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Evaluation of Tree Diameter and Height Measurements in UAV Data through the Integration of Remote Sensing and Machine Learning Methods

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ABSTRACT

This study evaluates the effects of various ground sampling distances on the diameter and height measurements of brutian pine trees in point cloud data from unmanned aerial vehicle photographs. The study is conducted within the Çandır Forest Management Directorate of the Isparta Regional Directorate of Forestry. The results serve as independent variables in machine learning methods to predict field-measured diameter and height values. Nine distinct machine learning techniques were employed, including AdaBoost Regression, Artificial Neural Networks, Deep Neural Networks, Decision Tree Regression, Gradient Boosting Regression, Linear Regression, Random Forest Regression, Support Vector Regression, and eXtreme Gradient Boosting Regression. The results reveal that predictions based on data with a low ground sampling distance exhibit the lowest correlation values for both diameter and height, while predictions made using data with a high ground sampling distance had the lowest correlation values. Deep Neural Network achieved the highest success rate for diameter estimation, while Decision Tree Regression exhibited the lowest success.

Keywords: Machine learning, unmanned aerial vehicle, remote sensing, point cloud

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İHA ile Ağaç Çapı ve Yüksekliği Ölçümlerinin Uzaktan Algılama ve Makine Öğrenmesi Yöntemleriyle Bütünleştirilerek Değerlendirilmesi

ÖZ

Bu çalışmada insansız hava aracı fotoğraflarından elde edilen nokta bulutu verilerinde farklı yerden örnekleme mesafelerinin kızılçam ağaçlarının çap ve yükseklik ölçümlerine etkisi değerlendirilmektedir. Çalışma Isparta Orman Bölge Müdürlüğü'ne bağlı Çandır Orman İşletme Müdürlüğü bünyesinde yer almaktadır. Sonuçlar, sahada ölçülen çap ve yükseklik değerlerini tahmin etmek için makine öğrenimi yöntemlerinde bağımsız değişkenler olarak hizmet etmektedir. Araştırmada, AdaBoost Regresyon, Yapay Sinir Ağları, Derin Sinir Ağları, Karar Ağacı Regresyonu, Gradient Boosting Regresyon, Doğrusal Regresyon, Rastgele Orman Regresyon, Destek Vektör Regresyonu ve eXtreme Gradient Boosting Regresyon dahil olmak üzere dokuz farklı makine öğrenme tekniği kullanıldı. Sonuçlar, düşük yerden örnekleme mesafesine sahip veriler kullanılarak yapılan tahminlerin çap ve yükseklik için en düşük korelasyon değerlerine sahip olduğunu, yüksek yerden örnekleme mesafesine sahip veriler kullanılarak yapılan tahminlerin ise en düşük korelasyon değerlerine sahip olduğunu göstermektedir. Çap tahmininde en yüksek başarı oranını Derin Sinir Ağı elde ederken, Karar Ağacı Regresyonu en düşük başarıyı elde etmiştir.

Anahtar Kelimeler: Makine öğrenmesi, insansız hava aracı, uzaktan algılama, nokta bulutu

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1. Introduction

Numerous scientific disciplines are actively engaged in extensive research on the vastbroad topic of remote sensing investigations. Data from various airborne sources, including satellite imagery and aerial photography, can be used in a variety of forestry applications after photogrammetric processing [1, 2]. Since remote sensing data can be used with Geographic Information Systems (GIS) [3], this integration has enabled remote sensing data to become a highly effective source of information [4]. Unmanned aerial vehicles (UAVs) are increasingly popular for remote sensing. They are cheaper and easier to operate than other aerial vehicles, allowing for fast and convenient solutions to emerging problems. Data collected by UAVs is frequently used for various purposes and inferences, particularly in forestry research [5]. This data can serve as a scientific basis for forest management and planning and may be useful in solving the forestry issues [6].

The amount of data has grown more than ever in recent years due to the widespread use of technology, and this growth is still going strong [7]. Furthermore, the development of computer technology has led to a significant increase in computational capacity, with data science and machine learning (ML: Machine Learning) emerging as two of the most researched topics. In order to get results quickly, machine learning—which is used to extract information from data—is frequently employed, particularly when working with large amounts of data [8]. UAV data is made into a more potent and valuable source of information when it is evaluated using ML [9]. ML techniques have been used successfully in a variety of forestry applications [10, 11, 12,13] and are recognized as a method that offers solutions to many engineering problems [14, 15]. In these studies, ML methods build prediction models using an UAV dataset to calculate the values of objects or situations investigated in forestry studies. The input for machine learning involves data acquired from the UAV, while the output comprises a predictive model that characterizes the forest ecosystem [16]. In an investigation on the application of ML in forestry, 274 studies were carried out in total between 2004 and 2023. 135 (58%) of the 274 research fell under the categories of modeling, remote sensing, and forest inventory [17]. This indicates that most researchers favor the combination of machine learning and remote sensing.

