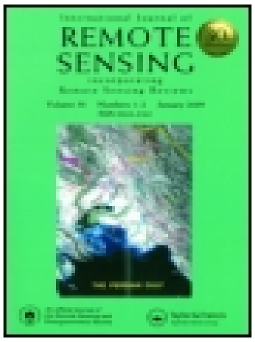

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Estimation of positions and heights from UAV-sensed imagery in tree plantations in agrosilvopastoral systems

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ABSTRACT

Plantations of typical Mediterranean tree species, such as cork oak (*Quercus suber* L.), holm oak (*Quercus ilex* L.), and umbrella pine (*Pinus pinea* L.), are important for the restoration of forest ecosystems in the region. While traditional forest inventories can provide early problem detection in these plantations, the cost and labour of the required fieldwork may exceed its potential benefits. Unmanned aerial vehicles (UAVs) provide a cheap and practical alternative to traditional inventories and individual tree measurement. We present a method to estimate heights and positions of individual trees, from remotely sensed imagery, obtained using a low-flying UAV with an integrated RGB sensor. In the summer of 2015, a 5 ha stand at the University of Évora was photographed with a low-flying (40 m) hexacopter. A 3D point cloud and orthophoto were created from the images. The point cloud was used to identify local maxima as candidates for tree positions and height estimates. Results showed that the height measured with the UAV was reliable on pines, whereas the reliability for oaks was dependent on the size of the trees: smaller trees were especially problematic as they tended to have an irregular crown shape, resulting in larger errors. However, the error showed a strong trend, and adequate models could be produced to improve the estimates.

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Tree height; local maxima; unmanned aerial vehicle; tree positions

1. Introduction

The cork oak (*Quercus suber* L.) woodlands are highly biodiverse Mediterranean ecosystems; one of the most important silvicultural features of this species is cork extraction, which is removed periodically without felling the trees (every 9–12 years). For countries like Spain and Portugal, cork is an important economic factor, together with holm oak (*Quercus ilex* L.) and umbrella pine (*Pinus pinea* L.). Other important species, such as blue gum (*Eucalyptus globulus* L.), are of great significance, not only from a commercial point of view but also for their high capacity for carbon sequestration and extraction of water and nutrients. Consequently, systematical and accurate management can strongly influence their environmental impacts. These woodlands can be described as 'complex forest management systems,' which can be characterized by a limited capacity to respond to

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systematic changes, intense human influence, and other factors (Montero and Cañellas 1999).

One typical characteristic of cork oak is growth in open forest stands, with low tree density values and high variability in size and age classes of individual trees. This heterogeneity and horizontal distribution motivated the idea for combined activities, so-called silvopastoral or agrosilvopastoral systems (Pinto-Correia, Ribeiro, and SÁ-Sousa 2011). Regularly obtaining information about resources, growth-and-yield, and other matters in forest plantations provides the essential data for proper management. The monitoring of stands and inventory in this way can be used for instance to (a) map plantings (i.e. species, area), (b) plan production forecasts from a recently developed plantation, and (c) establish sample plots to obtain yield model data (FAO 2010; Koh and Wilcove 2008). However, the current situation of plantations is mainly based on governmental documentation and reports, of variable accuracy, on planted areas that lack consistent monitoring (Sterling and Ducharne 2008; Grainger 2008; Puyravaud, Davidar, and Laurance 2010; Caccetta, Furby, and Wallace 2012). Plantation species, like cork oak, with open or structurally complex canopies can promote forest connectivity and dense native understory regrowth (Fonseca et al. 2009; Najera and Simonetti 2010). The commercial use of cork has resulted in extensive plantations spanning thousands of hectares in Portugal. This has provided an opportunity to examine important tree characteristics (i.e. precise tree positions, heights, growth) with a high level of detail and precision at an individual tree level, using modern remote-sensing approaches and techniques based on unmanned aerial vehicles (UAV) platforms, for regular updates of forest inventories.

Currently, remote sensing is used in a variety of applications: forest mapping, monitoring, and more recently, taking inventory. Their purpose includes assessment of forest structural types (Torresan et al. 2016), forest cover and its changes (Ullah et al. 2016), and ecological interactions between structural and functional components (Steinaker et al. 2016). The choice regarding which remote-sensing technology (space borne, UAV platform) to use is significant and is largely dependent on the purpose of the investigation.

