https://doi.org/10.26682/ajuod.2023.26.1.13
Journal of University of Duhok., Vol. 26, No.1(Agri. and Vet. Sciences), Pp 122-132, 2023

HEIGHT MEASUREMENTS OF PINUS BRUTIA TEN. FROM UAV- 1" CMOS DIGITAL CAMERA POINT CLOUDS IN GEVERKE - DUHOK GOVERNORATE, KURDISTAN REGION OF IRAQ

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(Received: November 29, 2022; Accepted for Publication: February 19, 2023)

ABSTRACT

In this study, purposely selected 61 Pinus brutia trees in Geverke - Duhok governorate, Kurdistan region of Iraq were used to measure tree height using the indirect field and the UAV-photogrammetric methods. Results depict that over the 59 observations, 68% of the indirect field measurements tree height values were higher than those obtained by UAV- photogrammetric measurements. According to the coefficient of determination (R^2) between the two methods, the fitted linear model explains 84.03% of the variability in tree height by field method. The correlation coefficient equals 91.67%, indicating a relatively strong direct relationship between the values of the two methods used to measure the tree heights. The standard error of the estimate shows the standard deviation of the residuals to be 0.361204 according to Fankhauser, K., et. al., (2018), Corte, Ana, et. al., (2020), and Guerra-H G et. al., (2016) obtained. R^2 values were 82%, 82%, and 81% respectively. Also, it was within the values range that, Teddy Ruslono. Et. al., (2021) found (64.4%-80.2%), which is more than the value that Vahid Nasiri, et. al., (2021) obtained (65%). The differences in R^2 values between the current study and the preceding studies are due to the differences in drone height, tree height, tree leaning angle, drone and sensor type, uneven and sloping terrain, GCPs setting up accuracy, automated algorithms utilized in measuring, and measuring skill.

KEYWORDS: tree height, point clouds, UAV, photogrammetric measurements, Pinus Brutia

1. INTRODUCTION

Tree height is the most important factor for estimating tree and stands volume, site productive capacity, and determining the social status of an individual tree's ability to access resources (Krause et al., 2019; Ganz et al., 2019). Accurate information about forests including typical principal forest inventory parameters (diameter at breast height, tree height, and tree composition) is essential for sustainable forest management (Díaz et al., 2015; Fernández et al., 2018). Sherrill et al. (2011), mentioned that tree heights have long been measured as part of efforts to quantify timber resources, and more recently also forest carbon stocks (Chave, 2005; Feldpausch et al., 2012). In addition, tree heights are often measured in ecological studies characterizing the life histories of individual tree species and populations (King & Clark, 2011; Banin et al., 2012).

A number of different methods are used to measure tree heights from the ground (Clark & Clark, 2001; Chave, 2005). The direct measurement of height is worthwhile only to measure tree height below 10 m particularly using a ladder or labeled pole or dropping the tape from the top (Goodwin, 2004). On the other hand, indirect measurement is the use of instruments based on trigonometrical and similar triangle principles (Pariyar & Mandal 2019). The instrument base height measurement become gradually popular in forest inventory (Korning & Thomsen 1994). However, traditional instruments like Abney's level, Clinometer, and Silva, require distance measurement because they can measure the top angle of the tree and the distance to the base. Rennie (1979), stated that many instruments can show high accuracy under optimum operating conditions but may create inconvenience under normal stand conditions that their actual operating will be low due to; 1- using the device is improperly, 2- taking the measurement is incorrectly, This may be due to mishandling the device which gives errors during measurement.

In recent decades, forestry remote sensing techniques have received more attention, resulting in the capacity to extract vital information for forest planning and sustainable management, such as forest structure, composition, volume, or growth (Banu et al. 2016). Lyons (1966), declared that the application of remote sensing in forestry has expanded from aerial photography data to satellite imagery data, due to the advances in sensors, computers, and computational tools. Over the years, remote sensing techniques have been increasingly used for assessing forest resources, both directly and indirectly (Hansen et al. 2013; Roise et al. 2016).