For research on forest inventory and planning, precise measurement of tree stem volumes is essential in forest ecosystems. It is important to take careful and accurate measurements, as data on tree trunk diameter and height are crucial for determining trunk volumes [18]. The diameter ($d_{1.3}$) and height of cut brutian pine (*Pinus brutia* Ten.) trees were measured in this study using point clouds (colored points with x, y, and z coordinate information) from data collected using different ground sampling distance (GSD) values. The ML utilized the results of diameter and height measurements from photographs and environmental variables as inputs, resulting in estimated diameter and height results for each tree based on ground measurements. Therefore, the study evaluated the effect of different GSDs on measurements of tree diameter and height using point cloud data acquired by a field-based UAV at different flight altitudes using ML. Additionally, the study also compared the performance of different ML methods employed. The study aimed to test the performance of different machine learning techniques. Various machine learning techniques, including Ada Boost Regression (ABR), Artificial Neural Network (ANN), Deep Neural Network (DNN), Decision Tree Regression (DTR), Gradient Boosting Regression (GBR), Linear Regression (LR), Random Forest Regression (RFR), Support Vector Regression (SVR), and eXtreme Gradient Boosting Regression (XGBR) were used, and the same test trees were used in all calculations to ensure an unbiased comparison.

2. Material and Method

2.1. Material

The research is conducted in the Çandır Forest Management Directorate of the Isparta Regional Directorate of Forestry (Fig. 1). With a surface size of 10348.4 ha, the Çandır Forest Management Directorate has an elevation range of 248 to 1877 m [19]. Brutian pine is the most prevalent tree species with 91.8% of the forest area under the management of the Çandır Forest Management Directorate [20].

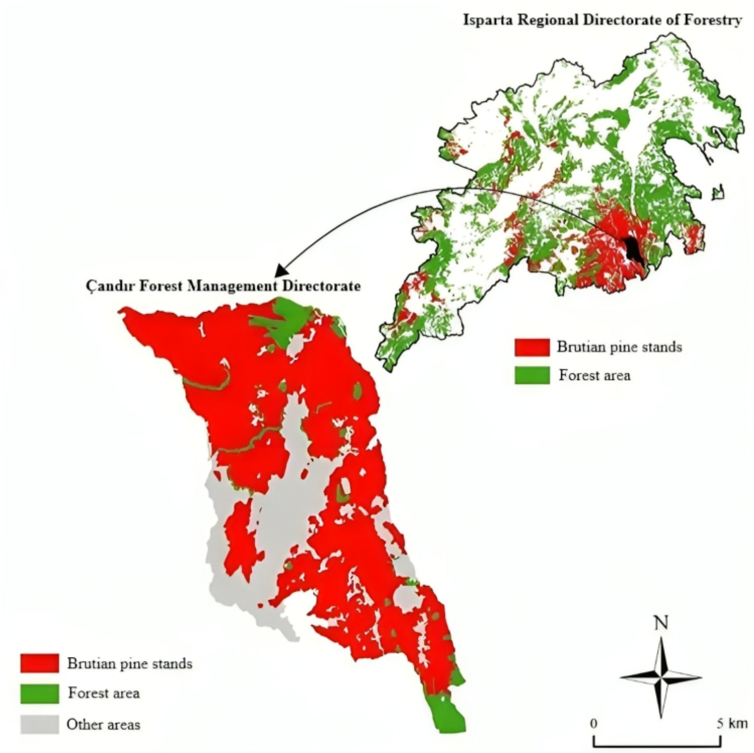

Figure. 1. Workspace location

Two distinct research areas in the Çandır Forest Management Directorate were found to include brutian pine trees with various trunk diameters and heights (Fig. 2). Brutian pine trees with trunk diameters between 8 and 36 cm can be found in the first study area (Stand-C), while brutian pine trees with chest diameters between 36 and 52 cm can be found in the second study area (Stand-D). More than 70% of the soil is shaded by trees in both sites. The Stand-C region is 3.2 ha in size and has an elevation range of 355–420 m, whereas the Stand-D area is 0.76 ha in size and has an elevation range of 322–371 m.

