Evaluation of Sugarcane Plant Height using UAV Remote Sensing

Photiwut Bunruang and Siwa Kaewplang*

Faculty of Engineering, Mahasarakham University, Khamriang Sub-district, Kantarawichai District, Maha Sarakham, 44150, Thailand

62010351001@msu.ac.th and siwa.kae@msu.ac.th*

Abstract. *The objective of this research is to evaluate the plant height (PH) of sugarcane during the 3 months pre-harvest using imagery-derived UAV. The study area is located in Muang Phimai District, Nakhon Ratchasima Province, Thailand, by taking aerial imagery by UAV with a 12M pixel camera was acquired by flying at an altitude of 90 meters and analyzed the correlations between PH data 120 data example of field and the data from by the UAV, including reflectance values, and digital elevation model (DEM). The analysis was carried out at ground sampling distance (GSD) 100 cm. Process data was processed using 3 methods of machine learning, such as generalized linear model, decision tree and support vector machine .The result showed correlation between measured PH and estimated PH the support vector machine best accuracy is R^2 = 0.82 and RMSE = 0.19, the method presented in this study can be used as a guideline for estimating the above-ground altitude of sugarcane by aerial images from a UAV 3 months prior to harvesting.*

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1. Introduction

Sugarcane is mostly grown in tropical and subtropical areas around the world and is also a very important source of cane sugar and raw materials for the production of ethanol and other industries [1]. Thailand is located in a tropical area and therefore receives ample amounts of solar energy throughout the year which is an important factor in cultivation [2]. Thailand is the second largest exporter of sugar in the world after Brazil [3]. Agriculture sugarcane cultivation in Thailand can create jobs for more than 1.5 million Thais, there are more than 336,800 sugarcane farmers and there are 51 sugar mills in the country, which is equivalent to 8% of the total agricultural land of Thailand [4].

One the problems faced by agriculture in sugarcane cultivations the monitoring of sugarcane growth throughout the planting area requires a period of times, also a group of labor and very high budget [5]. It is also difficult to monitor the entire area, therefore a remote sensing technology from unmanned aircraft is a viable alternative. Because that how reduce labor time and provide detailed information highlands to explore [6].

Plant height (PH) is an important agronomical parameter to assess the growth status precision [7]. Most commonly height data is collected with a measuring rule [8]. The height of the plant can affect the biomass or even the yield.

Several studies, both national and international, have addressed the importance of plant height in yield estimates [8-10]. For instance, plant height data obtained from plant surface models have been found to be correlated between the height of plants and fresh biomass [11]. UAVs are used to estimate the height of plants such as rice [8], barley [11], maize [12], wheat [13] and sugarcane [14]. Han, X et al. [15] measured and calibrated PH values from fixed-wing UAV images using SfM flying at an altitude of 120 m AGL to estimate the height of the sorghum plant with reasonable accuracy in a relatively large farm area. The results show correlations where the decision coefficient (R^2) was equal. 0.85 mean error square root (RMSE) equal to 20 percent.

However, it is surprising that many studies on the application of UAV-based remote sensing for evaluation PH sugarcane by reflection value and digital elevation model (DEM), which estimate sugarcane plant height 3 months pre-harvesting. From RGB images and DEM at ground sample distance of 100 and 10 cm, respectively. When comparing the performance of machine learning such as the Generalized linear model, Decision Tree and Support Vector Machine functions assess the statistical reliability of the model with the coefficient of determination (R^2) and the root mean square error (RMSE).

2. Materials and Method

2.1 Study Area

The study area was the field-grown sugarcane in Amphoe Muang Phimai, Nakhon Ratchasima, Thailand. (15°07'44.21" N 102°23'25.41"E), see Fig. 1 at an average elevation of 159 m MSL. The study area has a warm temperate semi-humid continental monsoon climate. The average annual temperature is 36.9 °C and the average annual rainfall is 1,037.4 mm/year.

Sugarcane cultivars were studied in Khon Kaen 3 by using rainwater and sugarcane canal at the first stage of planting sugarcane plantation period on January 15th, 2019. (Date of planting: DOP) Researchers collected data on October 26th, 2019. (DOP: 284 days).

