ALEPPO PINE ALLOMETRIC MODELING THROUGH INTEGRATING UAV IMAGE-BASED POINT CLOUDS AND GROUND-BASED DATA

Fernando J. Aguilar1,* Abderrahim Nemmaoui1, Manuel A. Aguilar1, Rafael Jiménez-Lao1

1 Department of Engineering and Research Centre CIAIMBITAL, University of Almería, Almería, Spain
(faguilar, an932, maguilar, rj020)@ual.es

KEY WORDS: Mediterranean Forest, Aleppo Pine, UAV, Point Cloud, Machine Learning, Allometric Models, AGB Mapping.

ABSTRACT:

Effective monitoring of Mediterranean forest is essential to determine the role of forest management in mitigating climate change and ensuring the maintenance of its environmental services. Most of the allometric models to estimate dry above-ground biomass (AGB) at tree level are based on knowing the diameter of the trunk at breast height (DBH). However, it is difficult, if not impossible, to estimate DBH from airborne/spaceborne sensors within the context of a remote sensing-oriented approach, being common to draw upon regression models to relate DBH to remotely sensed dendrometric variables such as total tree height (H) and tree crown diameter (CD). This study uses UAV (unmanned aerial vehicle) image-based data to estimate the dendrometric variables H and CD of the repopulated Aleppo pine (Pinus halepensis Mill.) located in a semi-arid continental Mediterranean forest of Almería (southeast of Spain). DBH data were gathered through field work. Both bivariate (DBH = Φ(H)) and multivariate (DBH = Ψ(H, CD)) allometric models were developed by applying least-squares-based regression and machine learning regression methods. The results showed that multivariate allometric models performed better than bivariate at predicting DBH, both in terms of goodness-of-fit and stability against changes in training or testing samples. In addition, least-squares-based regression (linear and potential) provided statistically similar results to those obtained from complex machine learning ensemble algorithms. In this way, the easy-to-apply multivariate linear allometric model $DBH = -4.84 + 1.73149\times H + 3.08114\times CD$ ($R^2 = 89.23\%$) would be recommended to locally estimate DBH in Aleppo pine from remotely sensed H and CD data.

1. INTRODUCTION

According to the general definition of forests by FAO, in 2015 there were around 88 million ha of forest area in Mediterranean countries, 18 million of them located in Spain (FAO, 2015). This means that forests occupied 10.04% of the total area of Mediterranean countries in 2015, equivalent to the combined size of Spain and Morocco, also storing 5066 billion tons of carbon, equivalent to 1.7% of global forest carbon (FAO, 2015).

Focusing on the importance of Mediterranean forest, the Mediterranean region has more than 25 million ha of Mediterranean forests and about 50 million ha of other Mediterranean wooded lands (e.g., open oak woodlands of Quercus species, such as Spanish Dehesas) (FAO and Plan Bleu, 2018) that can effectively contribute to carbon storage and climate change mitigation. Furthermore, they host a large variety of forest ecosystems, contain an impressive plant and animal diversity, and generate a large number of environmental services (ES) that make crucial contributions to rural development, poverty alleviation, food security, as well as the agricultural, water, tourism, and energy sectors (Vilà-Cabrera et al., 2018).

We know that forest area in Mediterranean countries has been increasing since 1990. For example, between 2000 and 2015 there has been an increase of 8 million ha in forest area (FAO and Plan Bleu, 2018). This increase in forest size is both the result of the European Common Agriculture Policy (as in the case of Spain) and forest regeneration in rural areas following abandonment (Nogueira and Rico, 2017). Unfortunately, an increasing forest area, despite being good news, tells us nothing about forest degradation and potential capacity to adapt to climate change. It is needed to take a closer look to cope with monitoring forest structure at stand and tree level. Note that forest structure is formed through the action of very diverse factors such as silvicultural practices, fires, droughts, heat waves, storms, and pests or diseases, being the key that explains, in turn, relevant variables of ecosystems such as biodiversity, erosion control, water availability and landscape complexity.

Taking into account the aforementioned antecedents, it seems clear that effective monitoring of Mediterranean forest structure turns out to be a key role for adapting to climate change (Pascual et al., 2020), ensuring at the same time the maintenance of ES and the preservation of the functional characteristics of Mediterranean forests (Vilà-Cabrera et al., 2018). But how to deal with it? The Intergovernmental Panel on Climate Change (IPCC) recommends combining remote sensing and ground-based data to estimate forest area, carbon stocks and changes at large scales (Espejo et al., 2020). However, this integrated approach requires the development of new allometric tools based on individual tree measures (tree-centric approach) collected from spaceborne or airborne sensors (e.g., total tree height (H) and tree crown diameter (CD)) to make full use of remote sensing techniques in implementing enhanced forest inventories and mapping carbon stocks (Coomes et al., 2017; Jucker et al., 2017; White et al., 2016).

