Rice Plant Nitrogen Concentration Monitoring by Unmanned Aerial Vehicle-Based Imagery

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ABSTRACT

Application of Unmanned aerial vehicles (UAVs) for remote sensing has given many advantages. The measurement of reflectance spectra in plant canopies can be the basis in detecting nitrogen content. Chlorophyll concentrations at different levels resulted in the reflectance spectra measured in the canopy, also being different. This study aimed to develop the method of Nitrogen monitoring using UAV imagery combined with Leaf Chart Color (LCC) to estimate plant nitrogen concentration in rice. To develop the Normalized Difference Vegetation Index (NDVI) indices, the Leaf Chart Color was used to measure the greenness of the leaf crop. A high-resolution digital camera modified with NDVI-7 filter mounted to UAV that sensitive to infrared wavelength. The flight altitude was 3, 10, and 15 m. To measure the strength of a linear association between LCC measurements and NDVI estimations, we used a Pearson one-tailed correlation. The Pearson coefficient indicates that the correlation is a strong negative correlation (-0.822) at 3 m altitude, weak correlation (-0.4562) at 10 m altitude, and no correlation at 15 m altitude.

CCS CONCEPTS

•Computing methodologies • Computing methodologies ~Modeling and simulation ~Model development and analysis ~Model verification and validation

KEYWORDS

Rice, plant nitrogen concentration, unmanned aerial vehicle

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1 Introduction

The performance of the Ministry of Agriculture of the 2014-2019 Working Cabinet has shown positive results. Based on data from the Central Statistics Agency, Indonesia's agricultural gross domestic product has risen 47.2% and accounts for 13.23% of the national gross domestic product [1]. To follow up on these achievements, the Ministry of Agriculture has established a strategic plan for the direction of food development policy 2020-2024 in the form of strengthening the professionalism of agricultural resources, agriculture modernization, and optimizing the use of land resources [2].

To answer these challenges is through precision farming. The concept of precision farming is handled site specifically based on local field needs. Provide input according to the specific needs of plants. This practice can give economic, productivity, and environmental benefits. The first step to do this is to get accurate information about variability in the field. Sensing and information extraction involves using various sensors to capture data on field conditions [3]. Monitoring plant conditions throughout plant growth are the primary step in precision agriculture [4].

In recent years, the application of unmanned aerial vehicles (UAVs) has been widely used to access remote sensing. The advantage of using a UAV is that it has a high spatial resolution, easy to control, and saves time [5]. These characteristics are ideal in Indonesia, which is that majorities are medium-small farmers.

Nutrition management in rice plants requires plant nitrogen content estimation. The measurement of reflectance spectra in plant canopies can be the basis in detecting nitrogen content. Chlorophyll concentrations at different levels resulted in the reflectance spectra measured in the canopy, also being different [3]. These spectra then extracted to calculate some vegetation indices correlate to the plant nitrogen concentration.

There are some studies of multispectral based crop nitrogen sensing for rice plants. Low-cost UAV system equipped with a high-resolution digital camera using the Crop Surface Model (CSM), which could use N monitoring in rice plants. The CSM correlates to plant nitrogen concentration, leaf area index, and fresh and dry aboveground biomass. The result shows that they have strong correlation to leaf area index (R^2 = 0.83) and fresh aboveground biomass (R^2 = 0.81), medium correlation in dry aboveground biomass (R^2 = 0.68), and weak correlation in plant nitrogen concentration (R^2 = 0.37) [6].

Other research has been developed a new index called I_{PCA} and uses other indices to estimate rice plant nitrogen concentration. The result shows that they have a moderate correlation (R^2 = 0.75 to 0.78) to plant nitrogen concentration. The indices are Green-Normalized Difference Vegetation Index (GNDVI), Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), and Principal component analysis index (I_{PCA}) [7]. Similar research uses NDVI to correlate rice plant nitrogen concentration in wheat. The NDVI values were highly correlated with the wheat yield (R^2 = 0.601–0.809) [8]. Other research, having a moderate correlation of NDVI and wheat plant nitrogen concentration (R^2 = 0.53–0.75) and best fit using red-edge inflection point (REIP) indices (R^2 = 0.58–0.89) [9].

Image processing used texture analysis developed from the Gray Level Co-occurrence Matrix (GLCM) has developed to estimate rice plant nitrogen concentration using the Normalized Difference Texture Index (NDTI). The result shows that it has a moderate correlation varies from 0.72 to 0.75 for the rice crop [10].

Most studies are used a multispectral camera with a high specification that usually consists of six kinds of cameras, implicate to the high price. It is not suitable for Indonesian farmers, which is that majorities are medium-small farmers. To solve this problem, a low-cost UAV camera is needed. A Standard RGB camera modified with a low-pass filter that enables near-infrared sensitivity and disables one of the red, green, and blue sensitivity begins to be widely used. This modified camera This camera has been proven to give good results [11].

