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SUPPORTING EFFICIENT MANAGEMENT OF OIL PALM PLANTATION USING REMOTE SENSING (RS), UNMANNED AERIAL VEHICLE (UAV), GEOGRAPHIC INFORMATION SYSTEM (GIS) AND GLOBAL NAVIGATION SATELLITE SYSTEM (GNSS)

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Abstract: This paper describes an approach to detect oil palm trees in Malaysia using Unmanned Aerial Vehicle (UAV) images. Malaysia is the world's second largest palm oil producer. Oil palm expansion and replanting can contribute to deforestation, biodiversity loss and a range of social issues. Ensuring successful oil palm management and replanting requires an effective monitoring program to collect information regarding the status of young trees. UAV imagery is low-cost alternative to field-based assessment, but it requires the development of image processing methods to easily and accurately extract the required information. In this paper, regarding tree detection, template matching and Local Maximum Filtering were tested on one representative plot and based on the better performance of Local Maximum Filter on that plot, this approach was applied in to the whole study area. The accuracy of detection was assessed through precision, Recall and F-measure and respectively are 0.7, 0.84 and 0.74. Height of tree as a parameter which changes consistently throughout its life was estimated in whole area and then distribution of height was assessed in the rest part of paper. Based on the height distributions, the most probable area which have older trees were introduced in order to replanting.

Keywords: high resolution imagery, pixel based analysis, local maximum filter, template matching, precision agriculture.

INTRODUCTION

Background

The oil palm (*Elaeis guineensis*) is a species of palms planted extensively in South-East Asia, especially in Indonesia, Malaysia, and Thailand. It has the highest oil-yielding capability among other oil crops, such as soybean, rapeseed, and sunflower (Basiron, 2007). Palm oil has become the most consumed vegetable oil in the world (35% as of 2016) (Khai et al., 2017). Palm oil becomes raw material in many products and is needed in great demand which causes the development of oil palm plantation to increase rapidly during the past decades. The cultivation of oil palm across the tropical countries raises a controversy because, on one hand, oil palm production is a major economic factor, but on the other hand, it endangers biodiversity and degrades the environment with a global impact on carbon emission (Koh and Wilcove, 2008). The most viable opportunity for carbon sequestration in this region is through precise management of agroforestry therefore these areas can be managed to balance economically necessary short-term production with long-term carbon sequestration. Estimation of Above-Ground Biomass (AGB) could provide a snapshot of the amount of carbon that resides in an ecosystem. It is useful to serve as an indicator of an effective carbon sink (Brown and Food and Agriculture Organization of the United Nations., 1997).

Due to controversial nature of oil palm plantation in tropical forest, accurate inventories and monitoring of oil palm areas are needed for plantation management and plant area expansion. Remote sensing is one of the most reliable measurement tool for accurate monitoring over large areas. Remote sensing image sensors carried out on both space borne and airborne platforms offer an effective way for direct measurements related to the oil palm plantation. In particular, successes have been reported in many studies such Kumar *et al.*, (2017), Shafri *et al.*, (2011) and Santoso *et al.*, (2011) which used different satellite and airborne images to detect diseases in oil palm in early stages or Santoso et al., (2017) and Shafri et al., (2009) which tried to count oil palm tree respectively with QuickBird high resolution image and airborne imaging spectrometer for applications (AISA) data. To estimate oil palm yield Chemura, Van Duren and Van Leeuwen (2015) used WorldView-2 multispectral data and Darmawan *et al,.* (2016) used ALOS PALSAR 2 to investigate age and yield of fresh fruit bunches.

However, there are still some limitations in the application of space borne remote sensing. On the one hand, the coarse resolutions satellite-based data often cannot meet the requirements of regional and local measurements. On the other hand, not only are the fine resolutions satellite-based data highly costly per scene, but the spatial resolution also remains not high enough for precision agriculture. In addition, satellite-based data are strictly limited by the revisit period, and it is difficult to expect cloud free image data acquired on a specific time especially for tropical countries where clouds are a serious hindrance for satellite image acquisition (Tian *et al.*, 2017). To this end, airborne remote sensing platforms may theoretically be used to make up the limitations of space borne devices, but the high cost and lack of operational flexibility due to restrictions in takeoff and landing sites have hindered research with regular spatial and temporal monitoring.

