Estimation of Paddy Rice Plant Height using UAV Remote Sensing

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Abstract. *The study aims to estimation paddy rice plant height (PH) using UAV remote sensing for evaluation of the growth status of rice in fields. The study area is in Kantharawichai District, Maha Sarakham Province, Thailand. Modeling to estimate the plant height of rice from the correlation between height data from 120 sample field measurements, and reflectance data and digital elevation model (DEM) data was obtained by RGB camera-equipped UAVs, the camera has a resolution of 12 million pixels, the flight recorded an image at an altitude above the ground of 90 meters. and consider the photo data at ground sample distance (GSD) of 5 cm. Analyzed to modeling with a generalized linear model algorithm, the analysis data was divided into two parts for modeling and testing 60 and 40 percent replicas, respectively. The results show that the relationship between measured PH and estimated PH has* R^2 *of 0.70 and RMSE of 0.13 meter. This study shows that the digital elevation model (DEM) from aerial photography with unmanned aerial vehicle, it is an important parameter in estimating the plant height of rice.*

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1. Introduction

Rice is one of the most important crops in Thailand because rice is a staple food for Thai people and generates income from exchanges or trades for farmers who have been growing rice for a long time. In addition, Thailand is located in a tropical climate and there are differences in landscape characteristics suitable for rice cultivation [1]. Most of the farmers in each area farm once a year in the form of in season rice fields, farmers therefore need to make a large and quality amount of rice [2]. Therefore, monitoring crops throughout the vegetation period, to assess plant growth and find solutions to problems [3]. It is necessary for optimization of productivity [4].

Plant height (PH) is one of the important agricultural parameters for assessing plant growth status, and widely used to evaluate above-ground biomass and effective grain yields [5,6]. Plant height may be an indicator of the ability to retain nutrients of a useful carbohydrate type [7] and plant height is something that reflects the change in growth over time. Basically, plant heights are measured manually and a measuring device is used by selecting representatives of a few plants per plot to show overall plant height status, manually measure PH in the field requires a lot of labor or time and access may be restricted for plants in large area plots [8]. Therefore, unmanned aerial long-range survey (UAV) technology is one that can digital elevation model from a photo, surveying with a UAV can overcome time constraints, manpower, investment cost and provide high-profile information in large areas [9].

According to several reports, studies have shown that UAV are used to estimate the plant heights of crops such as sugarcane [10], cotton [11], maize [12], wheat [13], sorghum [14], barley [15,16] and rice [17]. The study report of Kawamura et al. (2020) study was conducted to estimate of plant height in an upland rice field in Laos using UAV. Consider the height value from the RGB image at a ground sample distance (GSD) of 1 cm and analyzed with simple linear regression. It was found that the best correlation of measured PH with estimation PH was R^2 of 0.712 and RMSE of 9.142 cm.

In this study, we aimed to estimation paddy rice Plant Height (PH) using UAV remote sensing for evaluation of the growth status of rice in fields. The study area is located in Kantharawichai District, Maha Sarakham Province, Thailand. Modeling to estimate the plant height of rice with reflectance derived value and digital elevation model (DEM) from RGB images at a ground sample distance of 5 cm, together with analysis with generalized linear model algorithm and assess the statistical reliability of the model with the coefficient of determination (R^2) and the root mean square error (RMSE).

2. Materials and Methods

2.1 Study Area

The study was conducted at rice field of Mahasarakham University, Kantharawichai District, Maha

Sarakham Province, Thailand (16°20'42.1" N, 103°12'21.7" E), as in the Fig. 1. The area has topography by about 155 meters above mean sea level, the cultivated land is sandy soil, weather is generally characterized by rain alternating with dry weather, the annual precipitation is 1493.7 millimeters and the average temperature throughout the year is 27.91 degrees Celsius.

The study was conducted in-season (July to November) of 2019, which relied on rainfall for growing photoperiod sensitive varieties, which is Khao Dawk Mali 105 rice on the rice field area of approximately 16 rai and sowing of rice grain was done by the end July 2019.

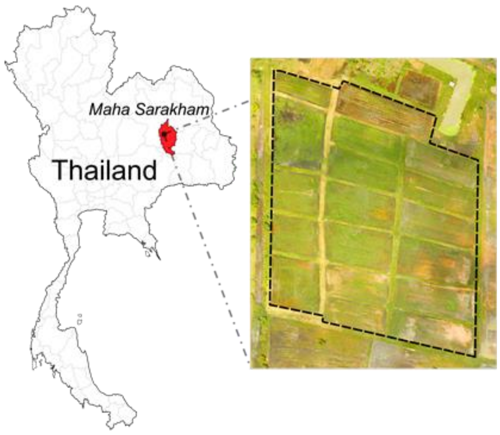

Fig. 1 The location of this study in Kantharawichai District, Maha Sarakham Province, Thailand.

