Calibrating LAI Parameter with Remote Sensing Data for SIMRIW-RS in Thailand

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***Abstract*— Rice is a major industrial crop in Thailand and has been cultivated country-wide. An ability to estimate rice production on a regional scale is therefore imperative for adaptation plan to climate change. For example, agricultural zoning can be adopted to optimize among locale characteristics, farmer practices, water resources, and expected yields. Recently, a crop simulation model called SIMRIW-RS has been validated for rice yield estimation, based on calibration of field parameter, namely accurate LAI values in early growing period. This paper presents a calibration of SIMRIW-RSand a methodology to incorporate remote sensing data products (NDVI and EVI2) into SIMRIW-RS by means of estimated LAI parameter. Based on data collected from rainfed paddy field in Nongchok District, Northeast-Bangkok during 2017-2018, our results show that the model calibrated with LAIestimated by NDVI can simulate LAI values for the entire crop with RMSE less than 1.0, and consequently achieve simulated yield with mean percentage error (MPE) around 2%. In addition, SIMRIW-RS also shows to be insensitive to pixel size when data from drone is upscaled to be ten times larger, which makes it compatible with medium- to high-resolution satellite images.This work concludes that SIMRIW-RS can be adapt to Thai rice, and NDVI product from remote sensing data in early stage can be used to provide field-to-field variations for SIMRIW-RS to work on a regional scale.**

Keywords—crop simulation model; EVI2; LAI; NDVI; remote sensing, rice yield estimation

I. INTRODUCTION

World's demand for rice in the last decade has been increasing [1], around 1.46% annually, from 447.2 million tons (MT) in 2009/10 to 509.5 MT in 2018/19. A study based on CERES Rice Model [2] reveals that climate change plays an important role on rice production; a deficit of precipitation 1 mm/day can reduce rice yield by 133kg/ha and a 1^{o}C of temperature rise can reduce the yield by 300kg/ha. These numbers may significantly affect Thailand as a world major rice production and exporter. According to the 1961–2015 World bank's historical data, Thailand's average precipitation and temperature changes in 2015 are –0.58 mm/day and 0.82^{o}C, respectively [3]. To put these numbers into perspective, average rice yield could be reduced by 12.75% [4].

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Since rice is cultivated country-wide, occupying half of the arable areas at 9.2 million hectares and involving 16 million farmers [5], the Royal Thai government has put great efforts to stabilize the socioeconomic of rice production. Since the past, government subsidy in various forms (pricing subsidy is the most common) have been implemented but their effectiveness is still questionable. The government does not have good tools to facilitate their schemes, especially to report the current and expected status of paddy field and rice yield. Remote sensing techniques has been used to develop a rice acreage monitoring platform by GISTDA and is currently operationalon a websitehttp://rice.gistda.or.th/ricefield.This service updates the paddy field area of Thailand every two weeks; however, it does not provide rice yield information. Concurrently, the Office of Agricultural Economics (OAE) jointly developed a technique called "crop cutting" with Japan International Cooperation Agency (JICA)'s experts to estimate the yield from multiple sample plots. This data is used to estimate the total yield by multiplying it with the paddy field area estimated from remote sensing. While this technique can satisfy the need for yield information to be displayed on geographic information system (GIS), it is expensive and time-consuming to achieve good accuracy. Moreover, it can only "estimate" based on current data but cannot "predict" the yield in advance which is becoming more importance to deal with climate change impacts as well as rice production stability.

Crop simulation is a mathematical model used for studying crop growth and yield based on specific conditions defined by set of input scenarios. Typical inputs are climate data, crop data, soil data, and field and irrigation management data. By preparing future climate data as input, the model can predict crop growth and yield for a desired crop calendar in advance, hence, farmers can have valuable information for appropriate actions in response to climate change. Similarly, the government can have an overall picture of rice crop production to make decision and setup measures such that the adverse impacts are minimized. Wide range of crop simulation models are presently available, DSSAT [6] is among the famous ones that requires many input parameters while CropSyst, WOFOST, and SPAC are reported to be rather complicated for end users [7]. AquaCrop [8], developed by the Food and Agriculture Organization (FAO), is considered more user-friendly in terms of input requirements and simulation settings. The model has been successfully tested and widely adopted for major crops in many countries [9,10]. Since AquaCrop does not support direct inputs from remote sensing products, its usage is limited to farm-scale where a set of input parameters represents a homogeneous farmland. Recent study in Thailand [11] shows how AquaCrop can take canopy cover (CC) as an input derived from NDVI product based on HJ-1A/B satellite images, achieving simulated yield with R^2=0.88. This promising result suggests that a combination of crop model and remote sensing products can be used to evaluate rice production in a regional scale. However, its calibration process requires significant amount of 28 satellite images which may not be practical for model deployment in different regions.

