting was the F-score, calculated based on Recall (producer's accuracy) and Precision (user's accuracy) according to equations (4)-(6). The comparison of errors arising from the use of different CHM rasters was performed using the False Negative Rate (FNR) and the False Discovery Rate (FDR) according to equation (7), and (8) (Maxwell *et al.*, 2021).

$$r = \frac{TP}{TP+FN}, \quad (4)$$

$$p = \frac{TP}{TP+FP}, \quad (5)$$

$$F = \frac{2*r*p}{r+p}, \quad (6)$$

$$FNR = \frac{FN}{TP+FN}, \quad (7)$$

$$FDR = \frac{FP}{TP+FP}, \quad (8)$$

where TP is the number of true positive detected treetops, FN is the number of false negatives, and FP is the number of false positives.

The heights of the trees are measured by detecting their tops. The algorithm assigns the height value of a cell from the CHM raster to each detected local maximum (Plowright, 2020). Thus, the results of the top detecting are used to measure the heights of individual trees and calculate the average height in the sample plots.

The estimation of tree height errors was used to determine the influence of UAV data collection parameters on the distribution of CHM heights. To compare the results of measuring the height of individual trees with different data collection parameters, the local maxima of identified trees were selected with their height parameters. The sample included trees for which ground-based height measurements were available and local maxima were detected during all iterations of the survey. For the purpose of comparing average height measurements, the results obtained from detecting

all treetops in sample plots were utilized, and the average height was calculated based on the ground data.

The root means square and *Bias* were used to assess the accuracy of the remote sensing method for height measure (Su *et al.*, 2020; Holiaka *et al.*, 2021). The heights determined by the remote sensing method are compared with the ground survey data using formulas (9)-(12).

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{n}}, \quad (9)$$

$$RMSE (\%) = 100 \cdot \frac{RMSE}{\bar{y}}, \quad (10)$$

$$Bias = \frac{\sum_{i=1}^n (\hat{y}_i - y_i)}{n}, \quad (11)$$

$$Bias (\%) = 100 \cdot \frac{Bias}{\bar{y}}, \quad (12)$$

where \hat{y}_i – the value determined remotely, y_i – the value according to the ground survey, and \bar{y} – the arithmetic mean.

Results and Discussion

During the photogrammetric processing, the image arrays with less than 90% overlap could not be aligned, which makes further analysis impossible. The exception is combination No. 8 (altitude 150 m), where all images with a longitudinal overlap of 80% were aligned. Thus, remote sensing data of forest stands collected with a longitudinal overlap of less than 90% and a survey altitude of up to 150 m are rather difficult to process photogrammetrically.

Estimating the proportion of the DEM area to the total polygon area at an acquisition altitude of 80 m, the proportion of classified terrain is 59%, at 120 m it is also 59%, at 150 m it is 52% and at the same height with reduced overlap 42%. Part of the polygon had an open area where there were no problems with determining the ground level. Reducing the spatial resolution of the input images significantly reduces the proportion

of points in the dense cloud located under the forest canopy, which makes it difficult to form a digital elevation model. DEM classification is quite complicated for closed stands of trees, as well as when there is undercover vegetation.

For remote sensing data collected from altitudes 80 and 120 m, the determined *F-score* value is in the range of 0.75-0.78. Using the data collected at an altitude of 150 m, the quality of individual tree detection deteriorated significantly, with the *F-score* value in the range of 0.68-0.70. The worst interpretation results

were obtained for the sample plot with the V_a site index (sample plot No. 8), which indicates the difficulty of detection the treetops in stands with a dense distribution of low trees.

The error rates that occurred during the identification of the tops are shown in Figure 2. The largest FNR errors were found for CHM models generated from data at a survey altitude of 150 m. A decrease in the proportion of detected treetops indicates that with such data collection parameters, CHM rasters reproduce the structure of stands in less detail.