Indirect tree measurement is also possible using remote sensing techniques as in traditional photogrammetric measurements derived from analog aerial imagery (Rogers 1949; Spurr 1960), digital aerial photogrammetry (St-Onge et al. 2015; Hernandez et al. 2016), Light Detection and Ranging (LIDAR) (Andersen et al. 2006; Maltamo & Packalen 2014; Kaartinen et al. 2012) and Interferometric Synthetic Aperture Radar (InSAR). Tree height and crown diameter can be further utilized to estimate individual tree characteristics, such as stem diameter and volume (Hyyppä, M. et al. 2005; Jucker, C. et al. 2017).

Drones are unmanned aerial vehicles (UAVS) were created in the early twentieth century and after the 1950s. Drones' primary used was for military tasks, where they were used for reconnaissance and surveillance. Drones of various sizes, forms, and capabilities have risen in popularity in civilian applications such as precision agriculture, forestry, biodiversity, meteorology, and emergency response in the previous decade (Colomina & Molina 2014). In the last few decades, there were many studies on Canopy Height Model (CHM) by using UAV to explore the capability of UAV to identify tree characteristics at a specific forest (Anderson et al. 2016).

Advances in the fields of the UAV technology and data processing have made it feasible to obtain very high-resolution imagery and 3D data (Kattenborn et al. 2014). Since the arrival of various modern remote sensing technologies, such as ALS (Airborne Laser Scanning) (Wulder, Bater et al. 2008). Point cloud and raster-derived tree heights have been typically validated against indirect field-based measurements (Apostol et al. 2016; Dempewolf et al. 2017; Imai et al. 2004).

A strong correlation observed between field and UAV tree height measurements. The R^2 registered was 0.82 in research conducted at mixed forest in Oregon, Colorado, South Carolina, Maine, Minnesota, New Jersey, and Pennsylvania (Fankhauser, K. E., et. al., 2018). Also (Krause, Sanders et al. 2019) found that the R^2 between the field & the UAV methods in measuring Scots pine height was 0.97 in the village of Britz-Berlin/Germany, while Guerra-H G et al (2016) reported that R^2 between field & image measurements for Pinus Pinea tree heights was 0.81 in Lugo -Spain.

Objectives

The current study aims to measure the heights of single trees through point clouds concept in pure Pinus Brutia Forest by using UAV photogrammetry technique and Agisoft software, then to compare the results with those got by using the haga instrument in order to estimate the correlation analysis.

2. MATERIALS AND METHODS

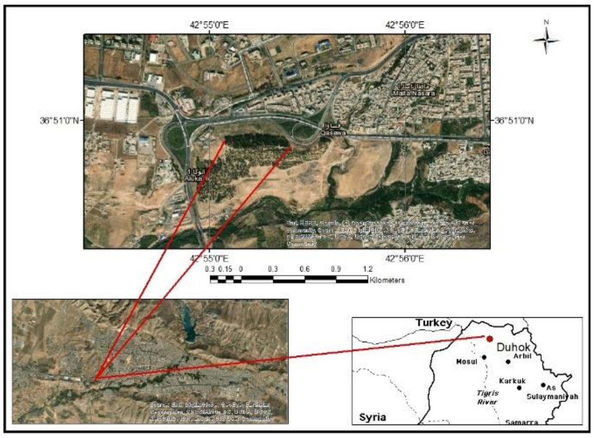
3.1 Description of the site:

Geverke area (Fig-1) is located about 3km far from Duhok city center to the west (36°50'55.8" latitude, 42°55'12.9" longitude). It is characterized by hilly terrain, its height range above sea level is between 714 - 736m, and occupy an area of about 15.5 hectares. It is a pure Pinus Brutia forest, the trees' heights are between 8-12m.

3.2 Materials

3.2.1 differential GPS (global positioning system): GPS uses a one-way ranging technique from GPS satellites, which are also broadcasting their estimated positions (Parkinson and Spilker, 1996). Fig-2, shows the instrument parts which consists of base, rover and radio, we used it for measuring and georeferencing the coordinates of six groun

d control points of the study area.



