Monitoring of Rice Growth with UAV-Derived Aerial Imagery

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Abstract. *This study aims to monitor rice growth by using the reflectance relation of (R-B)/(R+B) and R/(R+G+B) to predict rice biomass before and after the heading stage. UAV-derived aerial imagery was obtained from an RGB camera attached on the UAV, which flew to take pictures at the altitude of 90 meters, with the front-overlap of 90% and side-overlap of 60%, to be used for calculating Green-Red Vegetation Index (GRVI) and Red Green Blue Index (RGBI). In addition, the field data were divided into two parts data for calibration and data for evaluation of three models through Rapid minder Studio 9.1, namely Generalized Linear Model, Deep Learning, and Random Forest. 120 sets of field biomass data were collected, 80 of which were for calibrating the models, and 40 for evaluating the models. After the evaluation of Coefficient of Determination (R^2) and Root Mean Square Error (RMSE), for the biomass of rice before the heading stage, it was found that for GRVI, R^2 and RMSE were 0.920 and 0961, respectively, and for RGBI, R2 and RMSE were 0.918 and 0.697, respectively. Meanwhile, for the biomass of rice after the heading stage, it was found that for GRVI, R^2 and RMSE were 0.854 and 1.648, respectively, and for RGBI, R^2 and RMSE were 0.810 and 1.530, respectively. For both periods, the most suitable prediction model was Random Forest. This shows that the reflectance relation of both equations based on GRVI and RGBI could be used to monitor rice growth.*

Received by	18 June 2019
Revised by	20 June 2019
Accepted by	25 June 2019

Keywords:

Remote Sensing, UAV, Rice, Biomass Rice, Vegetation Index

1. Introduction

In Thailand, rice farming has long been carried out by farmers as rice is an important crop. Most of the farmers in each area [1] do rice farming once a year in the form of in-season rice fields, so it's necessary to produce a large amount of quality yield. Monitoring rice growth based on rice age is another means to appropriately identify rice growth and growth criteria, such as appropriateness of water in the rice field, steady growth of rice, rice pest, rice weed, and rice size for adding nutrients. Monitoring rice growth enables farmers to solve various problems in the rice fields effectively from growing to harvesting. As a result, management of rice in the rice fields is very important to rice yield, and remote sensing technology has become important for [2] Growth at each rice age is a significant step for precision agriculture [3] and remote sensing can provide farmers with highly precise data [4] At present, various forms of unmanned aerial vehicles are used, such as those in precision agriculture [5] The UAV-derived aerial imagery technology is a survey method which saves time and uses little labor. Many studies examined the use of remote sensing technology for monitoring growth of plants or rice in rice fields [6]. Currently, remote sensing technology has been adopted for studies of rice fields both domestically and internationally. It was found from overseas studies that the use of remote sensing technology for investigating rice fields, monitoring rice growth, predicting rice yield and monitoring plant growth using precision agriculture is very essential for rice field management, and rice and plant growth monitoring to increase agricultural productivity. Consequently, the remote sensing method has been adopted to monitor growth of plant indexes by time period [7] According to the study of [8] camera-attached UAV was used for remote sensing to measure plant height, monitor plant growth, predict plant yield, and identify the needs for an appropriate quantity of nutrients to increase productivity and reduce environmental pollution[9] predicted biomass of rice before the heading stage of BNDVI and GRVI using remote sensing by UAV and found this method effective. From a study by [10] RGB waves were used for predicting Chlorophyll in wheat leaves using the reflectance relation of (R-B)/(R+B). For a study by [11] they used reflectance relation of R/(R+G+B) for studying the quantity of Chlorophyll in cabbage leaves. A study of found that it was feasible to adopt camera-attached drones and reflectance relation of (R-B)/(R+B) [12]and R/(R+G+B) to monitor rice growth. Therefore, this study has adopted remote sensing technology using RGB-camera-attached UAV to use the imagery for calculating the reflectance relation of (R-B)/(R+B) and R/(R+G+B) through a field survey, monitoring of rice growth in order to create models for predicting biomass of rice before and after the heading stage, predicting reliability of the models using RMSE, and comparing validity of RMSE in evaluating the models.