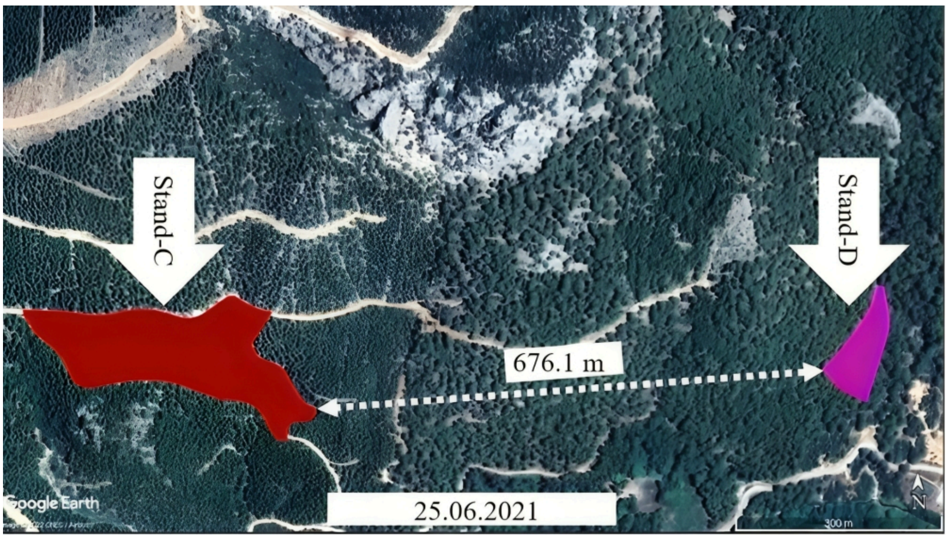

Figure. 2. Stand-C and Stand-D areas

The study made use of DJI's Mavic Air model UAV, which was released in 2018. In addition to its 430 gram weight, 21 minute flight time and link to GPS, the UAV offers a CMOS 1/2.3-inch sensor, 12 MP resolution, 2.8 aperture and 85° field of view [21]. Ground control points (GCP) of 50x50 cm were set up in the field and measurements were taken using Global Positioning System (GPS) compatible with TUSAGA-Active (Turkey National Fixed GPS Network-Active), as it is well known that the use of GCPs is crucial for increasing positional accuracy in photogrammetric studies [22, 23, 24]. These measurements were conducted using a South/Galaxy G6 precision GPS [25]. In the study, ArcGIS software [26] was favored for spatial analysis and map creation, whereas Microsoft Office software [27] was preferred for the creation of the data collection. Pix4d "Mapper" photogrammetry software was used to process the aerial photographs taken by the UAV, increase the spatial accuracy by marking the GCPs on the UAV photographs and diameter-height measurements of the cut trees [28]. Pix4d "Capture" software was used to fly the UAV in accordance with the photogrammetric acquisition conditions.

2.2. Method

2.2.1. Field research

The chopped brutian pine trees diameter and height measurements were catalogued for the field research. Except for trees that had fallen on top of one another in the study regions or where measurements could not be made, trees of various diameters were chosen at random. The bottom of the tree trunks (d_0) were secured with A4 papers that had numbers inscribed on them in a size that could be seen in the UAV photos when the trees were numbered. In order to make it easier to measure the diameter and height of these trees in UAV data, 5x5 cm marker sheets were also fixed at the breast height ($d_{1.3}$) and the end of the trunk (d_{end}) of these trees. A tape measure was used to measure the height of the designated trees, and a diameter gauge was used to measure their diameter. The diameter and height of 175 trees were measured in the field, 150 of which were in Stand-C and 25 in Stand-D. Following the measurements of the trees, the GCPs coordinates were measured and uniformly distributed along the perimeter of the study areas. Following the installation and measurements GCPs in the field, UAV flights were done (Fig. 3). The flying speed was 4.75 m/sec, the overlap rate was 80%, and the camera angle was 90° for all flights.

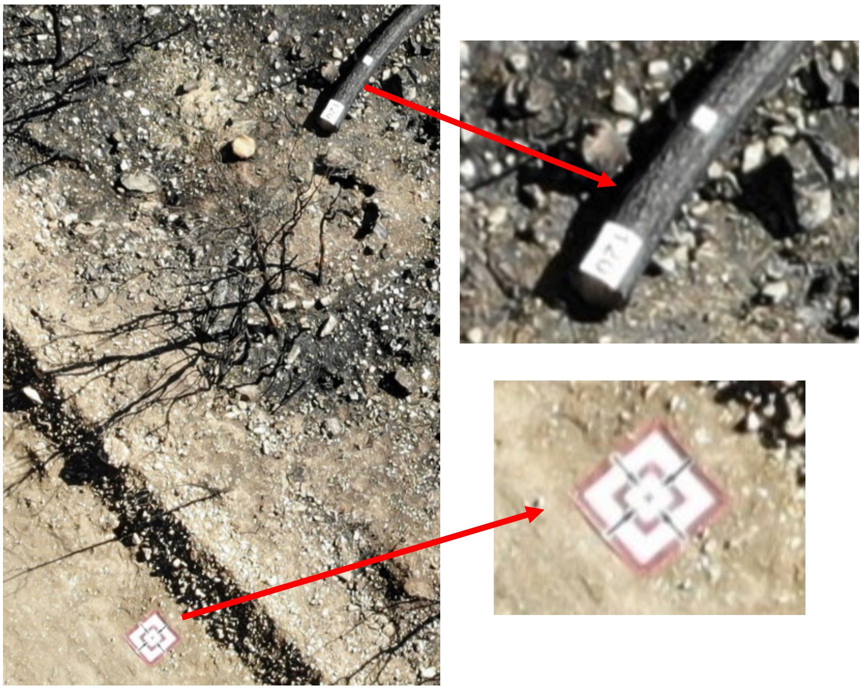

Figure. 3. UAV photos show a ground control point and marker sheets

2.2.2. UAV images processing and measurements

In this work, point clouds were created from UAV images using the Structure from Motion (SfM) technique. The SfM approach arranges the positions and matches the objects in the UAV photographs using the metadata [29]. Point clouds with 1.5 cm (42 m altitude) and 1.7 cm (38 m altitude) GSD in the Stand-C and Stand-D areas respectively, were used as Low GSD data (L_{GSD}). Point clouds with GSDs of 1.95 cm (55 m altitude) in Stand-C and 2.15 cm (52 m altitude) in Stand-D were used as High GSD data (H_{GSD}). RMSE (Root Mean Square Error) average positional error values of 2.6 cm in Stand-C and 1.5 cm in Stand-D were found after processing the UAV photos.