Meanwhile, UAV platforms provide various types of cost-effective remote sensing data, including true color, multispectral, hyperspectral, LiDAR, microwave, and thermal data, at very high spatial resolutions and at flexible acquisition periods. It is more flexible and controllable than traditional satellite remote sensing in terms of flying height, viewing angles, and forward and side overlap. UAV applications in oil palms have already become a commercially practiced norm in major plantation companies in Malaysia and Indonesia where each company runs their own UAV team. Also, several studies have used UAV images as the core data collected such as Lim *et al.*, (2015) which proposed calculation of tree height and canopy crown from drone images or Dimitrios Panagiotidis, Azadeh Abdollahnejad and Chiteculo, (2016) which used high-resolution UAV imagery to determine tree height and crown diameter in Czech Republic.

In order to estimate AGB, number of tree and height of trees are important and necessary practices. However, they are costly and labor-intensive practices to be carried out on field level. They are prone to human error. UAV imagery could be a solution to this issue as it provides a bird's eye view of the plantation and a way of counting the trees automatically. Number of studies such as Hassaan *et al.*, (2016) and Kalantar *et al.*, (2016) have used UAV images in order to counting individual tree however oil palm tree height extraction from UAV image has not been discussed.

Objective

As a first step, the present study aims to detect individual oil palm trees and their representative heights from UAV images in oil palm plantation site in Malaysia.

METHODOLOGY

Study area

The study was carried out in Lurah Bilut in the district of Bentong and Pahang in Malaysia (Figure 1). The study area is located within longitude 101.93° N to 101.95° N and latitude 3.68° E to 3.64° E, covering an area of about 97 km^2. The altitude ranging between 97 m and 194m above sea level. The climate is classified as tropical. The temperature here averages 26.8 °C. Precipitation here averages 2419 mm.

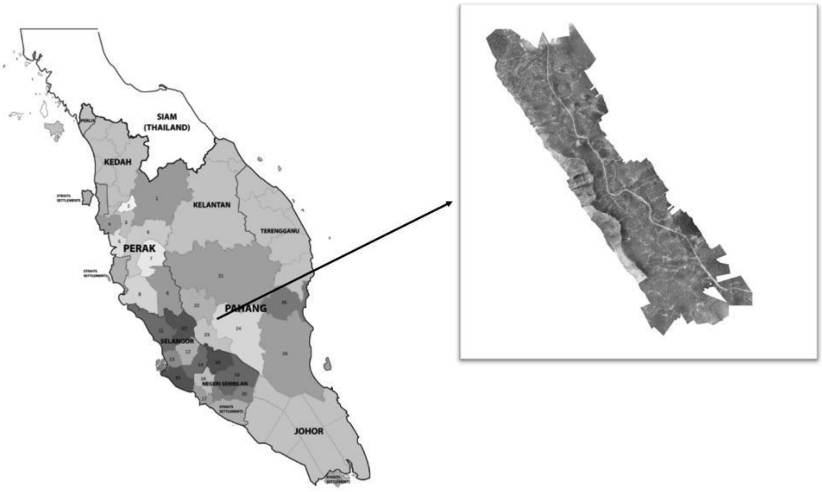

Figure 1: Location of study area.

UAV image

Orthorectified UAV images along with DTM and DSM were acquired from Felda Global Ventures Holdings Berhad (FGV). The image covers 6.97 km^2 of FGV plantation site and consist of 731 RGB images. All images were taken by Canon PowerShot S100 (5.2 mm) boarded on UAV on 6th March 2016 with ground resolution of 9.22 cm/pix. In order to speed up computation time the area was divided in to 8 plots (Figure2).