UAV platforms are attractive for a variety of reasons, including low operational and material costs, acquisition of data at regular time intervals, and high spatial resolution data that is critical at stand level in sustainable forestry (Tang and Shao 2015), when additionally considering the facts that (a) dynamics of forest spatial structure is essential in the construction/update of inventories and (b) field measurement of forest structures is a labour-intensive and time-consuming approach. In addition, UAVs are capable of improving the accuracy of data acquisition and providing fine spatial scale data for sustainable resource management. The capability for a UAV to be deployed quickly and easily also facilitates updating inventories. Using UAVs in forest inventory research is also of great interest, especially with respect to the finely detailed, multi-temporal component of the data, and their potential use in sampling applications (Wallace, Musk, and Lucieer 2014). However, only a few studies have used UAVs for forest inventory purposes (Lisein et al. 2013; Gatziolis et al. 2015). There is currently insufficient literature clarifying the significance of UAVs in forestry, using inexpensive GPS and small format high-resolution aerial imagery based on uncalibrated photo cameras and reviewing the main achievements of these studies. Consumer-grade cameras lead to large perspective distortions, poor camera geometry, and a lack of spectral consistency. In addition, the use of inexpensive GPS and the lack of inertial measurement units cause poor positioning accuracy. These factors posed challenges in the past with respect to 3D geometry generation from UAV imagery. However, the recent adoption of structure-from-motion (SfM) algorithms in photogrammetry has made UAV-SfM a suitable tool for forest inventory purposes (Lisein et al. 2013; Dandois and Ellis 2013).

Recent studies showed the ability for 3D model reconstruction based on SfM point clouds of forested areas (Puliti et al. 2015; Wallace et al. 2016), especially from low-altitude flights (Wallace, Musk, and Lucieer 2014). According to Spetsakis and Aloimonos (1990) and Remondino et al. (2011), SfM, which is based on overlapping images, is a technique that evolved from the machine vision community, for the identification of key points. These points are derived from differences in position between two or more images, based on the 'speeded up robust features' (Bay et al. 2008) and 'scale-invariant feature transform' (Lowe 2004) algorithms. In their work, Haala et al. (2011) showed the possibility of denser 3D object reconstruction based on high overlapping rate of images derived from UAV flights. Particular attention lies in single tree extraction (Culvenor 2002), tree height, tree crown detection, tree density, and further structure parameters, like stem volume. A combination of medium-accurate sensors in conjunction with low altitude flights can result in significant differences between the actual ground coverage and image footprint per image during the flight. However, technical limitations can hinder the acquisition of images, especially in remote and steep (forested) regions.

Tree height is a significant predictor for tree growth, and it can provide important information for the site productivity since it is strongly related to the site index. However, site index computations only utilize the heights of the dominant and, in some cases, co-dominant trees. To better determine tree development, other important factors such as density of planting, rainfall, soil moisture, and management need to be addressed. For instance, density of the plantation not only affects the soil nutrient dynamics, above ground biomass, and crown characteristics (Armstrong, Johns, and Tubby 1999; Benomar, DesRochers, and Larocque 2013) but also wood quality (Cassidy, Palmer, and Smith 2013). Regular information about the increment can also be efficiently used in growth models and volume prediction. Generally, high-quality canopy height models (CHMs) can be used for vegetation measurements (Popescu 2007; Dandois and Ellis 2013). Studies by Reitberger et al. (2009) and Tompalski et al. (2015) showed that tree top detection, and therefore horizontal positions and number of trees, can be directly derived either from point clouds or CHM. For the estimation of the height and tree positions, local maxima and an inverse watershed algorithm can be used simultaneously, or it can be directly measured from CHMs, as suggested by Tiede, Hochleitner, and Blaschke (2005), Edson and Wing (2011), and Panagiotidis et al. (2016).

In this study, we developed a method for qualitative data acquisition based on modern remote-sensing approaches, using a very high-resolution optical sensor for the determination of tree positions and heights of the trees. The purpose of the study is to show how the proposed methodology could be deployed on a typical agrosilvopastoral plantation system (by assessing for example the error on species heights) and improve the relevant management data acquisition for building high precision management plans for large-scale forest hedgerow plantations.