Many research start using a conventional RGB (Red-Green-Blue) camera mounted to a UAV to determine nitrogen content on a rice leaf. The result indicated that conventional RGB cameras could use to estimate nitrogen content in rice plants with reasonably good results [7, 12].

The basic ground-base crops Nitrogen monitoring was done by laboratory analysis (Kjeldahl method). This method is time-consuming, need cost, and requires complicated procedures. To solve this problem, the International Rice Research Institute (IRRI) issued a Leaf Color Chart (LCC) that could be used to analyze nitrogen status on the leaves of the crops. The advantage of LCC used is easy to use, and low price. But the disadvantage is required on-site labor and involves subjective measurements.

The combination of ground-based monitoring using LCC and low-cost aerial-based imagery is expected to provide new opportunities for Indonesian agriculture. This technology is expected to improve measurement accuracy, ease of operation, and has an affordable price so that precision farming can be applied in Indonesia.

This study aimed to develop the method of Nitrogen monitoring using UAV imagery combined with Leaf Chart Color to estimate plant nitrogen concentration in rice.

2 Materials and Methods

2.1 Experimental Design

The study was carried out in the experimental field of Muara, Bogor, West Java, Indonesia (6.6115º S, 106.7914º E). The rice cultivar Inpari-24 in five doses nitrogen rates (0, 100, 200, 250, and 300 kg ha−1) as N0, N1, N2, N3, and N4. The experiment uses a completely randomized block design. The size of each plot was 4 x 5 m, each with three plot replications, as shown in Figure 1.

2.2 Data Collection

The UAV used in this study was a quadcopter DJI Phantom 3 4K (Shenzhen DJI Sciences and Technologies Ltd, China). It was equipped with a 12,4 MP RGB camera, which captures high-resolution (3000 x 4000 pixel) images. The camera modified with a 4K LENS 4.35 mm NDVI-7 Agriculture Mapping Lens filter (Blue) that sensitive to near-infrared wavelengths. This modified camera was built to overcome the problem of the high price of original multispectral cameras.

Images were captured five times per plot and saved as a JPEG image. The flight took place on 13/9/2019 (42 Days After Plant) between 11:00 a.m. and 2:00 p.m. in stable ambient light conditions at an altitude of 3, 10, and 15 m above the plant canopy.

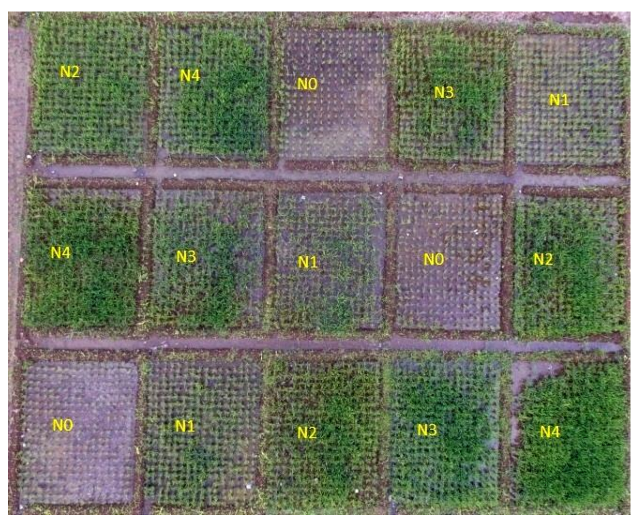

Figure 1: Rice plot experiment at Muara, Bogor, West Java, Indonesia.

2.3 Ground Measurement

In addition to the UAV campaigns, the ground measurement was done using the Leaf Color Chart (LCC). LCC has four green strips level (values to 2, 3, 4, and 5), with color ranging from yellow-green to dark green. The LCC shows the green level of the rice leaf, which indicates the nitrogen content in the rice leaf.

2.4 Image Processing

The Matlab image processing toolbox was used to process all the images. It provides a standard algorithm for image processing, analysis, visualization, and algorithm development. Figure 2 shows the processing steps conducted to process the image.

2.5 Vegetation Index

Spectral reflectance measures from the UAV used to calculate the vegetation index. The index was a Normalized Difference Vegetation Index (NDVI), as shown in Equation (1). Because we used a blue filter as the visible light absorption channel, the equation would be [13]:

$$NDVI = (NIR - B)/(NIR + B) \quad (1)$$

where *NIR* was the reflectance of the near-infrared band, *B* was the reflectance of the blue band.

The calculation resulted from values of -1 to +1; if negative indicates water, if values close to 0 indicate no plants and values close to +1 (0.8 to 0.9) indicate very green plants.