Fig(1):- The research site

Fig(2):- Parts of differential GPS

3.2.2 Unmanned aerial vehicle (UAV) and its RGB camera:

The drone used in this study is DJI Phantom 4 pro (Fig-3) with a weight of 1.38 kg and a coverage range of up to 5 km, and a maximum flight time of 30 minutes per one battery. This Quadro copter is a serial model popular among agricultural producers, breeders, agronomists and researchers (Guan S, et al. 2019)**.**

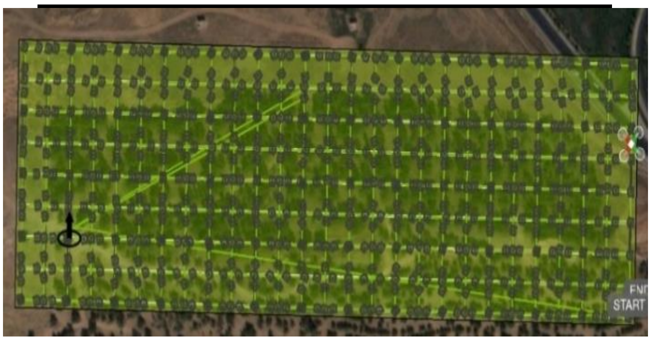
It is equipped with an RGB camera having a 20-megapixel resolution capable of taking photos and videos, it has three visible bands (Blue, Green and Red) with 8.8 mm focal length. The camera has 80° field of view from a flying height of about 55 m, and its sensor type is CMOS (FC6310). The camera was used to create 3D reconstruction models for the study area. The photographs were processed and analyzed in Agisoft Meta shape software to derive the 5 models; Dense cloud, 3D model, Tiled model, DEM and Ortho mosaic. Each model needs 1.5 hours for processing. Each image is tagged with a GPS, which provides information such as its latitude and longitude as well as the altitude at which it was taken.

3.3 Methods

3.3.1 flight plan design: The photos were acquired following two directions, west-east and south-north with the details shown in table-1 and figure-3:

Table(1):- flying plan details

No.	Details	values
1	Drone height	52.5 m
2	front overlap	80%
3	side overlap	70%
4	Photos number	667
5	Ground resolution	1.35 cm
6	Coverage area	15.5 hec



Fig(3):- flight plan design

3.3.2 Field work:

3.3.2.1 locating ground control points (GCPs) and photo acquisition

The fieldwork started on 22 of November 2021, the 1st step was to install the Base GS10 of GPS, then we connected the base to the radio to receive the signal on the Rover (GS15). After the Rover received the signal, we checked the location reading on the Rover if it is accurate or not. The radio is able to receive signal from a distance of 15 kilometers away. After that we located the points using the Rover and saved the coordinates. The drone fly from start point and started to acquired photos in two directions; west-east and south-north at a fixed flight height, then landing on the same start point after minutes of flying.

3.3.2.2 measuring tree heights by Haga

Individual tree height was measured using the Haga instrument following the steps below:

1- The adjustment scale of the Haga instrument must be turned to select the corresponding height and the distance from the tree must be equivalent to the tree height.

2- Sight the bottom of the tree, then register the (hb) reading.

3- Sight the highest top point of the tree, then write down the (hc) reading.

4- Calculate the tree height by subtracting hb from hc.

3.3.3 Office work:

It includes the following steps:

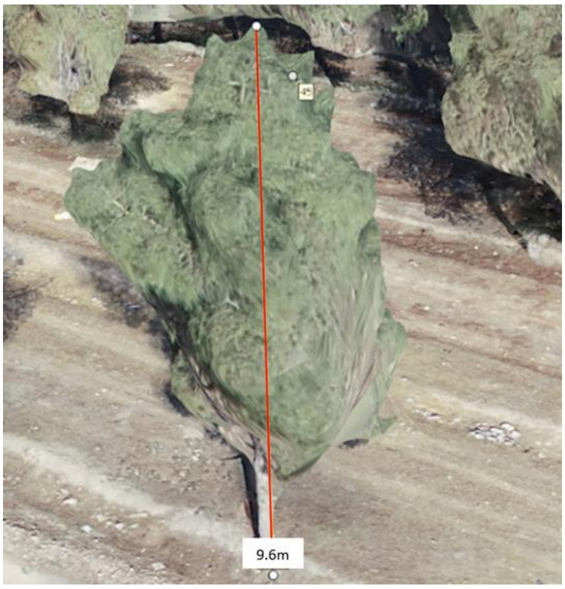
1- Photographic processing: The researcher used the Agisoft Metashape (version:1.8.0.13111) software for processing 667 photo that having a ground resolution of 1.35 cm/pixel, the processing time was 1 hours and 36 minutes.