2. Materials and methods

2.1. *Characterization of the study area*

The research area is located south of Valverde, close to the city of Evora in Portugal as can be seen in Figure 1. It extends geographically from 38.529362° N 8.027115° W to 38.520275° N 8.018060° W, in the coordinate reference system WGS84. The plantation is composed mainly of cork oak, holm oak, and umbrella pine. In this particular case, the plantation is composed of blocks including cork oaks from seeds, cork oak from seedlings (1 year in nursery), and both of the cork oak plantations mixed with pine trees for competition assessment. The plantation was established in 1995 using a distance among trees to be 2 m that corresponds to the density of approximately 2500 trees per hectare.

There is regular inventory carried out in this field, which includes the measurement of height (using a telescopic pole), diameter at the base, diameter at breast height, and crown diameter using measuring tape. The tree positions were measured in the year after establishment using a total station.

2.2. *UAV-based data acquisition*

We used commercial UAV hexacopter DJI F550, equipped with Samsung K-Zoom camera with resolution 20.7 MP. The copter was guided using the DJI ground station, with the route planned for a height of 50 m, at a speed of 2 m s^{-1}. With the photo acquisition set to 1 s, this results in frontal overlapping of 85%; side overlapping was 70%. The camera

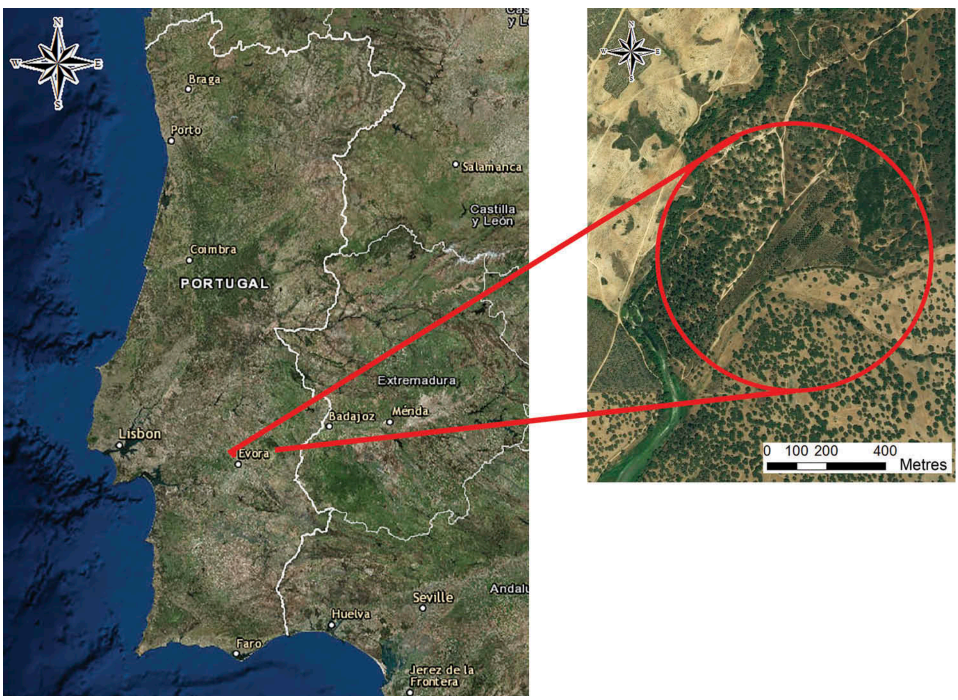

Figure 1. Location of the research area in Portugal, south of Valverde 38° 31′ 27.51″ N, 8° 1′ 23.58″ W (*source*: Google Earth, elaborated in ArcGIS10.3.1 by ESRI©).

was in automatic mode. However, approximately 5% of the images had to be discarded due to blurring and poor quality caused by the movement of the hexacopter. We used manual evaluation by human observer based on the sharpness of tree crowns and detail of the images. Mostly, images at the areas of rotation of vehicle were removed.