Within available remote sensing techniques, the recently emerged computer vision algorithm Structure from Motion (SfM) with Multi-View Stereo (MVS) (Furukawa and Ponce, 2010) has boosted efficiency in building very dense and accurate 3D point clouds of comparable quality to laser-based methods (Wallace et al., 2016). When coupled with Unmanned Aerial
Vehicle (UAV) very-high resolution images, it has demonstrated to be able to generate a Canopy Height Model (CHM) that can be successfully used to estimate total tree height in forest inventories (Goodbody et al., 2017; Lisein et al., 2013; Panagiotidis et al., 2017; White et al., 2013).

On the other hand, tree dry above-ground biomass (AGB) is traditionally estimated using forest inventory data from sample plots and allometric models that usually rely on stem diameter (diameter at breast height: DBH) and H as key inputs (Chave et al., 2014). However, it is impossible to measure DBH from airborne or spaceborne sensors, being necessary to carry out traditional field work or terrestrial laser scanning inventories to obtain this dendrometric variable (Peñalver et al., 2021). In this regards, it is crucial to develop locally calibrated allometric models to allow predicting DBH from other dendrometric variables such as H and CD that can be estimated from airborne or spaceborne sensors. The fitting of this site-specific allometric relationships can be faced by using both least-squares-based regression and machine learning regression methods (Aguilar et al., 2021).

This work uses UAV image-based data to estimate the dendrometric variables H and CD in a Mediterranean forest mainly composed of repopulated Aleppo pine (*Pinus halepensis Mill*). DBH data were collected almost simultaneously through field work, allowing the development of bivariate and multivariate allometric models to predict DBH from H and CD. These models were fitted by using both least-squares-based regression (linear and potential models) and supervised machine-learning regression methods. These locally obtained allometric models could be used to improve forest AGB and carbon estimation, especially in large-scale inventories where only H and CD can be estimated from airborne or spaceborne sensors.

### 2. MATERIALS AND METHODS

#### 2.1 Study Site

The study site is located at “Sierra de María-Los Vélez” Natural Park (Fig. 1). This Natural Park is a Spanish protected natural area located northwest of the province of Almería (southeast of Spain), Andalusia.

![Figure 1. Location of the study area. a) Province of Almería (Spain) in yellow. b) Region of “Los Vélez” (in red). c) Limits of the “Sierra de María-Los Vélez” Natural Park (in green). d) Reference field plots represented as white dots.](image_url)

“Sierra de María-Los Vélez” was declared a natural park in 1987, occupying an area of 22,562 ha and a maximum elevation of 2,045 m AMSL. It presents an average annual rainfall of about 400 mm, with an average annual temperature of 11° C and semiarid continental Mediterranean climate.

Although in the most humid areas of the natural park there can be small forests of Larch pine and deciduous trees, the most representative forest ecosystem in this area presents a two layers structure. The emergent upper layer (dominant trees) is composed of repopulated Aleppo pine (*Pinus halepensis Mill*), while the lower canopy layer (understory vegetation) is mainly formed of little holm oak trees (*Quercus ilex L.*) and different species of shrubs (Aguilar et al., 2019a). This forest structure is considered very representative of the Mediterranean forest.

#### 2.2 Field Data and Processing Methods

The test field sites of this work consisted of 18 square plots of 100 m side (1 hectare) that were selected trying to represent the variability of the stand density and tree height of the Aleppo pine population in the Natural Park (white dots in Fig. 1).

High resolution UAV images for each reference plot were obtained in March 2021 by using a DJI Phantom 4 Advanced®. Its 8.8 mm focal length integrated RGB camera is equipped with a 20 megapixel 1" CMOS sensor (2.52 μm/pixel) fitted to a 3-axis stabilized gimbal to maintain nadir image capture. The flying height of the mission was set to approximately 75 m above ground, which allowed yielding an average ground sample distance of 2.1 cm. High forward and side overlaps of 90% and 85%, respectively, were set in the UAV flight plan of each reference plot to avoid potential forest occlusions.

Between seven and eight ground control points (GCP) constituted of rectangular 60x40 cm wood panels (black and white chess-board style painted) targets were evenly distributed over each reference plot, trying to choose open terrain sites to ensure their visibility in the UAV images. Those GCP were surveyed with a couple of GNSS RTK multiband receivers Emid Reach RS2 (rover and base). The geographical coordinates of the base in each reference plot were obtained by applying the differential corrections provided through NTRIP caster from the continuous reference GPS station of Huércal-Overa (Andalusian network of GPS positioning). The rover receiver was used to measure the ETRS89 UTM 30N projected coordinates and EGM08 REDNAP (Spanish High Precision Levelling Network) orthometric heights of each GCP in RTK mode using the base receiver as a reference.

All images for each reference plot were photogrammetrically processed using the SfM-MVS algorithm implemented in the software Agisoft Metashape Professional 1.7.2 (Agisoft LLC, St. Petersburg, Russia), a well-known SfM-MVS software capable of producing image-based high quality point clouds that has been widely employed to conduct UAV-based forest inventories (e.g., Chen et al., 2021; Jensen and Mathews, 2016; Panagiotidis et al., 2017; Wallace et al., 2016). Metashape was also used to produce a high-resolution RGB 3 cm/pixel orthoimage.

