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Selecting The Most Optimum Sentinel-2A Based Vegetation Index to Estimate the Leaf Area Index of Three Rice Cultivars

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Abstract

The estimation of leaf area index (LAI) becomes important as LAI is one of the parameters in analyzing the crop growth model. Crop growth has different characteristics and it's strongly influenced by environmental conditions and factors. The growth tends to occur in a short period and covers a large area. Therefore, an approach to analyzing the pattern of changes in crop growth based on LAI spatially is needed. Remote sensing offers an effective and efficient approach to monitoring crop growth characteristics, which can be done in a time series with a wide area coverage by detecting and monitoring the physical characteristics of the crop. The most famous and commonly used parameters to estimate LAI are vegetation indices which are usually calculated based on the ratio of the red and NIR wavelength, known as a spectral signature. The objectives of the research are to examine the Spatio-temporal correlation between LAI of three rice cultivars Sentinel-2A based vegetation indices and to select the most optimum vegetation index in estimating LAI. The field experiment was set up comprising 81 plots, each had a size of 10m x 10 m to resemble a pixel of Sentinel-2A imagery. The results of the analysis show that the vegetation index has a strong correlation with LAI. The Comparison of the four calculated vegetation indices in estimating LAI was performed using a linear regression model and followed by comparing R-squared, RMSE, and Correctness. In general, the EVI2 vegetation index provides the most optimum representation in capturing crop growth patterns based on LAI compared to NDVI, ARVI and SAVI vegetation indices calculated from Sentinel-2A satellite imagery indicated by the better-validated model with the result of RMSE value are 1.12 on V1, 1.11 on V2 and 0.70 on V3. The result of EVI2 Correctness also showed the highest value compared to the other vegetation indices with values of more than 60%, 64.15% on V1, 65.51% on V2, and 78.69% on V3. Further analysis by separating two growth stages could overcome the bias that appears in the LAI data for one life of the crop cycle which is indicated by the decrease of RMSE value on each cultivar planted for both vegetative and generative phases, except for cultivar V3 for the generative phase. The separation of data into two growth stages also increase the percentage value of correctness reaching a number above 60% and there was a value that reached 87%.

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1. Introduction

Leaf area index (LAI) quantifies the amount of leaf area in an ecosystem and is a critical variable in processes such as photosynthesis, respiration, and precipitation interception (Fang et al., 2019; Alton, 2016; Asner et al., 1998; Boussetta et al., 2013; Jarlan et al., 2008). LAI is also one of the parameters used in the analysis of the crop growth model. The growth of rice plants tends to occur in a short period and covers a large area, therefore an approach is needed such as monitoring from the planting phase to harvest which is close to near real-time. One of the most effective and efficient approaches to monitoring plants is by using remote sensing methods, which can be done in a time series with a wide area coverage. Remote sensing is the process of detecting and monitoring the physical characteristics of an area by measuring its reflected and emitted radiation at a distance usually from satellite or aircraft (USGS, 2022). By optimizing the use of remote sensing methods, we can analyze crop growth models spatially.

LAI derived from remote sensing data has been widely utilized to estimate crop growth (Liu et al., 2012; Dente et al., 2008; Guérif dan Duke, 2000). Since calculating LAI by using a destructive sample is time-consuming, the LAI value needs to be estimated. The most common and widely used parameters for estimating LAI are remote sensing-based vegetation indices, which are usually calculated from the reflectance of red light and near-infrared radiation (NIR) from the vegetation surface. These parameters are based on the spectral reflection characteristic of plant leaves which preferentially absorb red light and rarely absorb NIR (Fukuda et al., 2021). In the previous research conducted by Qin et al., (2021) comparing vegetation indices from Sentinel-2 and Landsat 8, the Sentinel-2A -derived vegetation index showed stronger relationships with LAI than the Landsat 8-derived vegetation index. Vegetation index analysis is one of the possible approaches to obtaining the spectral characteristics of plants known as a spectral signature. Gnyp et al., (2013) conducted a vegetation index calculation analysis to obtain the relationship between reflectance and agricultural crop characteristics. The spectral signature can represent the condition and characteristics of the plant. Liu et al., (2012) estimated crop green LAI by using imagery data-based vegetation indices. To get the most optimum vegetation index to estimate LAI by comparing several vegetation indices, Lee et al., (2018) was selecting the vegetation index using a statistical regression model with compared its results.

The objectives of the research are to examine the Spatio-temporal correlation between LAI of three rice cultivars on three fertilizer rates and three planting Techniques Sentinel-2A-based vegetation indices, and to select the most optimum vegetation index in estimating LAI. The result of this research is a model to estimate LAI.

2. Methodology

2.1 Time, Location, and Experimental Design

The research was conducted from April to November 2020, at an irrigated rice field area during the second planting session. The location of the field research is in Pasir Kaliki Village, Rawamerta District, Karawang Regency, West Java (Figure 1).

The field measurement and observation had been carried out during the research period in one life-of-cycle crop every 10 days following Sentinel-2A data acquisition for each 10-meters x 10-meters plot area. The field experimental plot was designed to facilitate the measurement of LAI and vegetation indices Sentinel-2A based imagery calculation according to fertilizer rates (F) as the main block, planting techniques (P), and rice cultivars (V) as the sub-blocks. Each treatment was replicated 3 times and produced 81 plots designed using the research design of split-plot randomized complete block design (RCBD). Each 10-meters x 10-meters plot size approximately represented 1 pixel of blue (B2), green (B3), red (B4), and 84 NIR (B8) bands of Sentinel-2A imagery.