The route was uploaded to the driving unit of the copter (Naza V2), though for security reasons, the take-off and landing of the copter were guided by manual radio control. Ground control points were marked and measured in the field using total station and used for orthorectification of the resulting point cloud later. They were carefully spread along the boundaries of the parcel. The flight campaign was executed in the summer of 2015 on selected days with no clouds and wind speeds of up to 5 m s^{-1}. Prior to the flight, the nearest flight tower was consulted and informed about the fly height and position of the UAV movement. In total, 5 flights were needed for the 5 ha plot, using current setting. The total images used for the model construction were 1779.

Image processing was done using the standard procedures in Agisoft Photoscan V. 1.2.6.2834 for photo alignment and dense cloud computation, as described in for example Puliti et al. (2015); Mikita, Janata, and Surový (2016). We used highest alignment for cameras, medium density for the dense cloud with mild depth filtering. The resulting spatial pixel resolution (as the maximum obtained from Agisoft Photoscan analysis) was 3.5 cm for orthophoto and 4.5 for digital elevation model and CHM. It is recommended to decrease this resolution for exporting the orthophoto for further analysis.

2.3. *Tree height-position estimation*

In order to extract the tree positions and heights from the UAV, based on individual tree level, an orthophoto of the study area was acquired in Agisoft PhotoScan and used together with the CHM in ESRI© ArcGIS 10.3.1. For both orthophoto and CHM, the pixel size was set at 0.05 m. To identify the highest pixel value in the CHM, the focal statistics filtering tool in ArcGIS 10.3.1 was used. This morphological filter is preferable since it can be used to eliminate the possibility of the multiple local maxima effect within a single crown area. The method used was adaptive filtering, based on the CHM height values. Initially, an image-smoothing step was applied to the CHM using low-pass filters to (a) reduce the noise effect and (b) regulate the values of the smoothing window (Pitkänen et al. 2004). Tree height was extracted directly from the CHM, using the local maxima algorithm. This consideration for the selection of markers is based on a spatial perspective, under the assumption that at or near the nadir view, treetops are usually located around the centres of the tree crown. Based on this assumption, values were approximated to the nearest integer number of pixels, using circular-shaped areas. Among several tested types, the best results were obtained by setting the kernel to a 1 m radius. Afterwards, the common pixel values were extracted, derived from the process of the focal statistics together with the CHM, to identify tree top location. The regional maximum pixel value in each kernel is usually found near the centre of the object and labelled as a treetop. The use of morphological filter of focal statistics for each input cell location allowed us to calculate the pixel values in the form of weights within a specified neighbourhood around it, by returning the mean, standard deviation, and/or the sum of values. To match the pixel values from the CHM with the result of the focal statistic, we used the following equation:

$$\text{Con}('\text{CHM}' ==' \text{focal statistics result}', 1) \tag{1}$$

This conditional tool (Con) performs an 'if/else' statement on each of the input cells using the raster calculator in ArcGIS 10.3.1. This process is necessary to return a binary file that allows the identification of areas in the study area covered by tree crowns and those representing bare ground by returning 0 in case of no data value and 1 for data value.

The accuracy of tree positions acquired from the UAV data was evaluated based upon field measurements. In total, there were three species present in the field (342 pine trees, 47 holm oaks, and 2315 cork oak trees); the mean height of the species was 7.2, 2.9, and 3.8 m, respectively.

2.4. *Statistical analysis*

The statistical analysis was performed using the commercial software 'IBM SPSS Statistics 23.' We used a visual evaluation of the algorithm performance in different species. The mean being defined by the following equation:

$$\text{Percentage } \% \text{ of found trees} = \frac{\text{automatically detected trees}}{\text{trees detected on ground}} \tag{2}$$

where the automatically detected trees were considered those trees whose estimated tree top position was within 1 m of their actual position. Trees without any maxima in this radius were considered not found. Subsequently, following parameters were tested for significance of success: species and height class. The height was identified only on detected trees and investigated with the height class variable. For evaluation of differences in success of detection of trees among species, we used ANOVA with Tukey and Scheffe test for evaluation of significance; the idea is to verify whether different species are detected with equal accuracy. Spearman correlation was used to evaluate whether error in height estimation is stable among different sized of trees. We choose the Spearman's correlation coefficient, which is more suitable for this particular analysis because of the non-linear shape of the relation among data.