SIMRIW-RS [12] is a rice crop simulation model that incorporates weather data, farm management, field parameters, cultivar parameters, while utilizing remote sensing information to optimize the model parameters. The authors mentioned that the Leaf Area Index (LAI) and LAI growth rate values correspond to soil fertility and water stress of the field. The model can calculate LAI values, establish a soil fertility map, and simulate rice growth and productions, even though climate data and farming management information (e.g., fertilizer, cultivar, and plating date) are not entirely available. However, at least 2 calibrations at early growing periods, with an estimated LAI from remote sensing data are required [13] to achieve good accuracy. If applied to a similar group of paddy fields in the same periods, SIMRIW-RS may require minimal remote sensing satellite images for calibration and, thus, is more practical to put into operations. On the other hand, it is also applicable for "big farm strategy" where remote sensing data from drone is possible.

This work presents a calibration procedure for SIMRIW-RS based on actual LAI from an experimental field in Bangkok and estimated LAI from multispectral images from drone. Our results show that SIMRIW-RS can achieve simulated LAI with RMSE at 0.95 and simulated yield with mean percentage error (MPE) at –2.07%. The rest of the paper is organized as follow. Section 2 elaborates material and methods. Section 3 provides results and discussion. Section 4 concludes this work.

II. MATERIAL AND METHOD

A. Experimental Field

The experimental field is a 6.88-hectare paddy field located at Nongchok district in Bangkok (13.936121,100.86953). The rice cultivar is RD–41 (100–day cycle) and RD–57 (110–day cycle). Fifty sample plots (1x1m^2) were selected throughout the field (evenly distributed by the field periphery as shown in Fig.1) for ground data collections including LAI, aboveground biomass, and multispectral image from drone. TABLE 1 shows field survey schedules in 2017 and 2018. Equipment used in this study is GPS Garmin Colorado 300, LAI-2200 Plant Canopy Analyzer, DJI Phantom 3 advanced with Parrot Sequoia multispectral camera, and a grain moisture meter.

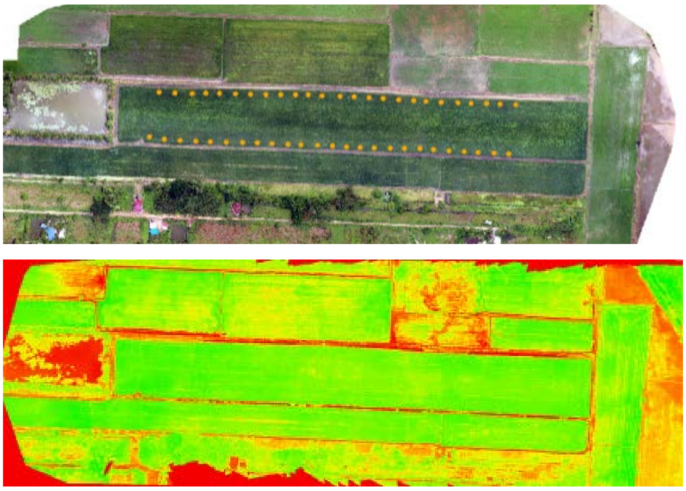

Fig. 1. The experimental field (upper) Orthorectified image and sample plot locations shown in orange dots, (lower) NDVI product (values increase from red to green colors)

TABLE 1. FIELD SURVEY DATES AND AVERAGE LAI VALUES

No.	2017			2018		
	Date	***DAP***[a]	***Average LAI***	***Date***	***DAP***	***Average LAI***
1	01/06	37	2.78	16/05	21	0.83
2	09/06	45	4.06	30/05	35	2.79
3	16/06	52	4.47	07/06	43	3.94
4	23/06	59	4.58	20/06	56	4.54
5	30/06	66	6.00	29/06	65	4.67
6	07/07	73	6.42	09/07	75	4.70
7	27/07	93	3.41	01/08	98	4.36
8	01/08	98	–			–

[a] DAP stands for Day After Planting

B. Field Data

- Leaf Area Index (LAI) is defined as one-sided green leaf area per unit ground surface area. It is used to characterize plant canopies. SIMWIW-RS calculates this value based on its initial value of field and cultivar parameters. It then simulates the aboveground dry matter and the yield based on this simulated LAI. Calibration of this value with actual LAI from the field can help optimizing the model's parameters and improve its accuracy. This study collected LAI values from 50 plots for the entire crop season in year 2017 and 2018. Actual LAI values are averaged to indicate therice growing periodand is shown as average LAI in Table 1.

