Tree Top Detection in UAV Data: Evaluating Accuracy of Different Estimation Techniques

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Abstract

The tree top point position is important for calculating many parameters and supporting various geometry and analyses. This study compares four methods, i.e., Local Maxima (LM), Template Matching (TM), Top Point Without Slope (TPWS) correction, and Top Point with Slope (TPS) correction, to estimate the tree top point position of Pinus eldarica using UAV-acquired RGB imagery (2 cm ground sampling distance) and high-density point clouds (1.27 points/cm³). The LM, and the TM methods are applied for estimating tree top point positions. The TPWS method uses the tree's shadow on terrain without slope correction, and finally, the fourth method uses the tree's shadow on the terrain with slope correction. Results were compared against Field Tree Top (FTT) point measurements. Findings reveal that LM and TPS were the most effective. LM provided the most accurate results overall, with a relative root-mean-square error (RRMSE) of 1.08, a mean error (ME) of 0.97, and a bias score (BS) of 0.23. Estimating the tree top point position with LM showed strong correlations ($R^2 = 0.94$) with FTT position. This study underscores the value of LM and TPS methods for precise tree top point position estimation, highlighting the need for future research into the estimation of tree top point position methods.

1. Introduction

Pine man-made forests are planted to solve environmental challenges and enhance ecosystem management in many countries. However, the success rate of the planting depends on many factors. The most important is the geometric assessment of previous programs, which is a good opportunity for decision-makers to promote sustainability and develop a better vision for the future. This ensures that the new program is more efficient in improving the chain of environmental conditions. Overall, geometric assessment of previous programs enhances the success of forest programs, particularly in the face of local conditions (Mohan et al., 2021).

Pine trees are one of the most popular species for developing man-made forests due to their various species, adaptation to the natural environment, and widespread natural changes. Pine trees are known for their economic and industrial reasons and help the income of local people. Also, pine trees are a good option for achieving man-made forests with their unique characteristics and making them a preferred choice all over the world (Braun, 2021 & Charnley, 2006).

Tree top point is an important geometric attribute in calculating the many parameters of pine trees. The detection of tree top points plays a main role in extracting geometric parameters from drone image data in man-made forests. Geometric information like tree counts, tree volume and tree heights are essential for decision-making in the forest field. Accurate estimation and monitoring of tree top points in pine trees is essential for forest management practices, as it is the first and important step in many geometric estimations. However, the effectiveness of these depends on a variety of factors and the most important are the spatial resolution of image data and the method of tree top point extraction selection (Wang et al., 2004 & Ghasemi et al., 2022).

Drones equipped with very high geospatial resolution cameras are present to measure tree top points in man-made forests, enabling more detail quickly and economically. However, accurately detecting the tree top point in these images faces a big challenge for some time. Various factors, like pixel size and choosing appropriate methods, are more common and significant than others. For instance, many methods have been tested to present tree detection to expert forests by drone image, and each of them has provided valuable results. Nevertheless, some limitations of the methods still exist, such as low image overlap for point cloud generation. (Diez et al., 2020 & Azizi et al., 2024).

In aerial images, the tree is a region of relatively high reflectance (spectral maximum) surrounded by a darker background. Therefore, the brightest points in the image are considered the tree top point position. Due to the location of the trees at different angles, seasonal conditions, the apparent movement of the sun during the flight, similar reflectance at different pixels, and the tree crown exposed to sunlight, it can incorrectly identify the exact position of the tree top point. Other disadvantages include the limitation to recognizing large and complex patterns, the long time spent especially in introducing sufficient and diverse patterns, and the relative inflexibility of the size and shape of the crown in different models (Template Matching). On the other hand, using point clouds alone can cause several problems in some cases. One of these problems is the presence of high noise in the preparation of point clouds. The use of noise reduction filters can only remove part of the noise. An-