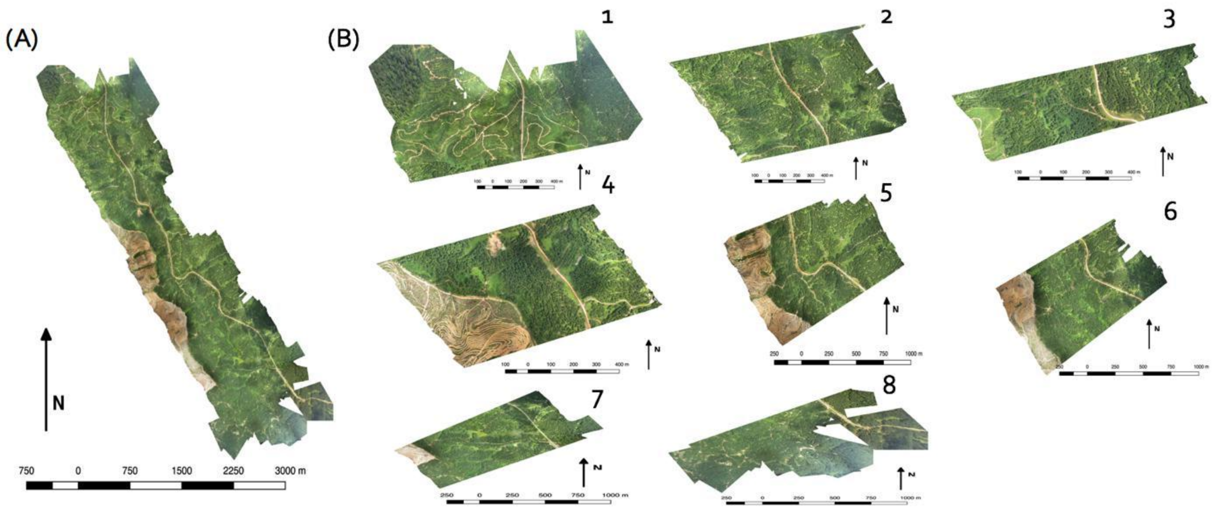

Figure 2: A) Whole view of study area B) Divided parts of area.

Individual Tree detection

To detect individual trees, Local Maximum Filter (LMF) and Template Matching were applied to one representative plot. Accuracy of both approaches were checked and the most accurate approach was selected for further analyses.

Local Maximum Filter (LMF)

In average brightness image the brightest pixels represent tree crown top points. However, the brightest point of the tree is not necessarily the crown top, while it depends on actual sun and sensor angle configuration too. It is important to have only one local maxima found in each crown for following steps. We have to make a decision about each pixel, whether or not it could be a maximum inside some neighborhood. Size of this neighborhood should correspond to expected crown size, but crown sizes can vary significantly over the region of interest. The use of statistical and topological analysis of a pixel neighborhood can help us with decision about appropriate local-maxima-window size.

In this regard, first Canopy Height Model (CHM) was generated by subtracting Digital Terrain Model (DTM) from Digital Surface Model (DSM) which were derived from UAV images previously. In the next step, LMF algorithm along with other filters (such as Maximum filter) were used to detect peaks (highest pixel value) in the CHM raster.

Template Matching (TM)

Template matching (TM) is a technique used to find an area in a larger image that matches a specific and smaller template image (i.e. a sub-image of that larger image), hence has been instrumental in tasks such as object recognition (Ahuja and Tuli, 2013). Template matching is a measure of the similarity between the image and the feature. Basically, the algorithm compares a template that contains the shape we attempt to find (here is an oil palm tree, to an image. In order to achieve high quality detection of trees, an optimized template was selected based on an iterated process. First, several templates were identified in the original image. Second, in order to select the best final template (with the best image quality), the performances of these templates were checked. Different thresholds were checked from 0.8 to 0.3, and the one which had more detected object was selected.

Accuracy assessment

To check the accuracy, common performance metrics (precision, recall and the F-measure) were calculated.

$$Precision = \frac{TP}{TP+TF} \tag{1}$$

$$Recall = \frac{Tp}{TP+NF} \tag{2}$$

$$F - measure = \frac{(1+\alpha)*Precision*Recall}{\alpha*Precision+Recall} \tag{3}$$

Where a True Positive (TP) is the number of correctly detected oil palm. A False Negative (FN) is an oil palm tree that is not detected. A False Positive (FP) shows a pixel that is recognized as an oil palm tree but it is something else. α is a non-negative scalar. In this study, α is set to 0.5 as suggested in (Liu et al., 2011). In this context, precision can be interpreted as the probability that a detected oil palm tree is valid and recall is the probability that the correct oil palm tree (ground truth) is detected. As shown in Equation (3), the F-measure is defined as the (weighted) harmonic mean between precision and recall. That is, the precision and recall are combined into a single performance measure. Consequently, it can be used as an overall performance metric.