2- Preparing point clouds: The number of dense point clouds was 247,394,696 points, and the processing time was1 hour and 36 minutes,

3- Preparing ortho-mosaic: The size was 46,571 x 27,391 pixel and the processing time was 28 minutes and 37 seconds,

4- Preparing DEM: the size was 24,584 x 14,385 pixel, the data source was the dense cloud, and the processing time was 6 minutes and 59 seconds.

5-Measuring tree height by using Agisoft software through 3-d point clouds (fig-4)



Fig(4):- Measuring tree height by using point clouds

3. RESULTS AND DISCUSSION

Table -2 depicts the values of tree height measurements by using Haga instrument and UAV point clouds along with Agisoft meta shape professional software.

Table(2):- Tree height measurements by traditional and UAV methods

Tree No.	H haga (m)	H UAV (m)	Tree No.	H haga (m)	H UAV (m)
1	9.3	9.08	31	9.1	8.56
2	9.6	9.43	32	9.1	9.18
3	7.5	7.61	33	10	10.2
4	9.5	9.19	34	10.9	9.97
5	8.5	8.3	35	8.1	8.6
6	10.5	9.66	36	7.4	7.96
7	6.8	7.6	37	8.1	7.82
8	7.5	7.84	38	8.2	7.61
9	9	8.33	39	9.6	9.38
10	9	8.98	40	9.7	9.15
11	5.7	5.36	41	9.7	9.05
12	8.5	8.35	42	9.1	8.99
13	7.5	8.23	43	7.8	7.7
14	7	7.69	44	7.9	8.23
15	9.7	8.82	45	9.7	9.2
16	7.4	7.09	46	10.5	9.82
17	8.7	8.35	47	8.6	9.1
18	8.2	8.29	48	10.1	9.59
19	9.1	9.32	49	10.7	9.89
20	8.8	8.98	50	9.4	9.2
21	10.6	10.6	51	8.5	8.13
22	9.1	8.53	52	8	7.96
23	9.4	9.76	53	11	10
24	9.9	9.48	54	7.8	7.7
25	6.6	6.5	55	8.5	8.8
26	10.5	9.32	56	7.8	8.3
27	8.5	7.94	57	9.2	8.73
28	8.5	8.47	58	11.7	10.2
29	9.4	8.52	59	10.5	10.2
30	7.5	7.5	60	8.8	9.63
			61	7.9	8.1

4.1 Statistical analysis results

I found that there are two abnormal points that bias the relationship, so I excluded them in order to improve the equation then, the number of observations used was 59.

The R-Squared statistic indicates that the model as fitted explains 84.03% of the variability in tree height by Haga. The correlation coefficient equals + 91.67%, indicating a relatively very strong relationship between the two height variables. The standard error of the estimate shows the standard deviation of the residuals is 0.351718. The difference between standard deviation and standard error is: The standard deviation indicates sample variability, whereas the standard error predicts population variability across samples. The RSS is the standard error of the estimate gives us an idea of how well a regression model fits a dataset. This value can be used to construct prediction limits for new observations.

Figure-5 shows the linear relationship between the tree height by haga and by UAV methods, and table-3 shows the results of fitting a linear model to describe the relationship between them. The equation of the fitted model is:

Tree height by field method = 2.52453 + 0.695144*Tree height by drone

Table(3):- Coefficients of tree height model

Coefficients Parameter	Least Squares Estimate	Standard Error	T Statistic	P-Value
Intercept	2.52453	0.361204	6.98922	0.0000
Slope	0.695144	0.040135	17.3202	0.0000

Table-4 depicts the analysis of variance (ANOVA), the P-value is less than 0.05. Accordingly, this means that there is a statistically significant relationship between Tree height by haga and drone methods at the 95.0% confidence level.