2. Objectives

To monitor rice growth using the reflectance relation of (R-B)/(R+B) and R/(R+G+B) and to predict biomass of rice using UAV-derived aerial imagery

3. Methodology

3.1 Study Area

The study areas were in-season rice fields which relied on rainfall for growing photoperiod sensitive varieties, which is jasmine rice 105 on the rice field area of approximately 1.5 rai, and transplantation of rice seedlings was done in early July 2018. Ban Nong Kung, Ban Thum Sub-district, Mueang District, Khon Kaen Province is located at 16°28'2.208" North and 102°40'30.144" East with topography as upland rice fields with heavy rain from August to September, and generally there is rainfall throughout the year. The average rainfall in Khon Kaen is approximately 1,231 mm, the average highest temperature is 36.45°C, and the average lowest temperature is 15.50 °C in the rice field area as illustrated in Fig. 1.

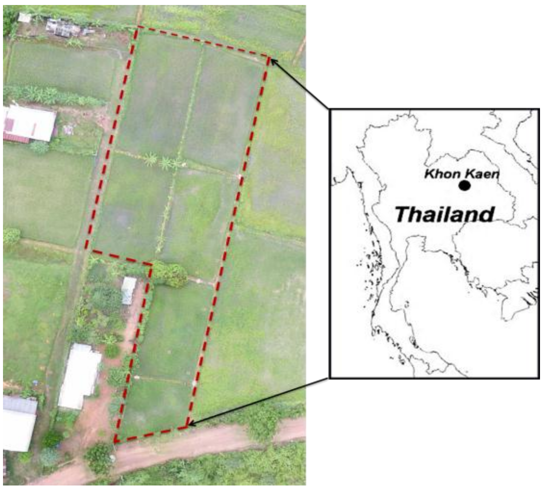

Fig. 1: Experimental Rice Plot, 1.5 Rai

3.2 Data of the UAV used in This Study

The researcher used the Phantom 3 Advanced UAV-derived aerial imagery which was recorded six times – first during tillering stage, second during vegetative stage, third during booting stage, fourth during late booting stage, fifth during milky stage, and sixth during ripening stage, using an RGB camera attached with the Phantom 3 Advanced UAV with a resolution of 12 million pixels, FOV FOV 94° 20 mm (equivalent to 35mm) f/2., and reflectance property in each wave range of approximately 350-600 nm. The UAV was planned to fly using PIX4D Application, at an altitude of 90 m, the front-overlap of 90% and side-overlap of 60%. The UAV-derived aerial imagery was processed by using Agisoft Photoscan Professional Program to adjust parameters of the camera, and perform geometric correction using six ground control points from surveying coordinates using Total Station camera. After imagery processing, the orthophoto map had a ground resolution of 0.02 m/pixel, and QGIS Desktop 2.18 was used to create a map for finding rice biomass.

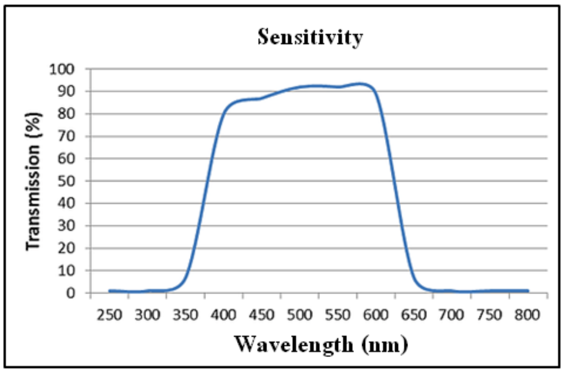

Fig. 2: Reflection properties for each wave, RGB Camera installed with Phantom 3 Advance

3.3 Field Data Collection Methods

Field data were collected six times: first during tillering stage, second during vegetative stage, third during booting stage, fourth during late booting stage, fifth during milky stage, and sixth during ripening stage [13] using an RGB camera attached with the Phantom 3 Advanced UAV. Then rice biomass data were collected under the sampling frame of 30x30 cm as shown in Fig. 3 for marking rice biomass samples in the experimental rice plot. 20 samples were collected at a time for six times, totaling 120 samples. After photo taking was complete, rice with root was dug up, soil was washed away, and the rice was weighed on a precision digital balance in gram. Then rice biomass was calculated in kg/m2 to prepare data for the Rapid miner Studio 9.1. The data were divided into two groups 80 samples for calibration data sets and 40 samples for evaluation data sets. After that, Red Green Blue Index (RGBI) and green-red vegetation index (GRVI) [14] were calculated.

