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RESEARCH ARTICLE

Estimating the contents of Chlorophyll, Nitrogen, and Yields on Rice through Sentinel-2 Vegetation Indices in Heterogeneous Land Management

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Abstract. Addressing the global food demand is an urgent priority for governments worldwide. Efficient and effective methods for gauging crop production are crucial. Relying solely on ground-based measurements proves inefficient and expensive, prompting exploration of remote sensing using vegetation indices as a viable alternative. This study sought to achieve three objectives: estimating chlorophyll content in paddy fields, evaluating leaf nitrogen content, and predicting yields. The investigation utilized Sentinel-2A satellite imagery, Soil Plant Analysis Development (SPAD) for chlorophyll measurement, and employed statistical and accuracy analyses. Findings revealed an increase in chlorophyll and leaf nitrogen content from the vegetative to maturity phases, followed by a decline at maturity. NDVI and GNDVI emerged as superior to SAVI and VARI for chlorophyll estimation, attributed to their spectral sensitivity. Likewise, nitrogen prediction showed similar trends, with NDVI and GNDVI exhibiting better RMSE values compared to SAVI and VARI, albeit marginally. However, yield prediction accuracy varied, with NDVI proving most accurate, followed by SAVI, VARI, and GNDVI, indicating the latter's reduced predictive precision due to nitrogen sensitivity. In scenarios where nitrogen is not the predominant yield-limiting factor, NDVI could outperform GNDVI in forecasting yield.

1. Introduction

Rice (Oryza sativa L.) is an important food crop in Indonesia, as it is consumed by approximately 98% of the population (Pratiwi, 2022). The two eminent issues related to rice production are (1) nitrogen fertilizer management (Sharifi, 2020) and (2) crop yield management which is significantly influenced by nutrient availability (Urmi et al., 2022). Compared to other plants, nitrogen (N) is an essential element for rice growth. However, excessive use of nitrogen fertilizers wastes resources and causes harmful environmental consequences because plants only absorb the required amounts (Qiu, Yang, Jiang, Xu, & Jiao, 2022). For instance, research by Park, et al. (2023) demonstrated that higher nitrogen fertilizer application does not always translate into higher rice yields. As they also showed that the increase in Nitrogen feralization can result in low quality of protein and amylose. Additionally, this study found that when nitrogen content rose, so did the amount of CO release from the paddy field. This shows the need for appropriate management and accurate real-time assessment of crop nitrogen status in the field to improve yield, efficiency, and crop quality (Wang et al., 2023). Remote sensing techniques that utilize spectral and thermal methods have been suggested as effective and efficient ways to quickly determine crop nitrogen status by analyzing vegetation canopy characteristics. According to (Guérif, Houlès, & Baret, 2007), reflective sensors are a promising new tool for obtaining non-destructive, quick estimates of plant nitrogen levels. These observations, especially in the visible and near-infrared spectra, can reveal leaf chlorophyll content, allowing for early detection of nutrient deficiencies, as canopy chlorophyll content closely relates to nitrogen content, linking remote sensing data to nitrogen indicators. Additionally, nitrogen stress reduces near-infrared reflectance and increases visible wavelength reflectance due to reduced chlorophyll and other pigments, making vegetation indexes that combine these spectral regions highly sensitive tools for detecting nitrogen stress and guiding fertilization practices.

Yield estimates are very crucial for maintaining food security. One of the data sources that can be used in crop yield estimation is remote sensing data. Remote sensing, with data of various spatial resolutions available over time, enables better predictions of crop yields and the factors responsible for these yields. This is because the accurate prediction of yields can guarantee the availability of foods for the next. Remote sensing plays substantial roles in predicting yields and other related phenomena, such as leaf Nitrogen and Chlorophyll with temporal coverages. With these characteristics, the results of the analysis using remote sensing products is capable of providing more accurate data in shorter time period than ground survey. Image analysis with the help of digital analysis could also improve the consistency and the accuracy of the results. Therefore, it is believed to have the capability for providing reliable and accurate data to decision-makers for determining the strategies that need to be pursued (Ali et al., 2022; Kaya & Polat, 2023).