The study used the Pix4dmapper application to measure the diameter and height of trees in point cloud data. The Pix4dmapper software generates 3-dimensional measurements in the point cloud that are all analyzed along with height data to obtain findings. The measurements made use of the multi-correct feature, and the measurement data were saved in the "Objects" layer. To increase accuracy, each marking made during the measurements was then marked on the UAV photos using the "Properties" window. During field surveys, markers (d_0, $d_{1.3}$, and d_{end}) were affixed to the trunks of the trees to measure their diameter and height. Tree trunks were measured for diameter and height while being as closely as possible to ensure accurate measurements. The diameter and height of the trees were measured twice and averaged (Fig. 4) to minimize measurement errors.

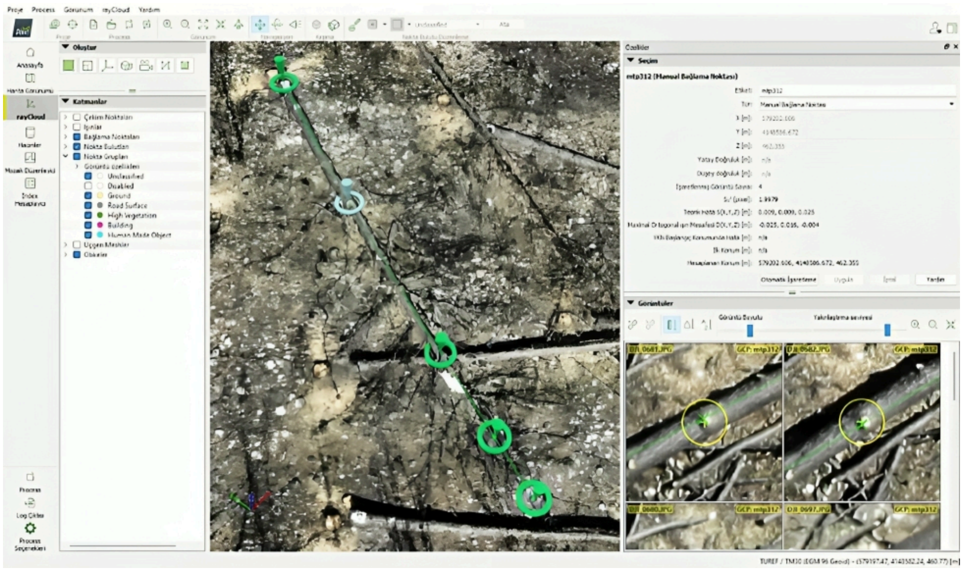
Figure. 4. Tree height measurements from point cloud data in Pix4dmapper

2.2.3. ML techniques and employed datasets

Four separate data sets were utilized for ML in the study. The data sets employed comprised measurements of the trunk diameter and height as well as slope and aspect values arising from the stance of the trunks in the field. The data set additionally includes the altitude values of the tree trunks' starting (d_0) and finishing (d_{end}) positions. The elevation values at the beginning and end of each log were calculated, and their disparities were used to calculate the trunk slope. To calculate the slope in percent, these discrepancies were multiplied by 100 and then divided by the log length. The coordinates of the tree's start and end points were used to calculate the trunk angle, which was then used to calculate the stand angles of the individual tree trunks. It was deemed permissible to employ slope, aspect, and altitude information for ML because these spatial properties are useful for measurements [30]. Spatial characteristics were included as independent variables in all 4 data sets. Furthermore, the diameter values recorded in the first data set L_{GSD} were used as independent variables in the first data set, and the diameter values recorded in the H_{GSD} data were used as independent variables in the second data set, the height values recorded in the L_{GSD} data in the third data set, and the height values recorded in the H_{GSD} data in the fourth data set. The reference diameter-height values derived from field measurements served as the dependent variable (target) in each of the four datasets. The purpose of this study was to compare the variations among these four datasets as well as the impact of ML, L_{GSD} and H_{GSD} values on the outcomes of measurements of tree diameter and height made using point cloud data.