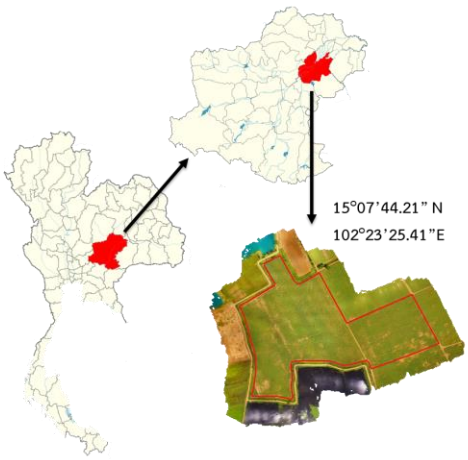

Fig. 1 The location of this study in Amphoe Muang Phimai, Nakhon Ratchasima, Thailand.

2.2 Field Data Collection

In this research, the collected data in the field were divided into 2 parts: the aerial photograph data collection and the ground data collection in the terrestrial data collection, a total of 120 samples were taken in order to measure the height of the sugarcane from the tip of the plant, while the collection of the coordinates utilized the tool called RTK GNSS network.

There were 8 ground control points (GPCs) scattered around the field to be used to modify geographic coordinates using the RTK GNSS network.

2.3 Unmanned Aerial Vehicle and Camera Setup

In this study, we used a DJI phantom 3 advanced to collect aerial photographs. The camera used for collected images is an RGB camera with a resolution of 12 megapixel, with its reflection value ranging from 450 to 660 nm, divided into blue (wavelength=450 nm), green (wavelength=550 nm), and red (wavelength=660 nm) as shown in Fig.2. Flight planning of the UAV with the PIX4D Application provided that the side-overlap was 60% and the forward overlap was 80%. The flight altitude was 90 m.

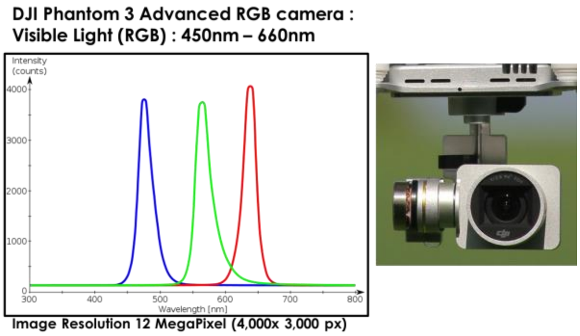

Fig. 2 DJI Phantom 3 advanced camera (RGB)

2.4 Image Processing and Data Extraction

Web ODM was used to generate orthomosaics and digital elevation model (DEM) and eight ground control points were used to calibrate geometric from surveying coordinates using RTK GNSS network. The Orthophoto Map was then used to extract R, G, and B reflectance values at Qgis 3.8 by extracting the reflections at the cane sampling point. And R, G, and B reflections are used to adjust the reflectivity compared to the reflectance from the calibration plate. (Calibration) and format the reflection value. In the form of standard equations as equations (1) – (3).

$$r = R/(R+G+B) \quad (1)$$

$$g = G/(R+G+B); \quad (2)$$

$$b = B/(R+G+B) \quad (3)$$

; where R, G and B are the reflection values of Red, Green and Blue from the image.

r g and b are the red, green, and blue reflections in standard formats.

The DEMs at ground level (DEM) is generated from ground level values with QGIS Desktop 3.8 and Digital surface model (DSM) were generated with RGB images. The canopy height model (CHM) was generated by computing the distances between DSM and DEM on Equation (4).

$$CHM = DSM - DEM \quad (4)$$

; where CHM is the canopy height model; DEM is the digital elevation model at ground level; DSM is the digital surface model were generated with RGB images.