3. Results

As a first step, positions and heights of detected trees were estimated from the UAV; the result in Figure 2 visually shows the high detection-rate ability of the applied algorithm, to estimate the positions and heights for the majority of the trees for all different species, independently of their age and size.

Then, the evaluation of the detection accuracy between the different species allowed us to find out in which cases the detection rate was higher, smaller, or similar, based on the differences of the structural characteristics (i.e. canopy structure) of the examined tree species. Figure 3 clearly shows the accuracy of individual trees found for each species. The three species present in the research plot show different performance, with umbrella pine having the highest accuracy. The two oak species (*Q. suber* and *Q. ilex*) show a lower rate of detection, but there is not found any difference among these two species.

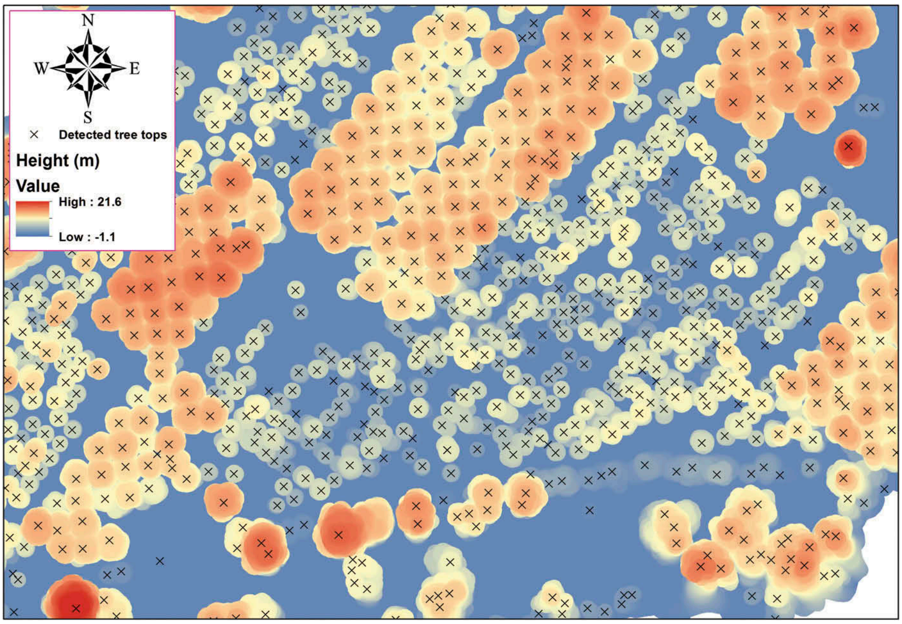

Figure 2. Illustration showing local maxima seeds identified as tree tops in local coordinate system.

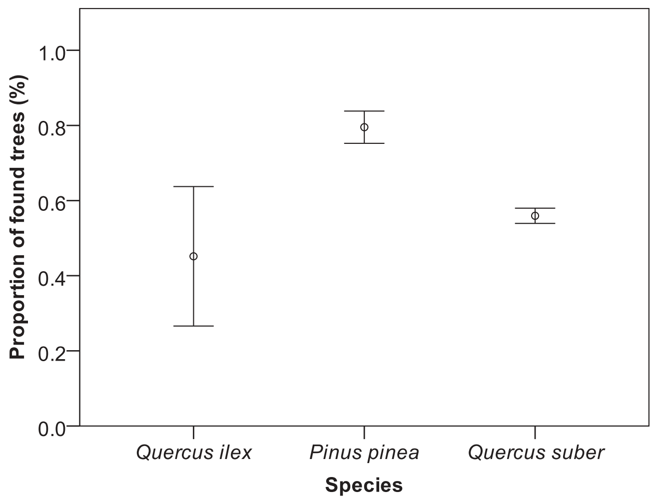

Figure 3. Accuracy of automatic tree detection algorithm in different species. Error bars indicate a 95% confidence interval.