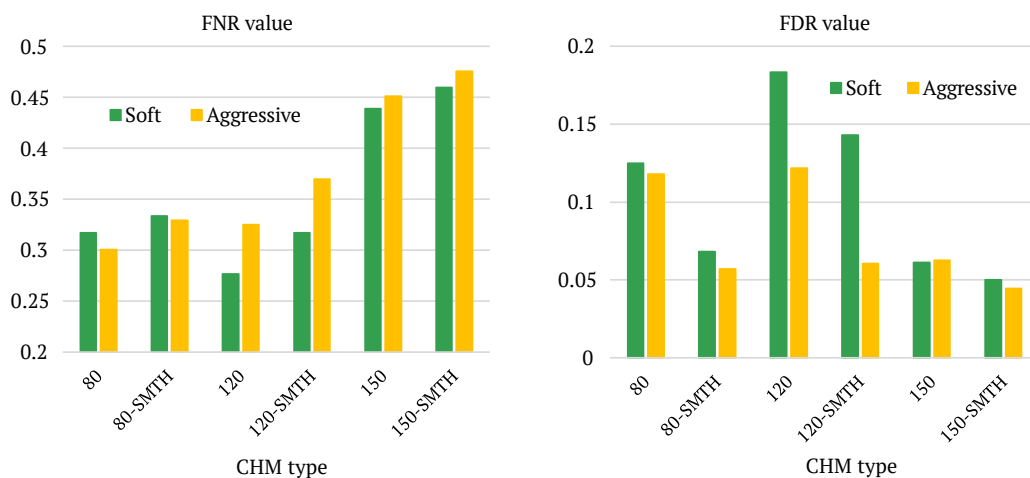


Figure 2. Indicators of tree-top detecting errors

Source: compiled by the author

The error characteristics indicate that the use of a soft degree of filtering during photogrammetry image processing does not reduce the FNR but causes FDR errors. In this case, the use of an aggressive degree of filtering during photogrammetric image processing allows to reduce the proportion of falsely discovered local maxima. Smoothing of the CHM raster avoids the occurrence of false detecting treetops but does not affect the overall quality of the peak *F-score*. The data

obtained from altitude of 120 m and the soft filter of the dense point cloud allowed us to detect the largest share of the tops, but the worst Precision was obtained due to a significant share of falsely detected tops.

To compare the results of height measurement, 30 trees were selected. The assessment of the statistical indicators of height measurement errors indicates that the remote method on average tends to underestimate the height (Table 4, Fig. 3).

Table 4. Errors in measuring the of individual trees height using UAV data

<i>CHM type</i>	<i>RMSE, m</i>	<i>RMSE (%)</i>	<i>Bias, m</i>	<i>Bias (%)</i>
a80	0.86	6.71	-0.14	-1.07
a80SMTH	0.91	7.11	-0.31	-2.43
m80	0.82	6.41	-0.16	-1.23
m80SMTH	0.91	7.11	-0.31	-2.43
a120	0.87	6.84	-0.35	-2.72
a120SMTH	0.98	7.66	-0.47	-3.66
m120	0.81	6.32	-0.21	-1.67
m120SMTH	0.83	6.47	-0.34	-2.64
a150	1.28	10.07	-0.95	-7.42
a150SMTH	1.35	10.55	-1.02	-8.00
m150	0.94	7.34	-0.56	-4.39
m150SMTH	0.98	7.67	-0.62	-4.86