The plot position was exactly fitted and overlaid with the pixel's position of Sentinel-2A imagery. The map of experimental plots is shown in Figure 1. The treatments in the RCBD are arranged as the following:

1. The rate of fertilizer application (F) is the main block, consisting of three levels:
   a. F1 is a recommended level according to (Permentan No.40/Permentan/OT.140/4/2007, 2007);
   b. F2 is a rate 30% higher than the recommendation;
   c. F3 is a rate 30% lower than the recommendation.
2. Planting technique (P) as the sub-block, consisting of three levels:
   a. P1 (*Jajar Tegel)* is a planting technique for each plant with equal spacing of 25 cm x 25 cm, and after every 10 plants the space is 50 cm and produces 1480 plants for every single plot of 10-meters x 10-meters of *Jajar Tegel*;
   b. P2 (*Jajar Legowo* 2:1 or single seed technique) is generally notated as 25 x 12,5 x 50. *Jajar Legowo* 2:1 is planting rice in blocks of two rows in parallel at space within the row of 25 cm and spacing between the row of 12.5 cm. Space between blocks is twice the distance within the row in the block (50 cm) and produces 2080 plants for every single plot of 10-meters x 10-meters of *Jajar Legowo* 2:1;
   c. P3 (*Jejer Manten* or twin seed technique) is generally notated as 5 x 5 x 25 x 30. *Jejer Manten* is planting rice within a row with equal spacing of 25 cm and spacing between rows of 30 cm. At each point, two seedlings are planted with a distance of 5 cm between the seedlings and produces 2178 plants for every single plot of 10-meters x 10-meters of *Jejer Manten.*
3. Three rice cultivars (V) as the sub-main block representing the three most commonly planted by the farmer in the study location, i.e.:
   a. V1 (IR-69);
   b. V2 (Inpari-32);
   c. V3 (Pandan Wangi).

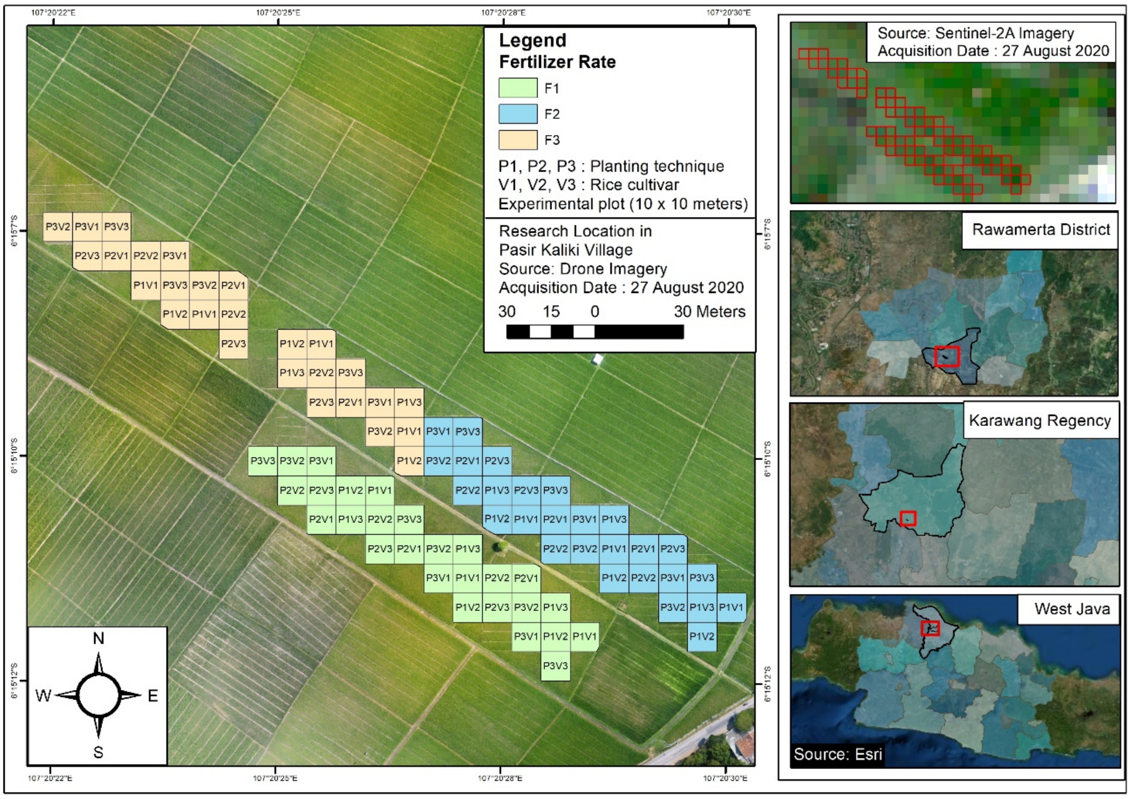

Figure 1. Research location and map of the experimental plot

2.2 Calculation of LAI

The leaf area index (LAI) is a dimensionless quantity and is defined as the projected area of leaves over a unit of land (m^2 m^2). In this study, a destructive sampling measurement was used to calculate LAI data on each experimental plot. The sample of rice plants was taken for each experimental plot. The sample of rice was separated into green leaves, brown leaves, stems, roots, panicles, and grains. The green leaves of each sample of rice were scanned by the printer scanner (EPSON L3110 and CanoScan LiDE 300) in A4 paper size. The total area of the green leaf was determined using digital image processing by the following formula:

$$LA = \frac{LP \times AS}{TP} \tag{1}$$

Where LA is the single plant leaf area, LP is the pixel number of green leaf, TP is the pixel number of the scanned image, and AS area of the scanned image in squared meters (equal to area A4 paper = 0.06237 m^2)