Traditional methods for obtaining accurate real-time nitrogen status and yield estimates are labor-intensive and slow in providing results. In traditional methods, assessing the nitrogen status of crops usually involves several approaches, such as soil testing, plant tissue analysis, and visual observation. In contrast, remote sensing offers a more advanced and comprehensive way to evaluate nitrogen status by using satellite or aerial imagery to detect variations in crop health and nitrogen levels across large areas. Remote sensing provides real-time, large-scale data that can complement or even replace traditional methods by identifying nitrogen deficiencies more quickly and accurately (Wright, Rasmussen, & Ramsey, 2005) Therefore, remote sensing techniques have been extensively investigated and recommended as an alternative for real-time non-destructive monitoring of nitrogen status and yield prediction in crops (Htun, Shamsuzzoha, & Ahamed, 2023; Xu et al., 2023). In remote sensing, vegetation index (VI) is one of the techniques that can provide information on nitrogen status and yields. Various vegetation indices obtained from remote sensing analysis have been reviewed by (Giovos, Tassopoulos, Kalivas, Lougkos, & Priovolou, 2021). In practice, the most commonly used index is Normalized Difference Vegetation Index (NDVI) (Giovos et al., 2021), which is calculated from the combination of two bands, namely red and near-infrared. (Nakano, Tanaka, Guan, & Ohdan (2023)used NDVI to predict rice yield and concluded that the growth stage was an important factor during application. Under dense canopy conditions, NDVI is easily saturated (Stamford, Vialet-Chabrand, Cameron, & Lawson, 2023) making it less sensitive to high plant physiological and biochemical levels (Qi, Jiang, Zhou, Xie, & Huang, 2023). According to previous studies, NDVI has some obstacles, as it only accurately provides information on the early stages of crop development. Gim et al., (2020) stated that the correlation coefficient values for the early planting stage are lower than those for the early flowering phase. The plant growth stage influences the sensitivity to vegetation indices for evaluating the state of a plant, especially in the early planting stage when soil background predominates (Gnyp et al., 2014) . Strong correlation results depend on the leaf area and soil background. This indicates that NDVI is not a good indicator of nitrogen management in mature plants. Although NDVI is the most commonly used vegetation index, it has limitations on the conditions of low and medium levels of coverage (Mandla, 2017)due to saturation tendency. Green Normalized Difference Vegetation Index (GNDVI) is a modified NDVI index used to avoid saturation at a higher leaf area index (LAI) (Tiruneh et al., 2022).

The performances of vegetation indices for estimating chlorophyll, leaf nitrogen contents and crop yields are influenced by the presence or the absence of vegetation, as well as biophysical parameters (M, Karegowda, R, & B, 2022). This phenomenon makes the study of VI in varied rice field settings significant in the agricultural sector. Previous investigations (Lima, et al., 2021; Wang et al., 2024) assumed that the heterogenous rice fields dictated the performance of any VIs, potentially leading to variation within a small area. In a diverse environment, the amount of vegetation cover, the amount of chlorophyll, and other elements that VIs use in their computations may differ in different parts of the rice fields. Because of this, there may be variations in the field's VI performance, with certain regions exhibiting higher correlations between the index values and targeted characteristics (such crop yield or chlorophyll content) than others. This heterogeneity may be caused by variations in topography, pest and disease pressure, soil fertility, and water management techniques. Disparities in VI performance can also be caused by changes in crop growth phases or planting density within the field. In this study, the comparison of NDVI, GNDVI, SAVI, and VARI for predicting chlorophyll, nitrogen, and yields in rice fields was carried out within a small area in Indonesia by using Sentinel 2A images. The study's use of four vegetation indices from sentinel 2A because it makes possible to thoroughly examine how well they predict yields, nitrogen, and chlorophyll in rice fields, offering insightful information for agricultural management and research in Indonesia with greater accuracy compared to the previously launched satellite images, such as Landsat having coarser resolution. The Sentinel 2A image was used due to its open access policy, good spatial resolution (10 m), and short time (5 days) of availability (Phiri et al., 2020; Sugianto, Rusdi, Budi, Farhan, & Akhyar, 2023). This study is significant because of the unique condition of the practices of rice cultivation in Indonesia, which is generally on small farmers' land with various management conditions. As a results, this needs a different combination of nutrients and fertilization management in order to optimum productivity (Li et al., 2019). The little amount of land that farmers hold has a significant impact on the variety in agricultural techniques in Indonesia and in this research location. In fact, the majority of farmers are elderly, and there is a great diversity in economic and educational backgrounds, which makes it challenging to apply novel agricultural techniques. The way these small agricultural fields are managed varies as a result. Considering the practices in the study area, generally it can be said that even in adjacent plots, planting dates, irrigation schedules, fertilization schedules, upkeep schedules, and harvesting practices differ (Connor et al., 2021). Estimating the relationship between chlorophyll, nitrogen, yield, and vegetation indices under these conditions is challenging due to the limited existing studies. Studies that utilize large areas, undoubtedly with smaller scales, cannot encompass the vast variability of land conditions and rice crops in narrower areas. High variability is highly likely to be found in smaller areas. The scarcity of studies addressing this issue is the main reason for this research. By using smaller areas but with more detailed observation scales, it will be possible to provide more precise fertilizer recommendations (such as Nitrogen). Therefore, this study aimed to (1) estimate the chlorophyll content on paddy fields, (2) estimate nitrogen content, and (3) predict yields.