2.2 UAV-RGB Image Acquisition

This study used the Phantom 3 Advanced UAV-derived aerial imagery which was recorded six times according to the six growth stages of the rice – first during initial tillering stage, second during tillering stage, third during panicle initation stage, fourth during flowering stage, fifth during milky and dough stage, and sixth during harvest maturity stage as detailed in the Fig. 2, using an RGB camera attached with the Phantom 3 Advanced UAV with a resolution of 12 million pixels, lens FOV 94C 20 mm (35 mm format equivalent) f/2 and reflectance property in each wave range of approximately 350-600 nm. The UAV was planned to fly the recording using the Pix4D capture application, at an altitude of 90 m, the front-overlap of 80% and side-overlap of 60% and use eight ground control points (GCP) scattered around the rice fields.

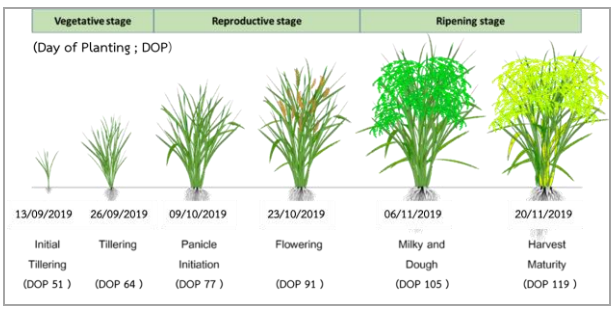

Fig. 2 The growth stage of the studied rice.

2.3 Field Data Collection

The field data were collected six times: first during initial tillering stage, second during tillering stage, third during panicle initation stage, fourth during flowering stage, fifth during milky and dough stage, and sixth during harvest maturity stage. After photo taking was complete, samples were randomly collected in the experimental rice plot, 20 samples were collected at a time for six times, totaling 120 samples, the rice that was dug up was measured the height from the root to the tip of the leaf. And use a tool called RTK GNSS to collect the coordinates of the sampling point, ground control points (GCP) and ground level values.

2.4 Image Processing and Data Extraction

The UAV-derived aerial imagery was processed by using Web ODM to adjust parameters of the camera, and perform coordinate correction of the image using eight ground control points from a coordinate survey using RTK GNSS. After imagery processing, the RGB orthomosaic and digital elevation model (DEM) had a ground sample distance (GSD) of 5 cm, and use QGIS Desktop 2.18 together with the sampling coordinates values to extract the red (R) green (G) and blue (B) reflectivity from the RGB orthomosaic, and adjust the reflectivity to be in the standard form red (r) green (g) and blue (b) calculated from Equations 1, 2 and 3, respectively.

$$r = R/(R+G+B) \tag{1}$$

$$g = G/(R+G+B) \tag{2}$$

$$b = B/(R+G+B) \tag{3}$$

; where R is the reflection of red light, G is the reflection of green light, and B is the reflection of blue light from the RGB orthomosaic.

The digital elevation models at ground level (DEM_0) are generated from ground level values with QGIS Desktop 2.18 and canopy level (DEM_i) were generated with RGB images. The canopy height model (CHM) was generated by computing the distances between DEM_i and DEM_0 on Equation 4. The three types of models created in this study can be easily explained as shown in Fig. 3. And use QGIS Desktop 2.18 together with the sampling coordinates values to extract the plant height from the canopy height model (PH_{CHM}).

$$CHM = DEM_i - DEM_0 \tag{4}$$

; where CHM is the canopy height model, DEM_0 is the digital elevation model at ground level, and DEM_i is the digital elevation model were generated with RGB images.

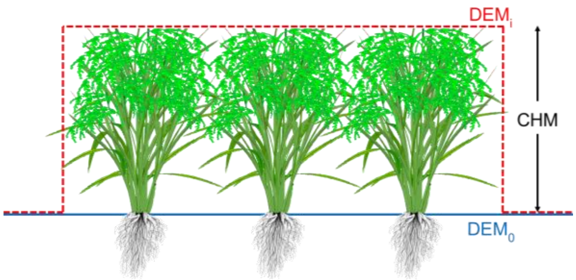

Fig. 3 The visual representation of the digital elevation model at ground level (DEM$_0$), digital elevation model of canopy level (DEM$_i$) and canopy height model (CHM).

Image processing and data extraction can be easily explained as shown in Fig. 4.

