




Estimation of Paddy Leaf Nitrogen Status using a Single Sensor Multispectral Camera

Muliady Muliady¹^a, Tien Sze Lim²^b, Voon Chet Koo²^c and Nathaniel Pius Winata¹^d

¹Department of Electrical Engineering, Maranatha Christian University, Jl. Surya Sumantri 65, Bandung, Indonesia

²Faculty of Engineering and Technology, Multimedia University, Malacca, Malaysia


Keywords: Paddy Leaf Nitrogen Status, Single Sensor Multispectral Camera, Normalized Difference Vegetation Index (NDVI), SPAD Meter, Regression.


Abstract: Rice consumption will be increasing by 26% in the next 25 years since 2010. The common practice to achieve high rice production is by fertilizing the paddy with a proper quantity of nutrients, especially nitrogen (N). A lot of previous researches were done to estimate the paddy N status, starting from using a simple Leaf Color Chart (LCC) to high technology hyperspectral images taken from a satellite. This research used a MAPIR Survey3 multispectral camera, which is affordable and gives the advantage of a quick and efficient practice. The problem came out due to the impossible to fully separate the spectral channels of the images, which causes low accuracy and imprecise data. This research objective is to correct the data by relating it with a SPAD meter. A total of 75 paddy plants were sampled in the panicle initiation stage from two paddy fields located at Margaasih and Cimahi, Jawa Barat, Indonesia. The Normalized Difference Vegetation Index (NDVI) for each image was calculated after calibrated, cropped, and segmented. The result is a regression of a 2nd order equation with 6.96% of mean error. The regression equation was used to create a SPAD color map to estimate the paddy leaf N-status.


1 INTRODUCTION


World rice demand is predicted will be increasing by 26% from 2010 to 2035 (Riaz & Hussain, 2020). The prediction was projected based on the population growth data from the United Nations and the income data from Food and Agricultural Policy Research Institute (FAPRI). The success in increasing the rice yield by the previous research is still needed to follow by a faster rice yield growth to compensate for the pressure on paddy lands in the developing world from urbanization, and climate change. One of the most important factors is crop management, particularly fertilizing practice. The appropriate time and amount of fertilizer will significantly improve rice productivity and reduce production costs. The conventional practice in implementing fertilizer management is by predicting the greenness level of the paddy leaves. The leaf greenness is directly

related to leaf nitrogen (N) status, which is needed to promote the growth of the paddy. Farmer experiences and skills to predict the leaf greenness level will be varied to each other, inaccurate, and imprecise. In addition, the complexity arises because the level of leaf greenness depends and changes on the life phase of the paddy. An inexpensive and easy-to-use tool, the Leaf Color Chart (LCC), has successfully improved the farmer decision-making process in N management and optimize N use at reasonably high yield levels (Ahmad et al., 2016). The disadvantage in using LCC is the need for a well-trained skilled farmer to interpret the color chart. A high technology device called Soil Plant Analysis Development (SPAD) chlorophyll meter is widely used to determine the leaf N level and increased the efficiency of N fertilizer (Hussain et al., 2009). The SPAD meter works on measuring the absorbances of the leaf in the red and near-infrared light wavelength

^a <https://orcid.org/0000-0003-0377-1524>

^b <https://orcid.org/0000-0002-7899-8750>

^c <https://orcid.org/0000-0002-3617-1069>

^d <https://orcid.org/0000-0001-6686-9305>

and calculates a SPAD value that is proportional to the chlorophyll in the leaf. This will need a lot of work and time if implemented in a large area of paddy fields. The modern electronic and computer device can be used to reduce time and work, (Zhang & Zhang, 2018) introduced several imaging technologies for plant high-throughput phenotyping, including detection of canopy chlorophyll content, leaf, and canopy senescence. (Muliady et al., 2021) gave a solution by using a smartphone camera with a light sensor, and a k-Nearest Neighbor (k-NN) machine-learning algorithm to estimate the paddy N status. The paddy leaf N status estimation becomes easy and affordable since almost everyone owns a smartphone with a camera. The work (Peter et al., 2017) demonstrated how a digital camera can be a low-cost and effective device for estimating the paddy leaf N status under field conditions. For a large paddy field area, the application of Unmanned Aerial Vehicle (UAV) in crop monitoring and pesticide spraying was evaluated (Mogili & Deepak, 2018). Finally, a promising result in developing low-cost multispectral imaging with a UAV system to create a Normalized Difference Vegetation Index (NDVI) map (Natividade et al., 2017). Farmers in low-middle income countries wish to have modern but affordable technology to assist their fertilizer management of large paddy fields efficiently.