These 4 data sets were examined by using nine different ML techniques such as boosting, regression, and neural networks. One of the popular ML technique is Ada Boost Regression (ABR), which combines weak regression models and modifies training weights according on misclassification errors [31]. A powerful ensemble model that can handle complex relationships and is noise-resistant is created by iteratively training weak models and integrating their predictions through weighted voting. Another machine learning approach called Decision Tree Regression (DTR) predicts continuous numerical values using a structure resembling a tree [32]. The input space is divided according to features, and training samples are assigned the average goal value. To ascertain the relationship between a dependent variable and independent variables, a statistical modeling technique known as linear regression (LR) fits a linear equation to observed data points [33]. Using decision trees and ensemble learning, Random Forest Regression (RFR) is a machine learning technique that produces accurate predictions and it is helpful in predictive modeling [34]. SVM and regression analysis are used in Support Vector Regression (SVR), a machine learning technique, to provide accurate predictions. It recognizes complex patterns and generates accurate predictions by transferring input data into a higher-dimensional feature space using a kernel function [35].

A machine learning technique called gradient boosting regression (GBR) starts with weak regression models and builds a robust prediction model from them. It provides excellent accuracy, robustness against anomalies, and adaptability in data administration [36]. Another boosting method is XGBoost Regression (XGBR) for predictive performance. It combines gradient boosting with tree-based models. It builds a collection of imperfect decision trees, trains new trees to correct errors, and use regularization to prevent overfitting [37].

Computer models that can learn from data and generalize are called artificial neural networks (ANNs), and they are based on biological neural networks. They can do tasks like pattern recognition, regression, and classification because they are built on networked nodes. Neural Networks (ANNs) are widely used in many fields, including finance, natural language processing, computer vision, and sentiment analysis [38]. Artificial neural networks called Deep Neural Networks (DNNs) are used to recognize and interpret complicated patterns in data. They are employed in computer vision, natural language processing, and speech recognition and perform particularly well on large-scale, high-dimensional datasets. DNNs have improved performance and opened up new applications for machine learning across a range of domains, revolutionizing the industry [38].

Of the 175 brutian pine measurement data, 80% (140 trees) were used for training and 20% (35 trees) were used for testing in each of these methods. To create a more unbiased comparison, all ML calculations used the same testing trees. Additionally, GridSearchCV [39] was used to improve all ML algorithm parameters in order to obtain the best outcomes. All ML algorithms used in this study's implementation were done in Python.

3. Results

Table 1 lists the descriptive statistics, correlation coefficients, and L_{GSD}, H_{GSD}, and reference diameter-height values for the diameter-height measurements obtained on point cloud data. When the diameter measurements' means are taken into account in the table, it becomes clear that both data sets (L_{GSD} and H_{GSD}) have mean values that are higher than the values for the reference diameters. The fact that the lowest values are 3-4.5 cm larger than the reference data, despite the fact that the greatest values are relatively near to the reference value, demonstrates that point cloud diameter measurements provide better findings than the reference, particularly for small diameter values. When the diameter measures' correlation coefficients are examined, it can be noted that, despite the L_{GSD} data showing a larger correlation than the H_{GSD} data, both data sets attain very significant correlations for the diameter measurements. The correlation coefficients and the statistics of the height measurements in the table show that the height measurements in both data sets in the point clouds produce results that are extremely near to the reference values. According to this graph, it can be concluded that UAV height measurements are more accurate than diameter measurements. It is further observed that the GSD values perform better on diameter measurements compared to length measurements.

Table 1. Statistics for diameter-height calculated from reference and UAV images (n = 175)

Measurements of diameter statistics (cm)	Reference	L_{GSD}	H_{GSD}		Reference	L_{GSD}	H_{GSD}	Measurements of height statistics (m)
	25.31	28.67	28.98	Mean	16.44	16.4	16.43	
	9.29	8.34	8.66	Standard deviation	4.1	4.07	4.07	
	61.5	61.36	61.35	Maximum	30.75	30.7	30.67	
	12	16.29	15.12	Minimum	8.23	8.21	8.28	
	-	0.950	0.949	Correlation	-	0.996	0.996	

Table 2 in the study provides the error values of the predictions generated using the diameter measurements taken in the point cloud data with L_{GSD} and H_{GSD} values and their correlations to the reference measurements. When the predictions of the L_{GSD} data are assessed, the DNN and ANN methods show the highest correlation with the reference data (r=0.946), whilst the DTR approach shows the lowest correlation (r=0.902). In the predictions made using the H_{GSD} data, the DNN approach showed the highest correlation (r=0.966), whereas the DTR method showed the lowest correlation (r=0.883). The lowest correlation values received from the

L_{GSD} data are higher than the value obtained from the H_{GSD} data, and it is understood that the values of the GSD are effective in these circumstances rather than the highest correlation values. Additionally, it can be observed that DNN and DTR are the most and least successful ML methods for diameter predictions, respectively.