2. Methods

The study area, as shown in Figure 1, is a small area located in two villages, namely Antirogo and Tegalgede, Sumbersari Subdistrict, Jember District, Indonesia. The total area covers 87.54 Ha, with agriculture serving as the main land use. This study was conducted for 5 months, from January to May 2023 in the rainy season.

In this study, the two main components of data used were primary and secondary data. The primary data consisted of (a) field measurement of yield per plot samples (b) leaf samples for measuring nitrogen content, and (c) field measurement of chlorophyll content by using chlorophyll meter (soil and

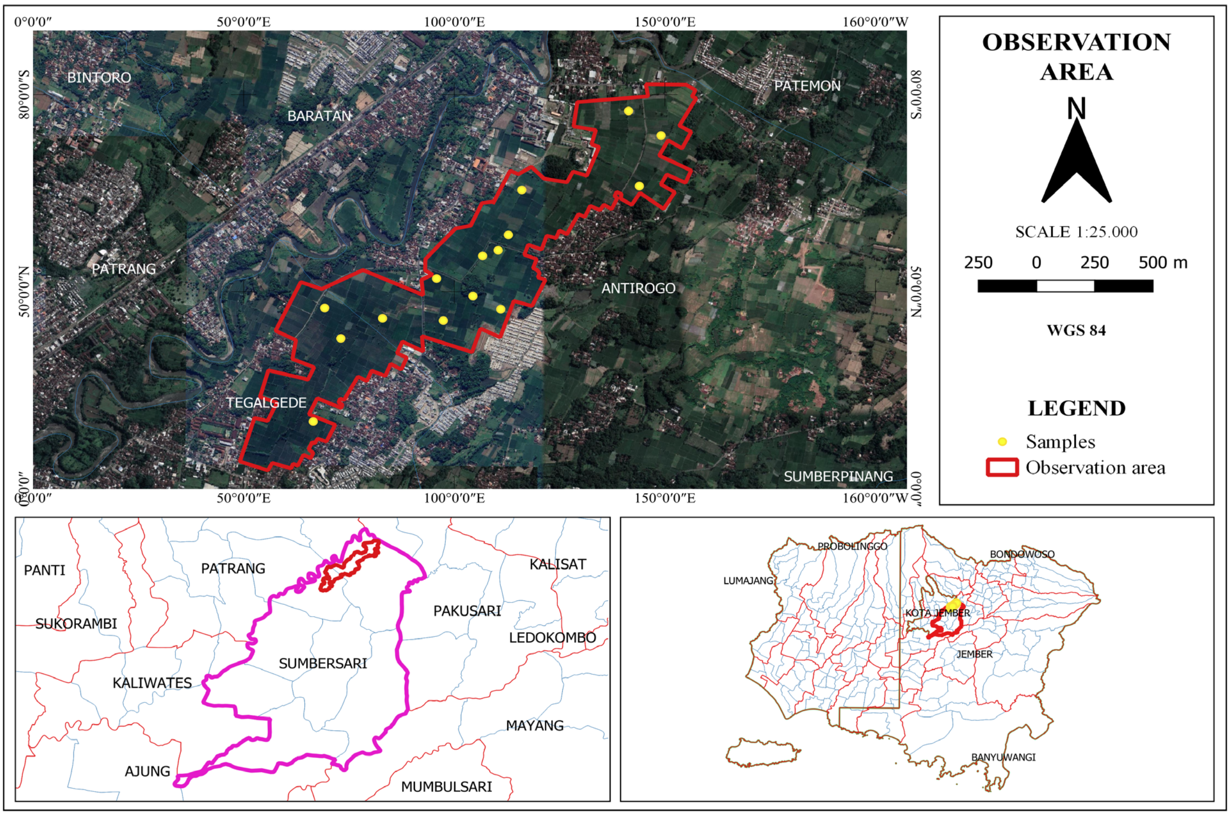

Figure 1. Study area

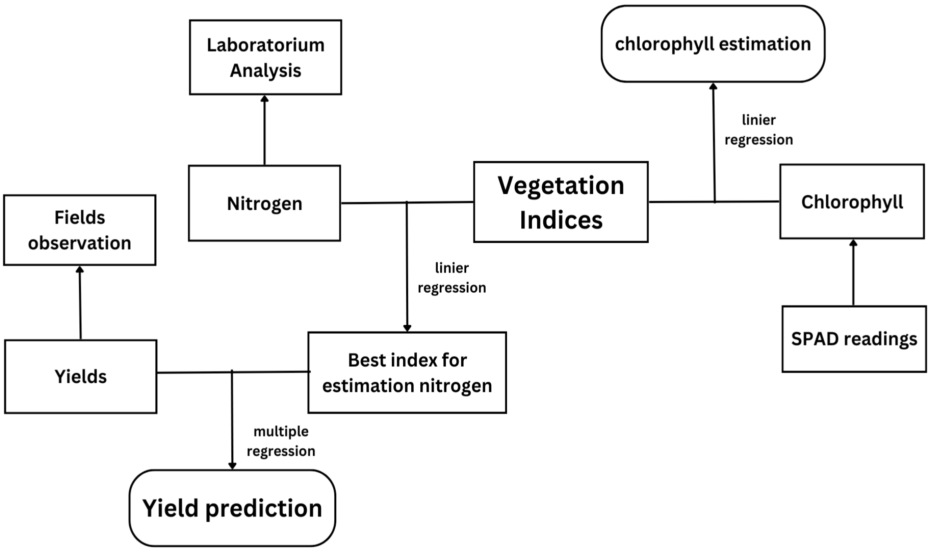

Figure 2. The procedure of data analysis

plant analysis development) Konica Minolta SPAD 502 Plus Chlorophyll meter. Figure 2 shows the procedures used in this study. The primary data used were (a) sentinel-2A images, which had been atmospherically and geometrically corrected and were downloaded from https://scihub.copernicus.eu/dhus/#/home. Furthermore, the three dates of images used were (a) January 20th 2023, (b) February 15th 2023, and (c) March 16th 2023.

Figure 2 showed the data analysis procedure used in this study. Downloaded images were analyzed by using four vegetation indices (VIs), namely NDVI, GNDVI, Soil Adjusted Vegetation Index (SAVI), and Visible Atmospherically Resistant Index (VARI). The formula of the VI's is represented at Table 1.