LA is measured immediately once a sample of rice is taken from experimental plots. For the age of plants between 7 and 17 days after transplanting (DAT), the leaf area was obtained by scanning the entire leaf of rice plants. The age of more than 17 days until harvest, around 5 to 7 green leaves for each sample of rice plant in each experimental plot were scanned. Then calculated using the SLA (Specific Leaf Area) approach. According to the plant population and 10-meters x 10-meters plot size, the LAI value of each plot is:

$$LAI = \frac{LA \times P}{100} \tag{2}$$

where LA is a single plant leaves area in each plot and P is plant population in one square meter and 100 is 10-meters x 10-meters plot size. The calculation of LAI using SLA is:

$$\mathrm{SLA} = \frac{\mathrm{LA}}{\mathrm{BLA}} \times (\mathrm{BL} + \mathrm{BLA}) \tag{3}$$

$$\mathrm{LAI} = \frac{\mathrm{SLA} \times \mathrm{P}}{100} \tag{4}$$

where BLA is the biomass of scanned green leaves and BL is the biomass of non-scanned green leaves. The biomass of the rice plant is obtained from the drying process in the oven at a temperature of 60 ºC within 48 hours.

2.3 Calculation of Sentinel-2A Imagery Vegetation Indices

Sentinel-2A level-2 (MS2A) product type was used in this research. Sentinel-2A has 12 spectral bands ranging from the Visible (VIS) and Near Infra-Red (NIR) to the Short Wave Infra-Red (SWIR) with different spatial resolutions. The blue (B2), red (B3), and NIR (B8) spectral bands were chosen with 10-meter x 10-meter spatial resolution to calculate vegetation indices (VI). Sentinel-2A imageries were acquired during the period of study, in one life cycle of the crop from transplanting (11 July) to harvesting (1 October for V1 and V3, 6 October for V2), the revisit frequency of the satellite is every 10 days. The data acquisition started on 18 July to 6 October 2020. Due to the cloud cover issue, a total of 7 temporal cloud-free Sentinel-2A data of the study area were used i.e., on 18 July, 28 July, 7 August, 27 August, 6 September, and 16 September or equal to 7, 17, 27, 37, 47, 57, and 67 DAT. Determination of the 10-day vegetation index based on Sentinel-2A imagery was performed by using four vegetation indices formulas, namely Normalized Difference Vegetation Index (NDVI), Atmospherically Resistant Vegetation Index (ARVI), Enhanced Vegetation Index 2 (EVI2), and Soil Adjusted Vegetation Index (SAVI). The selection of those vegetation indices was based on the bands which are used in the formula for calculating the vegetation index. The bands used to calculate the four vegetation indices have 10-meter x 10-meter spatial resolution. Therefore, the four indices were chosen as the experimental plots were made with the size of 10-meter x 10-meter by replicating the spatial resolution of those bands. The formulas used in this research are presented in Table 1.

Table 1. Vegetation Indices (VI) formula

No.	Formula	References
1	$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$	(Rouse *et al.*, 1974)
2	$ARVI = \frac{(NIR - Red - y(Red - Blue))}{(NIR + Red - y(Red - Blue))}$	(Bannari *et al.*, 1995)
3	$EVI2 = 2.5\,\frac{(NIR - Red)}{(NIR + 2.4Red + 1)}$	(Jiang *et al.*, 2008)
4	$SAVI = \frac{(NIR - Red)}{(NIR + Red + L)}(1 + L)$	(Goel dan Qin, 1994)

2.4 Data Preparation

The average value of LAI and vegetation indices for each plot that has the same treatment were calculated because the value is similar. The 27 sets of Spatio-temporal data were produced from 91 experimental plots. Afterward, to obtain a different distribution of data for each rice cultivar planted,

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the data set was divided into 3 data sets based on the 3 rice cultivars, namely V1, V2, and V3. The step was done to obtain a pattern of varietal data distribution consisting of different fertilizer rates and planting techniques.

2.5 Model Development and Selection

Correlation between LAI and vegetation indices was carried out to get the empirical formula that represents the Spatio-temporal relationship. R-squared became a parameter that was considered for the next stage to indicate how well the model predicted LAI. The range of R-squared can be from 0 to 1. The higher R-squared value indicates the goodness of fit for the linear regression model to express the result. A linear regression model was carried out to estimate the LAI value by using the vegetation indices value. The linear regression model expressed:

$$\mathrm{LAI} = \mathrm{ax} + \mathrm{b} \quad (5)$$

The method used in data validation is RMSE (Root Mean Squared Error), which measures the difference between the value of the prediction of a model as an estimate and the observed value. The range of RMSE can be from 0 to ∞. The estimation method which has a smaller RMSE is said to be more accurate than the estimation method which has a larger RMSE. The formula expressed:

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

where, y : observation data
$\hat{y}$: estimated data

Another method used is the Mean Absolute Percentage Error (MAPE). MAPE is used to see how well the results of the model are. MAPE is defined as (deMyttenaere, et al., 2016):

$$\mathrm{MAPE} = \frac{100}{N} \times \sum_{i=1}^{N} \left| \frac{x_i - \hat{x}_i}{x_i} \right| \quad (7)$$

where N is the number of data, x_i is actual observation values, and $\hat{x}_i$ is prediction values. The correctness value is the opposite value of MAPE. It is defined as:

$$\mathrm{Correctness} = 100 - \mathrm{MAPE} \quad (8)$$

Both values are in percentage form. The high value of correctness (close to 100%) indicates a high degree of accuracy. The data is divided into 2, namely calibration and validation with the composition of 80% and 20%. The validation data was used to test how well the model was by using the linear regression formula in estimating LAI value and tested with RMSE and Correctness.