2 METHODS

The use of high technology devices or high-cost technology with the support of computer science does not guarantee the quality in estimating the paddy leaf N content result. The comparison of a commercial multispectral camera Parrot Sequoia that costs USD3,500 while a low-cost multispectral camera Mapir Survey3 only costs USD400. This research used Mapir Survey3 camera with a 3.37mm wide lens which is affordable and can minimize the effect of the visible light in estimating the paddy leaf N status but still has the advantage of quick and efficient field practice.

The main weakness of this affordable multispectral camera is it only has one sensor to collect three light wavelengths simultaneously. This will cause contamination between each light wavelength and sensitivity to the noise that comes from the surrounding environment. Another downside of using is it gives a lower NDVI value than it is supposed to, even a shaded area gives a higher NDVI value than the unshaded area. Normally at the beginning of the panicle phase, paddy will have a

0.63 to 0.72 NDVI value (Lestari et al., 2020). This research objective is to correct and map the calculated NDVI value of multispectral image from a Mapir Survey3 Camera with a SPAD meter.

The experiments were taken in two paddy fields in Jawa Barat - Indonesia, which is located in the southern and northern part of Bandung city. The first paddy field is located at Ciawitali, Citeureup, Kecamatan Cimahi Utara-Cimahi, and the second one is located at Cibisoro, Nanjung, Kecamatan Margaasih-Bandung. The work consists of three steps which are processing and calculating the multispectral images into NDVI value, measuring the leaf's SPAD value, and regression analysis. All the data was taken at the vegetation stage of the paddy, right before the panicle stage, about 67 days after transplanting. It is usually considered as the time for the farmer to fertilize their paddy field, and high concern about the nutrition is needed to prepare the paddy for the reproductive phase. The multispectral images were taken manually at a high angle position. This position allowed the canopy of the paddy plant to be captured for estimating the leaf N status as suggested in (Yu et al., 2013).

2.1 Multispectral Images

The selection of Mapir Survey3 Camera filter will highly influence the contrast between the soil and the paddy plant. As suggested in Mapir's manual guide, the one with Orange Cyan Near-Infrared (OCN) filter has better contrast than the generally used Red Green Near-Infrared (RGN) filter. One of the most frequently used Vegetation Indices (VIs) is a normalized ratio between the red and near-infrared bands be known as the Normalized Difference Vegetation Index (NDVI) (Xue & Su, 2017). The NDVI simply shows the plant photosynthetic activity in values between -1 and 1. A low NDVI value indicates moisture-stressed vegetation and a higher value indicates a higher density of green vegetation.

The field experiment shows that the multispectral images were affected by the intensity and the direction of the sunlight. A calibration target in Figure 1 is supplied by Mapir, was used to compensate for the light intensity of the paddy images, and then calibrate them in a computer using Mapir Camera Control application. The calibration target has a QR code on the right side and four pieces of calibration surface on the left side. The calibration process uses a linear regression between 4 points comparing pixel values to known target reflectance. The calibration target and the paddy

images should be taken under the same or similar light intensity.



Figure 1: The calibration target.

The paddy plants with a minimum of 10 tillers were randomly chosen for data analysis, 25 paddy plants from Ciawitali field, and 50 paddy plants from Cibisoro field. Each paddy plant was marked with a number and captured in 3 different canopy angles to minimize the effect of sunlight direction. From these 3 images, their NDVI value will be calculated and then averaged to represent the NDVI value of the paddy plant. Figure 2 shows the image sample of OCN paddy plant, the one located at the center of the image is considered as the object that will be analyzed.



Figure 2: The paddy plant in OCN image.

The direction of sunlight usually generates a shaded area on the image that should be avoided. By referring to the NDVI color chart on the right side, the leaf with a shaded area in Figure 3 has a higher NDVI value (dark green) compared to the other areas. To minimize this error the images should be taken in the mid-day, about 10.00 A.M. to 2.00 P.M, which will give a minimum shaded area for the leaf canopy.

After the images were processed and calibrated using Mapir Control Camera application, they were

cropped manually to have only one paddy plant. Before the NDVI value is calculated, the image will be segmented.

