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HEIGHT MEASUREMENT AND OIL PALM YIELD PREDICTION USING UNMANNED AERIAL VEHICLE (UAV) DATA TO CREATE CANOPY HEIGHT MODEL (CHM)

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ABSTRACT:

Oil palms are currently in high demand, which tend to increase even higher as a source of alternative energy for humans, especially in Southeast Asian countries. This leads to the study that focuses on the height measurement, using an unmanned aerial vehicle (UAV), and age analysis of oil palm trees planted within the experimental plots in order to predict their yield. The methodology described in the paper provides using Canopy Height Model (CHM) for height measurement and prediction of the oil palm yield by multiple linear regression. The results indicated that the errors caused by overlapping age ranges were found in 3 out of 12 experimental plots. Furthermore, the primary factors influencing the oil palm yield prediction included the age (9 years and above) and canopy density (over 41% of the area), while the secondary factors supporting more accuracy included the total plot area, canopy area, and canopy height, with the coefficient of determination or R-squared at 0.98. In this study, we learned that the aforementioned factors could be concluded from the data collected by an UAV, which reduced the time for measuring the height of each tree manually, resulting in more accurate yield prediction.

Key-words: *Oil palm yield, Unmanned Aerial Vehicle, Canopy Height Model, Height measurement*

1. INTRODUCTION

The energy generated from fossil fuels–such as petroleum, natural gas, and coal–is non-renewable and deemed non-eco-friendly, causing environmental pollution to the earth. Alternative or renewal energy, therefore, becomes an efficient solution to address this issue. Becoming a source of alternative energy and bioenergy for transportation and industry development (Fitrianto et al., 2017; Sumathi et al., 2008), oil palms have been vastly cultivated across Southeast Asia (Chong et al., 2017; Zheng et al., 2021; Farobie & Hartulistiyoso, 2022). Ranked the third of the world after Indonesia and Malaysia, respectively (FAO, 2020), the oil palm plantations in Thailand cover the area of 9,405 square kilometers, 283.16 of which is found in the western region, especially in Prachuap Khiri Khan where the oil palm plantations spread across the area of 218.18 square kilometers. In Bang Saphan Noi, a district located in this province, the oil palm plantations cover the area of 81.59 square kilometers (Agricultural Product Data, 2018).

As a result of technological advance, the popular remote survey has been applied to agricultural industry in terms of mapping, locating suitable areas for oil palm cultivation (Shaharum et al., 2020), monitoring and improving agricultural yield (Dansagoonpon & Tripathi, 2013, Amirruddin et al., 2020; Shen, et al., 2022), predicting yield (Piekutowska, et al., 2021) and carbon emission of each type of crops (Kiew et al., 2020). During the past 20 years the technology of unmanned aerial vehicle (UAV) has been applied to a number of studies in various fields, including environment, forestry and ecosystem, and wildfire effect. For agriculture, UAVs have been used to develop the precision agriculture (Akhtman, et al., 2017; Tsouros et al., 2019; Zheng, et al., 2021; Velusamy, et al., 2022) and analyze crop health (Izzuddin et al., 2020; Kurihara et al., 2022).

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Satellite images and LiDAR have been also applied to the digital elevation model (DEM), digital surface model (DSM), and canopy height model (CHM) in order to analyze the areas for slope indication and water flow planning. In this regard, Ahmad et al. (2017) reported the high accuracy of the data generated from the DEM, DSM, and CHM using LiDAR. In addition, the photogrammetry was applied to the study of Lisein et al. (2013) in order to create the CHM with the images taken by the UAV along with the data from LiDAR and linear regressions to classify the high and outstanding canopies in the forest area from the CHM.

This study of oil palm yield prediction in Bang Saphan Noi, Prachuap Khiri Khan, has the objectives to measure the oil palm height by using the UAV and analyze the oil palm age within the experimental plots. The results can provide the accurate yield prediction (Hernández et al., 2022) for further yield efficiency improvement to the plots (Fawcett et al., 2019). The analysis of the data collected by the UAV can lead to the planning and implementation of agricultural policies in provincial level, as well as the efficiency improvement to low yield plots for future production and marketing planning by the agriculturists.

2. STUDY AREA

As the last district before entering the southern region of Thailand, Bang Saphan Noi is one of the districts in Prachuap Khiri Khan, located at 11°4′30″N to 11°2′57″ N and 99°16'39″E to 99°17'03″E (**Fig. 1**). The west of the study area is the Tenasserim Range, forming a barrier between Thailand and Myanmar from north to south. With the Gulf of Thailand in the east, a coastal undulating plain, covering the area of 671.97 square kilometers is situated in the center of the study area, divided into 5 subdistricts: Pak Phraek, Bang Saphan, Sai Thong, Chang Raek and Chaiyarat. The area of 448.28 square kilometers (66.71% of the total area) is utilized for agricultural purposes, 105.47 square kilometers (23.53% of the total agricultural area) of which is covered by oil palm plantations, equivalent to 15.69% of the total area of Bang Saphan Noi (Land Development Department, 2018).