2.6 LAI Based Vegetation Index Estimation Model

The vegetation index becomes an important function in capturing specific information about the characteristics of the rice (LAI). Temporal spatial data from Sentinel-2A imagery were used to be analyzed to get the calculated vegetation indices (NDVI, ARVI, EVI2, and SAVI). A vegetation index is an approach to obtaining the spectral signature characteristics of rice plants. The correlation between the results of the calculation of vegetation indices and LAI was analyzed. Furthermore, the linear regression model was carried out to estimate the LAI value by using each calculated vegetation index. The analysis results were validated by considering several statistical parameters such as RMSE and

Correctness to get the most optimum vegetation index to estimate LAI. The flowchart of LAI based vegetation index estimation model is shown in Figure 2.

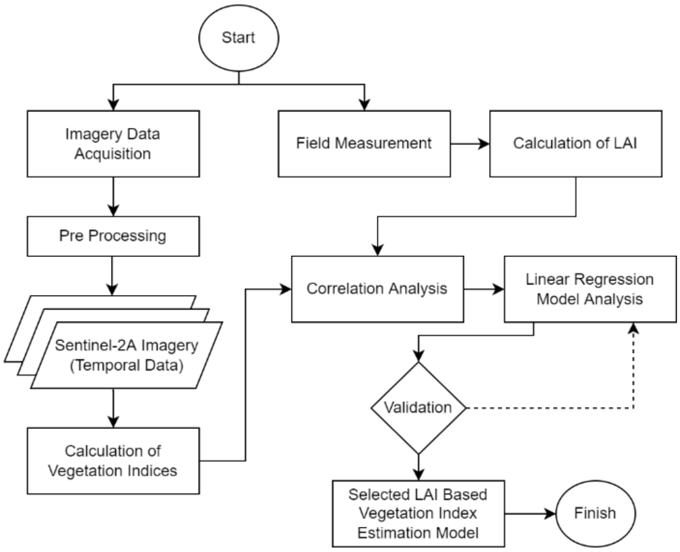

Figure 2. Flowchart of LAI-based vegetation index estimation model

3. Results and Discussion

3.1 Relationship between LAI and vegetation index

The relationship between LAI and vegetation index became the first step to be overserved and analyzed. The observation of the distribution pattern of the LAI and the vegetation index data considers whether the dynamics of the data distribution pattern are relatively similar. Afterward, the analysis of correlation (r) indicates the relation between LAI and vegetation index statistically.

The dynamics of the vegetation indices and LAI for all cultivars were generally uniform and had the same pattern, increasing in value until reaching a maximum at the maximum vegetative growth stage on 47 DAT (day after transplanting), and decreasing towards harvest time or generative stage after 47 DAT as presented in Figure 3 for average treatment of V1, V2, and V3. These results showed the same pattern as the research conducted by (Shihua *et al.*, 2014). Based on the pattern, it can be identified that there is a relationship between LAI and vegetation indices. The pattern confirmed that changes in the value of the vegetation index showed the same pattern as the value of LAI, when the LAI increased, the value of the vegetation index also increased and vice versa. Research conducted by Eriksson *et al.*, (2006) stated that the value of the reflection reflected by the plant has an impact on the value captured by the sensor. Crop growth also affected changes in LAI values and had an impact on changes in vegetation index values, as stated by Kawamura *et al.*, (2018) that the structure of the plant canopy affects the value of the spectral reflection.

Correlation (r) analysis for each vegetation index with LAI had been carried out to be tested statistically whether the LAI value correlates with the vegetation index value. The result of the correlation analysis showed a good relationship between LAI and vegetation indices on each cultivar. The correlation between LAI and vegetation indices on V1 and V3 indicated that NDVI, EVI2, and SAVI had the same correlation value of 0.92. Meanwhile, on V2, EVI2 became the vegetation index with the highest correlation value of 0.93. The correlation results showed that the values were not significantly different for each vegetation index. Based on these results, each calculated vegetation index had a good correlation in capturing changes in crop growth characteristics (LAI). The result of the correlation analysis is presented in Table 2.