Table 2. Diameter estimations using ML techniques with correlation and error values

		DNN	RFR	ABR	XGBR	DTR	ANN	GBR	LR	SVR
L_{GSD}	Correlation	0.946	0.937	0.916	0.928	0.902	0.946	0.939	0.933	0.938
	RMSE*	0.064	0.069	0.079	0.073	0.084	0.063	0.067	0.070	0.068
	MAE**	0.052	0.054	0.061	0.060	0.068	0.050	0.054	0.052	0.057
H_{GSD}	Correlation	0.966	0.953	0.960	0.959	0.883	0.961	0.957	0.961	0.949
	RMSE	0.051	0.059	0.055	0.056	0.092	0.055	0.057	0.054	0.062
	MAE	0.044	0.050	0.047	0.047	0.074	0.044	0.050	0.045	0.050

* Root mean square error (cm), ** Mean absolute error (cm)

Based on the data in Table 2, the DNN method produced the best results and the DTR method produced the worst results for the diameter estimations made in the L_{GSD} and H_{GSD} data. Graphs showing the distribution of the prediction and reference data for 35 brutian pine trees whose diameter was estimated using these methods were created (Fig. 5). When the graphs are examined, it can be shown that for both data sets, the DNN method's distribution is more linear than the DTR approach.

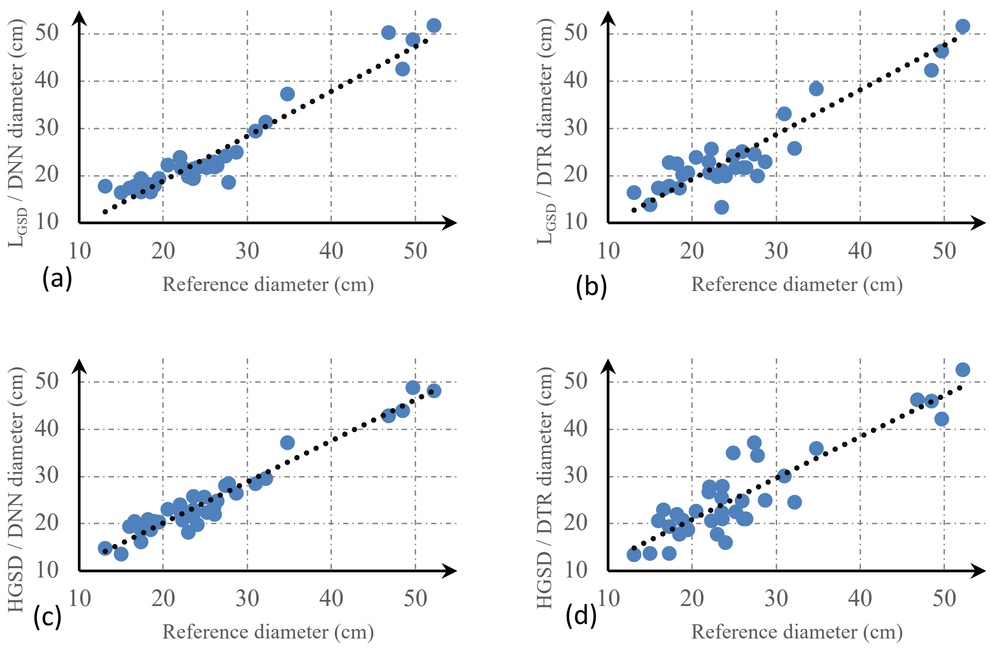

Figure. 5. Scatter plots of the diameter values for the reference and expected; a) DNN method (LGSD); b) DTR method (LGSD); c) DNN method (HGSD); d) DTR method (HGSD)

In the study, Table 3 provides the error values of the height estimations derived using the ML algorithms on point cloud data with L_{GSD} and H_{GSD} values, as well as their correlations with the reference measurements. In the table, the DNN, ANN, and LR methods produced the highest correlation (r=0.996), whereas the SVR approach produced the lowest correlation (r=0.939) in L_{GSD}. In the ML predictions using the H_{GSD} data, the DNN approach produced the highest correlation (r=0.996), whereas the SVR method produced the lowest correlation (r=0.938). The smallest correlation values obtained from the L_{GSD} data are higher than the value obtained from the H_{GSD} data, and it is understood that, similarly to diameter predictions, in height predictions the ML values are effective at lower correlation values rather than higher correlation values. Additionally, it can be shown that DNN and SVR are the most and least successful ML methods for height predictions, respectively.

Table 3. Height estimates by ML techniques with correlation and error values

		DNN	RFR	ABR	XGBR	DTR	ANN	GBR	LR	SVR
L_{GSD}	Correlation	0.996	0.995	0.995	0.990	0.991	0.996	0.995	0.996	0.939
	RMSE*	0.018	0.020	0.021	0.028	0.026	0.018	0.019	0.019	0.070
	MAE**	0.009	0.009	0.015	0.013	0.015	0.011	0.010	0.010	0.070
H_{GSD}	Correlation	0.996	0.995	0.994	0.989	0.993	0.994	0.994	0.995	0.938
	RMSE	0.017	0.020	0.021	0.029	0.024	0.023	0.021	0.019	0.070
	MAE	0.008	0.010	0.015	0.014	0.013	0.018	0.011	0.010	0.051

* Root mean square error (cm), ** Mean absolute error (cm)

Based on the information in Table 3, graphs showing the distribution of the prediction and reference data for 35 brutian pine trees whose diameter was predicted by these methods were created (Fig. 6). The DNN method produced the most successful result, and the SVR method produced the least successful result, in both datasets for the height predictions. When the graphs are examined, it can be shown that for both data sets, the DNN approach's distribution is more linear than the SVR method.