$$\text{Biomass} = \frac{\text{Weight of rice with root in the frame (kg)}}{\text{Area of the sampling frame of } 0.30\text{x}0.30\ (\text{m}^2)} \quad (1)$$

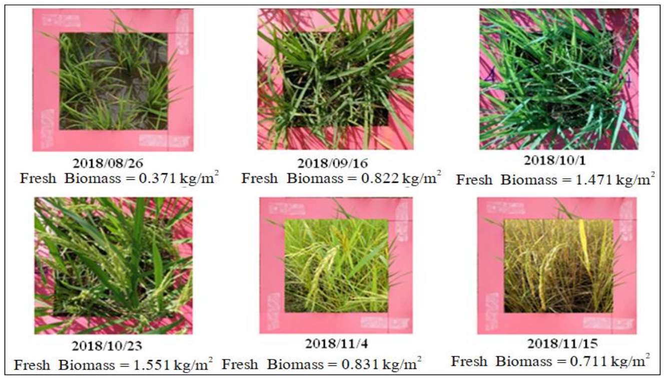

Fig. 3: Frame area to collect sample of rice biomass 0.3x0.3 m^2

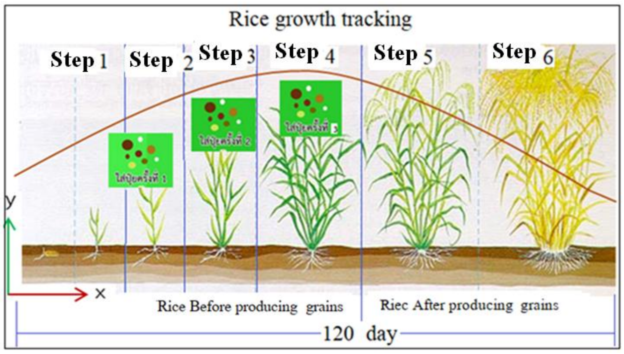

Fig. 4: Correlation Rice Before producing grains & Riec After producing grains.

Fig. 5: Photo of rice plot in each period for 6 times

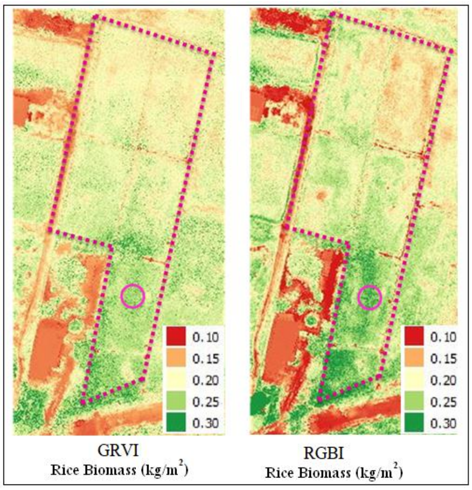

Fig. 6: Map shows the amount of RGBI and GRVI biomass value

3.4 Prediction of Biomass from Plant Indices

To predict Red Green Blue Index (RGBI) and green-red vegetation index (GRVI), perform calculation of RGBI and GRVI based on Equations 2 and 3 to find a relationship with the rice biomass obtained from the field survey in a linear function based on the three models [15].

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

$$GRVI = (G-R)/(G+R) \quad (3)$$

; where G is reflectance in the green light wave

R is reflectance in the red light wave

B is reflectance in the blue light wave

After RGBI and GRVI were calculated, use each picture element in the sampling frame of 0.3x0.3 m^2 from 120 samples to calculate GRVI and RGBI of each sampling frame. The processed resolution of the picture element was 0.05x0.05 m^2, and there were 225 picture elements in each sampling frame. Then the result of RGBI and GRVI calculation was analyzed using Rapid miner Studio 9.1.