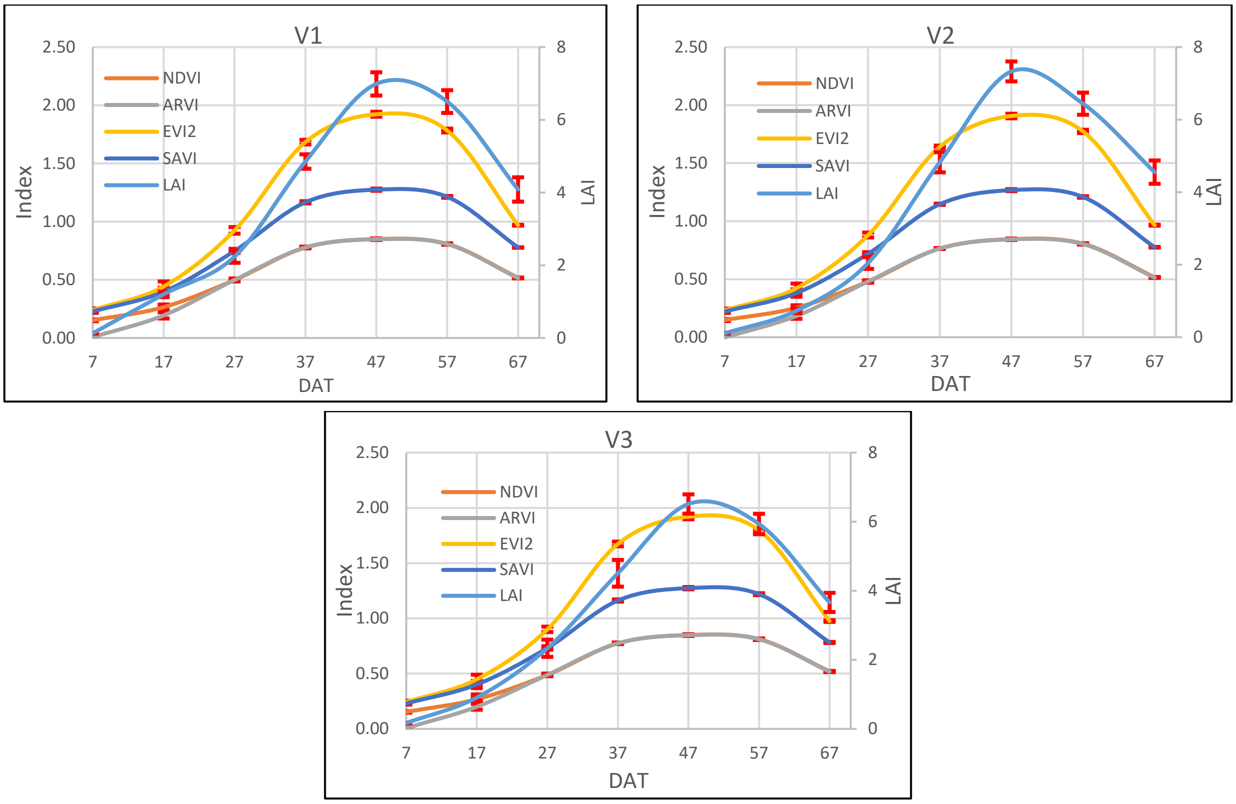

Figure 3. Dynamics of temporal variations of vegetation indices and LAI on three rice cultivars

Table 2. Correlation (r) between vegetation indices and LAI on three rice cultivars

Cultivar	NDVI	ARVI	EVI2	SAVI
V1	0.92	0.91	0.93	0.92
V2	0.92	0.91	0.92	0.92
V3	0.92	0.91	0.92	0.92

3.2 Model Development and Selection

As a result, there was a relationship between LAI and the vegetation index, consecutively the linear regression model analysis was carried out to obtain an index-based LAI value estimation formula. LAI calculated based on the leaf area of vegetation, was an important vegetation growth parameter of canopy structure (Duan *et al.*, 2019). The index-based LAI value is also a parameter to build a spatial-temporal-based crop model.

A linear regression model between the vegetation index and LAI was carried out to estimate the LAI value by using the vegetation index value. The linear regression model was divided into 3 based on the variety planted in the field experiment, namely V1, V2, and V3. The results of the linear regression model analysis can be seen in Figures 4, 5, and 6.

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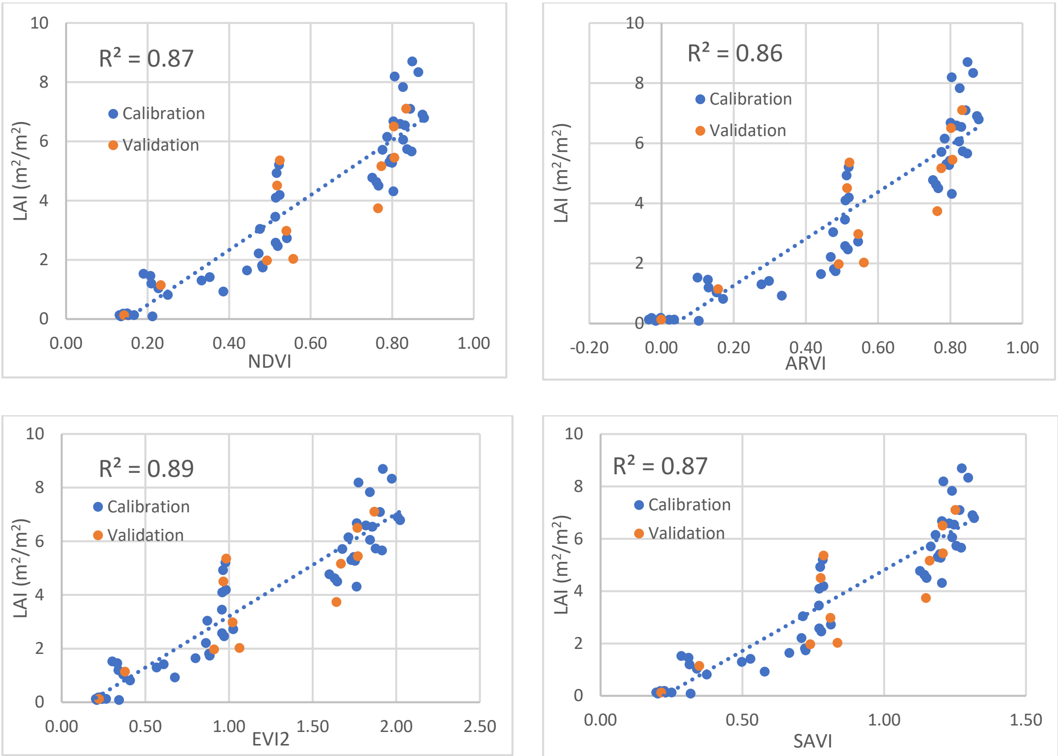

Figure 4. Results of the linear regression model analysis to estimate LAI with vegetation index (NDVI, ARVI, EVI2, and SAVI) on V1