The seven-eight surveyed GCP were manually marked on the digital images to carry out an iterative bundle adjustment to estimate the 3D coordinates of the automatically matched features (sparse point cloud) (Aguilar et al., 2019b). Next, a camera self-calibration process was performed in each reference plot to optimize the camera model, always maintaining fixed the focal length. After estimating internal and external camera...
The point cloud corresponding to each reference plot was automatically classified into ground and non-ground points through applying the filtering algorithm triangular irregular network (TIN) iterative approach proposed by Axelson (2000) and implemented into Agisoft Metashape. After a trial and error procedure, the set of chosen parameters was cell size = 10 m, distance = 0.3 m and angle = 30°. Those potential outliers in the automatically filtered ground points were automatically removed by adapting the parametric method for error detection in digital elevation models published by Felicisimo (1994) to be used on scattered points, then setting the neighbourhood size radius to 15 cm. In addition, a local maxima filtering with a neighbourhood radius of 10 cm was applied to each UAV point cloud to obtain the corresponding Canopy Surface Model (CSM).

Both CSM and DTM derived point clouds were finally interpolated to 5 cm grid spacing products by using the Gaussian Markov Random Field (GMRF) algorithm developed by Aguilar et al. (2016) (https://github.com/3DLAB-UAL/dem-gmrf). The grid DTM was finally subtracted to the grid CSM to obtain a 5 cm grid spacing Canopy Height Model (CHM).

Stratified random sampling was carried out in the 18 reference plots to manually digitize onto the RGB 3 cm/pixel orthoimage the 2D crown boundary (shp file) of 785 Aleppo pines, also estimating their corresponding total tree height and planimetric coordinates from the previously obtained CHM (given by the point with maximum height within the digitized crown boundary of each sample tree). The crown diameter of each tree was computed from the area of its crown boundary. This office work was done in the ArcGIS environment.

Fieldwork was carried out between the end of May and the beginning of June 2021 to locate and measure the DBH and total tree height parameters were those recommended by Tinkham and Swayze (2021) to carry out individual tree detection from CHM. In this way, the photo alignment process was performed on the original images (i.e., without changing their original spatial resolution or “High Accuracy” setting), while the dense cloud was computed by selecting “High quality” (i.e., original image size downsampling by factor of four) and “Mild” depth filtering settings.

The potential model used in this study was based on the allometric model proposed by Jucker et al. (2017). After taking logarithms to linearize the potential expression, we obtain the following equations:

\[ DBH = \alpha + \beta H + \gamma CD + \varepsilon \]

where \( DBH = \) diameter at breast height (cm)
\( H = \) total tree height (m)
\( CD = \) crown diameter (m)
\( \alpha, \beta, \gamma = \) regression coefficients for H and CD
\( \varepsilon = \) fitting error

The allometric linear model tested took the following form:

\[ DBH = \alpha + \beta H + \varepsilon \quad \text{Bivariate model,} \]

\[ DBH = \alpha + \beta H + \gamma CD + \varepsilon \quad \text{Multivariate model,} \]

2.3 Allometric Models

Seven allometric models were tested to predict DBH from the explanatory variables H (bivariate model) and H + CD (multivariate model). One of them was based on traditional linear regression, while another used a potential form. The remaining five focused on supervised machine learning algorithms. An individual-based modeling approach was used by considering each individual tree measurement as an instance of the relationships modelled.

Some error indicators of the DBH values predicted by the regression models were calculated according to the following expressions:

\[ Bias(\%) = \frac{100}{N} \sum_{i=1}^{N} \left( \frac{DBH_{\text{measured}} - DBH_{\text{predicted}}}{DBH_{\text{measured}}} \right), \]

\[ RMSE (cm) = \sqrt{\frac{\sum_{i=1}^{N} (DBH_{\text{measured}} - DBH_{\text{predicted}})^2}{N}}, \]

\[ relative \ RMSE (\%) = 100 \frac{RMSE}{DBH_{\text{predicted}}}, \]
where $DBH_p = DBH$ predicted
$DBH_o = DBH$ observed
$N = \text{number of pine trees in the testing dataset}$
$DBHo = \text{mean value of DBH observed values}$

Note that the Bias indicator constitute a measure of the systematic error of the model, while RMSE (root-mean-square error) is a quantitative indicator of its random error. The entire procedure mentioned above was coded in Python 3.8 with the support of the scikit-learn and catboost libraries.

3. RESULTS

3.1 Field Measured Tree Height vs Tree Height Estimated from Image-Based Point Clouds

Figure 2 graphically shows the good agreement between the total tree height measured with a hypsometer ($H_{\text{hyp}}$) during the field work and that estimated from the photogrammetrically derived CHM ($H_{\text{CHM}}$) for the sample of 451 Aleppo pines. In fact, the coefficient of correlation (Pearson’s r) between $H_{\text{CHM}}$ and $H_{\text{hyp}}$ took a high value of 0.9929. Moreover, the RMSE value of the residuals (prediction errors) was only 40.65 cm, which meant a very low relative RMSE of 4.57% (< 5%) with respect to the mean value of the tree height measured with a hypsometer.