- Normalized Difference Vegetation Index (NDVI) and 2-band Enhanced Vegetation Index (EVI2) are typical data products from remote sensing data. NDVI is used to identify vegetation and its condition of the area and is defined as

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (1)$$

where NIR and Red are the spectral reflectance measurements in the red (visible) and near-infrared bands, respectively. The possible values are in ±1 interval. Highervalues indicate better vegetation conditions in the vegetative regions.

- EVI2 is a variation of EVI when the blue band is not available. It is designed to enhance vegetation signal sensitivity in high biomass area and is more responsive to canopy variations than NDVI. It is defined as

$$EVI2 = 2.5 * \frac{NIR - Red}{NIR + 2.4 * Red + 1} \quad (2)$$

To apply SIMRIW-RS at regional scale while retaining field-to-field variation, remote sensing data can be used in lieu of actual LAI for model calibration.The calibration using Normalized Backscattering Coefficient from COSMO-SkyMed (SAR) data to estimate LAI values was proposed in [13] and successfully achieved simulated yield at 3.5% error in Vientiane, Laos PDR. Similarly, this work attempts to find the relationship between NDVI/EVI2 versus actual LAI values and evaluates if both remote sensing data products can be used to estimate LAI for model calibration. Actual LAI values in 2018 were used for regression whereas LAI values in 2017 were used for performance evaluation. On each field survey, remote sensing data were collected using Parrot Sequoia multispectral and CCD cameras installed on DJI Phantom 3 advanced with 10cm ground sample distance (GSD) or 10cm/pixel. Therefore, each plot contains 10x10 pixels, its corresponding NDVI/EVI2 indices are an average value from 100 pixels in the plot.

Fig. 2. Field survey activities.

- Weather data are mandatory inputs for SIMRIW-RS to calculate relevant parameters and to simulate rice growth conditions. A nearby weather station transfer data automatically to our server at Chulabhorn Satellite Receiving Station (CSRS). Received data are processed into a daily data format, which are accumulated rainfall (mm/day), average temperature (Celsius/day), daytime (hours/day), and solar radiation (W/m^2/day).

- Yield data were collected on each plot for a total of 50 plots by reaping the rice plant within circular area of 1m^2, threshing rice and carefully separating the grain, drying the grain by sunlight until its moisture content is < 20%, and weighting the grain and stump and finally record the values.

C. Experimental Setup

There are two issues to be investigated in this work, to find a suitable growing period to estimate LAI values from EVI2/NDVI for model calibration; and to evaluate the effects of resizing data pixel from 10x10cm^2 to 1x1m^2. The latter is to understand the results when satellite data is to be applied to the model in the future. As mentioned in [13], at least two calibrations of LAI in early growing period are essential to achieve accurate simulated LAI and yield from SIMWIR-RS. Therefore, the experimental steps are designed as follow.

- In response to early growing period criteria, only data from the 1st, 2nd, and 3rd field surveys were used to find relationship between actual LAI and EVI2/NDVI from drone images. The regression performance is evaluated in terms of RMSE on another data sets.

- Use the regression formulas and NDVI/EVI2 products to estimate LAI values to calibrate SIMRIW-RS, based on the following timing strategies. Method I: use NDVI/EVI2 from the 1st and 2nd field surveys, Method II: use NDVI/EVI2 from the 2nd and 3rd field surveys, and Method III: use NDVI/EVI2 from the 1st and 3rd field surveys.

- Let SIMRIW-RS generate simulated LAI and simulated yield and evaluate RMSE of the simulated LAI with the 4th, 5th, and 6th field survey and evaluate MPE of the simulated yield with the actual yield.

- Determine which method performs the best in terms of RMSE and MPE indices.

- Resizing pixel size from 10x10cm^2 to 1x1m^{2}using standard software and repeat the experiment steps.

III. Results and Discussion

A. Estimating LAI from Remote Sensing Data

Field data collected in 2018were used for regression between actual LAI values and NDVI/EVI2 products. Both linear and nonlinear regressions were performed to maximize a coefficient of determination, R^2, and were compared based on RMSE evaluated by data collected in 2017. Figure 3 clearly states that nonlinear regressions outperform linear regressions for both indices. Especially for NDVI, R^2 value from exponential regression improves significantly (R^2=0.8923) because NDVI tends to saturate at LAI value greater than 3.0. We estimated LAI using EVI2/NDVI from field data collected in 2017, and calculated RMSE based on actual LAI for performance comparison purpose.Table 2summarizes regression characteristics and RMSE performance. Linear regressions were chosen as they provide lower RMSE.