3. Modeling and resampling

To achieve the suitable to a mathematical model by a comparative analysis plant height (PH) data and data from UAV consist of reflection value (r, g, b) and height from the canopy height model (H_{CHM}). We establish three mathematical models: Generalized Linear Model, Decision Tree and Support Vector Machine. The data will be analyzed through the program called Rapid Miner Studio 9.1 and the data were divided into 2 groups: namely 60% (N=72) for calibration the data sets and 40% (N=48) for evaluation the data sets.

The coefficient of determination (R^2), and root mean square error (RMSE) were used as assessment metrics to measure the performance of the mathematical model and to determine how best the model could predict the data. Equations (5)-(6) are used to calculate R^2, and RMSE.

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

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

; where N is the total sample size; y_i is the ith measured height of the sample; $y^\wedge_i$ is the ith predicted value, and y^-_i is the ith mean measured value.

4. Results

From the analysis of the correlation between analysis plant height (PH) data and data from UAV consist of reflection value (r, g, b) and height from the canopy height model (H_{CHM}). Able to analyze the correlation of data with correlation expressed as a coefficient of correlation (R) in the form of a Correlation Heatmap. As shown in Fig. 3. Where the R-value has no units and ranges from -1 to 1.

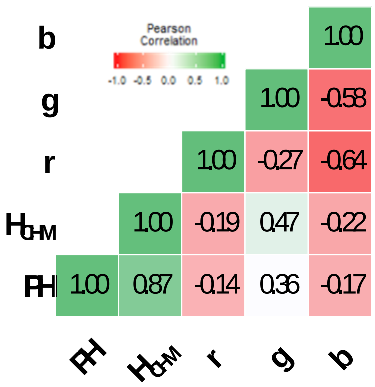

Fig. 3 Correlation Heatmap from height sugarcane field and data UAV-RGB images.

From Fig. 3, the results show that the sugarcane height is most correlated with the H_{CHM} (R=0.87) and the g- band minor. (R=0.36) Making it possible to create the relative equation of height as the equation (7).

$$PH = 0.839(H_{CHM}) + 1.091(r) - 1.373(g) + 1.43 \qquad (7)$$

; where PH is plant height from the field surveys, in meter; H_{CHM} is height from the canopy height model, in meter.

The average field height value measured in the field was 120 samples. The data were divided into two groups, namely 60 % (N=72) for calibration data sets, and 40 % (N=48) for evaluation data sets. The R^2 values of the Generalized Linear Model, Decision Tree and Support Vector Machine are reported in Table 1. The algorithm Support Vector Machine gives the maximum R^2=0.82 and RMSE=0.19 for evaluation datasets, respectively.

Model	R^2	RMSE
Generalized Linear Model	0.80	0.19
Decision Tree	0.76	0.22
Support Vector Machine	0.82	0.19

Table 1 The R^2 values and the RMSE values of regression algorithms indicating P<0.005.

The plots of the height of sugarcane estimated by equation (7) are showed in Fig. 4 (objects outside the study areas are masked out) and Scatter plots of observed the height of sugarcane versus predicted the height of sugarcane for validation data are shown in Figs. 5 - 7. This study used a one-way ANOVA test and was also used for testing the similarity between the regression models when three different models were used. It turned out that the three models are statistically not different. (i.e., p-value<0.005, N=48):

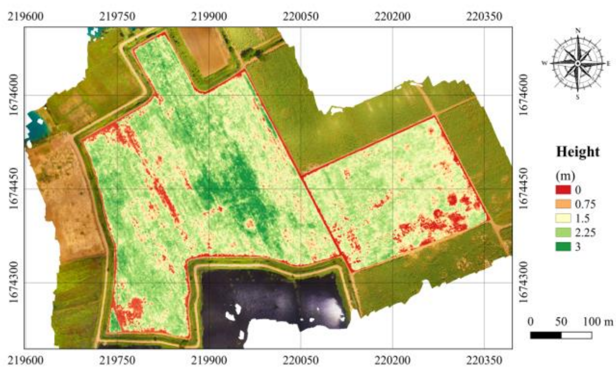

Fig. 4 Map shows the plant height of sugarcane in 3 months pre-harvest.