These results evidenced the high geometrical accuracy of the CHMs generated from UAV image-based point clouds, which allowed us to expand the sample of Aleppo pines to 785 by adding those that could not be measured during field work with the hypsometer due to occlusions caused by surrounding trees.

Similar results have been reported by other authors, who generally have found high agreement between field and remote-sensed data for total tree heights (Goodbody et al., 2017; Guerra-Hernández et al., 2016; Lisein et al., 2013; Panagiotidis et al., 2017; Wallace et al., 2016). It has been also demonstrated that tree heights computed from photogrammetrically derived CHM can even improve the results provided by terrestrial laser scanning, which usually yields underestimated tree heights (Shimizu et al., 2022).

Traditional least-squares-based regression methods (linear and potential) proved to be very competitive, providing results statistically similar to those yielded by complex ensemble boosting algorithms. RFR worked significantly worse (p<0.05) than boosting or least-squares-based regression methods, in addition to a greater variability in prediction when varying training samples. It is necessary to consider that ensemble learning is a branch of machine learning that builds and combines multiple learners (decision trees) to improve the outcomes of the learning process. RFR, as an ensemble bagging method, uses bootstrap samples randomly generated from the original dataset to train several tree models, then aggregating the ensembles to obtain final predictions by majority voting. Because RFR generally improves predictions by decreasing variance and avoiding overfitting, it is most advisable when developing models that include multiple explanatory variables. (Aguilar et al., 2021).

3.2 Bivariate Regression Models

Table 1 shows the goodness-of-fit ($R^2$) statistics of the seven bivariate allometric models tested in which the explanatory variable was only H. Regarding $R^2$ mean value, potential and linear allometric models were at the top of the list, providing fit figures close to 80%, although they did not return significantly different values compared to those based on boosting machine learning regression methods. In contrast, RFR (bagging algorithm) and DTR (just one decision tree) performed significantly worse (p<0.05) than the other competitors. DTR showed noticeably poorer performance, exhibiting a low $R^2$ mean value of 62% along with high variability (standard deviation of $R^2$) across the 100 randomly varying repetitions of the training and test data sets. It is worth noting that small changes in the learning sample can cause dramatic changes in the constructed tree when it is only based on a decision tree, leading to unstable and not robust results. In this sense, most recent studies have adopted multi-tree bagging and boosting ensemble algorithms (Luo et al., 2021; Zhang et al., 2020).

![Figure 2. Comparison between tree heights measured with a hypsometer (field work) and extracted from the image-based CHM. Red line refers to 1:1 line.](image)

![Figure 2](image)

Table 1. Statistics of $R^2$ for bivariate allometric models $DBH = \Psi(H)$. Mean values with different superscript letters are significantly different (p<0.05) (two-sample t-test).

| Regression method | $R^2$ mean value (%) | $R^2$ standard deviation (%) | $R^2$ range (min-max %) |
|-------------------|----------------------|-----------------------------|-------------------------|
| Potential         | 79.61$^a$            | 2.40                        | 72.56-85.86             |
| Linear            | 79.41$^a$            | 2.44                        | 73.80-84-53             |
| CatBoost          | 77.88$^a$            | 2.71                        | 68.12-84.57             |
| GBoost            | 77.73$^a$            | 2.88                        | 70.17-83.87             |
| AdaBoost          | 77.30$^a$            | 2.46                        | 69.61-83.17             |
| RFR               | 70.58$^b$            | 3.95                        | 61.11-80.00             |
| DTR               | 62.01$^b$            | 5.41                        | 49.17-74.12             |

Table 2. Statistics of systematic and random error for bivariate allometric models $DBH = \Phi(H)$. Figures in parentheses correspond to the standard deviation.

| Regression method | Mean Bias (%) | Mean RMSE (cm) | Relative RMSE (%) |
|-------------------|--------------|----------------|-------------------|
| Potential         | 4.38 (1.87)  | 4.24 (0.17)    | 19.00 (0.81)      |
| Linear            | 4.15 (1.81)  | 4.29 (0.21)    | 19.20 (0.97)      |
| CatBoost          | 4.24 (1.90)  | 4.41 (0.21)    | 19.80 (1.03)      |
| GBoost            | 4.33 (2.10)  | 4.42 (0.24)    | 19.79 (1.12)      |
| AdaBoost          | 5.40 (2.28)  | 4.45 (0.19)    | 19.91 (0.89)      |
| RFR               | 3.88 (2.23)  | 5.09 (0.27)    | 22.78 (1.21)      |
| DTR               | 3.00 (2.26)  | 5.72 (0.30)    | 25.66 (1.40)      |
In the case of random error, the group of best performance allometric models (linear, potential and boosting) yielded mean RMSE values lower than 5 cm in the prediction of DBH, which meant a reasonably low relative RMSE ranging between 19% and 20% approximately (Table 2).