2.6 Statistical Analysis

Descriptive statistic analysis was used to describe, summarizing, and organizing data from LCC measurements and NDVI estimations. This analysis will perform the distribution, central tendency, and variability of collected data. After that, we also calculate the coefficient of variation (CV) to measure the dispersion of data points around the mean. CV is the standard deviation divided by the mean.

To measure the strength of a linear association between LCC measurements and NDVI estimations, we used a Pearson one-tailed correlation.

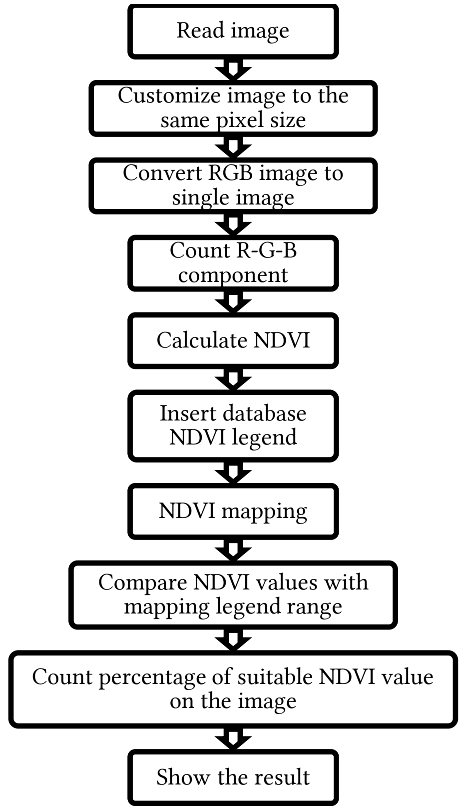

Figure 2: Flow chart for image processing.

3 Results and Discussion

3.1 NDVI Mapping

In the measurement of LCC value on each nitrogen treatments, the LCC value varies from 2 to 4. For the control treatment (N0), the LCC value is 2. The N1, N2, and N3 treatment have the LCC value of 3, and N4 its value is 4. It means that the risen dosage of nitrogen fertilizer, it will rise the greenness of the crop leaves.

NDVI algorithm created with Matlab software has been done to process the image from the UAV. The NDVI mapping transforms the LCC value to unique tone mapping. Tone mapping is the process of applying a color to a calculated index value. The values of tone mapping are shown in Figure 3.

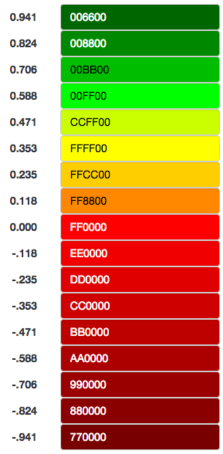

Figure 3: NDVI tone mapping used in Matlab [14].

For each image that captured from varies altitude flight was processed using Matlab follows the procedure in Figure 2. The image result is shown in Figure 4 to Figure 6. Visually, the program has been able to distinguish the greenness level of rice plants leaves. At N0 treatment, the greenness is least and risen to N1, N2, N3, and maximum at N4.

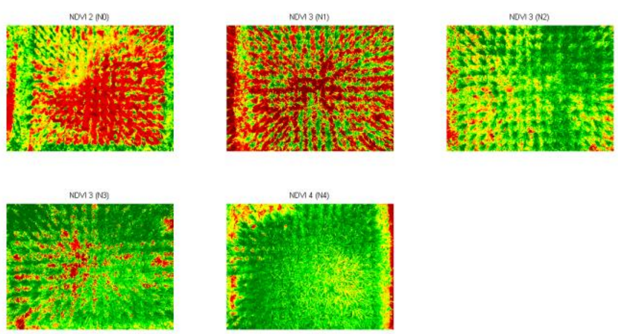

Figure 4: NDVI mapping from the image of altitude 3 m.

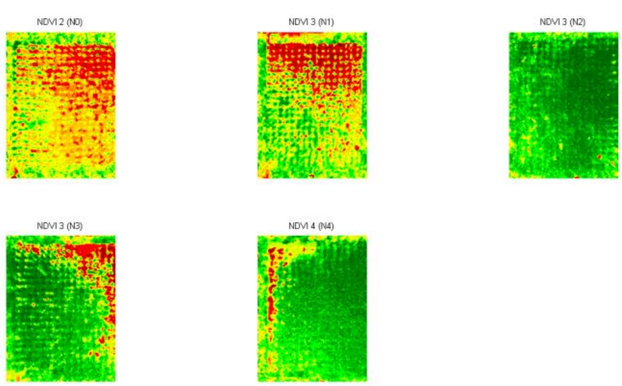

Figure 5: NDVI mapping from the image of altitude 10 m.