RESULTS AND DISCUSSION

Detection performance

To detect individual trees, LMF on CHM and TM on RBG image were done on plot No. 4 where image distortion and blurriness are less in compare to the other plots. The accuracy of both methods is shown in table 1. Figures 3 and 4 show detected trees by LMF on CHM in pixel coordination and TM with threshold 0.3 for plot 4.

Table 1: Table of Accuracy of representative plot.

Approach	Precision	Recall	F-measure
LMF on CHM	0.69	0.83	0.73
TM	0.66	0.67	0.65

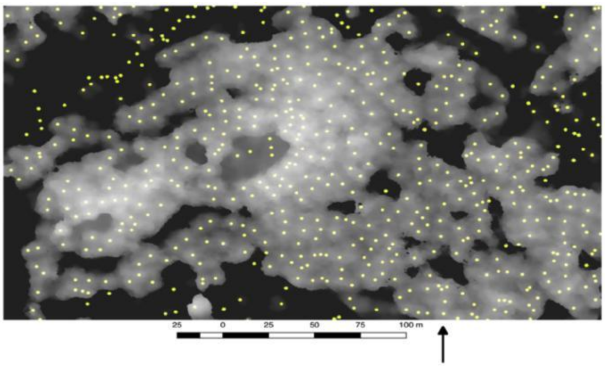

Figure 3: Detected trees by LMF on CHM in pixel coordination for plot 4.

Figure 4: Detected trees by TM with threshold 0.3 for plot 4.

LMF on CHM works well in most of area however the performance decrease in dense area. Contradictory to TM, in this approach shadows are not counted as trees which makes it more precise. The main challenge of LFM on CHM in this study was the weak differentiation power between background vegetation and oil palm trees.

As it is shown in Figure 4, the detected oil palm trees by TM were represented as red rectangles. Most of the trees were detected accurately, however, the main challenge was that some trees were counted twice or more especially, in dense areas. In areas where palm trees are separated, the template matching algorithm works better.

Based on better performance of local maximum filter on CHM in compare with template matching, local maximum filter was selected as main algorithm and applied on the other plots and their accuracies are shown in table 2.

Table 2: Accuracy of oil palm detection by LMF.

Plot No.	Precision	Recall	F-measure
1	0.62	0.79	0.66
2	0.70	0.85	0.74
3	0.72	0.87	0.76
4	0.69	0.83	0.73
5	0.75	0.88	0.78
6	0.7	0.87	0.74
7	0.7	0.89	0.75
8	0.72	0.8	0.74
Avg.	**0.70**	**0.84**	**0.74**

Regarding calculated accuracies, the least accuracy belongs to plot 1, where big area of plot has distortion mainly because of UAV flight pattern. Also, on other plots where images have distortion the detection performance decrease therefore for the future process on this image it is suggested that in order to speed up analysis and increase accuracy, eliminate those distorted parts from the main image.

Height of oil palms

Detected oil palms by LMF were transferred from pixel coordination to XY coordination in QGIS 2.18 and the height of each tree was calculated based on DSM. Figure 5 shows all detected trees and their representative.