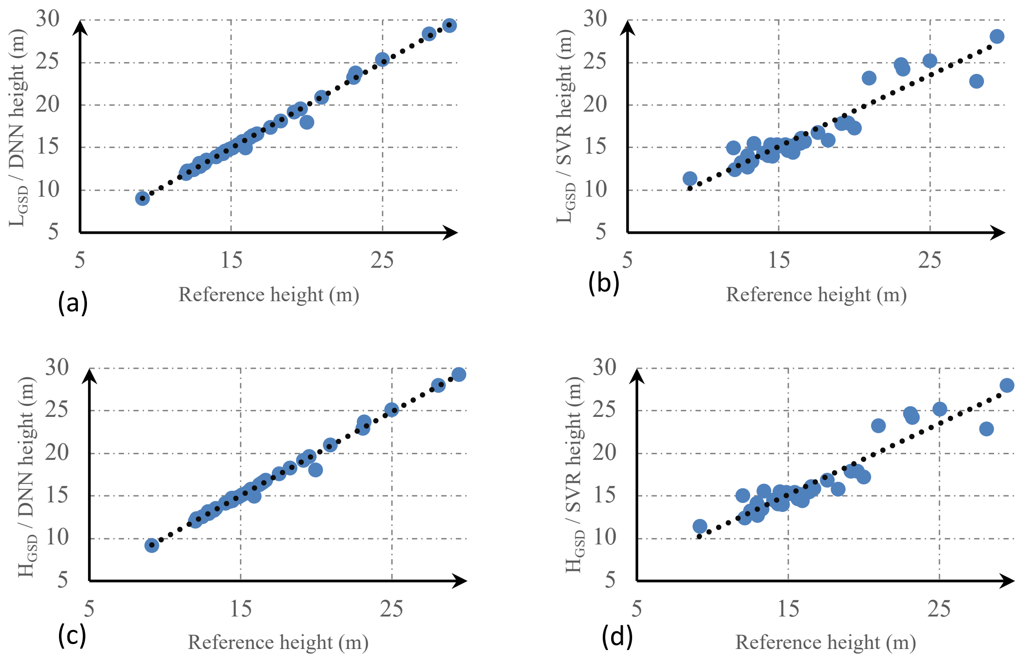

Figure 6. Scatter plots showing the expected and reference height values; a) DNN method (LGSD); b) SVR method (LGSD); c) DNN method (HGSD); d) SVR method (HGSD)

As a consequence of measurements taken using point clouds with L_{GSD} and H_{GSD} values, the correlation values and their averages of the prediction values of the nine distinct ML approaches employed in the study are provided in Table 4. When the table is analyzed, the top 3 methods for estimating diameter in the L_{GSD} data are DNN (r=0.946), ANN (r=0.946), and GBR (r=0.939), while the methods with the lowest correlation values for estimating diameter are DTR (r=0.902), ABR (r=0.916), and XGBR (r=0.928). DNN, ANN, and LR were the top 3 most successful algorithms for estimating diameter in the H_{GSD} data, whereas DTR, SVR, and RFR produced the least successful results (r=0.883, 0.949, and 0.953). When the average correlations of ML approaches used to forecast diameter are examined, the top 3 most effective methods are DNN (r=0.956), ANN (r=0.953), and GBR (0.948), whereas DTR (r=0.893) and ABR (r=0.938) produce the least successful predictions.

Table 4. Diameter and height correlation scores for ML algorithms

Data \ ML Algo.	DNN	RFR	ABR	XGBR	DTR	ANN	GBR	LR	SVR
L_{GSD} diameter	0.946	0.937	0.916	0.928	0.902	0.946	0.939	0.933	0.938
H_{GSD} diameter	0.966	0.953	0.960	0.959	0.883	0.961	0.957	0.961	0.949
Mean correlation for diameters	0.956	0.945	0.938	0.943	0.893	0.953	0.948	0.947	0.943
L_{GSD} height	0.996	0.995	0.995	0.990	0.991	0.996	0.995	0.996	0.939
H_{GSD} height	0.996	0.995	0.994	0.989	0.993	0.994	0.994	0.995	0.938
Mean correlation for heights	0.996	0.995	0.995	0.990	0.992	0.995	0.995	0.996	0.938

DNN (r=0.996), ANN (r=0.996), and LR (r=0.996) were the top 3 methods for height estimations in the L_{GSD} data, whereas SVR (r=0.939) and XGBR (r=0.990) were the least successful (Table 4). DNN (r=0.996), RFR (r=0.995), and LR (r=0.995) were the top 3 methods for height predictions in the H_{GSD} data, whereas SVR (r=0.938) and XGBR (r=0.989) produced the least accurate results. When the average correlations of ML approaches for height predictions are examined, DNN (r=0.996) and LR (r=0.996) produce the best results, while SVR (r=0.938) and XGBR (r=0.990) produce the worst results. According to this data, it can be seen that the DNN and ANN approaches produced the best predictions, while the SVR and DTR methods produced the worst predictions.