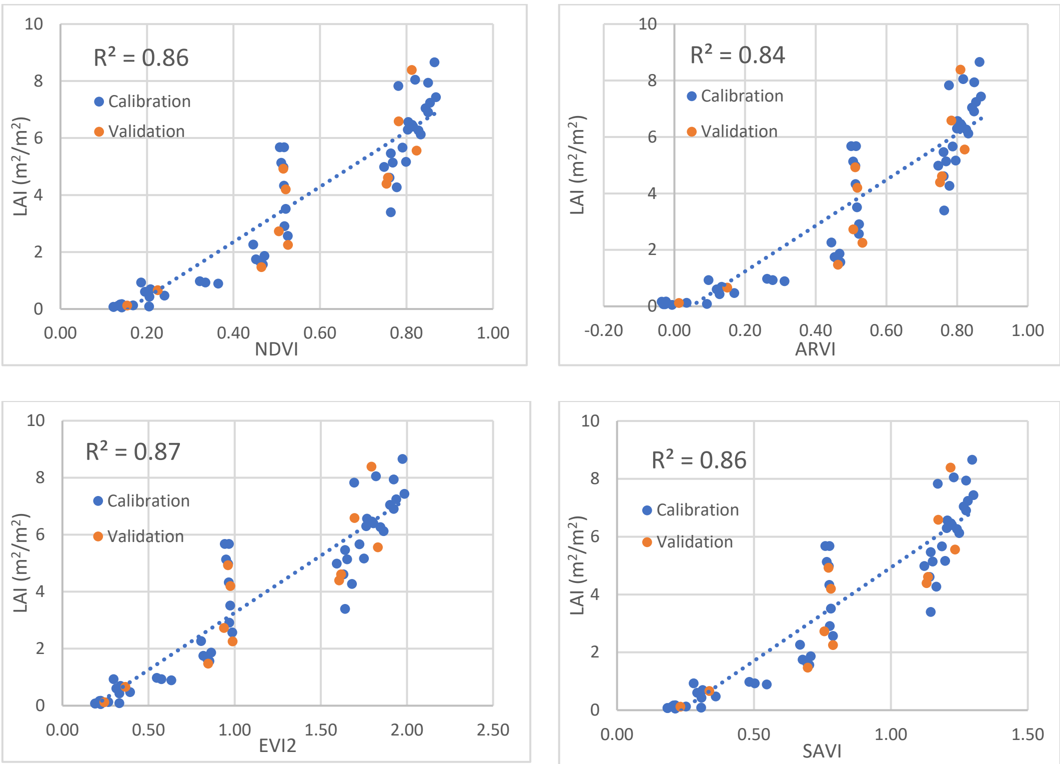

Figure 5. Results of the linear regression model analysis to estimate LAI with vegetation index (NDVI, ARVI, EVI2, and SAVI) on V2

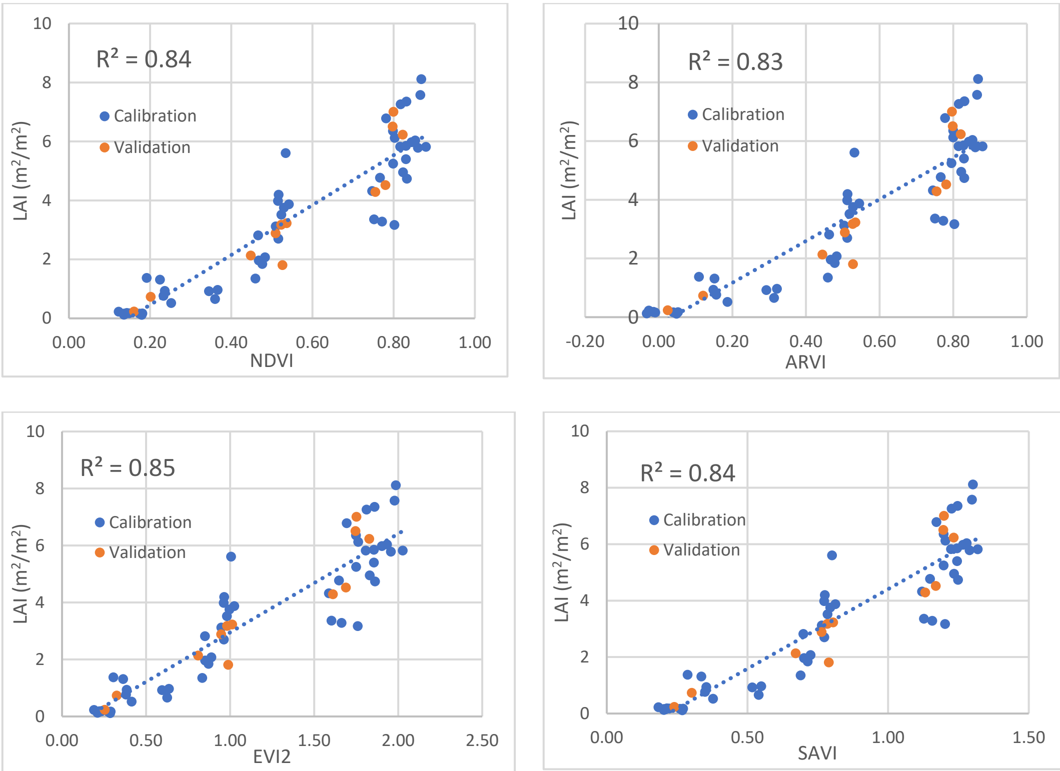

Figure 6. The results of the linear regression model analysis to estimate LAI with vegetation index (NDVI, ARVI, EVI2, and SAVI) on V3

The selection of the linear regression model (Figures 4, 5, and 6) to estimate the LAI of 3 planted rice cultivars was carried out using several vegetation indices by considering several statistical parameters, namely R-squared, RMSE, and Correctness as presented in Table 3. The R-squared of the linear regression model of V1 ranged from 086 to 0.89, V2 ranged from 0.85 to 0.87 and V3 ranged from 0.83 to 0.85. The result of RMSE statistical analysis for V1 ranged from 1.12 to 1.17, V2 ranged from 1.11 to 1.23 and V3 ranged from 0.70 to 0.89. Meanwhile, the result of Correctness for V1 ranged from 36.73% to 64.15%, V2 ranged from 34.94% to 65.51% and V3 ranged from 64.23% to 78.69%.