All the 120 samples of rice biomass data obtained from the field survey were input on Rapid miner 9.1 based on the set models, which were Generalized Linear Model, Deep Learning, and Random Forest. The data were divided into two groups, namely 80 samples for calibration data sets, and 40 samples for evaluation data sets. Predicted biomass served as a dependent variable (Y), and biomass served as an independent variable (X) through a linear function based on GRVI and RGBI data. Then the Coefficient of Determination (R^2) and Root Mean Square Error (RMSE) [17] were calculated based on Equation 4.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \quad (4)$$

Where y_i is rice biomass derived from the model (kg/ m^2)

$\hat{y}_i$ is rice biomass derived from a field survey (kg/ m^2)

n is the number of samples

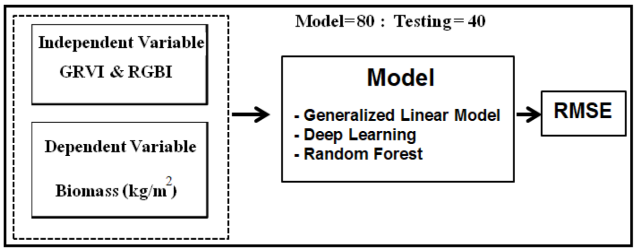

Fig.7: Research process diagram

4. Research Results

From the study to monitor rice growth using reflectance relation of (R-B)/(R+B) and R/(R+G+B) to predict rice biomass before the heading stage (1-4) and after the heading stage (5-6) through UAV-derived aerial imagery [16] from an RGB camera attached on the UAV, which flew to take pictures to be used for calculating Green-Red vegetation index (GRVI) and Red Green Blue Index (RGBI), and collection of field data analyzed through Rapid miner Studio 9.1 in three models, namely Generalized Linear Model, Deep Learning, and Random Forest, with 120 sets of field data of rice biomass before and after the heading stage, which were divided into two sets 80 sets as calibration data sets, and 40 sets as evaluation data sets, having predicted biomass as a dependent variable (Y) and biomass as an independent variable (X) through a linear function based on GRVI and RGBI, and calculation of Coefficient of Determination (R^2) and Root Mean Square Error,[17] it was found that

GRVI of rice before the heading stage (1-4) had R^2 of 0.836, 0.868, and 0.920, respectively, and RMSE of 1.405, 1.221, and 0.961, respectively, while RGBI had R^2 of 0.567, 0.614, and 0.918, respectively, and average RMSE of 1.621, 1.554, and 0.697, respectively. The model with good prediction was Random Forest as in Table 1.

Testing Model	Generalized Linear Model		Deep Learning		Random Forest	
	R^2	RMSE	R^2	RMSE	R^2	RMSE
GRVI	0.836	1.405	0.868	1.221	0.920	0.961
RGBI	0.567	1.621	0.614	1.554	0.918	0.697

Table 1: Biomass Rice Before producing grains [1]-[4]

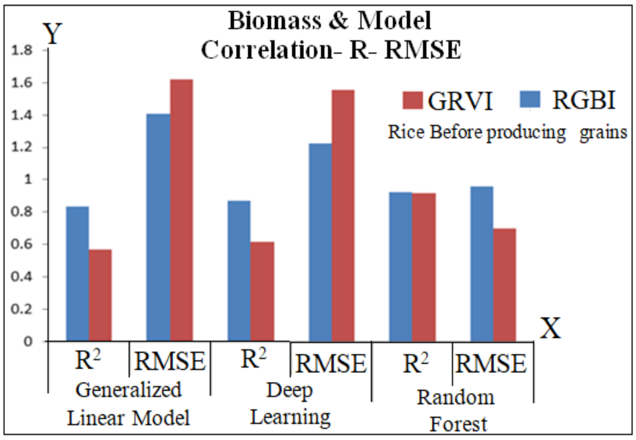

Fig. 8: Graph shows the comparison of all 3 models

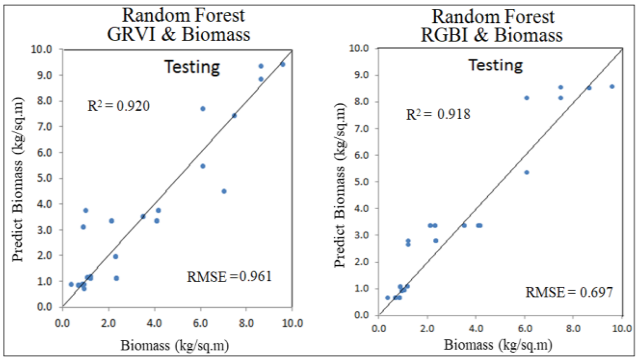

Fig. 9: Test result of random forest model, GRVI and RGBI plant index

The range of rice grains after the period 5-6 found that the GRVI decision coefficient (R^2) was 0.378, 0.419, 0.854 respectively and the square root value of the mean square error (RMSE) was 2.706, 2.662 and 1.648 and RGBI plant index showed that the decision coefficient (R^2) respectively was 0.462, 0.475, 0.810 and the square root of the mean square error (RMSE) was 2.654, 2.620 and 1.530, respectively. The predicted model was Random Forest. According to Table 2