4. Discussion and Conclusion

To better comprehend the many linkages influencing the development of forest ecosystems, diameter-height models are required [40, 41]. The diameter-height relationship is influenced by various topographic characteristics, including slope, aspect, elevation, etc. Therefore, topographic factors should be added to the model in addition to the breast diameter variable to improve the accuracy of diameter-height models [41, 42, 43, 44]. Along with tree diameter-height variables, topographic factors were included in this study's ML approaches as input variables with the goal of evaluating the impact of GSD values on manual measurements taken from UAV data [45].

Effective forest planning and design is necessary to sustain forest resources efficiently. To ensure optimal design, stand volume parameters such as breast height, diameter, height, and number of trees should be calculated as closely as possible to the actual data [46]. It is well known that stand volume parameters are often measured by researchers using UAV technology. Researchers found that UAV data produced highly successful results, like as this work, when they used the data to estimate tree height and crown breadth [47, 48]. Biomass estimation [49,50], tree volume estimation [51], and post-felling tree trunk volume estimation [52] studies have all effectively used UAV data. Researchers have had success using UAVs and ML to map woody biomass that remains in the field after production [53], identify species automatically [54], and locate tree roots [55]. The benefits of UAVs in terms of labor, money, and time are cited in nearly all the related studies in the literature. Specifically, it is well known that UAV data can be a very useful and powerful tool when combined with artificial intelligence methods like ML. Compared to other remote sensing instruments, UAVs are typically thought to be more precise, effective, and economical.

Similar to the research conducted by Akay et al. [56] and Akgül et al. [57], this study examined the impact of ground sampling interval on the assessment of tree height and diameter in UAV-generated photogrammetric data. In contrast to these research, the outcomes were assessed using machine learning techniques, and the impact of ground sample intervals on the effectiveness of ML methods was examined. Instead of using digital elevation models, this study used point cloud data, as opposed to Akgül et al. [57] and Zhou et al. [52]. Point cloud data is preferred in this study because it is more reliable than orthomosaic data for measuring tree height [45]. This is despite the fact that it is well known that using orthomosaic data in the measurement of short lengths, such as tree diameter measurement, can provide more accurate results and save labor/time [58, 59]. Furthermore, since ground control points are known to enhance UAV image quality and yield more dependable results [60, 61, 62, 63], they were also employed in this study, resulting in an increase in the positional accuracy of the photogrammetric data generated.

According to the study's findings, the manual diameter measurements performed on the L_{GSD} data yielded a correlation value of 0.950, but the DNN method (the most successful ML method) obtained a correlation value of 0.946. The diameter measurements based on the H_{GSD} data had a correlation value of 0.949, and the most effective ML approach, the DNN method, had a correlation value of 0.966. Manual height measurements on the L_{GSD} and H_{GSD} data yielded correlation values of 0.996, respectively, while 0.996 correlation values were obtained using the DNN approach in ML estimations for both data sets. It can be seen in this context that ML approaches enhance diameter measurements, particularly in data with H_{GSD} values. Since the production of data with L_{GSD} values is more expensive (in terms of flight time, UAV energy consumption, energy and time consumption during the processing of UAV images in the computer environment) than the production of data without H_{GSD} values, it is believed that ML methods will be helpful for achieving precise results, especially in point cloud data with H_{GSD} values. Given that the greatest GSD difference between the L_{GSD} and H_{GSD} data in this investigation is 6.5 mm, it is projected that if this difference widens, so might the success difference between the two sets of data. These findings also demonstrate that, albeit marginally, the diameter measurement and ML estimation results obtained from the L_{GSD} data outperform those obtained from the H_{GSD} data and demonstrate the significance of the GSD values in measurements and estimations [64, 65, 66].

From the most successful approach to the least successful method, DNN (r=0.976), ANN (r=0.974), GBR (r=0.972), LR (r=0.971), RFR (0.970), XGBR (r=0.967), ABR (r=0.966), DTR (r=0.942) and SVR (r=0.941) had the average correlation values for the diameter and height estimates. It is believed that DNN and ANN approaches can be applied in research of a similar nature to reduce costs and time. It is anticipated that field work can be reduced, sufficient trees can be measured in the field to learn ML methods, and the diameters and heights of unmeasured trees can be estimated with a very high degree of accuracy using the integration of ML and UAV photogrammetry [67, 68, 69]. Overall, these findings emphasize the utility of GSD values in UAV photogrammetry-generated data for measurements, especially in precision investigations recording tiny distances. To optimize cost and time, combining remote sensing with ML techniques is recommended.

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Conflict of Interest Statement

The authors declare that there is no conflict of interest**.**

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