Source: compiled by the author

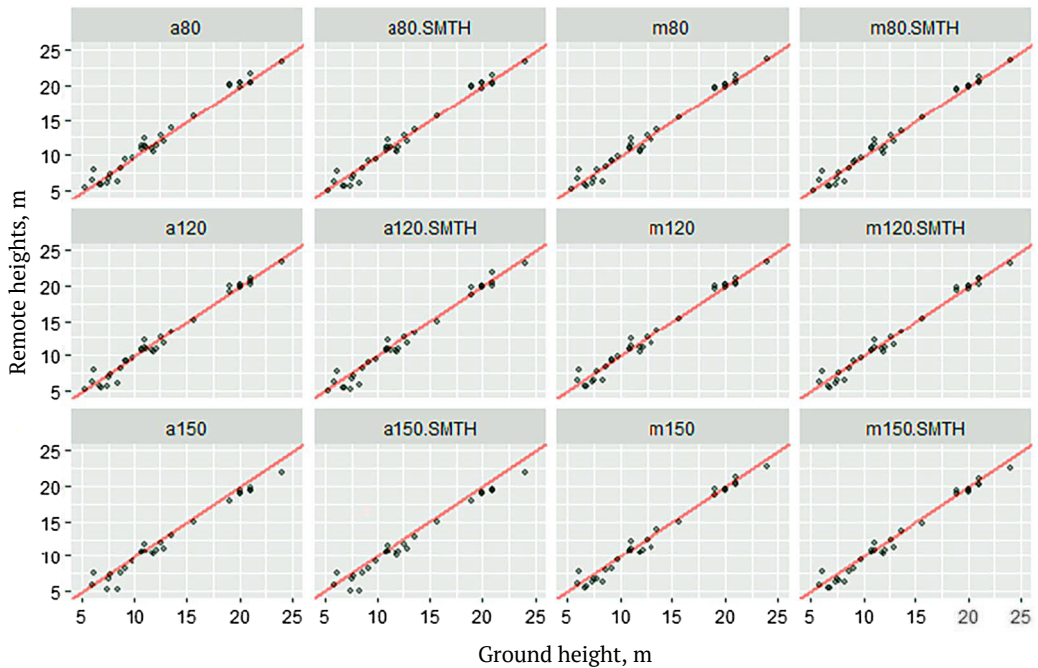


Figure 3. Results of measuring the height of individual trees using CHM data and ground-based methods

Source: compiled by the author

It was found that the underestimation of height is observed for trees up to 10 m in height. For trees with heights of 10-20 m, the remote sensing is comparable to the ground data, while for trees over 20 m in height, the remote sensing data show higher heights. In general, the *Bias* for the models generated from 80 m altitude ranges from -0.1 m to -0.3 m; for the models generated from 120 m altitude, it ranges from -0.2 m to -0.5 m, and the largest deviations are found for the models from 150 m altitude (Fig. 3). This indicates that the

data with lower spatial resolution reproduce crown tops worse. To assess the effects of using different remote sensing inputs images in determining the average height, data within the sample plots were used. The average height based on ground data was determined using height curve. The average height from UAV data was calculated as the arithmetic mean of the identified trees in the sample plots (Table 5). Underestimation of the average height by remote sensing is observed for the natural origin of sample plot No. 3 with single low trees.

Table 5. Determined average heights by sample plots and type of data

Type of height determination data	Average heights estimated by sample plots, m							
	1	2	3	4	5	6	7	8
a80	21.2	7.3	5.0	10.9	15.0	21.4	11.0	5.4
a80SMTH	20.7	7.3	5.4	10.6	14.7	21.3	10.9	5.4
m80	20.7	8.1	5.7	10.7	14.9	21.2	11.0	5.4
m80SMTH	20.8	7.8	6.1	11.0	14.7	21.2	10.9	5.3
a120	20.5	7.4	5.6	10.9	14.8	21.0	10.9	5.3
a120SMTH	20.3	7.4	5.2	11.0	13.6	21.0	10.8	5.1
m120	20.9	7.7	5.4	10.0	14.2	21.0	11.0	5.2
m120SMTH	21.0	7.5	5.3	9.7	13.8	21.0	11.0	5.2
a150	20.0	7.7	5.6	11.1	13.9	20.2	10.5	5.2
a150SMTH	20.0	7.8	5.4	11.0	14.2	20.1	10.5	5.2
m150	20.7	7.6	5.9	10.7	13.8	20.6	10.9	5.0
m150SMTH	20.7	7.6	5.9	10.7	13.8	20.6	10.9	5.0
Ground (control)	20.8	8.2	7.3	11.7	15.1	21.7	10.0	5.4

Source: compiled by the author

With the change in CHM, the *RMSE* values for the determined average heights on the sample plots do not differ significantly and are around 1 m for all canopy height models. The *Bias* value for all models is in the range of 3-6%. If we evaluate the change in the *Bias*, we still observe a similar trend as when determining the heights of individual trees, namely, a decrease in

the quality of spatial resolution of images leads to an underestimation of the average height (Table 6). The *Bias* value did not exceed 0.5 m for all models from altitude of 80 m and for the aggressive CHM from altitude of 120 m, while for the rest, the systematic error was more than 0.5 m. Smoothing the CHM during accounting leads to an increase in systematic error.