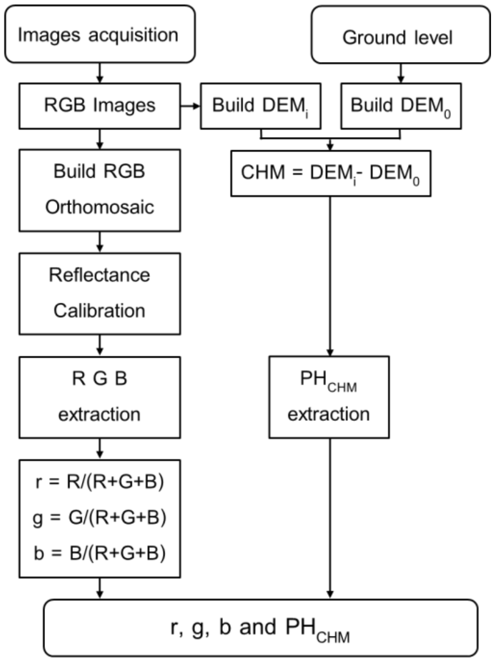

Fig. 4 Flowchart showing methods of image processing and data extraction.

3. Modeling and Resampling

Modeling by combining the reflectance, red (r), green (g), blue (b), plant height from the canopy height model (PH$_{CHM}$) and measured plant height (PH$_M$) data the 120 samples from the field surveys, were input on Rapid miner 9.1 based on the set models, the analysis was done by generalized linear model. The data were divided into two groups, namely 60 % (N=72) for modeling data sets, and 40 % (N=48) for testing data sets. The coefficient of determination (R^2) and the root mean square error (RMSE) were used to evaluate the plant height estimation model performance, the R^2 and RMSE were calculated from the Equation 5 and 6, respectively. Modeling and Resampling can be easily explained as shown in Fig. 5.

$$\mathrm{R}^2 = 1 - \frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{N} (y_i - \bar{y}_i)^2} \tag{5}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y}_i)^2} \tag{6}$$

; where N is the number of samples, y_i is the measured plant height form a field survey, $y^\wedge_i$ is the estimated value, and $\bar{y}_i$ is the mean of the measured value.

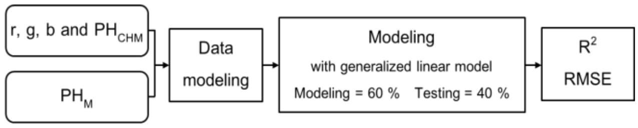

Fig. 5 Modeling process diagram.

4. Results

4.1 Data Relationships

The collection of data analyzed through Rapid Miner Studio 9.1 with a generalized linear model, 120 data sets, the correlation of the reflectance value, red (r), green (g), blue (b), plant height from the canopy height model (PH$_{CHM}$) and measured plant height (PH$_M$) from the field surveys, it is expressed as a correlation coefficient in the form of correlation heatmap as in the Fig. 6, the correlation coefficient value of the relationship between PH$_M$ and r is -0.16, the correlation coefficient value of the relationship between PH$_M$ and g is 0.26, the correlation coefficient value of the relationship between PH$_M$ and b is -0.09 and the R value of the relationship between PH$_M$ and PH$_{CHM}$ is 0.84.

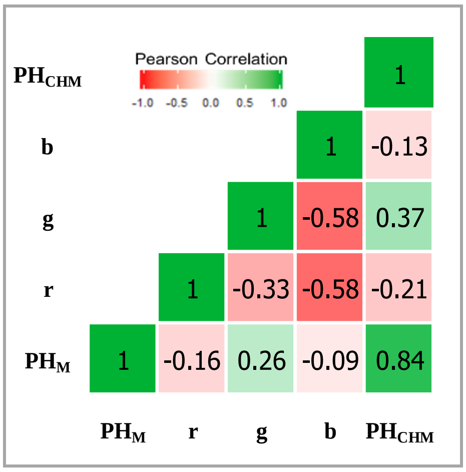

Fig. 6 Correlation Heatmap show the relationship of the reflectance value, red (r), green (g), blue (b), plant height from the canopy height model (PH$_{CHM}$) and measured plant height (PH$_M$) from the field surveys.

And from the results of the relationship of the reflectance value, red (r), green (g), blue (b), plant height from the canopy height model (PH_{CHM}) and measured plant height (PH_M) from the field surveys, it was found that PH_M was the most correlated with PH_{CHM}, the correlation coefficient of 0.84.