Table(4):- Analysis of Variance D20

Source	Sum of Squares	Df	Mean Square	F-Ratio	P-Value
Model	37.1101	1	37.1101	299.99	0.00
Residual	7.0512	57	0.1237		
Total (Corr.)	44.1613	58			

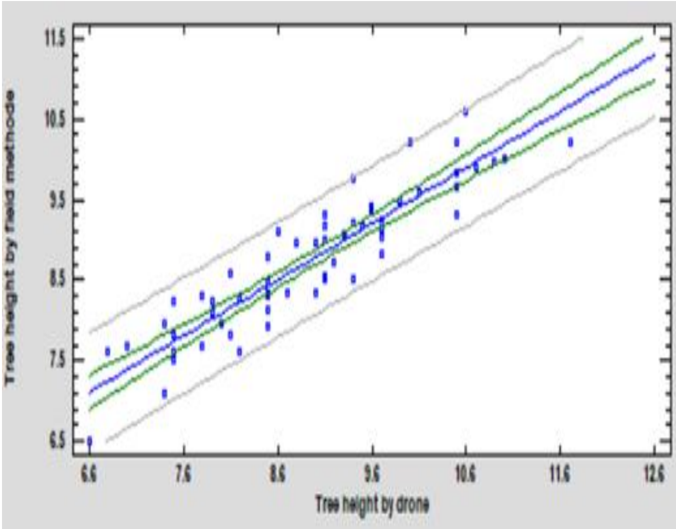
The mean absolute error (MAE) of 0.288314 is the average value of the residuals (figure-6). The Durbin-Watson statistic tests the residuals to determine if there is any significant correlation based on the order in which they occur in data file. Since the P-value is less than 0.05, there is sign of serial autocorrelation in the residuals at the 95.0% confidence level. The mean absolute error F- ratio is the ratio of the between group variance to the within group variance. The F-ratio is used in an ANOVA that provides more insight into data compared to using only the mean or median.

The F- ratio equation is as follows:

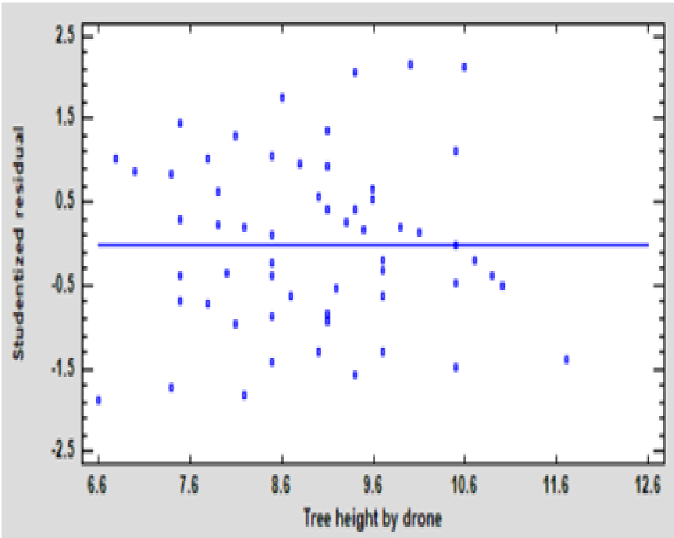
F=MSB/ MSW

MSB= Mean of Squares Between

MSW= Mean of Squares Within



Fig(5):- the relationship fitting curve

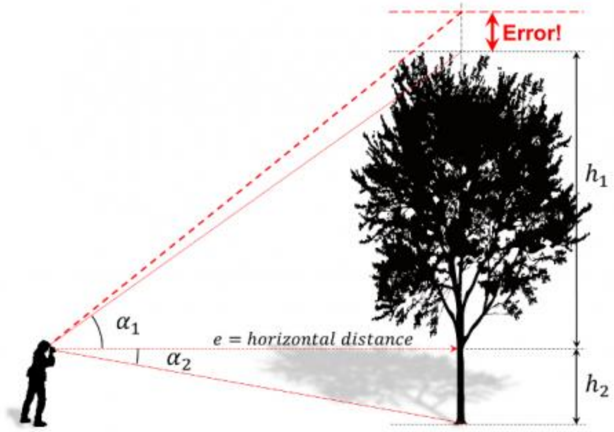


Fig(6):- Residual plot

4.2 Comparison between tree height by haga and UAV methods

Krause, S., et al. (2019), reported that indirect field tree height measurements tend to be overestimated when compared with direct field methods. In addition to that, the drone-based photogrammetric techniques have a proclivity to underestimate tree heights. In our study, we found that over the 59 observations, 68% of the indirect field measurements tree height values are higher than those obtained by UAV- photogrammetric measurements (table-5). The differences in tree heights ranges between 0.02-1.5m.