### 3.3 Multivariate Regression Models

Table 3 presents the goodness-of-fit statistics of the seven multivariate allometric models tested in this work (DBH = \( \Phi(H, CD) \)). Note that the prediction results were clearly better than those provided by the bivariate allometric models shown in Table 1, especially in the case of machine-learning regression methods, explaining between about 87% and 90% of the variance of the observed data. Again, there were no significant differences (p < 0.05) between least squares regression methods and machine learning, in this case also including RFR, which clearly performed better than when applied to the bivariate allometric model. DTR was again ranked the worst, although notably improved its performance when dealing with multivariate regression. All the tested models showed lower variability in R\(^2\) when varying training samples, which meant that multivariate regression provided greater stability than bivariate. These findings point to the need to have CD, obviously together with H, as a key variable to build accurate allometric models to predict DBH. Similar results were recently reported by Aguilar et al. (2021) working in teak plantations in Ecuador.

![Figure 3](image)

**Figure 3.** Plots of the observed/predicted values of DBH for a test dataset case (157 Aleppo pine trees not used for training) given by two multivariate allometric models (DBH = \( \Phi(H, CD) \)). Top: Linear Regression (R\(^2\) = 89.02%). Bottom: Decision Tree Regression (R\(^2\) = 79.86%). Red line refers to 1:1 line.

#### Table 3. Statistics of R\(^2\) for multivariate allometric models DBH = \( \Phi(H, CD) \). Mean values with different superscript letters are significantly different (p<0.05) (two-sample t-test).

| Regression method | \( R^2 \) mean value (%) | \( R^2 \) standard deviation (%) | \( R^2 \) range (min-max %) |
|-------------------|--------------------------|-------------------------------|---------------------------|
| CatBoost          | 89.37\(^a\)              | 1.42                          | 82.67-93.45               |
| GBost             | 89.17\(^a\)              | 1.42                          | 84.78-91.69               |
| Linear            | 89.08\(^a\)              | 1.23                          | 86.16-91.77               |
| RFR               | 87.98\(^b\)              | 1.57                          | 84.86-92.12               |
| Potential         | 87.75\(^b\)              | 1.61                          | 82.66-91.76               |
| AdaBoost          | 87.41\(^b\)              | 1.58                          | 82.53-91.03               |
| DTR               | 79.63\(^b\)              | 2.97                          | 71.68-85.71               |

#### Table 4. Statistics of systematic and random error for multivariate allometric models DBH = \( \Phi(H, CD) \). Figures in parentheses correspond to the standard deviation.

| Regression method | Mean Bias (cm) | Mean RMSE (cm) | Relative RMSE (%) |
|-------------------|----------------|----------------|-------------------|
| CatBoost          | 2.18 (1.24)    | 3.04 (0.18)    | 13.64 (0.76)      |
| GBost             | 2.48 (1.41)    | 3.04 (0.17)    | 13.61 (0.74)      |
| Linear            | 2.90 (1.52)    | 3.07 (0.15)    | 13.74 (0.73)      |
| RFR               | 2.01 (1.24)    | 3.21 (0.19)    | 14.41 (0.84)      |
| Potential         | 2.81 (1.45)    | 3.24 (0.19)    | 14.64 (0.85)      |
| AdaBoost          | 3.98 (1.55)    | 3.27 (0.18)    | 14.73 (0.78)      |
| DTR               | 1.77 (1.76)    | 4.15 (0.26)    | 18.63 (1.16)      |

3.4 **Recommended Allometric Model**

In view of the results described in sections 3.2 and 3.3, the multivariate allometric model based on Linear Regression (Equation 2) would be the most appropriate locally adjusted model to predict the DBH of Aleppo pine as a function of H and CD in “Sierra de María-Los Vélez” Natural Park. In fact, its goodness of fit was statistically similar to that obtained when applying more complex and sophisticated machine learning regression methods, such as Categorical Boosting or Gradient Boosting, showing even slightly higher stability (i.e., lower standard deviation) against changes in the training data set (Table 3). It should be noted that machine learning or deep learning regression methods are capable of modelling complex non-linear allometric relationships, thus surpassing the linear regression method when applied to tree species that present this type of morphology (Aguilar et al., 2021; Bayat et al., 2020; Chen et al., 2020; Erkanlı, 2016; Vieira et al., 2018). However, this potential improvement is not applicable if the allometric relationships are mostly linear, which may be common in some pine species (Filho et al., 2019). Furthermore, linear models have the advantage that they are easy to fit and apply (for example, simply by using an Excel tabulator).

Figure 4 shows the fit of observed and predicted values of DBH for the entire dataset (785 Aleppo pines) according to the multivariate linear allometric model. It can be seen that the model is unbiased, also explaining up to 89.23% of the variance of the observed DBH values (\( R^2 \) adjusted = 89.20%). In addition, the
Under these conditions, and although these results are not presented in this paper due to lack of space, the vertical accuracy assessment of the UAV image-based extracted DTMs (UAV-DTM) was performed using airborne LiDAR data available for the study area, yielding systematic error (bias) values of 8.1 cm and 7.6 cm for the mean and median DTM vertical error, respectively. It meant that the UAV-DTM slightly overestimated the z-terrain reference values provided by the LiDAR data. In any case, this reasonably low bias in the construction of the ground reference (DTM) should be interpreted as adequate to support the generation of CHMs aimed at estimating AGB maps over the natural park studied.