4.2 Evaluation of the Estimation Ability

From the study to estimation of plant height for evaluation of the growth status of rice in fields using reflectance relation of the reflectance value, red (r), green (g), blue (b), and plant height from the canopy height model (PH_{CHM}), obtained from aerial imagery with RGB camera mounted UAV, and collection of data analyzed through Rapid Miner Studio 9.1 with a generalized linear model, 120 data sets, were divided into two groups, namely 60 % (N=72) for modeling data sets, and 40 % (N=48) for testing data sets, and calculation of coefficient of determination (R^2) and root mean square error (RMSE). It was found that modeling has only one parameter used to estimate the plant height is PH_{CHM}, by can show the estimated plant height (PH_E) equation as Equation 7, and the relationship between PH_M and PH_{CHM}, has R^2 of 0.72, is shown in scatter plots as shown in Fig. 7.

$$PH_E = 1.201(PH_{CHM}) + 0.352 \tag{7}$$

; where PH_E is estimated plant height and PH_{CHM} is plant height from the canopy height model.

And from testing the model estimate the plant height, it was found that the relationship between measured plant height (PH_M) and estimated plant height (PH_E) has R^2 of 0.70 and RMSE of 0.13 meter ($p < 0.005$). The relationship between measured PH (PH_M) and estimated PH (PH_E) show in the form of scatter plots as in the Fig. 8 and show the plant height of rice in 6 growth stages, i.e., initial tillering stage, tillering stage, panicle initation stage, flowering stage, milky and dough stage, and harvest maturity stage, in a map format as in the Fig. 9.

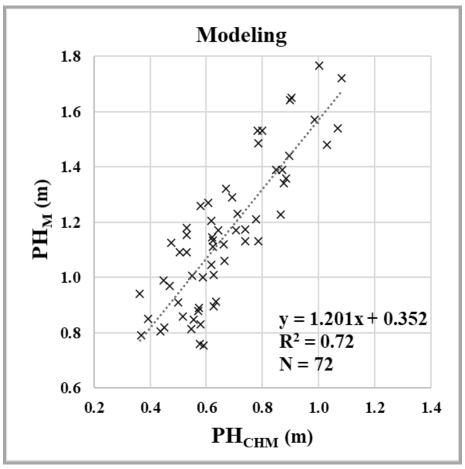

Fig. 7 Scatter plots show the relationship between PH_M and PH_{CHM}.

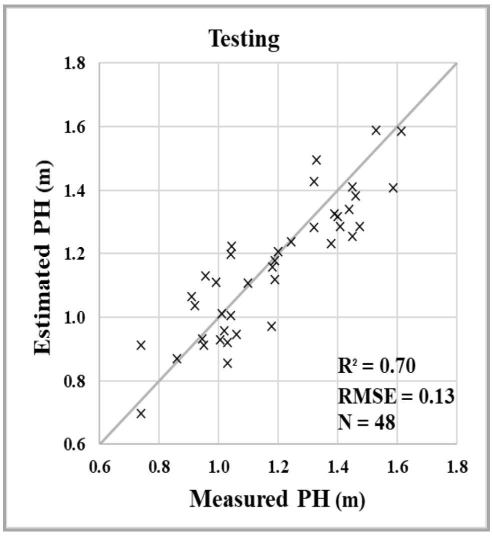

Fig. 8 Scatter plots show the relationship between measured PH and estimated PH.

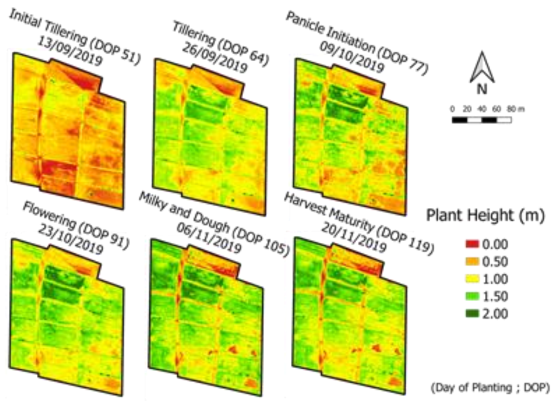

Fig. 9 Map shows the plant height of rice in 6 growth stages.

5. Discussion and Conclusion

From the study to estimation of plant height (PH) for evaluation of the growth status of rice in fields using reflectance relation of the reflectance value, red (r), green (g), blue (b), and plant height from the canopy height model (PH_{CHM}), obtained from aerial imagery with RGB camera mounted UAV, and collection of data analyzed through Rapid miner Studio 9.1 with a generalized linear model, 120 data sets, were divided into two groups, namely 60 % (N=72) for modeling data sets, and 40 % (N=48) for testing data sets, and calculation of coefficient of determination (R^2) and root mean square error (RMSE), it was found that the relationship between measured PH and estimated PH has R^2 of 0.70 and RMSE of 0.13 meter. The study results are consistent with relevant research [17], and shows that the digital elevation model (DEM) from aerial photography with unmanned aerial vehicle, it is an important parameter in estimating the plant height of rice.

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