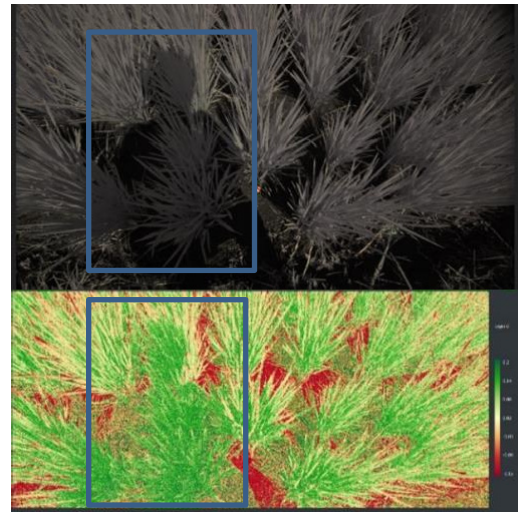


Figure 3: The shaded area increases the NDVI value.

2.1.1 Segmentation

The cropped OCN images were segmented in two steps process, the first one is to eliminate the soil background by separating the pixels with the Near-Infrared (NIR) intensity value of more than 8000 as paddy leaves. The second segmentation is to classify the leaves into several groups based on the nearest NIR band intensity which is shown in Figure 4. The group with the most pixels is selected to represent the paddy plant for example the violet pixels in Figure 4.



Figure 4: The image segmentation process.

2.1.2 NDVI Calculation

The leaf NDVI value was calculated using Equation 1 after the segmentation process was done. The result is shown in Figure 5 with the color map. The final NDVI value that represents the paddy plant was obtained by calculating the average NDVI of all segmented leaf pixels. The calculation and color plotting was done in Matlab.

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

Where:

NIR is a reflectance in the near-infrared band; O is a reflectance in the orange band

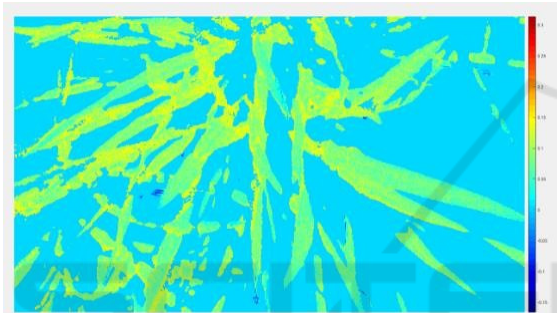


Figure 5: The color map of NDVI value.

2.2 SPAD Value

TYS-4N model of the SPAD meter was used as a benchmark to be compared with the NDVI value. The reference (Yuan et al., 2016) suggested measuring the SPAD value at one-third from the fourth leaf tip. To minimize the human error in measuring the SPAD value, each leaf was measured a minimum of 5 times, and conduct the measuring to a minimum of 5 tillers with a full open fourth leaf. The average value was calculated after eliminating the outlier and represent the SPAD value of the paddy plant.

2.3 Regression Analysis

The sampled data were collected from the Ciawitali paddy field is 25 paddy plants and the other 50 paddy plants from the Cibisoro paddy field. Since each paddy plant was captured 3 times, the total of images was 225. Although the sampled data were carefully taken and repeated several times, some of the data need to be checked. The imprecise and

untrusted data will be eliminated. The imprecise data was defined by a significant difference in NDVI value between 3 OCN images. As an example, the paddy plant number 11 in the Ciawitali field has calculated NDVI from the first until third OCN images respectively, 0.092, 0.017, and 0.042. Finally, only 15 data set from the Ciawitali field in blue color, and 49 data set from the Cibisoro field in orange color were selected and plotted in Figure 6. The paddy in the Ciawitali has a relatively lower SPAD value than the paddy in the Cibisoro field.

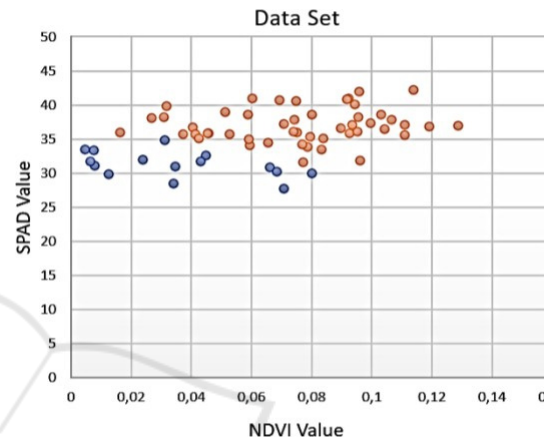


Figure 6: The final data set distribution.