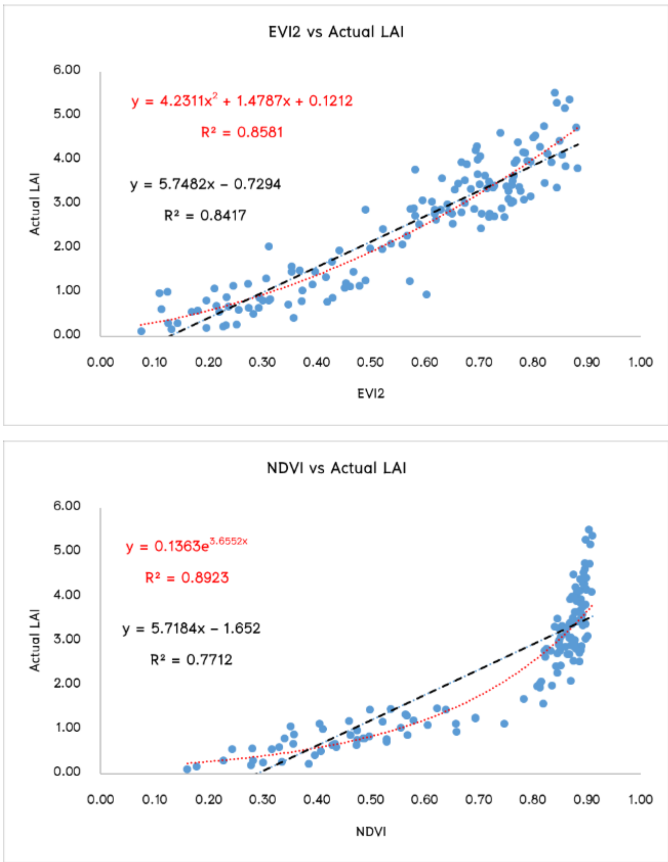

Fig. 3. Linear and nonlinear regressions between (top) actual LAI versus EVI2 and (bottom) actual LAI versus NDVI at early growing stage.

TABLE2PERFORMANCE COMPARISON BETWEEN LINEAR AND NONLINEAR REGRESSIONS BASED ON EVI2/NDVI PRODUCTS

	Linear Regression	Nonlinear Regression
EVI2	$LAI = 5.7482 * EVI2 - 0.7294$ $R^2 = 0.8417, RMSE = 1.205$	$LAI = 4.2311 * EVI2^2 + 1.4787 * EVI2 + 0.8581$ $R^2 = 0.8581, RMSE = 1.276$
NDVI	$LAI = 5.7184 * NDVI - 1.652$ $R^2 = 0.7712, RMSE = 1.376$	$LAI = 0.1363 * e^{3.6552*NDVI}$ $R^2 = 0.8923, RMSE = 1.587$

B. *Evaluating Rice Growing Period for SIMRIW-RS Calibration*

To achieve good simulation results, SIMRIW-RS shall be calibrated with LAI values from the field or from remote sensing data in early growing period. Previous discussion has shown how to estimate LAI from EVI2/NDVI products. Here, we investigate the growing period that determines suitable times to estimate LAI values. It is worth noting that, from this point on, only field survey data in 2017 were used because its corresponding yield data was ready. Method–I, –II, and –III correspond to DAP equals to 37/45 days, 45/52 days, and 37/52 days, respectively. For a given method, LAI is estimated by EVI2 and NDVI products as inputs to SIMRIW-RS to simulate LAI and finally the rice yield values. Since each pixel is 10x10cm^2, all the values of 100 pixels are average on each plot for a total of 50 plots. The RMSE of simulated LAI compared to actual LAIfor all methods, at later growing period—59/66/73 days, are stacked up as shown in Fig. 4. Both EVI2 and NDVI calibrations exhibit similar RMSE pattern but NDVI, particularly based on Method–I, seems to achieve lower RMSE on most plots. Similarly, NDVI with Method–I show the lowest MPE for simulated yields. These performance indices are summarized in TABLE 3. (Best results are shown in bold.) Method–Ithat uses 37/45 days estimation of LAI are recommended because they represent low dispersion region of the trend lines (actual LAI is less than 2.0) as shown in Fig. 3. By the same token, Method–III is too late to provide good estimation of LAI at 52 days.