Finally, the LiDAR data used as ground truth were provided by the PNOA (National Plan of Aerial Orthophotography of Spain). Data were taken on December 7, 2014, by means of a Leica ALS60 discrete return sensor with up to four returns measured per pulse and an average flight height of 2700 m. The point density of the test area, considering overlapping, turned out to be 0.97 points/m² (all returns). The nominal (at nadir) horizontal accuracy (RMSExy) and nominal vertical accuracy (RMSEz) after processing had values lower than 0.3 m and 0.2 m, respectively.

4. CONCLUSIONS

In this study, several allometric models were tested to relate DBH (dependent variable) and H and CD (explanatory variables) in the case of the population of Aleppo pine trees in “Sierra de María-Los Vélez” Natural Park. Since UAV carrying visible sensors and gaining ground in local and small-scale data acquisition, UAV image-based point clouds to build CHMs and high-resolution orthoimages were successfully tested to estimate total tree height (Pearson’s $r = 0.9929$; relative RMSE = 4.57%) and tree crown diameter, increasing the efficiency in obtaining these parameters compared to traditional field inventory. Furthermore, this UAV-based technique has proved to be very useful to estimate tree heights that could not be measured during field work (hypsometer) due to occlusions caused by surrounding trees.

Multivariate allometric models (including H and CD as explanatory variables) performed better at predicting DBH, both in terms of goodness-of-fit and stability of regression models against changes in training samples, than those based solely on H. It highlights the need to count on CD, in addition to H, to build accurate predictions of DBH. Within the tested multivariate allometric models, the linear model showed statistically similar goodness-of-fit than that provided by ensemble machine learning regression methods. This finding is attributed to the linear relationships between DBH and H/CD in the case of Aleppo pine. The machine learning regression method based on just one decision tree (i.e., DTR) performed significantly worse than linear, potential and ensemble machine learning regression methods.

According to the results obtained in this work, the easy-to-apply multivariate linear allometric model would be the recommended model to estimate DBH in Aleppo pine, and consequently AGB at tree level, from total tree height and crown diameter collected from airborne or spaceborne sensors. This remote sensing-oriented approach is gaining importance in recent years because it enables large-scale mapping of AGB for forest management and monitoring in the context of mitigating climate change (Reducing Emissions from Deforestation and forest Degradation (REDD) monitoring programmes).
ACKNOWLEDGEMENTS
This study was funded by the following projects: 1) “Enabling interdisciplinarian collaboration to foster Mediterranean forest sustainable management and socio-economic evaluation (ECO2-FOREST)” (Proyecto Retos Junta de Andalucia, Spain. Grant number P18-RT-3237). 2) “Intervention strategies for an integrated and sustainable management of the Mediterranean forest based on an interdisciplinary analysis and its economic assessment” (Programa Operativo FEDER Andalucia 2014-2020, Spain. Grant number UAL2020-SEJ-D1931). The authors wish to thank the support of the Territorial Delegation in Almeria of the Ministry of Agriculture, Fisheries and Sustainable Development of Andalusia. Special thanks are due to Jaime de Lara, Director-Conservator of the Natural Park of Sierra de María-Los Vélez. Finally, this work takes part of the general research lines promoted by the AgriFood Campus of International Excellence ceiA3, Spain (http://www.ceiA3.es/).

REFERENCES
AgUILAR, F.J., AGUILAR, M.A., BLANCO, J.L., NemMAOUI, A., Garcia-Lorca, A.M., 2016. Analysis and validation of grid DEM generation based on Gaussian markov random field. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. - ISPRS Arch. 41, 277–284. https://doi.org/10.5194/isprsarchives-XLI-B2-277-2016.

AgUILAR, F.J., NemMAOUI, A., AGUILAR, M.A., PeñALVER, A., 2021. Building Tree Allometry Relationships Based on TLS Point Clouds and Machine Learning Regression. Appl. Sci. 11, 10139. https://doi.org/10.3390/APP11210139.

AgUILAR, F.J., NemMAOUI, A., AGUILAR, M.A., PeñALVER, A., 2019a. Fusion of terrestrial laser scanning and RPAS image-based point clouds in Mediterranean forest inventories. Dyna 94, 131–136. https://doi.org/10.6036/8892.

AgUILAR, F.J., RivAS, J.R., NemMAOUI, A., PeñALVER, A., AgUILAR, M.A., 2019b. UAV-Based Digital Terrain Model Generation under Leaf-Off Conditions to Support Tcek Plantations Inventories in Tropical Dry Forests. A Case of the Coastal Region of Ecuador. Sensors 19, 1934. https://doi.org/10.3390/s19081934.

AxELSSON, P., 2000. DEM generation from laser scanner data using adaptive TIN models. Int. Arch. Photogramm. Remote Sens. 33 part B, 110–117. https://doi.org/10.1016/j.isprsjprs.2005.10.005.

BayAT, M., BetTINGER, P., HeIDARI, S., KhALYANI, A.H., Jourgholami, M., Hamidi, S.K., 2020. Estimation of Tree Heights in an Uneven-Aged, Mixed Forest in Northern Iran Using Artificial Intelligence and Empirical Models. Forests 11(3), 324. https://doi.org/10.3390/F11030324.