The regression equation was expressed in 1st and 2nd order using Equation 2. The results were shown in Figure 7, with the red and blue line is constructed from the 1st order and 2nd equation respectively. Both of the equations have several similarities, which are the same mean error of 6.96%, and correlation of 0.39, a closed value of slope (B), and y-axis intercept (C).

$$y = Ax^2 + Bx + C \quad (2)$$

1st order: A=0, B=42.55, C=32.84

2nd order: A=-21.72, B=45.27, C=32.77

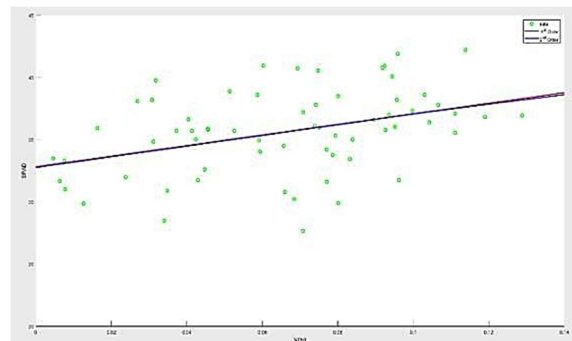


Figure 7: The regression line.

3 RESULTS AND DISCUSSION

The 2nd order regression was implemented to create a color map that shows the SPAD value of the Cibisoro paddy field. Figure 8 is a Cibisoro paddy field stitching image from the OCN images were taken by DJI Phantom 4 Pro Obsidian. The field in a red rectangular indicates the new paddy just planted. The yellow rectangular is kale vegetable field.

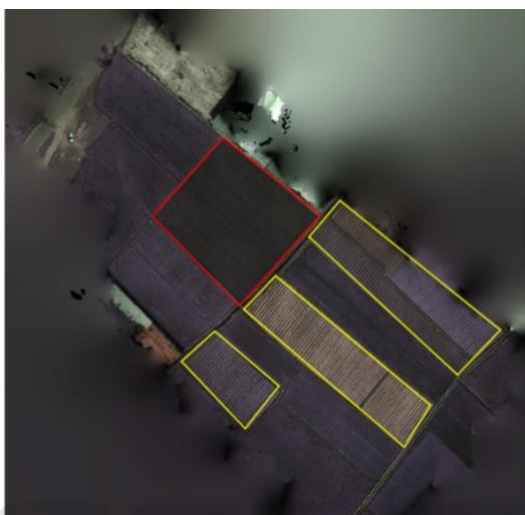


Figure 8: OCN image.

Figure 9 shows the NDVI color map of the Cibisoro paddy field, with the NDVI value between 0.1 to 0.3. The map also shows the heterogenous of the paddy leaf N status, but could not give more information about the fertilizer sufficiency regarding the inaccurate NDVI value.

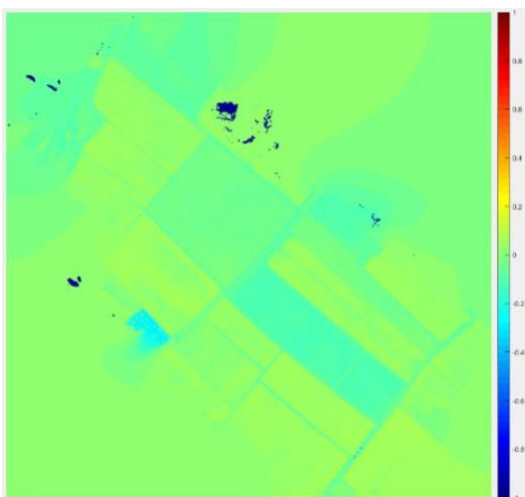


Figure 9: NDVI color map.

Figure 10 is the SPAD color map and shows the distribution of the paddy N status. A high yield paddy usually has a SPAD value between 35.4 to 40.1 (Swain & Jagtap Sandip, 2010). The grey marking on the map is the paddy with a low SPAD value of about 30 that indicates the deficiency of N fertilizer. In practice, this SPAD color map will help the farmers to analyze their paddy field, and the treatment needs to conduct to gain a high rice yield.

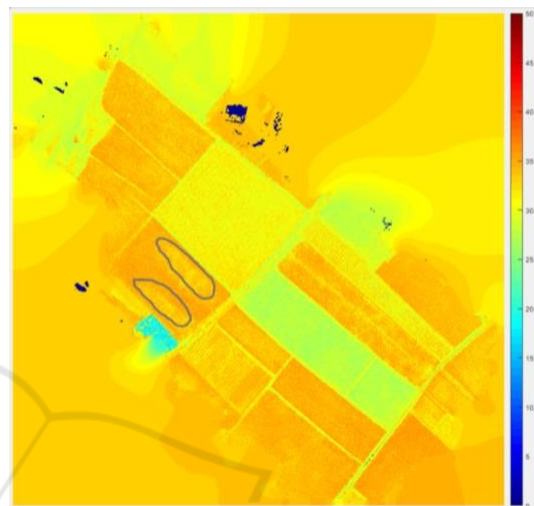


Figure 10: SPAD color map.