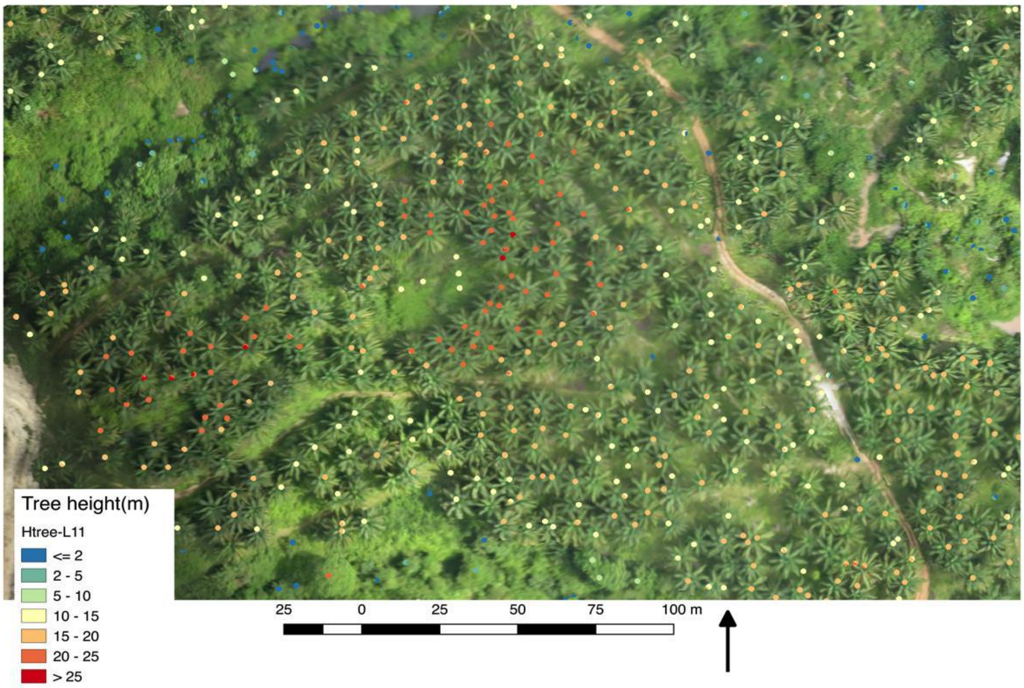

Figure 5: Classification of detected oil palms based on their heights.

Height distribution of oil palms

To investigate about oil palm characteristics, based on frequency of heights, histogram of height distribution in each plot was generated (Figure 6-13). Under normal plantation conditions, and particularly with heterogeneous planting material, there are often marked palm-to-palm differences, but the average increase in height will be from 0.3 to 0.6m per year. In high forest, palms may reach a height of 30m but elsewhere they reach no more than 15 or 18m. A plantation will normally be replanted when the average height exceeds about 10m, usually after 25 years or so mainly because decrease in yield and difficulty in harvesting (Corley and Tinker, 2003). The taller the palm, the older it is likely to be and more likely to being replant.

As it was mentioned previously, plot 1 has the most image distortion among other plots, this plot is located close to the forest vegetation and has been newly cultivated therefor as it is seen in Figure 6 the most frequent height in this plot is one to three meter. It this plot there are some error in terms of height which are mainly related to some errors in DSM therefore based on the less detection accuracy and newly cultivate texture, this area could be extracted in case of replanting.
The most frequent height in plot 2 (Figure 7) is around 16.5 m and in plot 3 (Figure 8) is 14m. By visual interpretation, it could be said that the only difference between plot 2 and 3, is that in compare to plot 2, plot 3 has bigger area covered by slightly shorter trees which are more likely to be younger.

The most frequent height in plot 4 (Figure 9) is 14.5 m however the most frequent height in the plot 5 (Figure 10) is around 16.5 m. By visual interpretation, it could be said that the only difference between plot 4 and 5, is that in compare to plot 4, plot 5 has smaller area covered by slightly shorter trees which are more likely to be younger. In other words, the majority of plot 5 area has covered by slightly older trees.

In the last plot (Figure 13), the most frequent height is 1-4 m and this plot also located in the border of oil palm plantation site and forest which is newly cultivated.

CONCLUSION

In all plots, there is a road which crosses from the middle of the plots and divides each plot into western and eastern part. It seems that the western parts of plots are slightly shorter and younger and could be said that the eastern parts have been cultivated slightly earlier than western part and as for replantation of older trees, it is suggested to start felling from western part of each plot especially from plot 5 which has the tallest trees and most likely older trees.

In conclusion, it should be noted that the local maxima approach works well for tree location estimates and local maxima are useful as seeds for tree crown delineation however this technique cannot differentiate between oil palm trees and other vegetation.

Regarding aim of oil palm plantation management in Malaysia which is ensuring biodiversity conservation through agroforestry systems, it is expected that integration of other algorithms with LMF can produce more accurate result in oil palm detection.