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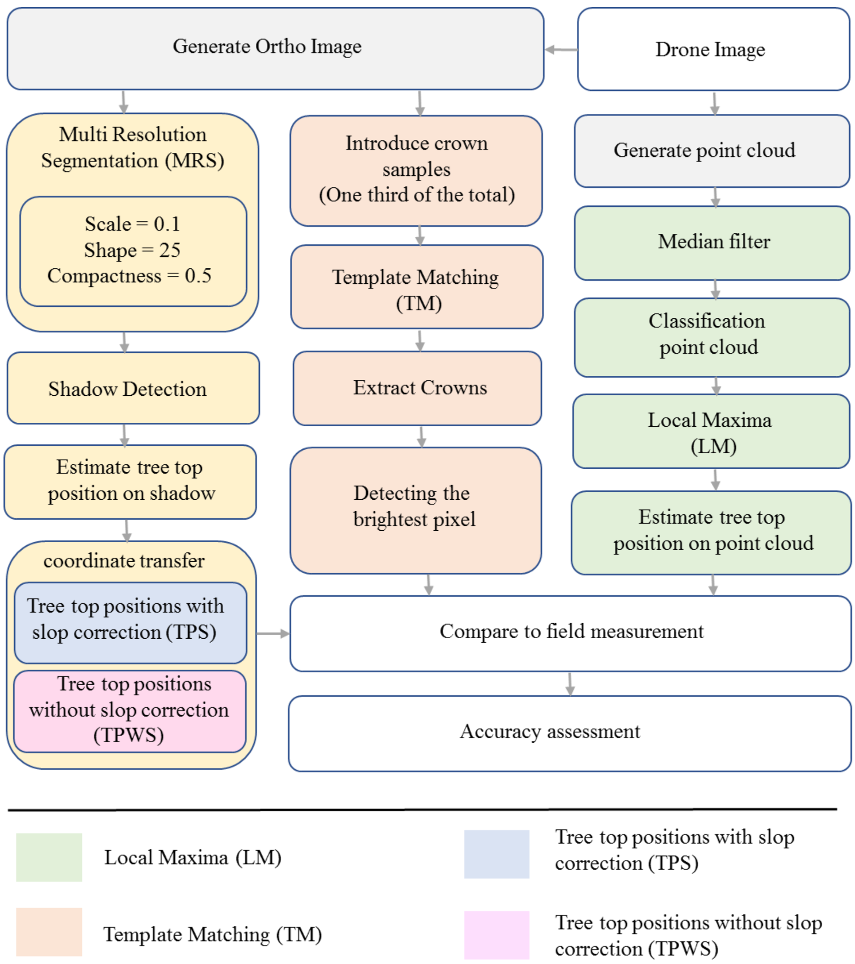
other is the presence of unwanted obstacles such as electricity poles, buildings, and the presence of boulders in nature, the removal of which may also make some tree points inaccessible. Also, due to the vastness of the area, unwanted obstacles slow down the crown extraction process and cause errors (local maxima) (Larsen et al., 2011 and Ko et al., 2025).
Some of these methods use a moving window to find the tree top point, which depends a lot on the species of tree and the size of the moving window. Also, detecting the most intense radiation in one pixel and similar radiation in some pixels increases the error in detection. Another method for tree tip detection is to use the visible part of the electromagnetic spectrum of the crown, which is limited in some cases by band selection. When using the visible part of the electromagnetic spectrum, the selected bands should be selected based on the highest distinction (difference) between the studied features in the bands. Since the data used in this study is only in RGB, the range of band selection is very limited (Saeed et al., 2024 & Zhang et al., 2024).

Despite the progress of various tree top point position methods, a notable gap exists. While methods such as the LM and TM offer valuable advantages, they remain limited in some cases and with special conditions. In this study, we calculated the tree top point position by shadow and then compared it with the tree top point position extracted by LM and TM. The highlight of this research is the consideration of topography using the shadow method. The relatively large distance between trees is one of the advantages of the study area, which makes the comparison more valuable and accurate. By evaluating and comparing these methods, researchers can have a more comprehensive view and make appropriate decisions in different conditions. Furthermore, the aim of this study is to provide strong recommendations based on the comparative results.



2. MATERIALS

2.1 Study area

The study was conducted in Bojnord, North Khorasan Province, Iran. The forest covers an area of 351 hectares, of which the study area is approximately 21 hectares. The geographical coordinates of the study area encompass N, Zone 40 N″57 ′28°37-E″49 ′25°57, located along the main road. The elevation is 1080 m above sea level. The dominant forest species is Pinus eldarica (titeled Tehran pine in Iran). The average rainfall and temperature are 250 mm and 15 °C, respectively. The climate of the region is cold and semi-arid according to Köppen criteria.