The indirect field measurements overestimation is due to that the observer can not shoot the exact tree top point because he is not able to see it as it is illustrated in figure-7.



Fig(7):- error in measuring tree height by using Haga instrument

Table(5):-Bias values between traditional and UAV tree height

Tree No.	TM	UM	Bias	Tree No.	TM	TU	Bias
1	9.3	9.08	0.22	31	9.1	8.56	0.54
2	9.6	9.43	0.17	32	9.1	9.18	-0.08
3	7.5	7.61	-0.11	33	10.0	10.2	-0.20
4	9.5	9.19	0.31	34	10.9	9.97	0.93
5	8.5	8.30	0.20	35	8.1	8.60	-0.50
6	10.5	9.66	0.84	36	7.4	7.96	-0.56
7	6.8	7.60	-0.80	37	8.1	7.82	0.28
8	7.5	7.84	-0.34	38	8.2	7.61	0.59
9	9.0	8.33	0.67	39	9.6	9.38	0.22
10	9.0	8.98	0.02	40	9.7	9.15	0.55
11	5.7	5.36	0.34	41	9.7	9.05	0.65
12	8.5	8.35	0.15	42	9.1	8.99	0.11
13	7.5	8.23	-0.73	43	7.8	7.70	0.10
14	7.0	7.69	-0.69	44	7.9	8.23	-0.33
15	9.7	8.82	0.88	45	9.7	9.20	0.50
16	7.4	7.09	0.31	46	10.5	9.82	0.68
17	8.7	8.35	0.35	47	8.6	9.10	-0.50
18	8.2	8.29	-0.09	48	10.1	9.59	0.51
19	9.1	9.32	-0.22	49	10.7	9.89	0.81
20	8.8	8.98	-0.18	50	9.4	9.20	0.20
21	10.6	10.6	0.00	51	8.5	8.13	0.37
22	9.1	8.53	0.57	52	8.0	7.96	0.04
23	9.4	9.76	-0.36	53	11	10.0	1.00
24	9.9	9.48	0.42	54	7.8	7.70	0.10
25	6.6	6.50	0.10	55	8.5	8.80	-0.30
26	10.5	9.32	1.18	56	7.8	8.30	-0.50
27	8.5	7.94	0.56	57	9.2	8.73	0.47
28	8.5	8.47	0.03	58	11.7	10.2	1.50
29	9.4	8.52	0.88	59	10.5	10.2	0.30
30	7.5	7.50	0.00	60	8.8	9.63	-0.83
				61	7.9	8.10	-0.20

TM: Traditional height values, UM: UAV height values

4.3 Comparison of the current study R^2 result with other studies

The Coefficient of determination that the researcher obtained in the current study (84.03%) is coincide with that Guerra-H G et al (2016) got. Guerra used an ALS (Airborne laser scanner) to measure Pinus pinea forest heights in Lugo -Spain Mediterranean forest, and the R^2 value he got was 81%. As well as, Corte, Ana, et. al., (2020), gained a similar result (R^2 =82.81) when utilized a UAV-lidar point clouds to measure the individual-tree height of 63 trees by using an automatic approach in an integrated Crop-Livestock-Eucalyptus benthamii forest system. The root means square error (RMSE) was 7.9%.

Also, the research conducted by Fankhauser, K., et. al., (2018) utilized an UAV system for measuring tree heights depicted the same result that the researcher got (R^2 was 82%, the RMSE was 2.92 m).

When measuring tree heights Teddy Ruslono. Et. al., (2021) found that, the R^2 values were from 64.4%-80.2% (at UAV flying height of 80m), for three different selected forests, and RMSE was from 1.109-1.343, which make the R^2 of the current study result within the mentioned range.

In the other hand, Vahid Nasiri, et. al., (2021) estimated tree height for a mixed forest by drone, and when they compared the results with field measurements, results depict that r was 80.8%, the root means square error was 10.1%, and R^2 was equal to 65% which is less than the value of the current study.

The differences in R^2 are due to the differenced in drone height, tree height, tree leaning angle, drone and sensor type, uneven and sloping terrain, GCPs setting up accuracy, automated algorithms utilized in measuring, measuring skill, etc… (Krause, S., et al. 2019, Teddy Ruslono. Et. al., 2021).