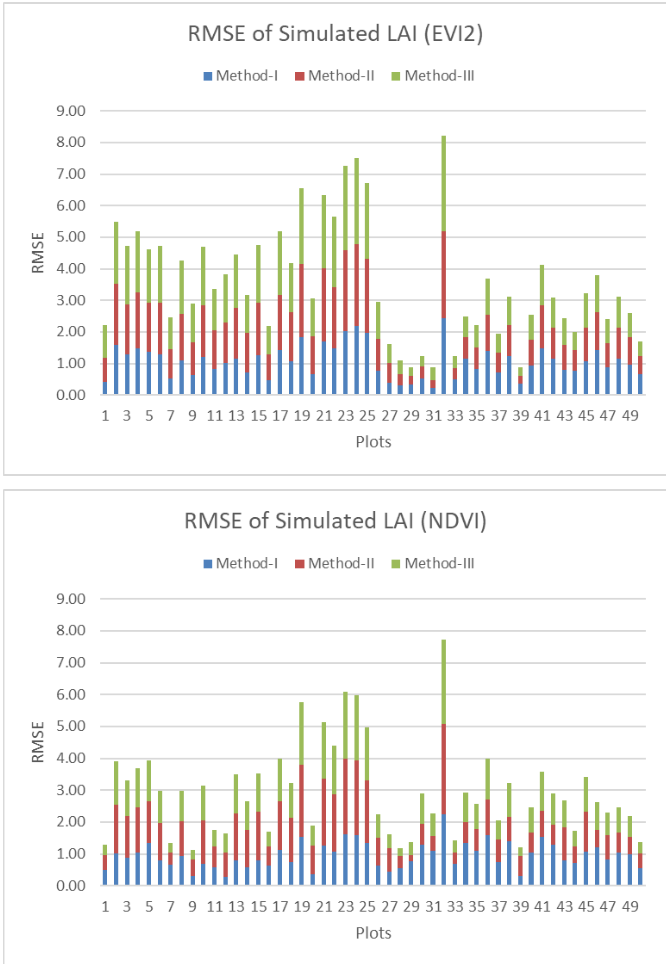

Fig.4. RMSE of simulated LAI, calibrated with (top) EVI2 and (bottom) NDVI.

C. *Resizing pixel size of drone image*

To apply SIMRIW-RS in a reginal scale, remote sensing from satellite is inevitable. While coverage is key advantage to satellite image, spatial resolution is its drawback especially for a sub-meter images because they are expensive and scarce. Nevertheless, satellite data resources at resolution 5–10 meters are becoming mainstream and some are freely available (such as data from CBERS–04 and Sentinel–2 satellites). As a result, we aim to quantify how SIMRIW-RS responses to medium- to high-resolution satellite images. By upscaling the pixel size hundred times larger (at 1x1m^2) and repeating the experiment. The results are shown in TABLE 3 and the difference is shown to be minimal. While Method–III exhibits lowest difference, it is not a choice. Method–I based on NDVI calibration is achieving the lowest RMSE and MPE at 0.93 and –2.25, respectively.

TABLE3 PERFORMANCE OF EVI2 AND NDVI CALIBRATIONS ON SIMULATED LAI AND SIMULATED YIELD.

Product	**Mode**	**Method**	**Pixel Sizes**		**Diff.**
			10x10cm^2	***1x1m^2***	
EVI2	RMSE (LAI)	I	1.06	1.05	0.02
		II	1.22	1.26	–0.03
		III	1.29	1.30	–0.01
	MPE (Yield)	I	–6.17	–7.31	1.14
		II	–10.27	–11.55	1.27
		III	–11.52	–12.26	0.74
NDVI	RMSE (LAI)	I	***0.95***	***0.93***	0.02
		II	1.04	1.05	0.00
		III	0.97	0.96	0.01
	MPE (Yield)	I	***–2.07***	***–2.25***	0.18
		II	–9.68	–9.92	0.23
		III	–6.32	–6.32	0.00

IV. CONCLUSIONS

In this study, the calibration procedure of SIMRIW-RS using field data and images from drone are investigated in Thailand. SIMRIW-RS can simulate rice growth and yield based on soil fertility in terms of simulated LAI values. However, the simulated values based on initial conditions may not reflect field-to-field variations correctly, so it needs calibration from external sources. Remote sensing data products, EVI2 and LAI, are shown to have a good relationship with actual LAI from the field with R^2 = 0.8417 and 0.7712. Our study shows that we can use them to estimate LAI values to calibrate SIMRIW-RS at early growing period (37/45 days) which NDVI is superior in terms of RMSE (for simulated LAI) and MPE (for simulated yield) at 0.95 and –2.07, respectively. As remote sensing data form satellite will enable SIMRIW-RS to apply on a regional scale, we therefore repeat the experiment on upscaled data pixels (ten times larger) and still obtaining very similar results. We conclude that SIMRIW-RS is potentially compatible with commonly available satellite data and our further performance investigation is underway.

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