These vegetation indices played a central role in achieving (1) Chlorophyll estimation, (2) Leaf Nitrogen concentration, and (2) yield prediction. To achieve the first and second aims, regression model was employed, while multiple regression was undertaken to determine the relationship between yields and the best vegetation indices. The relationship between yields, nitrogen content, and chlorophyll content and vegetation indices (e.g., NDVI, GNDVI, SAVI, and VARI) can be quantitatively analyzed using regression models. They make it easier to anticipate these factors using vegetation indices, highlight important correlations, and offer findings that are easy to interpret.

The best vegetation indices were determined from the results obtained through the analysis of nitrogen and vegetation

Table 1. Vegetation indices formula

No	Vegetation Indices	Formula	References
1	Normalized Difference Vegetation Index (NDVI)		(Rouse et al., 1974, as cited in Somvanshi & Kumari, 2020)
2	Green Normalized Difference Vegetation Index (GNDVI)		(Gitelson et al., 1996, as cited in Radočaj, Šiljeg, Marinović, & Jurišić, 2023)
3	Soil Adjusted Vegetation Index (SAVI)		(Huete, 1988, as cited in Somvanshi & Kumari, 2020)
4	Visible Atmospherically Resistant Index (VARI)		(Gitelson et al., 2002, as cited in, Meivel & Maheswari, 2022)

Table 2. The average of chlorophyll content, nitrogen, and vegetation indices on different observation times (O1, O2, and O3)