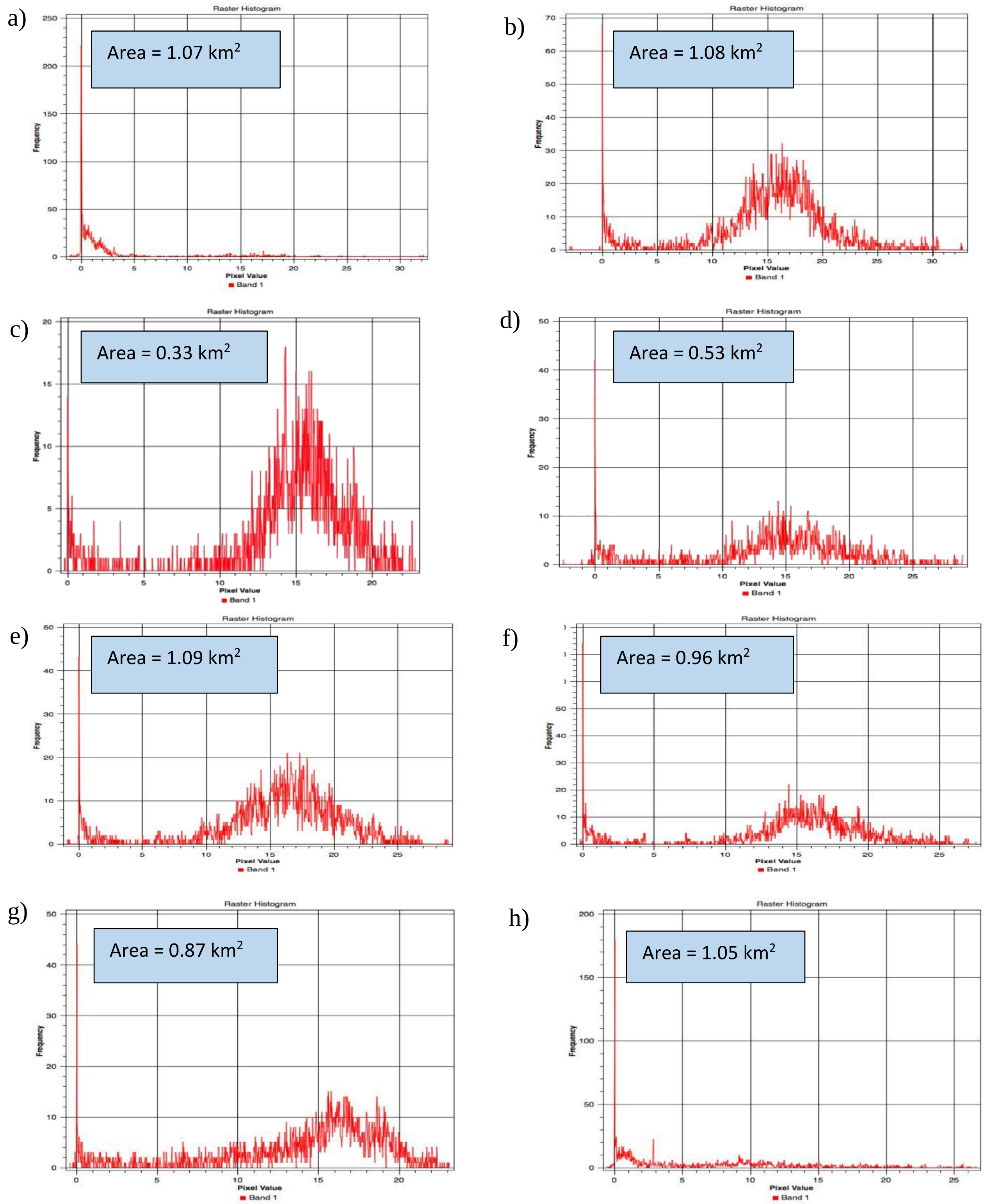

Figure 6: Histogram of height distribution- (a) plot 1, (b) plot 2, (c) plot 3, (d) plot 4, (e) plot 5, (f) plot 6, (g) plot 7 and (h) plot 8.

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