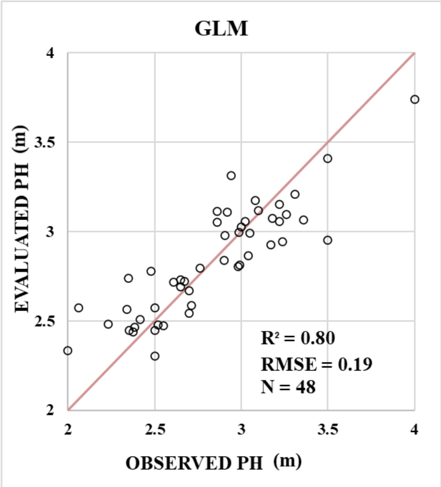

Fig. 5 The scattering plots with the R^2 and RMSE values the plant height of sugarcane from analysis with Generalized Linear Model.

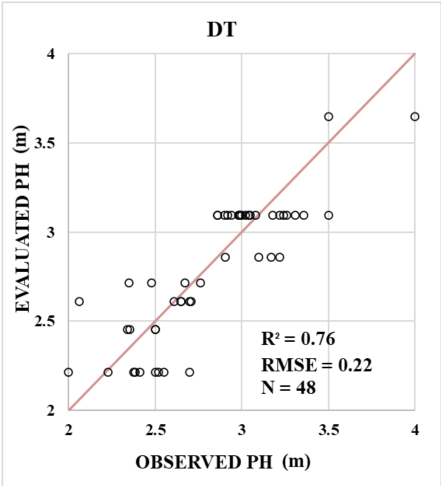

Fig. 6 The scattering plots with the R^2 and RMSE values the plant height of sugarcane from analysis with Decision Tree.

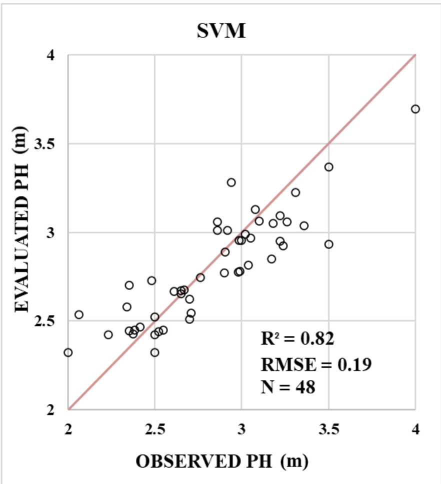

Fig. 7 The scattering plots with the R^2 and RMSE values the plant height of sugarcane from analysis with Support Vector Machine.

5. Discussion and Conclusion

From the study of evaluation the plant height (PH) of sugarcane at 3 mount pre-harvest using reflectance relation of the reflectance value, red (r), green (g), blue (b), and height from the canopy height model (H_{CHM}), through UAV-derived aerial imagery from an RGB camera attached on the UAV, and collection of data analyzed with a generalized linear model, decision Tree and support vector machine 120 data sets for evaluation data sets, and calculation of coefficient of determination (R^2) and root mean square error (RMSE). The Support Vector Machine found the relationship between the measured plant height and the most assessed plant height with R^2 of 0.82 and RMSE at 0.19 m. The study results are consistent with relevant research [15], shows that the digital elevation model (DEM) using UAV-Based Remote Sensing can be used as a guide to evaluated the PH of the sugarcane at 3 mount pre-harvest.

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Biographies

Photiwut Bunruang was born in 1997 at Buriram province, Thailand. He received his Bachelor degree from Department of Civil Engineering, Faculty of Engineering, Mahasarakham University, Thailand, in 2018.

Siwa Kaewplang was born in Thailand. He received his Ph.D. from Chulalongkorn University, Thailand in 2014. He is a lecturer of civil engineering at Mahasarakham University, Thailand. His research interests include digital photogrammetry, climate change, environmental modeling, geographic information system, geostatistics, GIS, global warming, remote sensing hyperspectral remote sensing, image classification, image processing, information technology, precision agriculture, natural resource management, tropical forest, tropical vegetation, and water resource management.