Table 6. Average height determination accuracy indicators using UAV data

<i>CHM type</i>	<i>RMSE, m</i>	<i>RMSE (%)</i>	<i>Bias, m</i>	<i>Bias (%)</i>
a80	1.00	7.98	-0.38	-2.99
a80SMTH	0.92	7.34	-0.49	-3.89
m80	0.78	6.23	-0.31	-2.50
m80SMTH	0.92	7.34	-0.49	-3.89
a120	0.84	6.72	-0.48	-3.79
a120SMTH	1.08	8.59	-0.73	-5.79
m120	1.07	8.52	-0.60	-4.79
m120SMTH	1.21	9.68	-0.71	-5.69
a150	1.01	8.04	-0.75	-5.99
a150SMTH	1.03	8.26	-0.75	-5.99
m150	0.95	7.57	-0.63	-4.99
m150SMTH	0.95	7.57	-0.63	-4.99

Source: compiled by the author

The area-based approach to forest management requires a correct inventory of tree stands. That is why the use of photogrammetry technology is promising in comparison with more expensive technologies. Identification of top trees in a stand based on CHM is quite simple and does not require significant computing power (Ferraz *et al.*, 2012).

The studies (Popescu & Wynne, 2004; Ottoy *et al.*, 2022) showed that to individual tree detection in plantations with different stand parameters, it is necessary to establish the dependence of crown radius on tree height. In contrast to previous publications, confidence interval parameters around the established regression of crown radius on tree height were used to avoid missing treetops. Thus, we used confidence intervals at the level of 2.5% of the established regression relationship to reduce the parameters of the treetop filtering function.

In the present study, no significant advantages were found in applying a smoothing filter to the canopy height model, as reported

by Mohan *et al.* (2017). However, differences in the results obtained may depend on the input materials used, the CHM resolution, or the characteristics of the studied forest stands. It has been established that the quality of remote-sensing input images has the greatest impact on errors in tree detection. For example, the study by J. Torres-Sánchez *et al.* (2018) shows that the best detecting results are obtained with the maximum degree of image overlap.

The confusion matrix data was used, which makes it possible to assess which errors deteriorate the individual tree detecting performance. Problems with the identification of trees less than 2 m in height that grew on the site of natural origin were identified. For studies of low stands, it is necessary to use data from a lower altitude than was used in our article and greater spatial resolution (Lin *et al.*, 2023). A. Bilous *et al.* (2021) indicate that the results of measuring the height of Scot's pine trees in mature stands using CHM data are more accurate than using handheld height clinometers.

As the spatial resolution of the remote sensing data changes, the mean square error for the determined average stand height does not differ significantly, as confirmed by S. Kameyama & K. Sugiura (2021). However, it was found that a decrease in the spatial resolution of the input remote sensing data leads to an increase in errors in measuring the height of individual trees. If we evaluate the *Bias* value for the determined average heights, we still observe the same tendency to underestimate them. Heights were underestimated for natural stands that had not formed a forest stand, and the effect of underestimating heights by remote sensing was also observed in the study of L. Lin *et al.* (2023) on low trees.

Errors of tree height estimating also depend on the errors in the digital elevation model. This is especially important in areas with closed stands where the ground surface is difficult to see, as well as in areas with complex terrain. Therefore, it is important to use the most accurate digital elevation models for establishing the stands parameters.

Conclusions

Based on the results of the study, it was found that remote sensing data with higher spatial resolution according to several criteria are best suited for determining pine stand parameters.