Using ANOVA analysis and selected *post hoc* tests (Tukey, Scheffe), we could conclude that the umbrella pine (coded as species b) is detected significantly better than both of the oak species (coded a and c) at a significant level of $\alpha = 0.05$ (Figure 3). More specifically, the differences between 'b' and 'a' as well as for 'b' and 'c' were found significant (0.000), whereas the differences for the oaks themselves did not differ in assessment and found insignificant (0.077 between 'a' and 'c' for Tukey and 0.096 for Scheffe). The analysis also showed the agreement between the two tests, with slightly

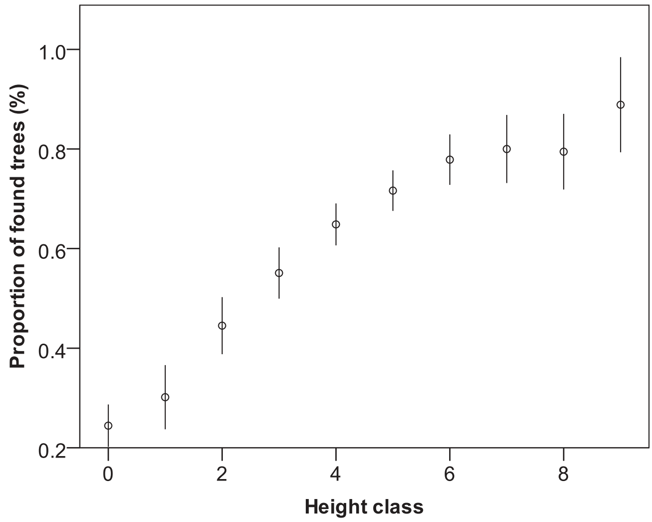

Figure 4. Performance of automatic tree detection algorithm in terms of error behaviour in height, in different tree height classes. Error bars indicate a 95% confidence interval.

higher estimation in case of Scheffe. However, the differences appear positive for the cork oak. Holm oak is not further presented in the study due to its number being too low for conclusive results.

Figure 4 shows the relative detection rate related to the size of the tree (class 0 represents trees with 0–1 m height). It is possible to observe that the percentage of detected trees grows with the tree size, starting above 20% for the smallest trees and peaking at 90% in the largest ones. There are several potential reasons for the small tree omission which are discussed in Section 4 (Figure 7).

The heights were estimated using the 3D point cloud and the normalized height for the estimated tree positions. We calculated root mean square error (RMSE) for tree species as well as tree sizes.

Figure 5 shows the differences in RMSE for the different species. The precision (spread of error, 95% CI) is relatively small in both cases; the accuracy (bias or systematic error) is larger for cork oak. The main reason for this is that the cork oak height is measured by its last shoot, which is, especially in smaller trees, represented by only one or two tiny branches. These branches are practically invisible from above.

Figure 6 shows the performance of height estimation over tree height classes. It is possible to see that the RMSE is rapidly decreasing with tree height and stabilizing on the trees with a height over 4 m.

4. Discussion

4.1. *Feasibility of UAVs in agro-silvopastoral tree plantation measurements*

Unmanned aerial vehicles are gaining more and more attention in last years in forest inventories and individual tree estimation (Puliti et al. 2015; Panagiotidis et al. 2016; Jakkola et al. 2017; Nevalainen et al. 2017). The obtained results in this work confirm that

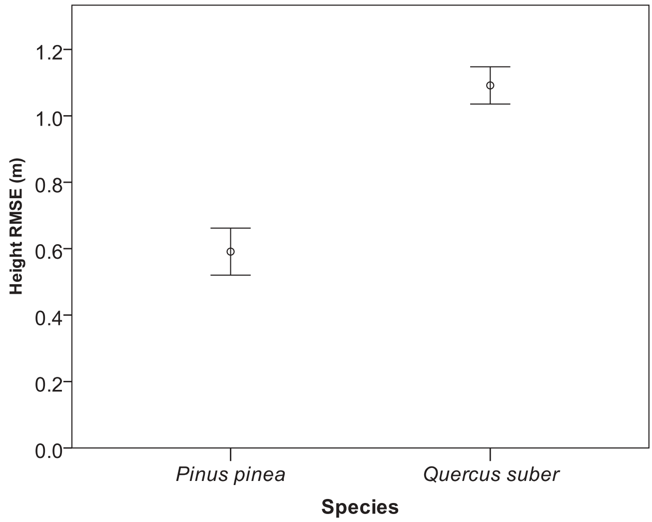

Figure 5. Root mean square error (RMSE) for two different species (pine and cork oak) present in the plot. Error bars indicate a 95% confidence interval.