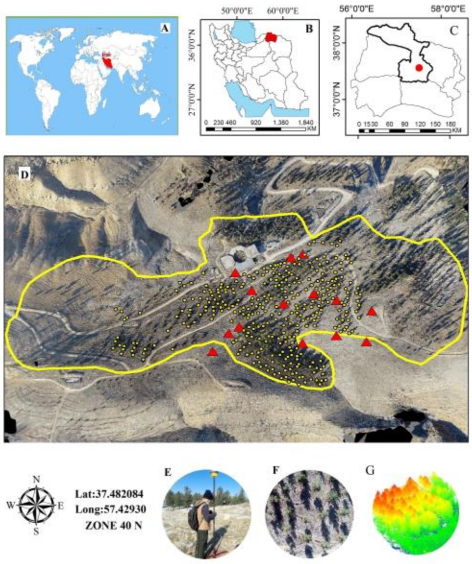


Figure 1. Global location of the study area. (A), Iran (B), Location and overview of the study area in North Khorasan Pardisan Park (C) Aerial view of the study site, indicating the location of sampled trees (yellow circles) and plot boundaries (yellow outline), with ground control points (red triangles) (D), Fieldwork (E), Ortho imagen (F) Digital Surface Model (DSM) (G)

2.2 Field data and Image acquisition

A total field survey of 151 pine trees was selected from a total of 324 trees (Figure 1). In the next step, two parameters, including the location of each tree and height, were accurately recorded. Global Positioning System (GPS) technology was employed for georeferencing, with Horizontal and vertical accuracy of less than 0.8 cm and 0.45 cm, respectively. The 151 tree height measurements were obtained non-destructively with a Leica total station TS02 (7$^{//}$ grad). Image acquisition was conducted on March 4, 2021, at 14:30 local time (UTC: 11:00 AM), resulting in 952 standardized and valid images covering the study area. All images were fully checked to avoid blurring and sun-synchronized effects. During the flight path, the tilt sensor was in the active mode. The date and time were selected for the appropriate shadow length, and the flight speed was set to 4 m/s to avoid motion errors in the images. Fourteen ground control points (GCPs) were also established before the flight. Table 1 shows more details.

Camera manufacturer	DJI
Camera model	FC6310
Focal length	24 mm
Dimension	5472×3448 Pixels
Volume	20 Mega pixels
Shutter speed	1/160 s
Horizontal resolution	72 dpi
Vertical resolution	72 dpi
Format	JPG
Color composite	RGB
Saturation	Normal
Resolution	Normal
Contrast	Normal
UAV speed	4 m/s
Tilt sensor	Active
GNSS	GPS/GLONASS

Table 1. Technical specifications of flight plan and image capturing

3. METHODS

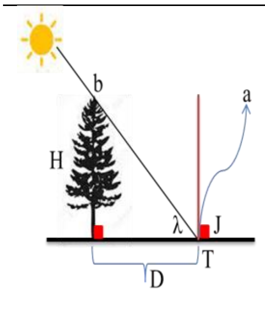
3.1 Using shadow to detect the tree top point

This method can be used in forests where the trees are sufficiently far apart and the tree top point is known. In the first step, all images were prepared with Pix4Dmapper Pro (v4.5.6 x64 Enterprise). Then, point clouds were prepared from paired images using the Structure from Motion (SfM) method. The entire point cloud was denoised with a median filter. This filter was selected based on previous experiences and studies (Yang et al., 2024). This research was carried out using four completely independent methods to obtain tree top point position. In the First step, by generating a point cloud and applying the local maximum (LM) algorithm, the tree top was extracted based on the point cloud. In second step, by using the ortho image from the Template Matching method, 50 crown images (one third of the existing crowns) were introduced as samples. Another 101 remaining crowns were recognized based on the introduced pattern and the tree top point of the crown was extracted from them (eCognition Developer 9.01 x64). In third step, the tree shadow was extracted using the MultiResolution Segmentation (MRS) method, where the critical parameters of compactness, scale, and shape were selected as 0.5, 0.1, and 25, respectively. The MRS parameter rates was selected based on trial and error and previous studies (Hosingholizade et al., 2025). A rectangle was completely fitted over the tree shadow to provide a regular geometric shape for all shadow measurements. The tree length was obtained along with the intersection points of the shadow with the rectangle. Then, in three cases:

1) calculating the shadow length at zero slope (Flat terrain),
2) calculating the shadow length on a negative slope (downhill), and
3) calculating the shadow length on a positive slope (uphill),

The tree length was calculated based on the shadow with topography correction and sun elevation angle, and fourth) without the topography correction (flat terrain for all trees) and sun angle for all trees (Arcmap 10.8.1).