Testing Model	Generalized Linear Model		Deep Learning		Random Forest	
	R^2	RMSE	R^2	RMSE	R^2	RMSE
GRVI	0.378	2.706	0.419	2.662	0.854	1.648
RGBI	0.462	2.654	0.475	2.620	0.810	1.530

Table 2: Biomass Rice After producing grains [5]-[6]

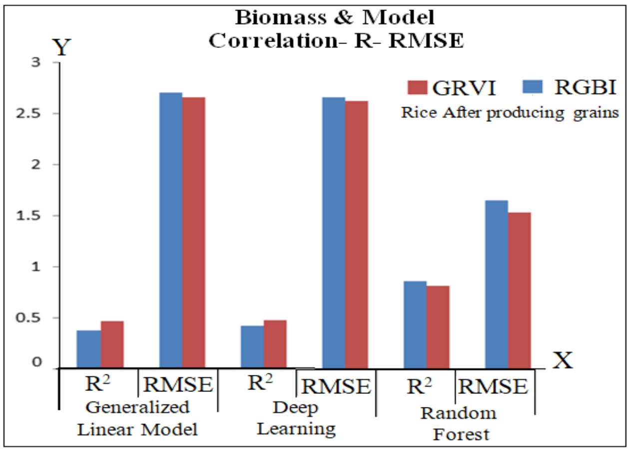

Fig. 10: Graph shows the comparison of all 3 models

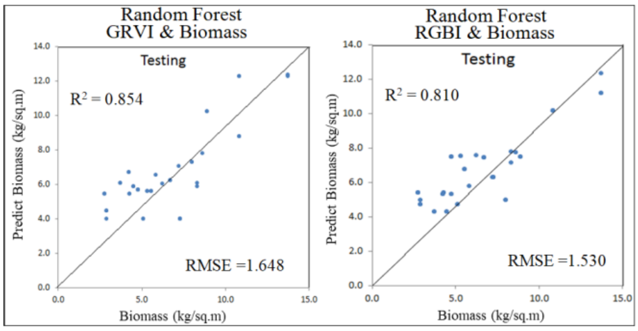

Fig. 11: Test result of random forest model, GRVI and RGBI plant index

5. Conclusions

From monitoring rice growth using reflectance relation of (R-B)/(R+B) and R/(R+G+B) to predict biomass before and after the heading stage through UAV-derived aerial imagery from an RGB camera attached on the UAV to take pictures at an altitude of 90 meters, with the front-overlap of 90% and side-overlap of 60%, to calculate Green-Red vegetation index (GRVI) and Red Green Blue Index (RGBI), and collection of field data, which were divided into two parts – calibration data sets and evaluation data sets for three models, namely Generalized Linear Model, Deep Learning, and Random Forest, it was found that from 120 sets of data, 80 data sets were used for calibration and 40 data sets were used for evaluation, From prediction of Coefficient of Determination (R^2) and Root Mean Square

Error (RMSE), it was found that for biomass before the heading stage, the model with good prediction was Random Forest; for GRVI, R^2 and RMSE were 0.920 and 0.961, respectively; for RGBI, R^2 and RMSE were 0.918 and 0.697, respectively. Meanwhile, for biomass after the heading stage, it was found that the model with good prediction was Random Forest; for GRVI, R^2 and RMSE were 0.854 and 1.648, respectively; for RGBI, R^2 and RMSE were 0.810 and 1.530, respectively. This suggests that the reflectance of both equations based on GRVI and RGBI could be used to monitor rice growth.

Acknowledgements

I would like to extend my sincere thanks to dad, mom, teachers and those providing data to support this study and for making this work possible.

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Biography

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