Based on the results shown in Table 5, the R-squared value of EVI2 showed the highest value for all planted cultivars with a value of 0.89 on V1, 0.87 on V2, and 0.85 on V3. The RMSE of EVI2 also produced the lowest value on every calculated vegetation index, 1.12 on V1, 1.11 on V2, and 0.70 on V3. However, the results of R-squared and RMSE were not significantly different for each calculated vegetation index. Meanwhile, the result of Correctness for EVI2 showed a better result compared to other vegetation indices with values of more than 60%, 64.15% on V1, 65.51% on V2, and 78.69% on V3.

Based on that, EVI2 became the most optimum vegetation index to estimate the LAI value compared to the other three vegetation indices that had been calculated. Moreover, the result also confirmed the visual pattern of EVI2 which further replicated the LAI values in Figure 3. Based on previous research, EVI2 had shown good accuracy in capturing changes in the temporal characteristics of rice crops (Kurnia Jayanti *et al.*, 2012).

Table 3. R-squared, RMSE, and Correctness results of the linear regression model analysis to estimate LAI with vegetation index (NDVI, ARVI, EVI2, and SAVI) on 3 rice cultivars

	Cultivar	Vegetation Index			
		NDVI	ARVI	EVI2	SAVI
R-squared	V1	0.87	0.86	0.89	0.87
	V2	0.86	0.85	0.87	0.86
	V3	0.84	0.83	0.85	0.84
RMSE	V1	1.13	1.17	1.12	1.13
	V2	1.14	1.23	1.11	1.14
	V3	0.77	0.89	0.70	0.77
Correctness (%)	V1	55.60	36.73	64.15	55.60
	V2	60.46	34.94	65.51	60.47
	V3	75.87	64.23	78.69	75.88

Based on the visual observations in Figures 4,5, and 6, there was an accumulation of LAI values in the closest vegetation index values. This happened because the adjacent vegetation index values had LAI values at two different crop growth stages. This appeared because there was a bias that needs to be corrected to get an accurate pattern. To overcome the bias, corrections were made by separating the two growth stages of rice crops, namely vegetative and generative which are marked by changes in the temporal pattern of LAI with the maximum value limit. Other researchers also took the same approach by differentiating the analysis according to the planting stage (Lee *et al.* 2018).

The data of the vegetative stage was started from 7 until 47 DAT. Due to the cloud cover issues, there were only two generative stage data (57 and 67 DAT). As explained in the paragraph above, the EVI2 model was the most optimum vegetation index to estimate the LAI value, the development of a linear regression model only used the EVI2 vegetation index. The results of the analysis of the linear regression model which is differentiated by stage can be seen in Figure 7 and the results of R-squared, RMSE, and Correctness are presented in Table 4.

Table 4. R-squared, RMSE, and Correctness results of the linear regression model analysis to estimate LAI with EVI2 on 3 rice cultivars

	Variety	Stage	
		Vegetative	Generative
R-squared	V1	0.92	0.66
	V2	0.94	0.49
	V3	0.89	0.55
RMSE	V1	0.81	0.94
	V2	0.99	0.73
	V3	0.63	1.02
Correctness (%)	V1	74.55	85.53
	V2	60.30	87.53
	V3	78.24	75.74