In the third and fourth cases, After calculating the length of the trees with the shadow, the surface and elevation coordinates for the tree top point of the crown were obtained using the equations in Fig 2. Finally, all four points obtained for the tree top point were compared and statistically evaluated with the insitu tree top point position.



(A)

$\hat{R}=\hat{J}+\hat{T}+\hat{\lambda}$

$\hat{J}=90^0$

$\hat{T}=180^0$

$\hat{\lambda}$= Sun Elevation

$x_b=x_a+l_{ab}\sin\hat{R}$

$y_b=y_a+l_{ab}\cos\hat{R}$

$\tan\lambda=D/l_{ab}$

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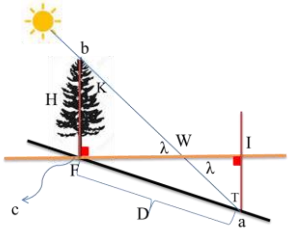
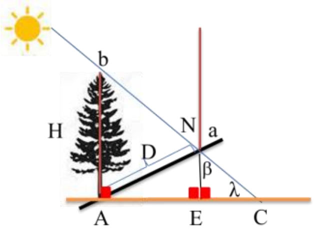


(B)

$$\hat{R}=360^0-T$$
$$Ia=H_c-H_a$$
$$FI=\sqrt{D^2-Ia^2}$$
$$WI=(\sin\hat{90}\times Ia)/\sin\hat{\lambda}$$
$$FW=FI-WI$$
$$bW=(\sin\hat{90}\times FW)/\sin\hat{K}$$
$$bW+Wa=ab$$
$$x_b=x_a+l_{a\,b}\sin\hat{R}$$
$$y_b=y_a+l_{a\,b}\cos\hat{R}$$



(C)

$$\hat{R}=360^0-\hat{N}$$
$$EC=(BE\times\sin\hat{\beta})$$
$$ac=\sqrt{(EC)^2+(BE)^2}$$
$$AE=\sqrt{D^2-(BE)^2}$$
$$bC=\frac{(AE+EC)\times\sin\hat{90}}{\sin\hat{K}}$$
$$ab=bC-aC$$
$$x_b=x_a+l_{ab}\sin\hat{R}$$
$$y_b=y_a+l_{ab}\cos\hat{R}$$

Figure 2. Three states of tree shadows on the ground: zero slope (flat state) (a), negative slope (downhill) (b), positive slope (uphill) (c).

4. Accuracy Assessments

Several statistical tests and performance measures were used to evaluate the accuracy of estimating the tree top position using the four different methods.First, the normality of the data was evaluated using the Shapiro-Wilk test. If the data followed a normal distribution, a paired t-test was conducted to compare the estimated tree top point position with the field tree top point position. If the data deviated from normality, the non-parametric Wilcoxon signed-rank test was used instead. To further evaluate the performance of the four methods, three key indicators were used, including Relative Root-Mean-Square Error (RRMSE) (Equation 1), Mean Error (ME) (Equation 2), and Bias Score (BS) (Equation 3).

$$RRMSE(\%)=\sqrt{\frac{\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(\hat{y}_i)^2}}\times 100 \tag{1}$$

$$ME=\frac{\left|\sum_{i=1}^{n}(y_i-\bar{y})^2-\sum_{i=1}^{n}(\hat{y}_i-y_i)^2\right|}{\sum_{i=1}^{n}(y_i-\bar{y})^2} \tag{2}$$

$$BS=\frac{\sum_{i=1}^{n}(y_i-\bar{y})^2}{\sum_{i=1}^{n}(\hat{y}-y_i)^2} \tag{3}$$

Where y_i is measured the field tree top, $\hat{y}_i$ is the estimated tree top, $\bar{y}$ is the average of the field tree top, and n is the total number of samples (151 trees). In equation 1, a RRMSE value close to zero indicates high accuracy and the efficiency of the method. In equation 2, a ME value equal to 1 indicates acceptable performance, while values less than zero indicates poor effectiveness. In equation 3, a BS greater than 1 indicates that the estimated values are larger than the field measurement, while a value less than 1 suggests an underestimation values (Yim et al., 2011).