Chave, J., Réjou-MéChin, M., Bûrquez, A., Chidumayo, E., ColGAN, M.S., Delitti, W.B.C., DUque, A., EID, T., Fernside, P.M., GoodMan, R.C., Henry, M., MartíNez-yrizar, A., Mugasha, W.A., Muller-Landau, H.C., Mencuccini, M., Nelson, B.W., Ngomanda, A., Nogueira, E.M., Ortiz-Malavas, E., PÉLissier, R., PloToN, P., Ryan, C.M., SalDarriga, J.G., VielleDent, G., 2014. Improved allometric models to estimate the aboveground biomass of tropical trees. glob. Change. Biol. 20, 3177–3190. https://doi.org/10.1111/gcb.12629.

Chen, J., Yang, H., Man, R., Wang, W., Sharma, M., Peng, C., Parton, J., Zhu, H., DENG, Z., 2020. Using machine learning to synthesize spatiotemporal data for modelling DBH-height and DBH-height-age relationships in boreal forests. For. Ecol. Manage. 466, 118104. https://doi.org/10.1016/j.foreco.2020.118104.

Chen, S., Liang, D., Ying, B., Zhu, W., Zhou, G., Wang, Y., 2021. Assessment of an improved individual tree detection method based on local-maximum algorithm from unmanned aerial vehicle RGB imagery in overlapping canopy mountain forests. Int. J. Remote Sens. 42, 106–125. https://doi.org/10.1080/01431161.2020.1809024.

Coomes, D.A., Dalponte, M., Jucker, T., Asner, G.P., Banin, L.F., Burslem, D.F.R.P., Lewis, S.L., Nils, R., Phillips, O.L., Phua, M.H., Qie, L., 2017. Area-based vs tree-centric approaches to mapping forest carbon in Southeast Asian forests from airborne laser scanning data. Remote Sens. 9, 77–88. https://doi.org/10.3390/rs9030017.

Ercanli, İ., 2020. Innovative deep learning artificial intelligence applications for predicting relationships between individual tree height and diameter at breast height. For. Ecol. Manage. 7(12), 1–18. https://doi.org/10.1108/S40663-020-00226-3.

Espejo, A., Federici, S., Green, C., Amuchastegui, N., D’Annunzio, R., Balzter, H., Bholanath, P., Brack, C., Brewer, C., Birigazzi, L., Cabrera, E., Carter, S., Chand, N., Donoghue, D., Eggleston, S., Fitzgerald, N., Foody, G., Galindo, G., Goeking, S., Grassi, G., Held, A., Herold, M., Kleint, C., Kurz, W., Lindquist, E., McRoberts, R., Mitchell, A., Naesset, E., Notman, E., Quegan, S., Rosenqvist, A., Rosxburgh, S., Sannier, C., Scott, C., Stahl, G., Stehman, S., Tupa, V., Wutt, P., Wilson, S., Woodcock, C., Wulder, M., 2020. Integration of remote-sensing and ground-based observations for estimation of emissions and removals of greenhouse gases in forests: Methods and guidance from the Global Forest Observations Initiative, Edition 3.0, U.N. Food and Agriculture Organization. Rome, Italy.

FAO, 2015. Global forest resources assessment 2015: Desk reference. Rome.

FAO and Plan Bleu, 2018. State of Mediterranean Forests 2018. Rome and Plan Bleu, Marseille.

Felicismio, A.M., 1994. Parametric statistical method for error detection in digital elevation models. ISPRS J. Photogramm. Remote Sens. 49, 29–33. https://doi.org/10.1016/0924-2716(94)00044-2.

Filho, S.V.S. da C., Arce, J.E., Monteño, R.A.N.R., Pelissari, A.L., 2019. Configuración de algoritmos de aprendizaje de máquina en la modelagem florestal: un estudio de caso na modelagem da relação hipsométrica. Ciência Forest. 29, 1501–1515. https://doi.org/10.5902/1980509820392.

Furukawa, Y., Ponce, J., 2010. Accurate, Dense, and Robust Multiview Stereo. IEEE Trans. Pattern Anal. Mach. Intell. 32, 1362–1376. https://doi.org/10.1109/TPAMI.2009.161.

Goodbody, T.R.H., Coops, N.C., Marshall, P.L., Tompalski, P., Crawford, P., 2017. Unmannned aerial systems for precision forest inventory purposes: A review and case study. For. Chron. 93, 71–81. https://doi.org/10.1016/J.FORECO.2020.118104.
Varela, R., 2016. Using high resolution UAV imagery to estimate tree variables in Pinus pinea plantation in Portugal. For. Syst. 25, 5. https://doi.org/10.5424/fs2016252-08895.

Jensen, J., Mathews, A., 2016. Assessment of Image-Based Point Cloud Products to Generate a Bare Earth Surface and Estimate Canopy Heights in a Woodland Ecosystem. Remote Sens. 8, 50. https://doi.org/10.3390/rs8010050.