Based on the survey data from altitude of 80 m (spatial resolution of 2.2 cm/pix), the smallest errors in determining the height and detecting the treetops were obtained. The *F-score* for the quality of individual treetop detection was in the range of 0.77-0.78. The *Bias* error in measuring the height of individual trees ranged from -0.14 to -0.31 m, and the average height of the stand was from -0.31 to -0.49 m.

Based on the data from the 120 m survey (3.3 cm/pix), the results were close to the

previous ones. The use of a soft degree of filtering when building a point cloud leads to false discovery treetops. The *F-score* was in the range of 0.75-0.77. The *bias* for measuring the height of individual trees ranged from -0.21 to -0.47 m, with the average height from -0.48 to -0.73 m (the smallest systematic error when using a point cloud with aggressive filtering and without CHM filtering).

The worst results were obtained for data taken from altitude of 150 m (4.1 cm/pix). The *F-score* values deteriorate to 0.68-0.70. The systematic error in determining the height of individual trees increases (*Bias* ranges from -0.56 to -1.02 m), and the average stand height from -0.63 to -0.75 m. In this case, the highest systematic error rates are for CHM with aggressive filtering.

It has been established that for forestry research, it is necessary to collect remote sensing data with a longitudinal image overlap of at least 90%. Reducing the spatial resolution of the input images to 4 cm/pix worsens the results of terrain surface classification and DEM creation.

The results of the study indicate that the quality of detecting individual Scots pines and determining their heights depends on the parameters of UAV data collection. The results obtained should be considered when planning the collection of optical data from UAVs in future studies, in particular, their potential impact on the accuracy of determining a wider range of stand parameters. Similar studies may be required to establish optimal parameters for collecting optical data in deciduous stands (on the territory of Ukraine). Errors in detecting and determining the heights of low trees indicate the need to find optimal parameters for UAV data collection separately for forest plantations and young stands.

Conflict of Interest

The author declares no conflict of interest.

Acknowledgements

Sincere gratitude is expressed to supervisor Andrii Bilous for administration and support of research activities, Dmytro Holiaka for assistance and help with the research, and Oleksandr Leśnik and Petro Diachuk for assistance with the collection of research data.