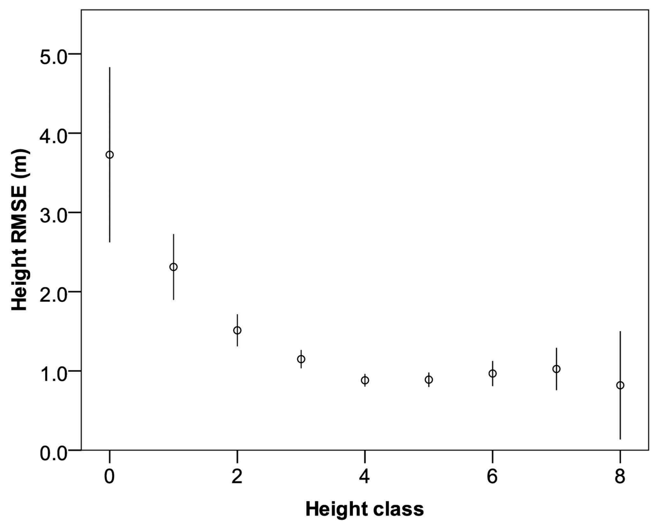

Figure 6. Root mean square error of height estimation related to the tree height for cork oak. Error bars indicate a 95% confidence interval.

with the applied methodology, it is possible to characterize essential attributes to create a forest inventory and also confirms the suitability of the use of low altitude flights with UAVs for the characterization of small plots and to improve forestry precision. Additionally, UAVs will enhance existing field inventories by rapidly capturing some of the metrics required; however, in the current state of the art, the cork oak crown diameters and DBH would have to be either measured in the field either estimated by allometric models for example. UAVs also outperform common aerial imagery due to the small size of these plots and the important need for repeated yearly monitoring.

Consequently, it would be nearly impractical to use the aeroplanes under such conditions. Local areas with lack of water or nutrients can easily be detected and later incorporated into the precision forestry management plans.

4.2. *Ergonomic and economical aspects*

Important information for the forest owners and practitioners is the question about ergonomy and economy of the utilization of UAV. We report here the requirements during our campaign but due to the enormous speed in evolution of the technology, it may be difficult to extrapolate the results further. The time necessary for data acquisition using UAV has to be divided into laboratory pre- and post-processing time and field time and eliminating (decreasing) the time common for the field inventory (e.g. transport to the place, etc.). The pre-processing time includes battery charge, the equipment verification (ca. 2.5 h); the post-processing time includes the photo manual evaluation (selecting and removing images with artefacts, blurred images) and setting the calculation (alignment, dense cloud calculation, etc.). After the creation of point cloud, follows the analysis in GIS environment to find local maxima and calculate the position and heights of individual trees. The total time for computer processing is roughly 5 h per flight but the computer time (calculations and automatic alignment) should also be taken into account. Depending on the density (frequency) of the images, this can take 4–8 h on common PC. The field campaign in this area usually requires several days 4–5 for minimum of two persons for height and diameter measurements; the positions are only measured once after the establishment, requiring approximately two more days. The UAV campaign would reduce the measurement time drastically; on the other hand, one has to take into account the accuracy reported in the work here. Chudý (2017) estimated the UAV time requirement to be less than 25% in the disaster areas compared to the field work; however, only smaller area was measured, which increases the load of transportation time.

4.3. *Accuracy and error assessment*

Different compositions of tree species and height/age classes in a forest plantation area like this case study provided us with the possibility to examine the performance of automated detection rate based on local maxima algorithm for height estimation. Optical cameras on low-flight UAVs can be used systematically for structural forest attributes estimation from an accurate CHM (Dandois and Ellis 2010), by means of regression models (Naesset, 2002). A high overlapping rate, as in our case, resulted in detection rates in almost all height classes. As can be seen in Figure 4, the detection rate is better in taller trees, similar to the work of Sperlich et al. (2014) and increases as the height class increases. This is slightly in contrast with our previous work (Panagiotidis et al. 2016), where bigger trees showed lower detection rates or commission errors – more peaks were found than actual trees existed. However, that study was done on mature forest stands. We found that the error also varies by species; umbrella pine shows a 0.6 m RMSE while cork oak shows a 1.1 m RMSE. These results are in accordance with Hernandez et al. (2016) who reported RMSE of 0.45 m on pines, however using only 52 specimens. To the best of our knowledge, no study on the height and position