5. Results and Discussion

In the present study, RGB drone data of 151 trees were used to estimate the tree top point in a man-made forest. Then, all the results are compared with the field tree top point. Table. 2 and Fig. 3 show that the distribution of geometric parameters such as DBH (p=0.738), crown area (p=0.831) and height (p=0.416) of pine trees did not significantly differ from the normal distribution. Although the only parameter required in this study was the height of pine trees, the distribution of other parameters such as DBH and crown area gives a better understanding of the distribution of trees in the case study (Table 2).

Parameters	Min	Max	Mean	STD	CV (%)
Height (m)	0.5	11.2	6.3	2.4	38.6
DBH (cm)	0.8	13.4	7.0	2.7	39.2
Crown area (m^2)	0.8	49.9	15.9	7.9	49.7

Table2. Summary of the statistical characteristics of 151 eldarica pine trees

As Table 2 shows, the case study has a very diverse range of geometric parameters, which provides a suitable challenge for more reliable results. Fig. 3 shows many of the trees in the study area in middle age. Statistically, 79% of the trees have a DBH between 20 and 30 cm, and 75% have a height between 2 and 10 m.

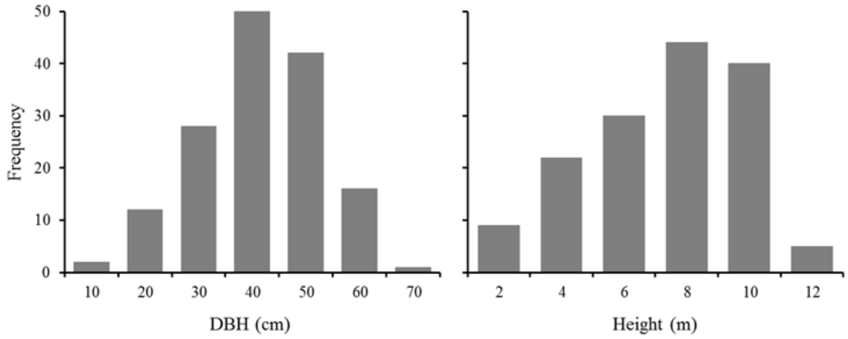


Figure 3. Frequency distribution of height (right) and diameter at the breast (left) of 151 pine.

Methods	Horizontal or Vertical Distance	Min (cm)	Max (cm)	Mean (cm)	STD	CV (%)
Local Maxima (LM)	HD	2.9	16	7.1	1.9	26%
	VD	7.8	32	11.3	2.5	22%
Template Matching (TM)	HD	9	28	15.4	6.8	44%
	VD	13	35	26	10.1	36%
With topographic correction	HD	4.1	23	19	3.1	16.3%
	VD	11.1	44	18	4.8	26.6%
Without topographic correction	HD	18	53	39	19.8	50.7%
	VD	25	89	56	31	55.3%
Field measurement (Reference)	HD		Reference data			
	VD		Reference data			

Table 3. Summary statistics based on the distance from the reference tree top point to the calculated tree top point

Table 3 shows that the tree top point estimated by the LM method provides a more accurate representation, and its statistical parameter is closer to the field tree top point. However, the points of the field and LM do not match exactly, which could be due to the presence of noise. Using a noise reduction filter does not completely eliminate noise, and some of the noise usually affects the final results. In contrast, the TM method has a wider range result, so the minimum and maximum estimated by this method have more difference between the minimum and maximum than the field tree top point. One reasons for this result could be the lack of sufficient patterns. On the other hand, the brightest pixel is not necessarily the tree top, and sometimes there may be changes in the pixel value of the tree top due to the imaging direction and the sun elevation angle. The low correlation between horizontal and vertical distance of the tree top points with TM compared to LM is obvious. On the other hand, On the other hand, tree top detection using shadow provided impressive results. As the RRMSE, ME and BS parameters show, the transfer of tree top coordinates from the ground to the tree top with topographic correction provides acceptable results. It also has the highest correspondence to the reference tree top point after the LM method, and its range is closer to tree top point. Meanwhile, coordinate transfer without considering the topographic correction provide a result that is completely far from reference (Table 3 and Table 4). Without considering the topographic correction, the tree height will be calculated with a high error, which will negatively affect the original tree top position in the calculation process (Table 4).