4. CONCLUSION

The current study focuses on determining the heights of Pinus brutia Ten trees by using UAV point clouds. The coefficient of determination indicates that the model as fitted explains 84.03% of the variability in tree height by the indirect field method. Results depicted that drone photogrammetric measurements can attain similar tree height values to that of indirect field measurements. We found that, over the 59 observations, 68% of the indirect field measurements tree height values are higher than those obtained by UAV- photogrammetric measurements**.**

The current study results encourage us to replace the insitu measurements of tree height when monitoring forests, and may provide a possibility to obtain yearly increments of tree heights.

5. RECOMMENDATIONS

According to the current study which is considered to be the 1st one applied in Kurdistan region/ IRAQ, we can register the following recommendations:

1- Studies are needed to determine the effect of various drone heights on tree height measurements

2- Testing the UAV suitability for obtaining the yearly increments of tree heights by applying multi flyover (each 3-4 months' period).

3- Comparison among different sensor types in measuring tree heights.

6. REFERENCES

Andersen, H.-E., et al. (2006). "A rigorous assessment of tree height measurements obtained using airborne lidar and conventional field methods." Canadian Journal of Remote Sensing 32(5): 355-366.

Anderson, T. J., et al. (2016). "2016 Canadian Cardiovascular Society guidelines for the management of dyslipidemia for the prevention of cardiovascular disease in the adult." Canadian Journal of Cardiology 32(11): 1263-1282.

Apostol, B., et al. (2016). "Height extraction and stand volume estimation based on fusion airborne LiDAR data and terrestrial measurements for a Norway spruce [Picea abies (L.) Karst.] test site in Romania." Notulae Botanicae Horti Agrobotanici Cluj-Napoca 44(1): 313-323.

Banin, L., et al. (2012). "What controls tropical forest architecture? Testing environmental, structural and floristic drivers." Global Ecology and Biogeography **21**(12): 1179-1190.

Banu, T. P., et al. (2016). "The use of drones in forestry." Journal of Environmental Science and Engineering B 5(11): 557-562.

Chave, J. (2005). "Measuring tree height for tropical forest trees-A field manual." Pan–Amazonia.

Clark, D. A. and D. B. Clark (2001). "Getting to the canopy: tree height growth in a neotropical rain forest." Ecology 82(5): 1460-1472.

Colomina, I. and P. Molina (2014). "Unmanned aerial systems for photogrammetry and remote sensing: A review." ISPRS Journal of photogrammetry and remote sensing 92: 79-97.

Corte, Ana, et. al., (2020), Measuring Individual Tree Diameter and Height Using GatorEye High-Density UAV-Lidar in an Integrated Crop-Livestock-Forest System, VL - 12, JO - Remote Sensing, DO - 10.3390/rs12050863

Dempewolf, J., et al. (2017). "Measurement of within-season tree height growth in a mixed forest stand using UAV imagery." Forests 8(7): 231.

Díaz-Varela, R. A., et al. (2015). "High-resolution airborne UAV imagery to assess olive tree crown parameters using 3D photo reconstruction: application in breeding trials." Remote Sensing **7**(4): 4213-4232.

Feldpausch, T. R., et al. (2012). "Tree height integrated into pantropical forest biomass estimates." Biogeosciences **9**(8): 3381-3403.

Fernández-Landa, A., et al. (2018). "High resolution forest inventory of pure and mixed stands at regional level combining National Forest Inventory field plots, Landsat, and low density lidar." International journal of remote sensing **39**(14): 4830-4844.

Fankhauser, K. E., Nikolay S. Strigul and Demetrios G., (2018), Augmentation of Traditional Forest Inventory and Airborne Laser Scanning with Unmanned Aerial Systems and Photogrammetry for Forest Monitoring, Remote Sens. 2018, 10, 1562; doi:10.3390/rs10101562

Ganz, S., et al. (2019). "Measuring tree height with remote sensing—A comparison of photogrammetric and LiDAR data with different field measurements." Forests **10**(8): 694.

Goodwin, A. (2004). "Measuring tall tree heights from the ground." TASFORESTS-HOBART- **15**: 85-98.

Guan S, et.al., (2019) Assessing Correlation of High-Resolution NDVI with Fertilizer Application Level and Yield of Rice and Wheat Crops using Small UAVs Remote Sens. 11 112 [8].