References

- [1] Bilous, A.M., Diachuk, P.P., Zadorozhniuk, R.M., Matsala, M.S., & Burianchuk, M.M. (2021). Accuracy of selected methods of measurement of tree heights. *Ukrainian Journal of Forest and Wood Science*, 12(1), 6-16. doi: [10.31548/forest2021.01.001](https://doi.org/10.31548/forest2021.01.001).
- [2] Duncanson, L.I., Cook, B.D., Hurtt, G.C., & Dubayah, R.O. (2014). An efficient, multi-layered crown delineation algorithm for mapping individual tree structure across multiple ecosystems. *Remote Sensing of Environment*, 154, 378-386. doi: [10.1016/j.rse.2013.07.044](https://doi.org/10.1016/j.rse.2013.07.044).
- [3] Ferraz, A., Bretar, F., Jacquemoud, S., Gonçalves, G., Pereira, L., Tomé, M., & Soares, P. (2012). 3-D mapping of a multi-layered Mediterranean forest using ALS data. *Remote Sensing of Environment*, 121, 210-223. doi: [10.1016/j.rse.2012.01.020](https://doi.org/10.1016/j.rse.2012.01.020).
- [4] Graham, A.N.V., Coops, N.C., Tompalski, P., Plowright, A., & Wilcox, M. (2020). Effect of ground surface interpolation methods on the accuracy of forest attribute modelling using unmanned aerial systems-based digital aerial photogrammetry. *International Journal of Remote Sensing*, 41(9), 3287-3306. doi: [10.1080/01431161.2019.1694722](https://doi.org/10.1080/01431161.2019.1694722).
- [5] Guimarães, N., Pádua, L., Marques, P., Silva, N., Peres, E., & Sousa, J.J. (2020). Forestry remote sensing from unmanned aerial vehicles: A review focusing on the data, processing and potentialities. *Remote Sensing*, 12(6), article number 1046. doi: [10.3390/rs12061046](https://doi.org/10.3390/rs12061046).
- [6] Heurich, M. (2008). Automatic recognition and measurement of single trees based on data from airborne laser scanning over the richly structured natural forests of the Bavarian Forest National Park. *Forest Ecology and Management*, 255(7), 241-2433. doi: [10.1016/j.foreco.2008.01.022](https://doi.org/10.1016/j.foreco.2008.01.022).
- [7] Holiaka, D., Kato, H., Yoschenko, V., Onda, Y., Igarashi, Y., Nanba, K., Diachuk, P., Holiaka, M., Zadorozhniuk, R., Kashparov, V., & Chyzhevskiy, I. (2021). Scots pine stands biomass assessment using 3D data from unmanned aerial vehicle imagery in the Chernobyl Exclusion Zone. *Journal of Environmental Management*, 295, article number 113319. doi: [10.1016/j.jenvman.2021.113319](https://doi.org/10.1016/j.jenvman.2021.113319).
- [8] Kameyama, S., & Sugiura, K. (2021). Effects of differences in structure from motion software on image processing of unmanned aerial vehicle photography and estimation of crown area and tree height in forests. *Remote Sensing*, 13(4), article number 626. doi: [10.3390/rs13040626](https://doi.org/10.3390/rs13040626).
- [9] Korpela, I. (2004). *Individual tree measurements by means of digital aerial photogrammetry*. Tampere: The Finnish Society. of Forest Science. doi: [10.14214/sf.sfm3](https://doi.org/10.14214/sf.sfm3).
- [10] Lin, L., Hao, Z., Post, C. J., & Mikhailova, E. A. (2023). Protection of coastal shelter forests using UAVs: Individual tree and tree-height detection in *Casuarina equisetifolia* L. forests. *Forests*, 14(2), article number 233. doi: [10.3390/f14020233](https://doi.org/10.3390/f14020233).
- [11] Ma, K., Chen, Z., Fu, L., Tian, W., Jiang, F., Yi, J., Du, Z., & Sun, H. (2022). Performance and sensitivity of individual tree segmentation methods for UAV-LiDAR in multiple forest types. *Remote Sensing*, 14(2), article number 298. doi: [10.3390/rs14020298](https://doi.org/10.3390/rs14020298).