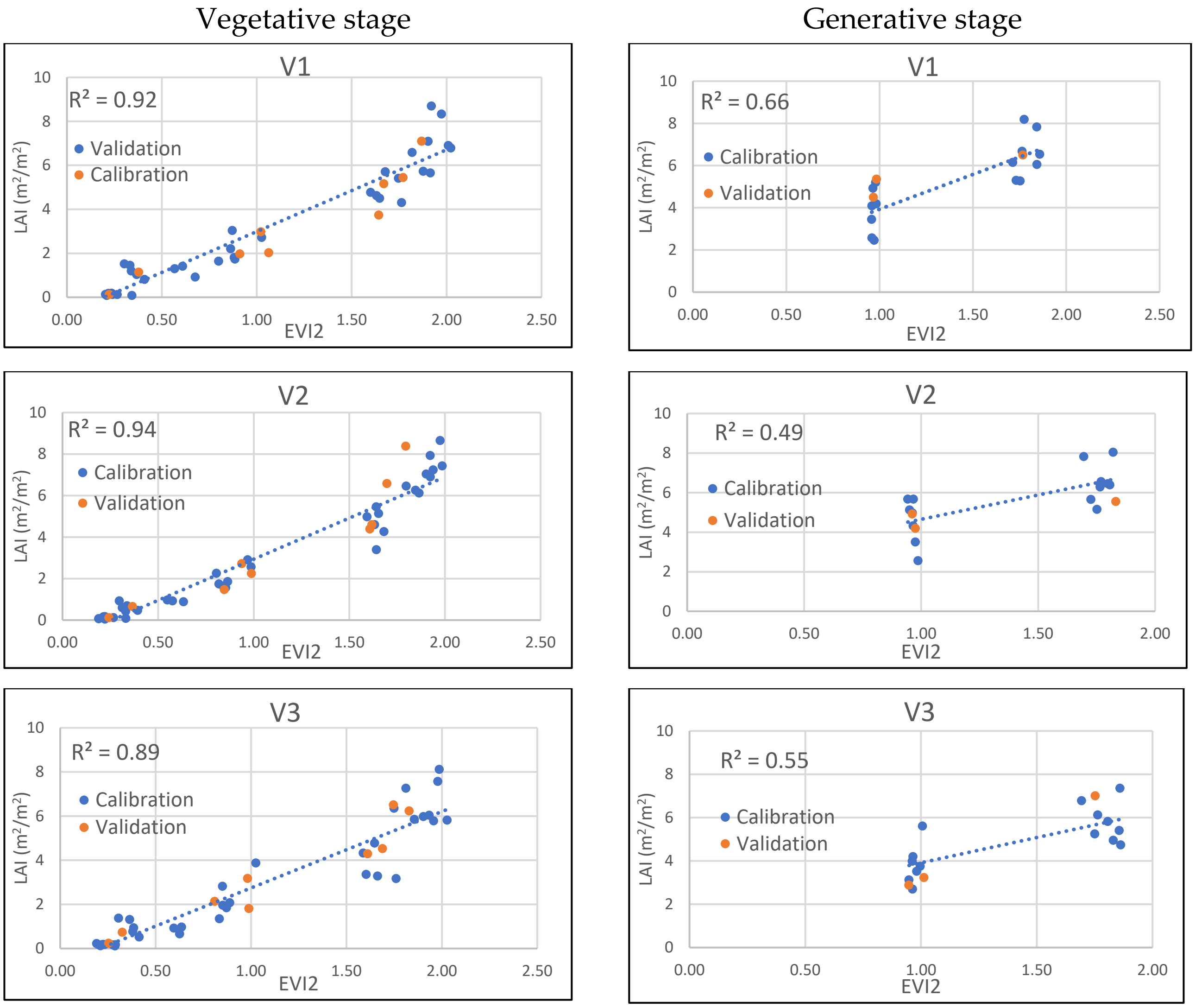

Figure 7. Results of the linear regression model analysis to estimate LAI with EVI2 vegetation index on 3 rice cultivars

There were differences in the results of the analysis using data from one life-of-cycle crop with data that was separated into two stages. The R-squared value (as presented in Tables 3 and 4) in the vegetative stage increased compared to the data for one life of cycle crop because the distribution pattern of the data was close to a linear line. However, it decreased in the generative stage, this was because in the generative stage there were only two temporal data sets, namely 57 and 67 DAT. As the range of R-squared can be from 0 to 1, the change in value for the vegetative stage was not very significant. While for the generative stage the change in the value of R-squared was quite significant. The results of the analysis for RMSE with data separated into two stages tended to be better than data for one life of cycle crop (as presented in Tables 3 and 4), there was only one increase in RMSE value, namely V3 for the generative stage. The separation of the analysis of the linear regression model into two stages was quite influential on the correctness value (as presented in Tables 3 and 4). After being separated into two stages, the correctness value tended to be better. The percentage of correctness values reached numbers above 60% and there was a value that reached 87%. Based on the results, separating the data into two growth stages could overcome the bias towards the vegetation index values of different LAI values at two different crop stages.

The utilization of the LAI estimation model spatially provides advantages in terms of time efficiency, the accuracy of results, and effectiveness used to observe wide areas. The representation of the actual value of the pixel imagery data used provided a good level of accuracy and reduced the bias generated by disturbances in surface objects. As explained earlier that LAI derived from remote sensing data has been widely utilized to estimate crop growth, The estimation of LAI for rice plants with EVI2 based on Sentinel-2A imagery is the base model for integrating temporal and spatial dynamics processes in building spatial-explicit crop dynamic model. Crop growth and production model are urgently needed to dynamically simulate the interactions of crop phenology, leaf area index, biomass, water use, and grain yield formation in response to variations in genotype, environment, and management (de Wit et al. 2015).

4. Conclusion

The analysis of the Sentinel-2A-based vegetation index of three rice cultivars on three different fertilizer rates and planting techniques showed that:

1. The dynamic of the vegetation indices and LAI were generally uniform and had a similar pattern. The value of LAI and vegetation indices showed a consistent pattern in all treatments (V1, V2, and V3).
2. The EVI2 linear regression model was the most optimum model for estimating the LAI value compared to NDVI, ARVI and SAVI vegetation indices calculated from Sentinel-2A satellite imagery indicated by the better-validated model with the result of RMSE value are 1.12 on V1, 1.11 on V2 and 0.70 on V3. The result of EVI2 Correctness also showed the highest value compared to the other vegetation indices with values of more than 60%, 64.15% on V1, 65.51% on V2, and 78.69% on V3.
3. The separation of linear regression model analysis data to estimate the LAI value with the vegetation index EVI2 into two crop growth stages of rice could overcome the bias in the LAI data for one life of the crop cycle which is indicated by the decrease of RMSE value on each cultivar planted for both vegetative and generative phase, except for cultivar V3 for the generative phase. Separating data into two growth stages could increase the percentage value of Correctness. The separation of data into two growth stages also increase the percentage of correctness values that reached numbers above 60% and there was a value that reached 87%.
4. The representation of the actual value of the pixel imagery data used provided a good level of accuracy and reduced the bias generated by disturbances in surface objects.
5. The utilization of the LAI estimation model spatially provides advantages in terms of time efficiency to measure LAI without any destructive methods and observe wide areas effectively. In the next step of research, the LAI estimation model can be integrated with the spatial dynamics processes in building a spatial-explicit crop dynamic model.

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