Observation	Chlorophyll	Nitrogen	Vegetation Indices			
			NDVI	GNDVI	SAVI	VARI
O1	34.95	2.41	0.3233	0.3300	0.4848	-0.0034
O2	44.82	3.38	0.5884	0.5024	0.7592	0.1790
O3	28.96	2.13	0.4361	0.3850	0.6506	0.1141

indices. This resulted in the single best vegetation index, which was used to determine the relationship between rice yield and vegetation indices. Observation of the leaf nitrogen content, chlorophyll content, and vegetation index was carried out three times, at 10, 40, and 70 days after planting (DAP). Based on the requirements, the age of planting was considered when selecting the sample sites. For each observation, 15 sample points were acquired, resulting in a total of 45 samples. The yield at 90 DAP of the rice was also observed using a total of 45 GPS-determined sample locations. Subsequently, the purposive sampling approach was used to determine the sample points. This approach is a sample selection technique with a more particular target in line with the study issue and the goals, which is assumed to be representative.

3. Result and Discussion

3.1 The Development of Vegetation Indices

Table 2 showed the variation of vegetation indices from three observations (O1, O2 and O3) conducted in the study area. Based on the results, different values ranging from O1 to O3 were identified, where O2 had higher values compared to those in O1 and O3 for chlorophyll, nitrogen, and vegetation indices. This was due to an increase in chlorophyll content in line with the development stages of rice. In this case, O1, O2, and O3 were related to the vegetative, generative, and maturity stages of rice development. The following are possible causes and these seems to agree with findings of the study conducted by Manessa, et al., (2023) as follow : (a) Rice plants frequently show an increase in chlorophyll content during the shift from the generative to the reproductive stages, which results in the changes in greenness that can be measured using indices like the NDVI and GNDVI; (b) Rice plant canopies have a tendency to grow and thicken during the generative phase, which is marked by bigger leaves. Higher values of vegetation indices, which are impacted by canopy structure, such as NDVI, GNDVI, SAVI, and VARI, are a result of this increased canopy density and foliage size; (c) Rice plants must absorb more nutrients during the generative phase in order to grow reproductively. Higher values of vegetation indices are usually the consequence of healthier and more vigorous plants, which is brought about by this increased nutrient intake; (d) The effect of soil reflectance on vegetation indices like SAVI and VARI decreases as the rice canopy grows and covers more area during the generative phase. Because these indices are especially intended to counteract the impacts of soil background, their values have been seen to rise during this phase.

Figure 3 shows the development of vegetation indices. As shown, SAVI exhibited the highest value, while the lower values were observed in VARI, GNDVI, and NDVI. Meanwhile, VARI had the lowest values because the index did not use the near-infrared band and only the visible band was employed. The reason for this is that because it accounts for soil background effects, SAVI (Soil-Adjusted Vegetation Index) usually produces higher numbers. SAVI adjusts for soil background affects by adding a soil adjustment factor, which raises index results. Therefore, this is most likely to relate to the presence of water and varied soil conditions in paddy fields. The significant overlap of NDVI and GNDVI was observed at the start of the graph in Figure 3. This showed that GNDVI was not capable of distinguishing the vegetation and the soil background in 10 DAP (Days After Planting). (Rehman, Lundy, & Linquist, (2022) stated that GNDVI is suitable for the assessment of the vegetation index in the maturity stage. Therefore, low values of GNDVI at 10 DAP were obtained because the rice was still at the beginning stage of development. Field evidence also showed that at 10 DAP, rice was still at the vegetative stage and the soil and water background backgrounds were the dominant feature. Consequently, the values of the reflectance were also dominated by soil and water reflectance's (Sukojo and Kurniawan, 2021). In O2 and O3, NDVI and GNDVI were in close values, with the GNDVI exhibiting greater values. Figure 1 showed more distinct values of indices in O2 (peak values), gradually decreasing as the rice matures. Bautista et al., (2022) had identified a generative period (which is coincide with O3 in this study) for rice to reach the peak NDVI, followed by a decrease in the values toward maturity.