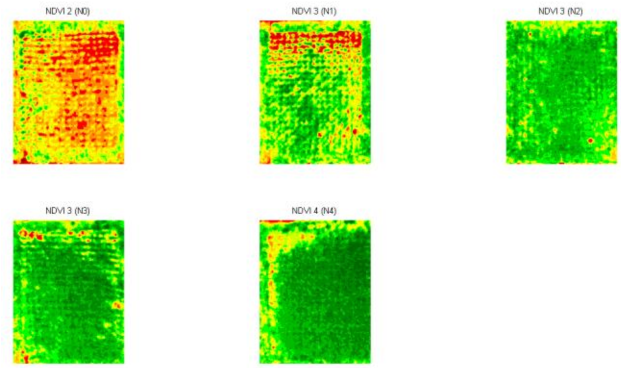

Figure 6: NDVI mapping from the image of altitude 15 m.

The greenness level on the same treatment is slightly different at a different altitude. At the 3 m altitude (Figure 4), it looks slightly red than others (Figure 5 – Figure 6). The higher the altitude, the greener the plants look. It means that they have slightly different NDVI values at the same treatment. The different NDVI values caused by the measured reflectance increased with height. This result suited with Stow *et al.*, which indicates that the measured NIR reflectance from the UAV was increased with height, especially in the first 25 m above ground. One factor that might have influenced these measurements was downdraft from the UAV causing ripples in plants and airs that can change its reflectance [15].

3.2 Correlation of LCC Measurements and Vegetation Indices

Table 1 shows the descriptive statistic for LCC measurements. The table describes that LCC measurement distribution is slightly skewed to the left. It showed by the negative sign of the skewness value. The mean value is same with the median value. It means that the distribution is almost symmetric. The mode value describes the most frequent value in data set. The coefficient of variation (CV) value is 18%, it shows that the measurements are proper and quite homogenous.

The calculated NDVI indices from the UAV imagery are presented in Table 2. The descriptive statistics for all altitude showed that all the distribution are almost symmetric, and the skewness to the right for the 3 m and 15 m altitude; and goes to left skewed for the 10 m altitude. The CV values are 19,5%; 19,2%; and 17,6% for the altitude of 3 m, 10 m, and 15 m. The CV values mean that the NDVI calculations are good for all altitudes.

A Pearson one-tailed correlation between the NDVI indices and the LCC measurements was used to measure the strength and direction of linear relationships between these variables. Based on these calculations, the results are shown in Table 3. The Pearson coefficient indicates that the correlation is a strong negative correlation (-0.822) at 3 m altitude, which means that high X variable scores go with low Y variable scores (and vice versa). At 10 m altitude, the value of r is -0.4562. Although technically a negative correlation, the relationship between these variables is only weak. The value of r is 0.0365 at 15 m altitude. Although technically a positive correlation, the relationship between these variables is weak (the nearer the value is to zero, the weaker the relationship). The coefficient of determination explained the proportion of variance data that correlates to the measurements. The values are 68 % at 3 m altitude, 21% at 10 m altitude, and not correlate at 15 m altitude. This phenomenon happens may be caused by the lower resolution at a higher altitude. This result similar to Bacsa et al., who that found the Pearson correlation coefficient between the NDVI and the LCC measurements is 0.48 [16].

Table 1: Descriptive statistics of LCC measurements

Parameter	Value
Mean	3,021
Standard Error	0,047
Median	3
Mode	3
Standard Deviation	0,543
Sample Variance	0,295
Skewness	-0,478
Minimum	2
Maximum	4
Coefficient of Variation (CV)	0,182

Table 2: Descriptive statistic for vegetation indices calculation values

Parameter	3 m altitude	10 m altitude	15 m altitude
Mean	32,400	32,561	42,562
Standard Error	0,836	0,814	1,265
Median	31,327	32,019	42,966
Standard Deviation	6,313	6,252	7,484
Sample Variance	39,851	39,088	56,007
Skewness	0,313	-0,244	0,306
Minimum	15,253	20,216	33,03623
Maximum	47,449	42,902	56,28533
Coefficient of Variation (CV)	0,195	0,192	0,176

Table 3: The correlation coefficient for NDVI indices to LCC measurements

Parameter	3 m altitude	10 m altitude	15 m altitude
r (Pearson coefficient)	-0.822^{*}	-0.456^{*}	$0.037^{n.s}$
r^2 (coefficient of determination)	0.676	0.208	0.0013
P-value	< 0.00001	0.000284	0.83733

4 Conclusions

Precision farming practice through efficient Nitrogen monitoring by UAV remote sensing has been giving us a new insight to increase agricultural output. This study proved a correlation between ground-based Nitrogen data obtained through Leaf Color Chart (LCC) measurements with NDVI extracted from UAV imagery. The correlation is negatively strong (-0.822) at 3 m altitude, weak correlation (-0.456) at 10 m altitude, and not correlate at 15 m altitude.

This study also indicates that an RGB camera modified with an NDVI filter could be employed to estimate Nitrogen concentration on rice plants. This research could be improved by adding the calculation of other indices that have a better correlation.

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