Guerra-Hernández, J., et al. (2016). "Comparison of ALS based models for estimating aboveground biomass in three types of Mediterranean forest." European Journal of Remote Sensing **49**(1): 185-204.

Hyyppä, J., et al. (2005). Using individual tree crown approach for forest volume extraction with aerial images and laser point clouds. Proceedings of The ISPRS Workshop Laser Scanning 2005, Citeseer.

Hansen, M. C., et al. (2013). "High-resolution global maps of 21st-century forest cover change." science **342**(6160): 850-853.

Hernandez, J. G., et al. (2016). "Using high resolution UAV imagery to estimate tree variables in Pinus pinea plantation in Portugal." Forest systems **25**(2): 16.

Imai, Y., et al. (2004). "Tree-height measuring characteristics of urban forests by LiDAR data different in resolution." International Society for Photogrammetry and Remote Sensing, Florida, USA 4.

Jucker, T., et al. (2017). "Allometric equations for integrating remote sensing imagery into forest monitoring programmes." Global change biology **23**(1): 177-190.

Kaartinen, H., et al. (2012). "An international comparison of individual tree detection and extraction using airborne laser scanning." Remote Sensing **4**(4): 950-974.

Kattenborn, T., et al. (2014). "Automatic single tree detection in plantations using UAV-based photogrammetric point clouds." The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences **40**(3): 139.

King, D. A. and D. A. Clark (2011). "Allometry of emergent tree species from saplings to above-canopy adults in a Costa Rican rain forest." Journal of Tropical Ecology **27**(6): 573-579.

Korning, J. and K. Thomsen (1994). "A new method for measuring tree height in tropical rain forest." Journal of Vegetation Science **5**(1): 139-140.

Krause, S., et al. (2019). "UAV-based photogrammetric tree height measurement for intensive forest monitoring." Remote Sensing **11**(7): 758.

Lyons, E. (1966). "Fixed air-base 70 mm photography, a new tool for forest sampling." The Forestry Chronicle **42**(4): 420-431.

Maltamo, M. and P. Packalen (2014). Species-specific management inventory in Finland. Forestry applications of airborne laser scanning, Springer**:** 241-252.

Pariyar, S. and R. A. Mandal (2019). "Comparative tree height measurement using different instrument." International Journal of Ecology and Environmental Sciences **1**(2): 12-17.

Parkinson, B. W. and J. J. Spilker (1996). Progress in astronautics and aeronautics: Global positioning system: Theory and applications, Aiaa.

Rennie, J. C. (1979). "Comparison of height-measurement techniques in a dense loblolly pine plantation." Southern Journal of Applied Forestry **3**(4): 146-148.

Rogers, E. J. (1949). "Estimating tree heights from shadows on vertical aerial photographs." Journal of Forestry **47**(3): 182-191.

Roise, J., et al. (2016). "Valuation and production possibilities on a working forest using multi-objective programming, Woodstock, timber NPV, and carbon storage and sequestration." Scandinavian Journal of Forest Research **31**(7): 674-680.

Sherrill, J. R., et al. (2011). "Total and merchantable stem volume equations for midrotation loblolly pine (Pinus taeda L.)." Southern Journal of Applied Forestry **35**(3): 105-108.

Spurr, S. H. (1960). "Photogrammetry and photo-interpretation. With a section on applications to forestry." Photogrammetry and photo-interpretation. With a section on applications to forestry.

St-Onge, B., et al. (2015). "Characterizing the height structure and composition of a boreal forest using an individual tree crown approach applied to photogrammetric point clouds." Forests 6(11): 3899-3922.

Teddy Ruslono. Et. al., (2021), Height, diameter and tree canopy cover estimation based on unmanned aerial vihicle imagery with various acquisition height, Media Konservasi Vol.26 No.1 April 2021: 17-27, DOI: 10.29244/medkon.26.1.17-27

Vahid Nasiri, et. al., (2021), Unmanned aerial vehicles (UAV)-based canopy height modeling under leaf-on and leaf-off conditions for determining tree height and crown diameter (case study: Hyrcanian mixed forest), Canadian Journal of Forest Research, https://doi.org/10.1139/cjfr-2020-0125

Wulder, M., et al. (2008). The role of LiDAR in sustainable forest management. For. Chron. 84, 807–826.