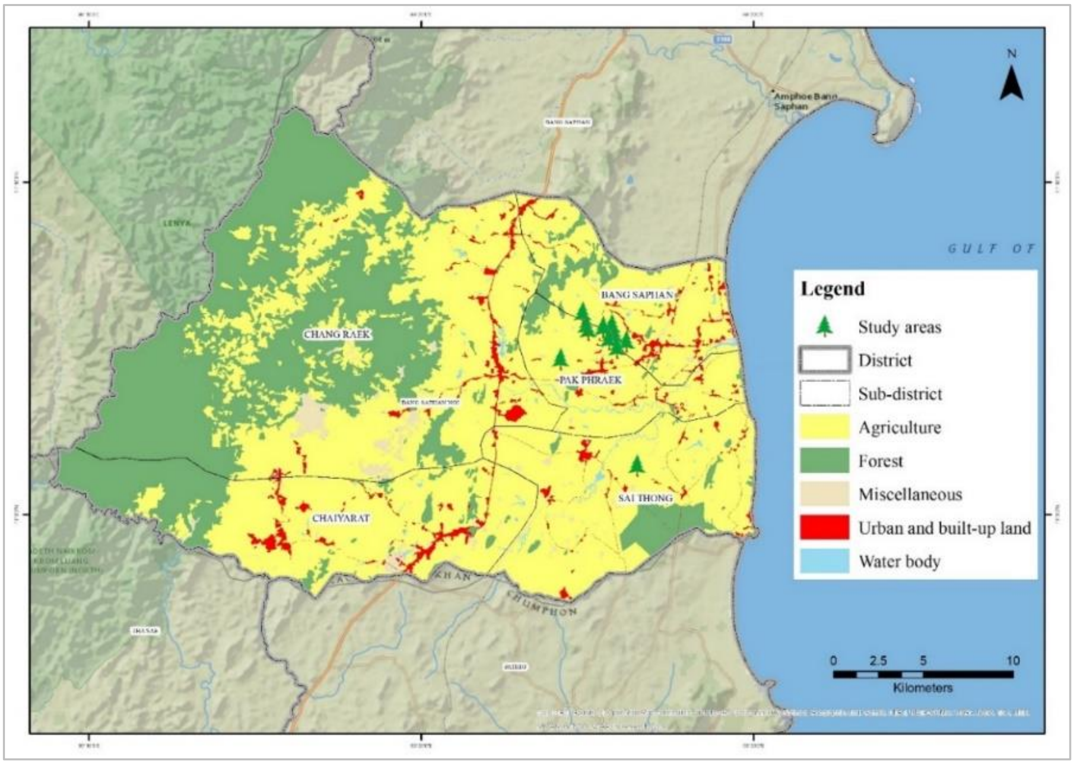


Fig. 1. Land Utilization Map of Bang Saphan Noi, Prachuap Khiri Khan.

3. DATA AND METHODS

3.1. Data Collection

The data was collected from 12 experimental plots following the purposive sampling and after obtaining permission to fly a UAV for data collection within the plots between August and September in the study areas. The selected UAV was DJI Phantom 4 Pro V 2.0, with the key features comprising: GPS/GLONASS satellite positioning systems; flying distance up to 7 kilometers; service ceiling up to 500 meters; wind speed resistance up to 36 kilometers/hour; operating frequency at 2.40-5.85 GHz; 1-inch CMOS camera (12.80 × 9.60 mm) with effective pixel of 20 MP (megapixels), FOV at 84˚, f/2.8-f/11, auto focus at 1 meter-∞; and 3-axis stabilization (pitch, roll, yaw) (DJI, 2018). The RGB color model applies to the captured images which are in JPEG format. The double grid flight path at 90-meter height was employed with the side lap at 70% and overlap at 80%, resulting in the ground sample distance in the images of 2.47 centimeters. Flight planning is very important to image quality and the results of this study are very important. In this study, image position overlays were used side lap at 70% and overlap at 80% to avoid overlaying of images that affect processing. Moreover, the high altitude at 90 meters has a huge effect on image quality. However, in this study was conducted from the height of oil palm trees with a GSD of 2.47 meters. From this quality, it was explained that the object could be separated at 2.47 meters, which was considered a high image quality.

In addition, the suitable flight period for this area was between 10.00 hours to 15.00 hours due to calm wind, resulting in the most appropriate images for this study.

3.2. Methodology

To measure the height of the oil palm trees in the study area, the UAV photogrammetry was applied, as well as the orthorectification which is the process of eliminating the relief and tilt displacement by using the terrain data and referring to the Universal Transverse Mercator (UTM). This resulted in more accurate position, size and shape of the objects presented in the adjusted images in accordance with the photogrammetric principle. Therefore, the orthoimages, digital terrain model (DTM) and digital surface model (DSM) were produced.

The DTM and DSM were then used to calculate the canopy height model (CHM) by analyzing the data with the geographic information system (GIS) using the raster calculator as presented in Equation 1 (Ve´ga & St-Onge, 2009; Mohan et al., 2017; Wang et al., 2021).

The formula is expressed as follows:

$$CHM = DSM - DTM \qquad [\mathrm{m}] \qquad (1)$$

where:

CHM = Canopy Height Model

DSM = Digital Surface Model

DTM = Digital Terrain Model

As a result of the above equation, the CHM provided the characteristics and height of the oil palm trees within the study area. The results from the model were used to identify the canopy shapes by converting the data from the raster images to vector graphic, which was then used to indicate the canopy density in the study area. Regarding the age analysis, 4 age ranges were classified seed, 0-3 years; young, 3-8 years; teen, 9-14 years; and mature, 15-25 years. The data collected by the questionnaire during a ground survey was later used to verify such age ranges, as presented in table 1.

Table 1.

Analysis of Age Ranges and Canopy Density.

Group	Class	Age Range	Canopy Density (%)
1	Seed	**0-3**	Less than 10
2	Young	**3-8**	10 – 40
3	Teen	**9-14**	41 – 80
4	Mature	**15-25**	More than 81

Source: Fitrianto et al. (2017).