- [12] Maxwell, A.E., Warner, T.A., & Guillén, L.A. (2021). Accuracy assessment in convolutional neural network-based deep learning remote sensing studies – Part 1: Literature review. *Remote Sensing*, 13(13), article number 2450. doi: [10.3390/rs13132450](https://doi.org/10.3390/rs13132450).
- [13] McRoberts, R.E., & Tomppo, E. (2007). Remote sensing support for national forest inventories. *Remote Sensing of Environment*, 110(4), 412-419. doi: [10.1016/j.rse.2006.09.034](https://doi.org/10.1016/j.rse.2006.09.034).
- [14] Mensuration description of forest land plots, Kyiv region, State Specialized Enterprise “Pivnichna Pushcha”, Paryshiv forestry (2017). Irpin: Ukrainian State Project Forest Management Production Association VO “Ukrderzhlisproekt”.
- [15] Mohan, M., Leite, R.V., Broadbent, E.N., Wan Mohd Jaafar, W.S., Srinivasan, S., Bajaj, S., Dalla Corte, A.P., do Amaral, C.H., Gopan, G., Saad, S.N.M., Muhmad Kamarulzaman, A.M., Prata, G.A., Llewelyn, E., Johnson, D.J., Doaemo, W., Bohlman, S., Almeyda Zambrano, A.M., & Cardil, A. (2021). Individual tree detection using UAV-lidar and UAV-SfM data: A tutorial for beginners. *Open Geosciences*, 13(1), 1028-1039. doi: [10.1515/geo-2020-0290](https://doi.org/10.1515/geo-2020-0290).
- [16] Mohan, M., Silva, C., Klauberg, C., Jat, P., Catts, G., Cardil, A., Hudak, A., & Dia, M. (2017). Individual tree detection from unmanned aerial vehicle (UAV) derived canopy height model in an open canopy mixed conifer forest. *Forests*, 8(9), article number 340. doi: [10.3390/f8090340](https://doi.org/10.3390/f8090340).
- [17] Myroniuk, V., Bell, D.M., Gregory, M.J., Vasylyshyn, R., & Bilous, A. (2022). Uncovering forest dynamics using historical forest inventory data and Landsat time series. *Forest Ecology and Management*, 513, article number 120184. doi: [10.1016/j.foreco.2022.120184](https://doi.org/10.1016/j.foreco.2022.120184).
- [18] Ota, T., Ogawa, M., Mizoue, N., Fukumoto, K., & Yoshida, S. (2017). Forest structure estimation from a UAV-based photogrammetric point cloud in managed temperate coniferous forests. *Forests*, 8(9), article number 343. doi: [10.3390/f8090343](https://doi.org/10.3390/f8090343).
- [19] Ottoy, S., Tziolas, N., Van Meerbeek, K., Aravidis, I., Tilkin, S., Sismanis, M., Stavrakoudis, D., Gitas, I. Z., Zalidis, G., & De Vocht, A. (2022). Effects of flight and smoothing parameters on the detection of taxus and olive trees with UAV-borne imagery. *Drones*, 6(8), article number 197. doi: [10.3390/drones6080197](https://doi.org/10.3390/drones6080197).
- [20] Pádua, L., Vanko, J., Hruška, J., Adão, T., Sousa, J.J., Peres, E., & Morais, R. (2017). UAS, sensors, and data processing in agroforestry: A review towards practical applications. *International Journal of Remote Sensing*, 38(8-10). doi: [10.1080/01431161.2017.1297548](https://doi.org/10.1080/01431161.2017.1297548).
- [21] Plowright, A. (2020). Canopy analysis in R using Forest Tools. Retrieved from https://cran.r-project.org/web/packages/ForestTools/vignettes/treetop_analysis.html.
- [22] Popescu, S.C., & Wynne, R.H. (2004). Seeing the trees in the forest. *Photogrammetric Engineering & Remote Sensing*, 70(5), 589-604. doi: [10.14358/PERS.70.5.589](https://doi.org/10.14358/PERS.70.5.589).
- [23] Silva, C.A., Hudak, A.T., Vierling, L.A., Valbuena, R., Cardil, A., Mohan, M., Almeida, D.R.A., Broadbent, E.N., Almeyda Zambrano, A.M., Wilkinson, B., Sharma, A., Drake, J.B., Medley, P.B., Vogel, J.G., Prata, G.A., Atkins, J.W., Hamamura, C., Johnson, D.J., & Klauberg, C. (2022). TREETOP: A Shiny-based application and R package for extracting forest information from LIDAR data for ecologists and conservationists. *Methods in Ecology and Evolution*, 13(6), 1164-1176. doi: [10.1111/2041-210X.13830](https://doi.org/10.1111/2041-210X.13830).