Table 4 illustrates the statistical performance of four methods used to detect tree top point positions. Among the evaluated tree top point methods, the LM achieved the lowest RRMSE, recording 1.08 compared to field measurements. These results show that the LM method provides the most accurate estimates of the tree top points. In contrast, tree top point detection with shadow without topographic correction method showed the highest RRMSE at 18.21 compared to field measurements, indicating a significant deviation from the measured values. The LM and treetop position with topographic correction also showed the lowest ME for both measurement methods, reaching a value of 0.97, which emphasizes its reliability. In summary, the results in Table 4 indicate that the LM and tree top point, with topographic correction, holds promise for accurately estimating tree top position.

Methods	RRMSE	ME	BS	R^2
Local Maxima (LM)	1.08	0.97	0.23	94%
Template Matching (TM)	7.61	0.73	0.54	78%
With topographic correction	3.14	0.89	0.36	88%
Without topographic correction	18.21	0.41	1.67	52%

Table 4. Tree top position assessment of 151 pine trees. RRMSE (Relative Root Mean Square Error), ME (Mean Error) and BS (Bias Score).

Figure 3 visually compares the different methods for determining the tree top position for a pine tree. The crown area is 21.14 m² (purple), and the LM method estimates the closest point (Orange point) to the measurement point (red point). The horizontal and vertical distances compared to field measurements are estimated to be 8 and 3 cm, respectively. Other methods, such as tree top point with topographic correction, TM and tree top point without topographic correction, have a greater deviation from the reference. This visual interpretation clearly highlights the performance differences. Overall, the LM and tree top point with topographic correction are the most reliable methods for detecting accurate tree top point positions.