The oil palm yield prediction in Bang Saphan Noi, Prachuap Khiri Khan was subject to 5 influencing factors, consisting of: canopy area, canopy density, canopy height, age, and total plot area. They were the independent variables while the yield of each plot was the dependent variable. Then the yield prediction was calculated using the multiple linear regression as presented in Equation 2 (Liu et al., 2021; Abrougui et al., 2019).

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + .. + \beta_i x_i + \varepsilon \tag{2}$$

where:

β = Coefficient of Estimation
x = Variable Influencing Oil Palm Yield in Experimental Plot
y = Yield of Experimental Plot

The result from the above multiple linear regression was later used to verify the data collected from each experimental plot. The accuracy and reliability of such data was assessed by the coefficient of determination or R-squared (Abrougui et al., 2019).

$$R^2 = \frac{RSS}{TSS} \tag{3}$$

$$RSS = \sum_{i=1}^{n} (f_i - \bar{f})^2 \tag{4}$$

$$TSS = \sum_{i=1}^{n} (Y_i - \bar{Y})^2 \tag{5}$$

where:

RSS and TSS coefficients represent the sum of squares and the total sum of squares where f and Y are the means of the predicted values (f_i) and observed data (Y_i). The entire process is shown in **Figure 2**.

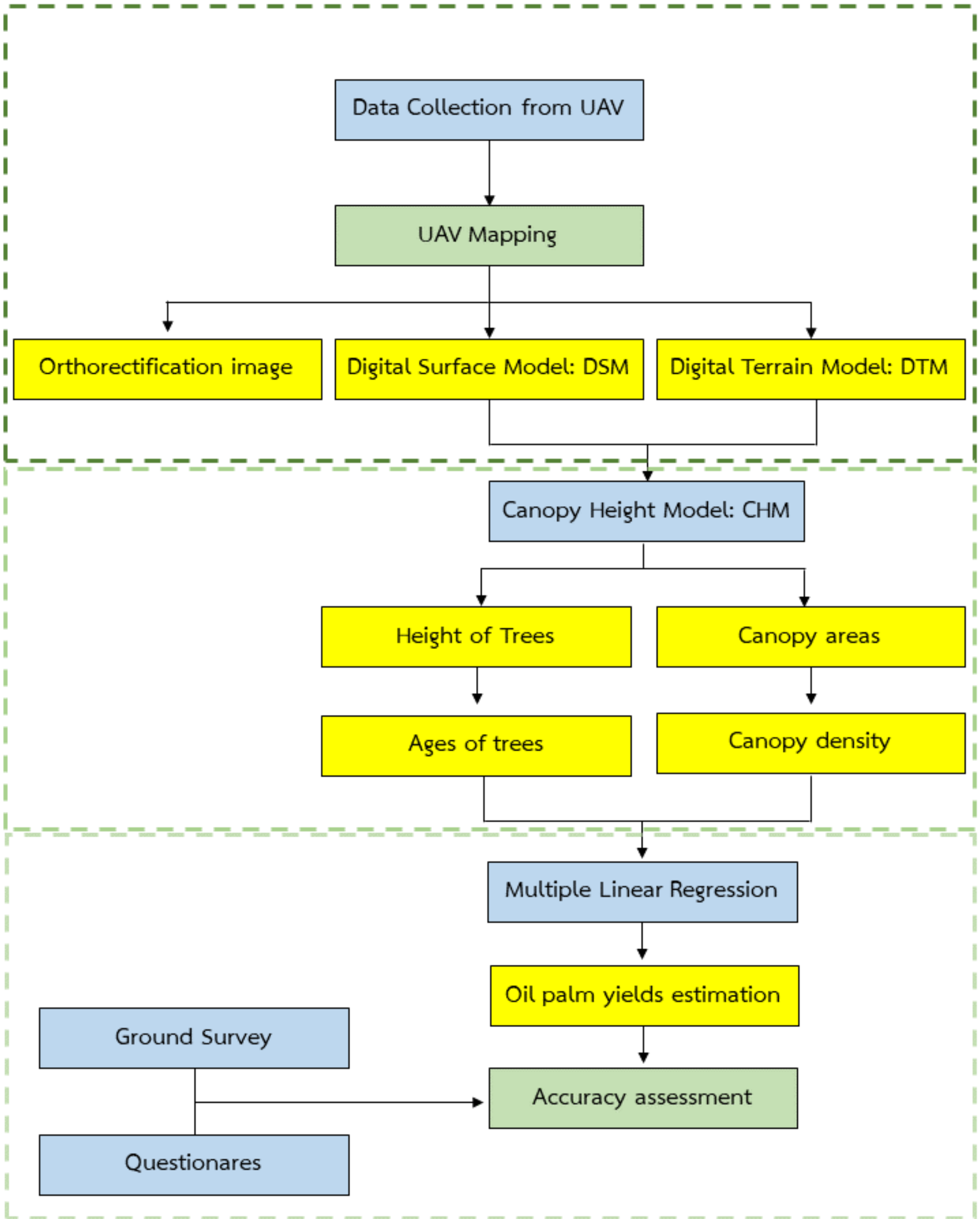


Fig. 2. Conceptual Framework Summarizing the Methodological Steps Used in This Research.