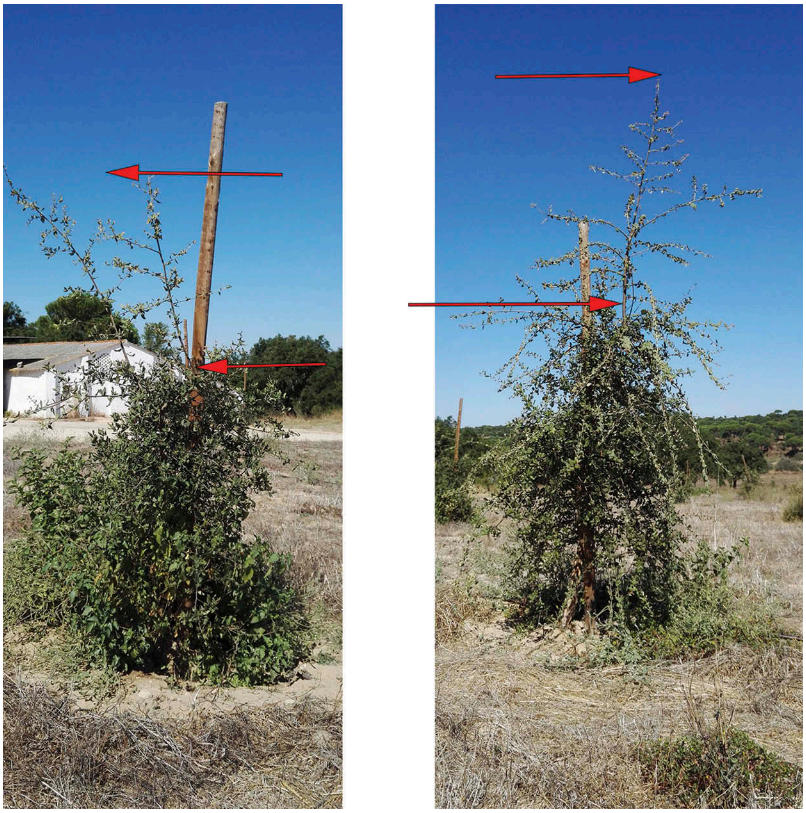

Figure 7. Examples of young cork oaks with individual shoots over the 'main' crown canopy. The arrows indicate the ground measurements and point cloud measurements.

estimation for cork oak was found. The larger error in cork oak detection is most likely because of the sparser canopy and lower density of leaves which, especially in small trees, causes omission errors (the trees are not found at all). The height errors are larger for cork oak, again with decreasing trends with height. The main reason for this behaviour can be explained by the shooting strategy as shown in Figure 7.

The annual shoots on young cork oak trees grow as long individual branches, which are practically invisible from above, making it very difficult to obtain the multi-view as described in Surový, Yoshimoto, and Panagiotidis (2016). In contrast, the shoots on a young pine usually appear all over the crown canopy (Surový, Ribeiro, and Pereira 2011). With age, the cork oak canopy becomes more compact and the shoots shorter; therefore, error in height measurement decreases based on the combination of these two reasons. This behaviour shows clearly decreasing trend (Figure 6).

5. Conclusion

In this study, we proposed a method for automated tree detection and height estimation in agrosilvo-pastoral plantation systems using unmanned aerial system as an alternative for data acquisition. The assessment of accuracy was found worse in the case of cork oak (*Q. suber*), approximately 50%, and holm oak (*Q. ilex*), approximately 43%, compared to the higher detectability of umbrella pine (*P. pinea*), approximately 80%. Clearly, tree species can significantly affect the detection rate. This can be adhered to the tree species structural properties (i.e. crown-shape formation) and age. Also, the size of the tree has positive correlation with accuracy and bias; larger trees are detected more and the height is detected with higher accuracy. Finally, the remote-sensing methods can significantly reduce time for field campaign and also help to increase the areas covered by regular monitoring executed by forestry services.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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