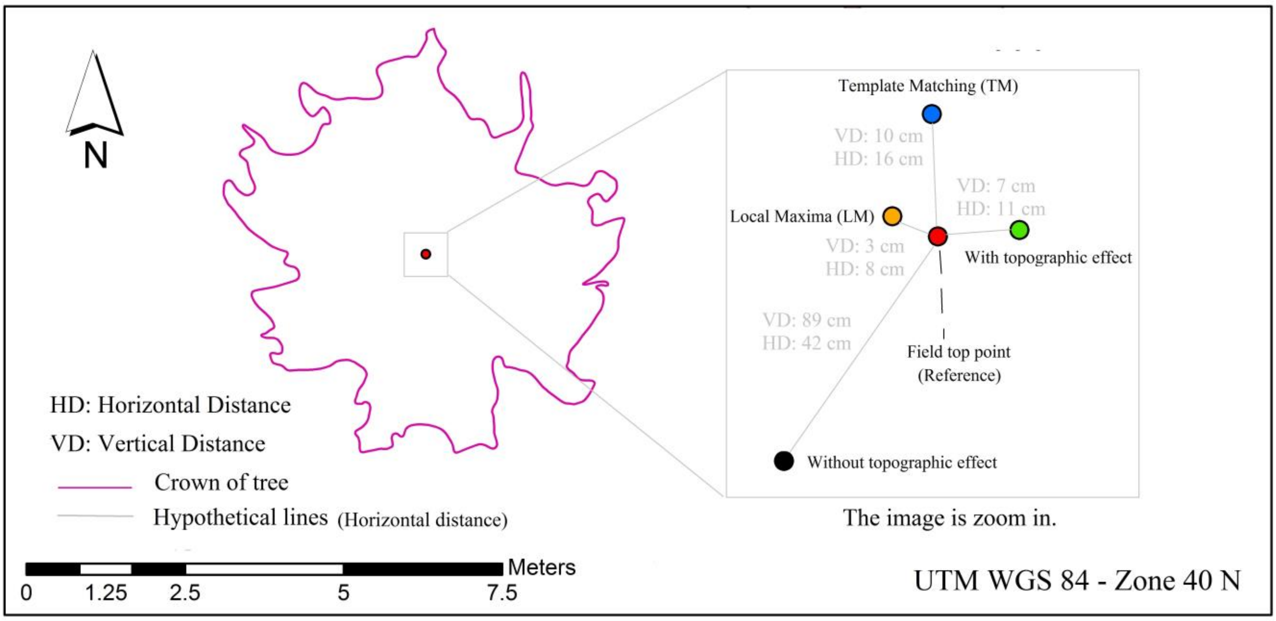


Figure 4. A samples of tree top point position with four methods

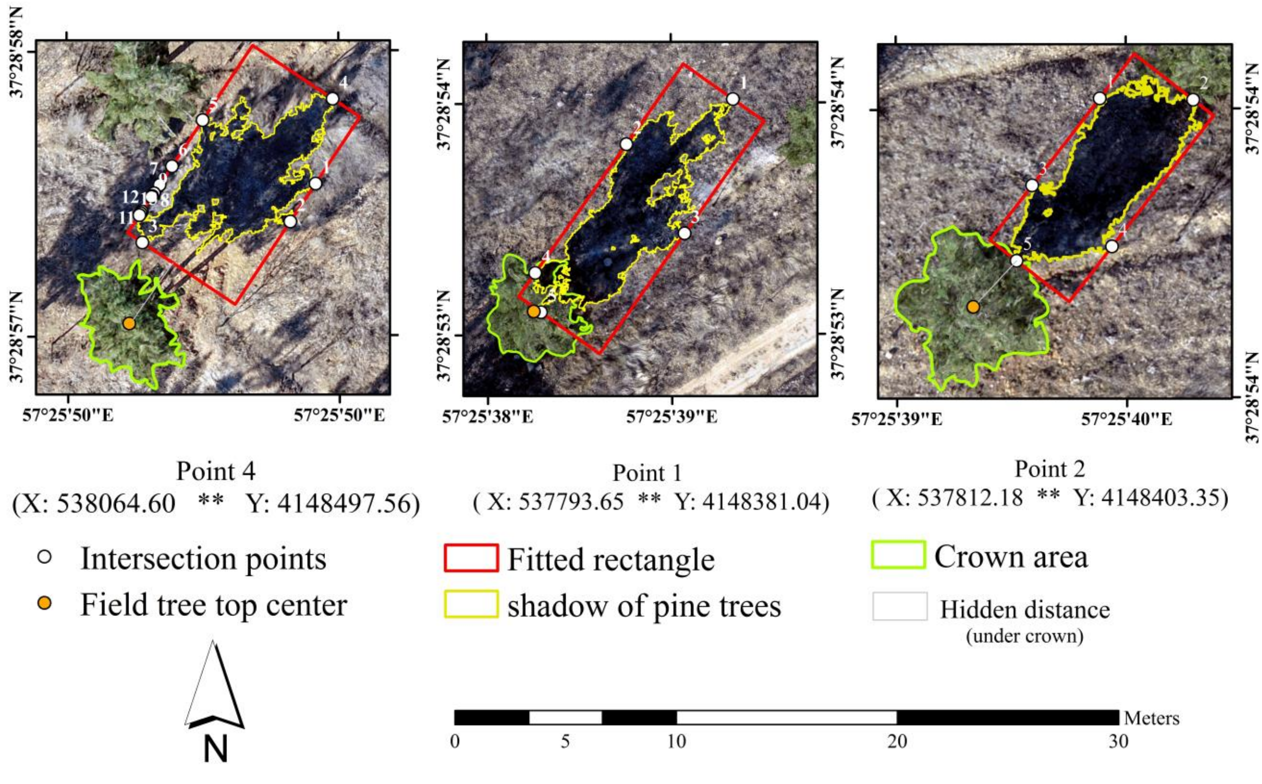


Figure 5. Three samples of pine trees for estimate tree top point position by shadow

6. Conclusion

This study aimed to estimate tree top position of pine trees with four independent methods. LM, TM and two other were performed based on shadow length on UAV imagery. The use of shadow length has been widely used in the literature for many geometric applications (Brigante et al, 2025). However, less attention has been paid to estimating tree top point position by shadow with the slope correction in man-made forest. Therefore, the present study proposed a novel method to estimate the tree top point position of single pine tree in a man-made forest using shadow on UAV RGB images. In general, results showed that estimation of tree top position by shadow and correction of slope significantly improved tree top position estimation. In other words, the estimated tree top point position with the corrected shadow length had no significant difference from the true values ($p = 0.652$). Finally, it can be concluded that topographic correction is necessary in estimating tree top positions using shadow length in mountainous areas. Furthermore, it is acknowledged that LM is more reliable than TM and tree top positions without topographic correction.

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