4. RESULTS AND DISCUSSIONS

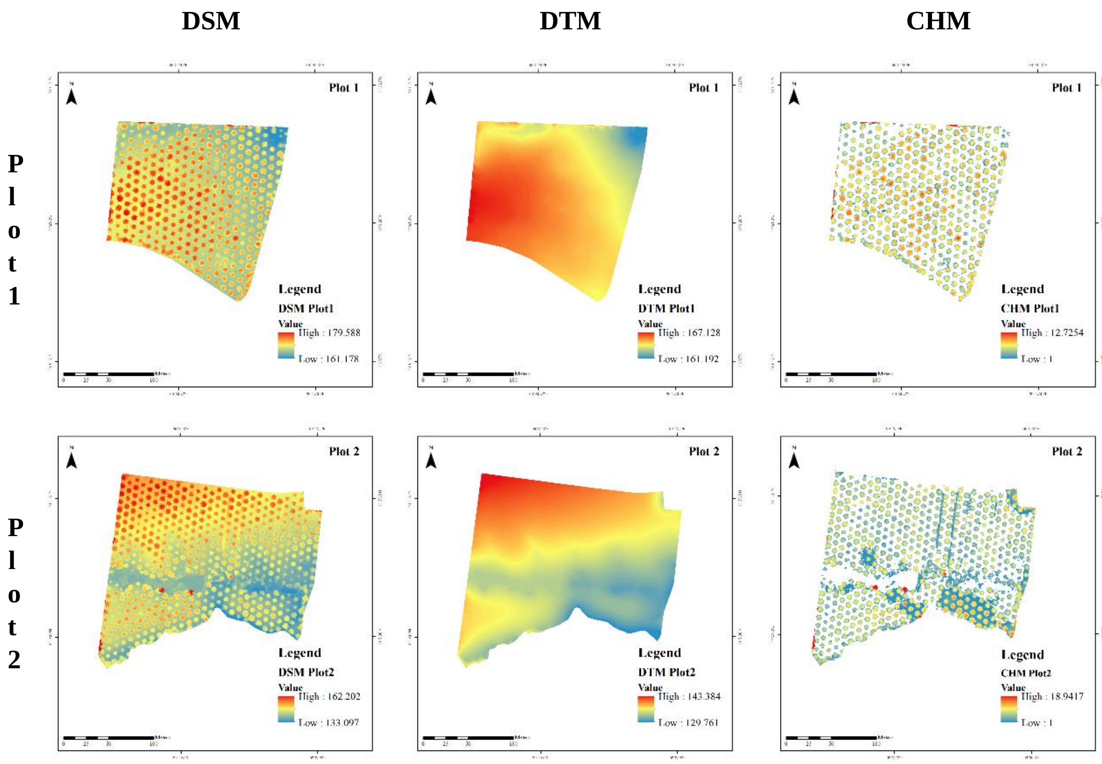
4.1. Analysis of Canopy Height Model Using Unmanned Aerial Vehicle

This study was to create the canopy height model (CHM), digital surface model (DSM) and digital terrain model (DTM) using the data collected from 12 experimental plots by an unmanned aerial vehicle (UAV). The results are presented in **Table 2** and **Figure 3** below (12 plots on the next 4 pages).

Table 2

Analysis Result of CHM in Experimental Plots.

Experimental Plot	Digital Surface Model (DSM) (m)			Digital Terrain Model (DTM) (m)			Canopy Height Model (CHM) (m)	
	Lowest	Average	Highest	Lowest	Average	Highest	Average	Highest
1	161.18	165.71	179.59	161.18	164.25	164.25	3.31	12.72
2	133.10	139.24	162.20	129.76	137.64	143.38	3.08	18.94
3	111.04	123.91	135.07	111.05	118.06	122.79	6.09	21.35
4	126.98	134.78	146.43	127.18	130.64	140.83	6.56	13.08
5	124.66	141.09	150.17	124.66	142.49	134.92	6.69	22.10
6	140.97	151.49	165.83	141.08	144.92	151.30	7.17	19.33
7	128.26	138.76	148.92	128.26	130.62	138.73	8.97	17.50
8	136.19	150.3	159.86	135.99	144.71	151.54	5.85	17.06
9	137.04	149.73	168.90	137.63	146.94	154.67	3.72	18.48
10	121.89	136.2	160.96	122.45	125.71	133.04	12.70	34.78
11	111.99	121.36	130.84	111.99	113.29	118.45	10.38	18.15
12	146.94	159.43	171.56	147.14	151.98	160.00	8.85	23.27