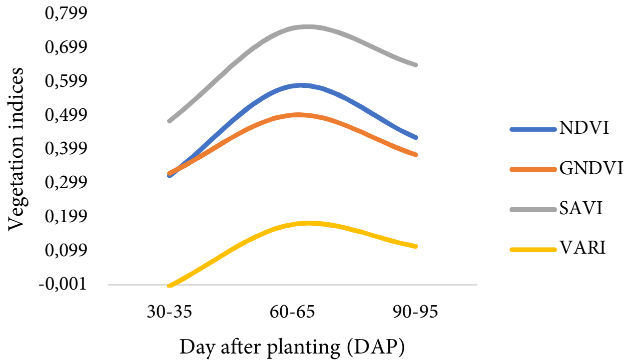

Figure 3. The development of vegetations indices for three different times of observation

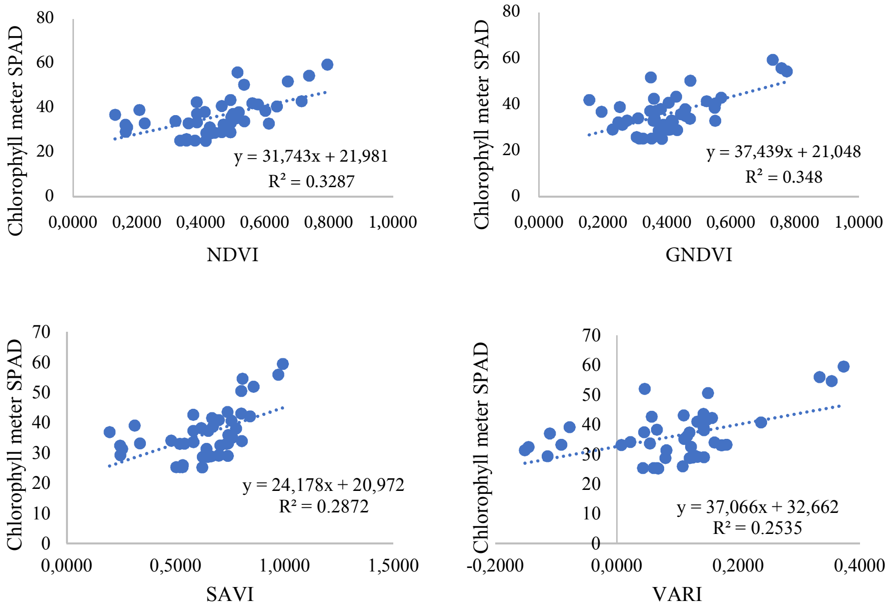

Figure 4. The relationships between vegetation indices and chlorophyll

3.2 The Relationship between Vegetation Indices and Chlorophyll Content

Figure 4 showed the relationships between vegetation indices and chlorophyll of the 45 samples, with R^2 values of 0.3994(NDVI), 0.3974 (GNDVI), 0.3627 (SAVI), and 0.3076 (VARI). These values are expected because using spectral bands that are extremely sensitive to both the total density of vegetation and the amount of chlorophyll, NDVI and GNDVI are computed. These indexes take advantage of the difference between visible and near-infrared (NIR) green bands, which are substantially absorbed and reflected by healthy vegetation, respectively. They are able to accurately record changes in the health of the vegetation because of their sensitivity. However, the near-infrared band is not included in the VARI (Visible Atmospherically Resistant Index), which only uses visible bands (Nuthammachot & Stratoulias, 2023). Therefore, in contexts such as rice fields, where vegetation qualities frequently show higher responses in the near-infrared band, it may not be able to accurately capture vegetation characteristics. Lower VARI values result from this restriction when compared to indices that include near-infrared data. The different of R^2 between SAVI and VARI can be due to the environmental reason, such as soil moisture, canopy structure, and atmospheric influences. SAVI's may provide a more accurate representation of chlorophyll content under diverse environmental conditions, leading to stronger correlations compared to VARI. This diverse environmental condition may be attributed to the differences in farming practices, such as fertilizer applications and irrigation. This diverse environmental condition may also be caused by different kind of fertilizer applications. Consequently, the performances of rice on all farmer fields were different, resulting in greater variabilities.