Jucker, T., Caspersen, J., Chave, J., Antin, C., Barbier, N., Bongers, F., Dalponte, M., van Ewijk, K.Y., Forrester, D.L., Haeni, M., Higgins, S.I., Holdaway, R.J., Ida, Y., Lorimer, C., Marshall, P.L., Momo, S., Moncrieff, G.R., Ploton, P., Poorter, L., Rahman, K.A., Schlund, M., Sonké, B., Sterck, F.J., Trugman, A.T., Usoltsev, V.A., Vanderwel, M.C., Waldner, P., Wedeux, B.M.M., Wirth, C., Wöll, H., Woods, M., Xiang, W., Zimmermann, N.E., Coomes, D.A., 2017. Allometric equations for integrating remote sensing imagery into forest monitoring programmes. Glob. Chang. Biol. 23, 177–190. https://doi.org/10.1111/gcb.13368.

Lisein, J., Pierrot-Deseilligny, M., Bonnet, S., Lejeune, P., 2013. A Photogrammetric Workflow for the Creation of a Forest Canopy Height Model from Small Unmanned Aerial System Imagery. Forests 4, 922–944. https://doi.org/10.3390/f4040922.

López-Serrano, F.R., García-Morote, A., Andrés-Abellán, M., Tendero, A., Del Cerro, A., 2005. Site and weather effects in allometries: A simple approach to climate change effect on pines. For. Ecol. Manage. 215, 251–270. https://doi.org/10.1016/J.FORECO.2005.05.014.

Luo, M., Wang, Y., Xie, Y., Zhou, L., Qiao, J., Qiu, S., Sun, Y., 2021. Combination of Feature Selection and CatBoost for Prediction: The First Application to the Estimation of Aboveground Biomass. Forests 12, 216. https://doi.org/10.3390/f12020216.

Nogueira, D.F., Rico, E.C., 2017. Cambios en los usos de suelo programas. Glob. Chang. Biol. 23, 177–190.

Oliveira, D.F., Rico, E.C., 2017. Cambios en los usos de suelo programas. Glob. Chang. Biol. 23, 177–190.

Pascual, A., Guerra-Hernández, J., Cosenza, D.N., Sandoval, V., 2020. The Role of Improved Positioning and Forest Structural Complexity When Performing Forest Inventory Using Airborne Laser Scanning. Remote Sens. 2020, Vol. 12, Page 413 12, 413. https://doi.org/10.3390/RS12030413.

Peñalver, A., Aguilar, F.J., Nemmaoui, A., Rivas, J.R., Triana, A.A., Aguilar, M.A., Llanderal, A., 2021. Precision y eficiencia del inventario de plantaciones de teca en Ecuador mediante escáner láser terrestre. Madera y Bosques 27(1), e2712097. https://doi.org/10.21829/MYB.2021.2712097.

Shimizu, K., Nishizono, T., Kitahara, F., Fukumoto, K., Saito, H., 2022. Integrating terrestrial laser scanning and unmanned aerial vehicle photogrammetry to estimate individual tree attributes in managed coniferous forests in Japan. Int. J. Appl. Earth Obs. Geoinf. 106, 102658. https://doi.org/10.1016/J.IJAG.2021.102658.

Tinkham, W.T., Swayne, N.C., 2021. Influence of Agisoft Metashape Parameters on UAS Structure from Motion Individual Tree Detection from Canopy Height Models. Forests 12, 250. https://doi.org/10.3390/F12020250.

Vieira, G., de Mendonça, A., da Silva, G., Zanetti, S., da Silva, M., Dos Santos, A., 2018. Prognoses of diameter and height of trees of eucalyptus using artificial intelligence. Sci. Total Environ. 619–620, 1473–1481. https://doi.org/10.1016/J.SCITOTENV.2017.11.138.

Vilà-Cabrera, A., Coll, L., Martínez-Vilalta, J., Retana, J., 2018. Forest management for adaptation to climate change in the Mediterranean basin: A synthesis of evidence. For. Ecol. Manage. 407, 16–22. https://doi.org/10.1016/J.FORECO.2017.10.021.

White, L., Lucieer, A., Malenovský, Z., Turner, D., Vopěnka, P., 2016. Assessment of forest structure using two UAV techniques: A comparison of airborne laser scanning and structure from motion (SfM) point clouds. Forests 7, 62. https://doi.org/10.3390/F7030062.

White, J.C., Coops, N.C., Wulder, M.A., Vastaranta, M., Yu, D., Ball, D., Woods, M., 2013. The Use of Image-Based Point Clouds for Forest Inventory: A Comparison with Airborne Laser Scanning. Forests 4, 518–536. https://doi.org/10.3390/F4030518.

White, J.C., Coops, N.C., Wulder, M.A., Vastaranta, M., Hikker, T., Tompalski, P., 2016. Remote Sensing Technologies for Enhancing Forest Inventories: A Review. Can. J. Remote Sens. 42, 619–641. https://doi.org/10.1080/07038992.2016.1207484.

Zhang, Y., Ma, J., Liang, S., Li, X., Li, M., 2020. An Evaluation of Eight Machine Learning Regression Algorithms for Forest Aboveground Biomass Estimation from Multiple Satellite Data Products. Remote Sens. 12, 4015. https://doi.org/10.3390/rs12244015.