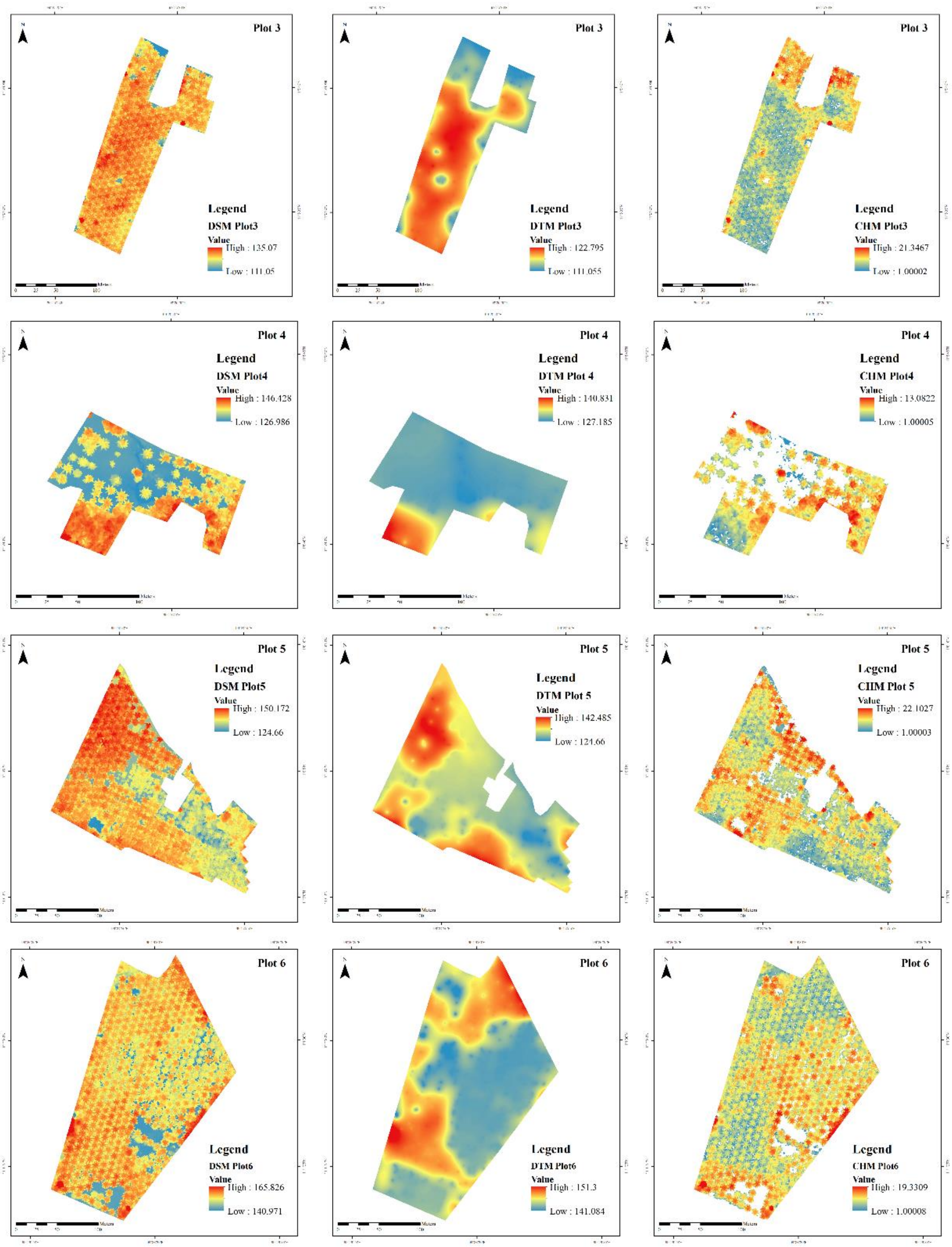
DSM **DTM** **CHM**

Plot 3

Plot 4

Plot 5

Plot 6



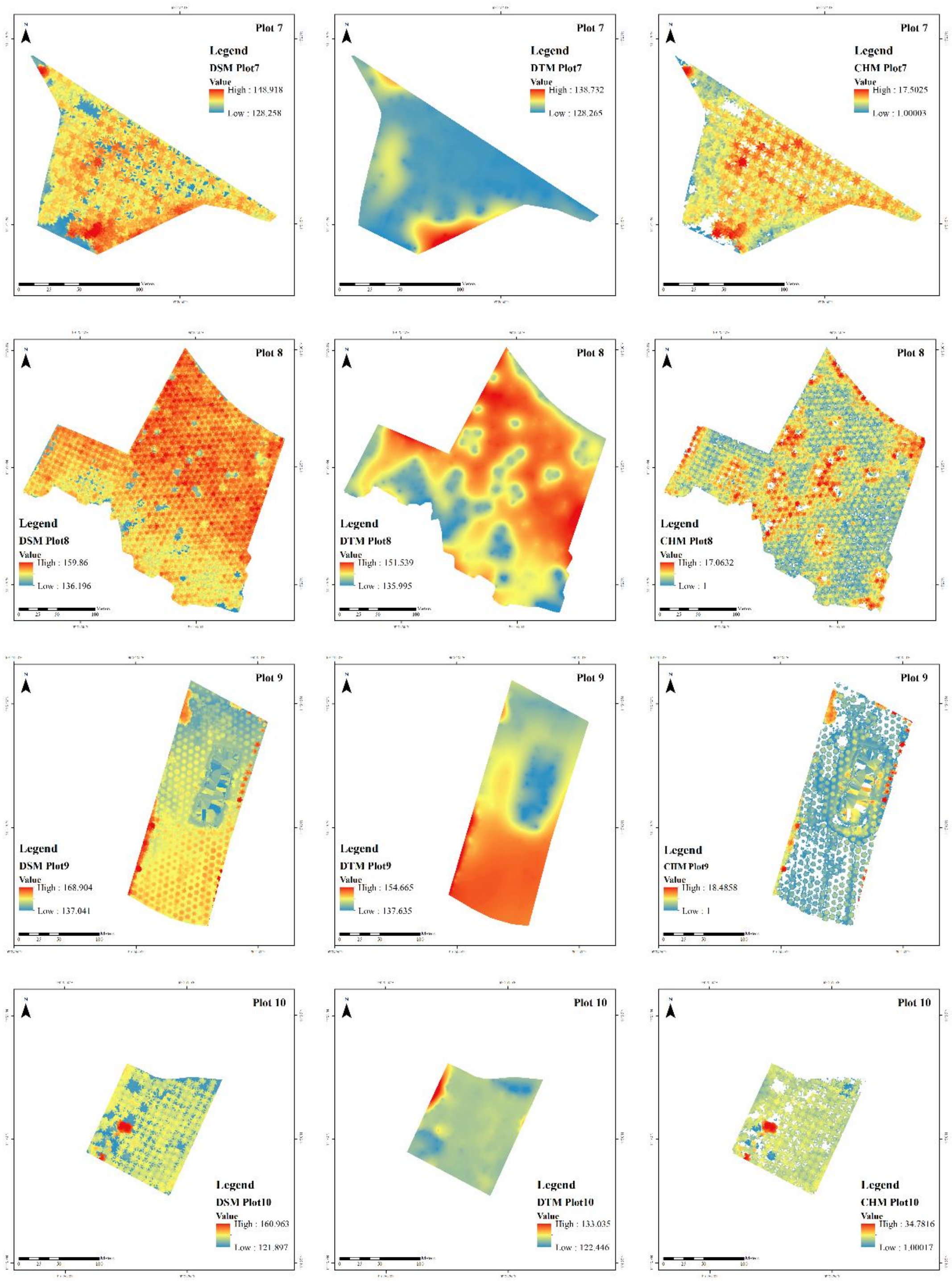
DSM **DTM** **CHM**

Plot 7

Plot 8

Plot 9

Plot 10



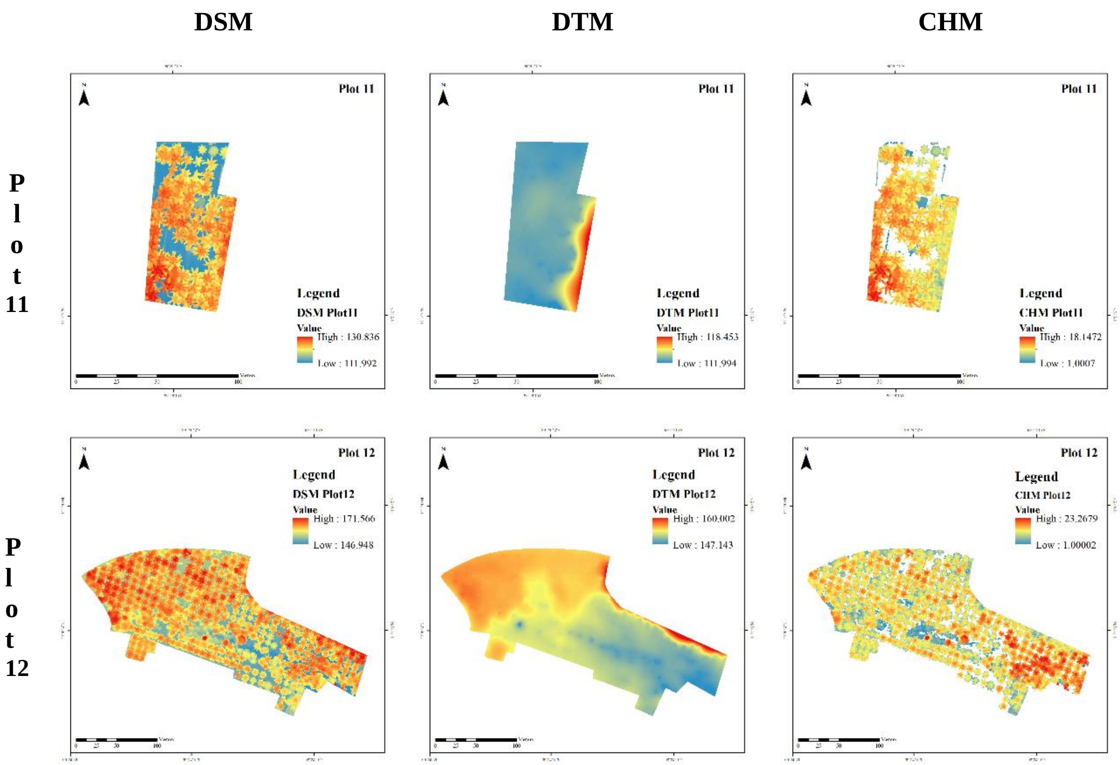


Fig. 3. Maps Presenting Analysis Result of CHM in Experimental Plots.

4.2. Correlation Analysis of Age and Canopy Density

Age Analysis Using UAV – The result indicated that the average density correlated to the standard age, consistent with the following ground survey results and as presented in **Table 3**.

Table 3.

Correlation Analysis of Age and Canopy Density.

Plot	**Plot Area (sq.m.)**	**Canopy Area (sq.m.)**	**Canopy Density (%)**	**Canopy Height (m.)**	**Standard Age (Years)**	**Observed Age (Years)**
1	28,748.77	11,334.23	39.43	3.31	3-8	3-8
2	37,161.50	13,110.29	35.28	3.08	3-8	3-8
3	18,748.27	17,985.79	95.93	6.09	15-25	15-25
4	9,609.61	5,931.07	61.72	6.56	9-14	9-14
5	29,750.12	24,921.43	83.77	6.69	15-25	15-25
6	40,522.48	34,493.05	85.12	7.17	15-25	15-25
7	13,648.26	12,087.24	88.56	8.97	15-25	15-25
8	56,106.23	53,468.95	95.28	5.85	15-25	15-25
9	28,954.94	12,124.31	41.87	3.71	9-14	3-8
10	15,688.13	12,912.50	82.31	12.70	15-25	9-14
11	4,714.09	3,555.78	77.43	10.38	9-14	15-25
12	34,854.01	27,963.56	80.23	8.85	15-25	15-25

Young oil palms trees, in the age range of 3-8 years, were found in Plots 1, 2 and 9 with more details as follows:

- Plot 1 covered the total area of 28,748.77 square meters, 11,334.23 of which was the canopy area with the canopy density of 39.43% and average canopy height of 3.31 meters. Compared to the age analysis table, the oil palm trees in this plot were in the age range of 3-8 years or young class.