- [24] Stereńczak, K., Kraszewski, B., Mielcarek, M., Piasecka, Ż., Lisiewicz, M., & Heurich, M. (2020). Mapping individual trees with airborne laser scanning data in an European lowland forest using a self-calibration algorithm. *International Journal of Applied Earth Observation and Geoinformation*, 93, article number 102191. doi: [10.1016/j.jag.2020.102191](https://doi.org/10.1016/j.jag.2020.102191).
- [25] Su, H., Shen, W., Wang, J., Ali, A., & Li, M. (2020). Machine learning and geostatistical approaches for estimating aboveground biomass in Chinese subtropical forests. *Forest Ecosystems*, 7(1), article number 64. doi: [10.1186/s40663-020-00276-7](https://doi.org/10.1186/s40663-020-00276-7).
- [26] Torres-Sánchez, J., López-Granados, F., Borra-Serrano, I., & Peña, J.M. (2018). Assessing UAV-collected image overlap influence on computation time and digital surface model accuracy in olive orchards. *Precision Agriculture*, 19(1), 115-133. doi: [10.1007/s11119-017-9502-0](https://doi.org/10.1007/s11119-017-9502-0).
- [27] Westoby, M.J., Brasington, J., Glasser, N.F., Hambrey, M.J., & Reynolds, J.M. (2012). 'Structure-from-Motion' photogrammetry: A low-cost, effective tool for geoscience applications. *Geomorphology*, 179, 300-314. doi: [10.1016/j.geomorph.2012.08.021](https://doi.org/10.1016/j.geomorph.2012.08.021).
- [28] White, J.C., Coops, N.C., Wulder, M.A., Vastaranta, M., Hilker, T., & Tompalski, P. (2016). Remote sensing technologies for enhancing forest inventories: A review. *Canadian Journal of Remote Sensing*, 42(5), 619-641. doi: [10.1080/07038992.2016.1207484](https://doi.org/10.1080/07038992.2016.1207484).

Вплив параметрів збору даних з БПЛА на встановлення таксаційних показників соснових деревостанів

Роман Михайлович Задорожнюк

Аспірант

Національний університет біоресурсів і природокористування України

03041, вул. Героїв Оборони 15, м. Київ, Україна

<https://orcid.org/0000-0001-6746-9733>

Анотація. Широкий спектр систем БПЛА, що застосовуються для досліджень лісів, потребують уніфікації підходів до збору даних. Метою дослідження було визначення оптимальних параметрів збору даних з БПЛА для отримання точної інформації про деревостани з урахуванням витрат ресурсів на її збір. Процес збору даних дистанційної зйомки складався з дев'яти комбінацій, що розділені на три рівні перекриття та три рівні просторового розрізнення (висоти зйомки), та зміною ступеня фільтрації щільної хмари точок під час обробки зображень. Дешифрування дерев у деревостані виконано із застосуванням мови програмування R та пакету «ForestTools». Використано результати оцінювання залежності радіусу крон дерев від їхньої висоти для встановлення параметрів функції змінного фільтру пошуку локальних максимумів для деревостанів сосни звичайної. Похибки ідентифікації верхівок оцінювались із застосуванням показнику F-score. Встановлені висоти порівнювались з польовими даними наземної таксації. Частка класифікованого рельєфу у щільній хмарі точок зменшувалась від загальної площі полігону з використанням зображень просторового розрізнення 4,1 см/пікс (висота зйомки 150 м). У роботі представлено результати оцінювання впливу просторового розрізнення оптичних зображень зібраних з БПЛА та їхнього перекриття на результати визначення таксаційних показників деревостанів. Визначено, що фотограмметричну зйомку з вхідними зображеннями з повздовжнім перекриттям меншим 90 % не доцільно застосувати для дослідження лісових ділянок за рахунок неможливості вирівнювання всіх зображень. Результати оцінки обліку дерев у деревостані показали, що найбільш доцільно застосувати зображення із просторовим розрізненням до 3,3 см/пікс (висота зйомки 120 м), в іншому випадку збільшується частка пропущених верхівок дерев. Зменшення просторового розрізнення даних дистанційної зйомки призводить до збільшення похибок у визначенні висоти окремих дерев, встановлені середні висоти дослідних ділянок мали таку ж тенденцію. Зважаючи на сукупність оцінених факторів застосування зображень із просторовим розрізненням понад 3,3 см/пікс не рекомендовано використовувати для досліджень лісових насаджень у зв'язку зі збільшення похибок дешифрування верхівок та встановлення висоти дерев. Отримані результати можна застосовувати для підбору параметрів збору даних під час досліджень деревостанів сосни звичайної, зокрема для оцінки показників їхнього запасу та фітомаси.

Ключові слова: фотограмметрія; цифрова модель навісу; дешифрування; визначення висоти; цифрова модель рельєфу