4 CONCLUSIONS

The research work process has successfully built a SPAD color map that can be used to estimate the paddy leaf N status. The SPAD value is presented clearly, and informatively in high contrast color. This quick and efficient analysis process starts with capturing the NDVI image using a drone attached with Mapiir Survey3 OCN camera when the paddy enters the panicle initiation phase and processes the images with a computer to have a SPAD color map. Future work can be improved by reducing the mean error using a machine learning algorithm.

REFERENCES

- Ahmad, N., Zada, A., Junaid, M., & Ali, A. (2016). Bridging the Yield Gap in Rice Production by Using Leaf Color Chart for Nitrogen Management. *Journal of Botany*, 2016. <https://doi.org/10.1155/2016/2728391>
- Hussain, M. Z., Khan, S. A., & Thiyagarajan, T. M. (2009). Increasing Nitrogen Use Efficiency in Rice (*Oryza Sativa L.*) with Chlorophyll Meter and Leaf

- Color Chart. *The IUP Journal of Soil and Water Sciences Vol II No 4 Pp 3654 November 2009*. <https://doi.org/10.2139/ssrn.1513199>
- Lestari, E. A. P., Supriatna, & Damayanti, A. (2020). Model of paddy rice phenology using Sentinel 2- A imagery with NDVI algorithm in Subang Regency. *IOP Conference Series: Earth and Environmental Science*, 481(1). <https://doi.org/10.1088/1755-1315/481/1/012069>
- Mogili, U. R., & Deepak, B. B. V. L. (2018). Review on Application of Drone Systems in Precision Agriculture. *Procedia Computer Science*, 133, 502–509. <https://doi.org/10.1016/j.procs.2018.07.063>
- Muliady, M., Tien Sze, L., Voon Chet, K., & Patra, S. (2021). Classification of rice plant nitrogen nutrient status using k-nearest neighbors (k-NN) with light intensity data. *Indonesian Journal of Electrical Engineering and Computer Science*, 22(1), 179. <https://doi.org/10.11591/ijeecs.v22.i1.pp179-186>
- Natividade, J., Prado, J., & Marques, L. (2017). Low-cost multi-spectral vegetation classification using an Unmanned Aerial Vehicle. *2017 IEEE International Conference on Autonomous Robot Systems and Competitions, ICARSC 2017*, 336–342. <https://doi.org/10.1109/ICARSC.2017.7964097>
- Peter, J., Rischbeck, P., Hu, Y., Kipp, S., Hu, Y., Barmeier, G., Mistele, B., & Schmidhalter, U. (2017). Use of a digital camera as alternative method for non-destructive detection of the leaf chlorophyll content and the nitrogen nutrition status in wheat. *Computers and Electronics in Agriculture*, 140, 25–33. <https://doi.org/10.1016/j.compag.2017.05.032>
- Riaz, U., & Hussain, S. (2020). *Overview and Perspectives of Food Security*. January.
- Swain, D. K., & Jagtap Sandip, S. (2010). Development of SPAD Values of Medium-and Long-duration Rice Variety for Site-specific Nitrogen Management. *Journal of Agronomy*, 9(2), 38–44. <https://doi.org/10.3923/ja.2010.38.44>
- Xue, J., & Su, B. (2017). Significant remote sensing vegetation indices: A review of developments and applications. *Journal of Sensors*, 2017. <https://doi.org/10.1155/2017/1353691>
- Yu, K., Li, F., Gnyp, M. L., Miao, Y., Bareth, G., & Chen, X. (2013). Remotely detecting canopy nitrogen concentration and uptake of paddy rice in the Northeast China Plain. *ISPRS Journal of Photogrammetry and Remote Sensing*, 78(April), 102–115. <https://doi.org/10.1016/j.isprsjprs.2013.01.008>
- Yuan, Z., Cao, Q., Zhang, K., Ata-Ul-Karim, S. T., Tan, Y., Zhu, Y., Cao, W., & Liu, X. (2016). Optimal leaf positions for SPAD meter measurement in rice. *Frontiers in Plant Science*, 7 (May 2016), 1–10. <https://doi.org/10.3389/fpls.2016.00719>
- Zhang, Y., & Zhang, N. (2018). Imaging technologies for plant high-throughput phenotyping: A review. *Frontiers of Agricultural Science and Engineering*. <https://doi.org/10.15302/J-FASE-2018242>