- Plot 2 covered the total area of 37,161.50 square meters, 13,110.29 of which was the canopy area with the canopy density of 35.28% and average canopy height of 3.08 meters. Compared to the age analysis table, the oil palm trees in this plot were in the age range of 3-8 years or young class.

- Plot 9 covered the total area of 28,954.94 square meters, 12,124.31 of which was the canopy area with the canopy density of 41.87% and average canopy height of 3.71 meters. However, compared to the age analysis table, the oil palm trees in this plot were in the age range of 9-14 years. The plot owner informed that the trees were planted 8 years ago; thus they were classified as young trees.

Teen oil palms trees, in the age range of 9-14 years, were found in Plots 4 and 10 with more details as follows:

- Plot 4 covered the total area of 9,609.61 square meters, 5,931.07 of which was the canopy area with the canopy density of 61.72% and average canopy height of 6.56 meters. Compared to the age analysis table, the oil palm trees in this plot were in the age range of 9-14 years or teen class. The plot owner informed that the trees were planted 12 years ago.

- Plot 10 covered the total area of 15,688.13 square meters, 12,912.50 of which was the canopy area with the canopy density of 82.31% and average canopy height of 12.7 meters. Compared to the age analysis table, the oil palm trees in this plot were in the age range of 9-14 years or teen class.

Mature oil palms trees, in the age range of 15-25 years, were found in Plots 3, 5, 6, 7, 8, 11 and 12 with more details as follows:

- Plot 3 covered the total area of 18,748.27 square meters, 17,985.79 of which was the canopy area with the canopy density of 95.93% and average canopy height of 6.09 meters.

- Plot 5 covered the total area of 29,750.12 square meters, 24,921.43 of which was the canopy area with the canopy density of 83.77% and average canopy height of 6.69 meters.

- Plot 6 covered the total area of 40,522.48 square meters, 34,493.05 of which was the canopy area with the canopy density of 85.12% and average canopy height of 7.17 meters.

- Plot 7 covered the total area of 13,648.26 square meters, 12,087.24 of which was the canopy area with the canopy density of 88.56% and average canopy height of 8.97 meters.

- Plot 8 covered the total area of 56,106.23 square meters, 53,468.95 of which was the canopy area with the canopy density of 95.28% and average canopy height of 5.85 meters.

- Plot 11 covered the total area of 4,714.09 square meters, 3,555.78 of which was the canopy area with the canopy density of 77.43% and average canopy height of 10.38 meters. The plot owner informed that the trees were planted 15 years ago.

- Plot 12 covered the total area of 27,963.56 square meters, 34,854.01 of which was the canopy area with the canopy density of 80.23% and average canopy height of 8.856 meters. The plot owner informed that the trees were planted between 15 and 25 years ago.

4.3. Oil Palm Yield Prediction Using UAV

In this study, the oil palm yield prediction in Bang Saphan Noi, Prachuap Khiri Khan was subject to 5 influencing factors, which were the independent variables, consisting of: canopy area, canopy density, canopy height, age, and plot area. However, it was found from the ground survey that Plot 1 has not yielded yet, thus only the data collected from the remaining 11 experimental plots could be used for analysis by multiple linear regression with the coefficient of determination or R-squared at 0.98. Therefore, it was suggested that the aforementioned influencing factors correlated with the yield per plot as follows:

Given the p-value level, the most influencing factor was the age, with the p-value of 0.006, followed by the canopy density, with the p-value of 0.026; the total plot area, with the p-value of 0.055; canopy area, with the p-value of 0.112; and canopy height, as the least influencing factor, with the p-value of 0.498. The multiple linear regression predicted the oil palm yield in the experimental plots as presented in **Table 4** and **Figure 4** below.

Table 4.

Yield Prediction of Experimental Plots.

Plot	Plot Area (sq.m.)	Canopy Area (sq.m.)	Canopy Density (%)	Canopy Height (m.)	Ages (Year)	Observed Product (kg.)	Predict Product (kg.)	Residuals
2	37,161.50	13,110.29	35.28	3.08	6	2,500.00	2,617.39	-117.389
3	18,748.27	17,985.79	95.93	6.09	21	2,500.00	2,493.88	6.118406
4	9,609.61	5,931.07	61.72	6.56	11	750.00	735.92	14.0846
5	29,750.12	24,921.43	83.77	6.69	16	2,700.00	2,678.77	21.22832
6	40,522.48	34,493.05	85.12	7.17	17	4,000.00	3,905.15	94.84679
7	13,648.26	12,087.24	88.56	8.97	19	2,000.00	1,940.13	59.86357
8	56,106.23	53,468.95	95.28	5.85	20	5,700.00	5,772.21	-72.2105
9	28,954.94	12,124.31	41.87	3.71	8	2,500.00	2,346.16	153.8367
10	15,688.13	12,912.50	82.31	12.70	14	1,200.00	1,079.27	120.7219
11	4,714.09	3,555.78	77.43	10.38	15	450.00	659.72	-209.722
12	34,854.01	27,963.56	80.23	8.85	14	2,700.00	2,771.38	-71.3783

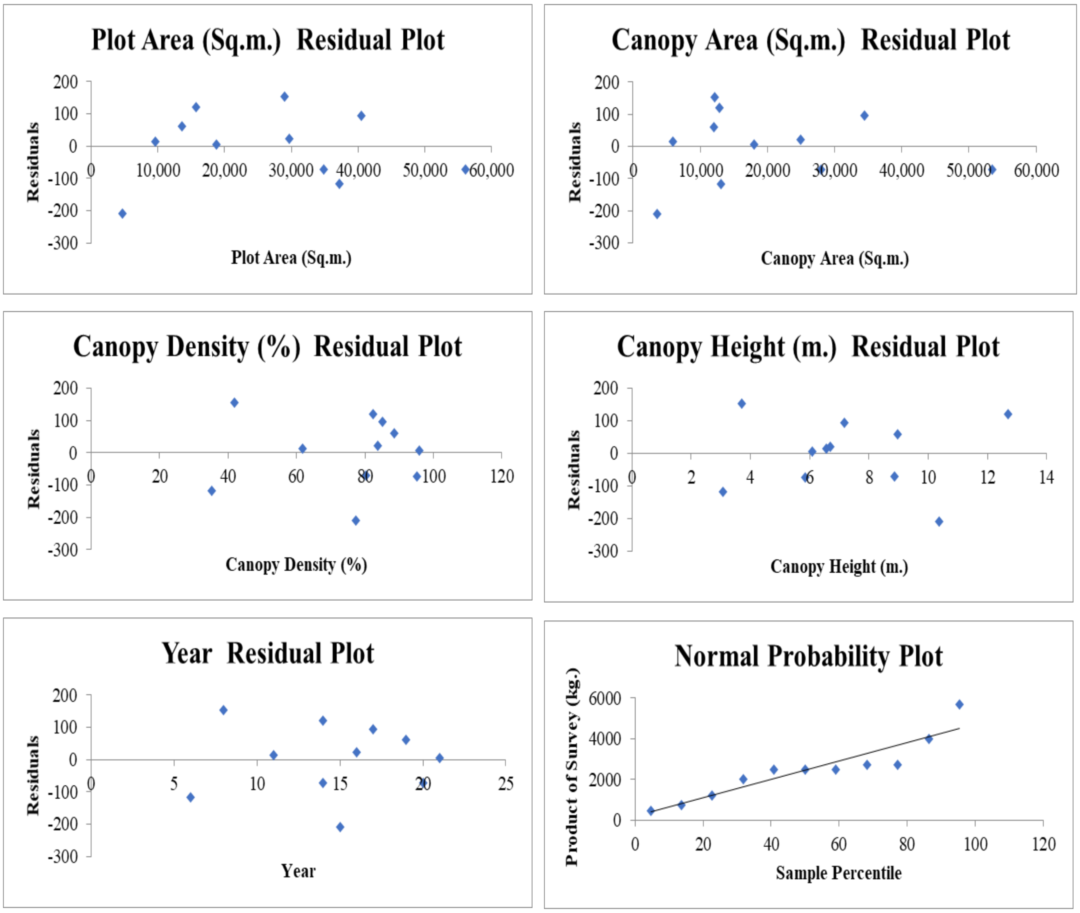


Fig. 4. Scatter Plot of Residual Factor of Estimate Oil Palm Production and Normal Probability Plot.

5. DISCUSSION

According to the results presented above, it is suggested that the oil palm yield prediction can be conducted via remote survey due to its efficiency (Chong et al., 2017), while the canopy height model (CHM) is used for analysis (Fawcett et al., 2019) of the data collected by various tools, including satellite images (Ve ´ ga & St-Onge, 2009) suitable for large areas due to the limitation on image resolution which is subject to the type of satellite. Another key tool is the light detection and ranging (LiDAR), providing high accuracy (Lisein et al.,2013) although it requires high costs for production and analysis. Therefore, in case of small plots, it is suggested to use an unmanned aerial vehicle (UAV) due to lower cost than the satellite images and LiDAR.

It was indicated that the most influencing factor in this study was the age of the oil palm trees as it affected the yield; the oil palm trees in the age range of 9-14 years (teen) yield the most, followed by 15-25 years (mature), and 3-8 years (young), during which the trees require more nutrients for growth. However, the trees with no yield are in the age range of 0-3 years (seed) (Fitrianto et al., 2017). Another influencing factor was canopy density, as a result of the agriculturists’ behaviors, such as trimming the canopy before or after harvesting, and controlling height for easy maintenance and harvesting. The secondary or supporting factors included the total plot area, canopy area, and canopy height.

However, the limitation of this study is overlapping age ranges and behaviors during harvesting, such as trimming the canopy, affected the canopy size, causing the inaccurate canopy density. Therefore, it is suggested that the physical factors and environmental and economic characteristics should be applied in any further studies to obtain more complete and accurate results.

6. CONCLUSIONS

The development of agricultural technology is becoming very popular nowadays, especially the use of data to forecast yields (Precision agriculture). Unmanned aerial vehicles are a powerful tool for storing data and can be processed. In this study, the application of an UAV for oil palm yield prediction and age classification in this study, it was indicated that the errors caused by overlapping age ranges were found in 3 out of 12 experimental plots. Regarding the oil palm yield, the most influencing factor was the age (9 years and above), followed by the canopy density canopy density (over 41% of the area), total plot area, canopy area, and canopy height, respectively, with the coefficient of determination or R-squared at 0.98. We learned that the aforementioned factors could be concluded from the data collected by an UAV, which reduced time for measuring the height of each tree manually, resulting in more accurate yield prediction. In addition, this study can be applied to agriculture which is an important product of Thailand and Southeast Asian countries. this research can be used to determine the growth of plants within the plot. And can use such methods to increase the productivity of farmers in the region.

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