3.3. The Relationship between Vegetation Indices and Nitrogen

Figure 5 illustrated the relationship between vegetation indices and leaf nitrogen contents, with R^2 values of 0.4406 (NDVI), 0.426 (GNDVI), 0.3982 (SAVI), and 0.3457 (VARI). This pattern of values seemed to be similar to those for the relationship between vegetation indices and chlorophyll. However, higher values were found on the relationship between vegetation indices and nitrogen. The contribution of vegetation indices on the predicted values of nitrogen were 44.06% (NDVI), 42.6% (GNDVI), 39.82% (SAVI), and 34.57% (VARI), respectively. This analysis suggests that while chlorophyll concentration is a major factor in NDVI measurements, there is often a stronger link between NDVI

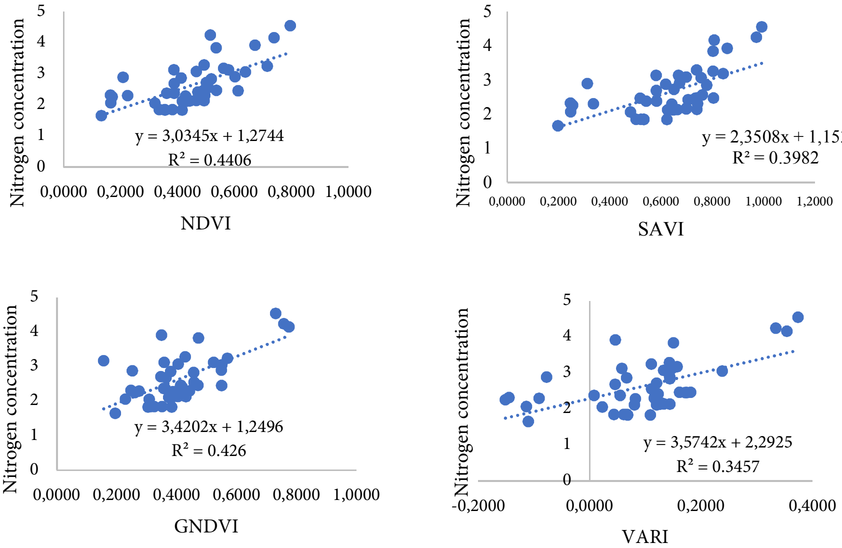

Figure 5. The relationships between vegetation indices and nitrogen

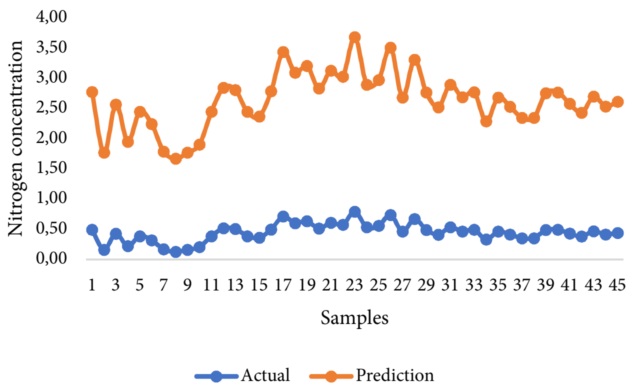

Figure 6. The relationship between actual and predicted nitrogen using NDVI

and nitrogen content. The complicated roles that nitrogen plays in plant physiology, such as its crucial role in the production of chlorophyll and its broader effects on the general health and vigor of plants, can be used to explain the stronger correlation observed between NDVI and nitrogen. Nitrogen influences not just the synthesis of chlorophyll but also other critical variables such as canopy shape and leaf area index (LAI), which have a more direct and extensive impact on NDVI values. For example, studies by Amirhusin et al., (2023) and Hussain, et al., (2022) have demonstrated how nitrogen affects rice height and tiler development. As a result, nitrogen is the most important nutrient of all, having a significant impact on plant growth, development, and overall quality. The analysis's findings also suggested that nitrogen tends to have a more uniform geographical distribution in plants, which enhances the nutrient's consistency with the NDVI. On the other hand, chlorophyll has a significant, albeit occasionally indirect, influence on the NDVI since it is the primary pigment in photosynthesis.

Based on the results of three observations at different age stages, NDVI exhibited the best vegetation index for assessing nitrogen uptake in rice due to its highest correlation coefficient, while the lowest was obtained in VARI. The NDVI method compared visible red and near-infrared wavelengths to determine plant green levels. This indicated that the greater the NDVI values, the more active the photosynthetic process (Phyu et al., 2020). A high NDVI index value indicates a low reflection of visible red radiation due to chlorophyll absorption, with a high near-infrared reflectance from leaves (Irfan et al., 2018).The NDVI method can assess nitrogen uptake in plants based on spectral values recorded and calculated. The strong relationship between NDVI and Chlorophyll content found in this study seems to agree with the finding by Padhan et al., (2023) who stated that the relationship between these two variables in rice crop showed strong correlation

The VARI vegetation index algorithm relying on the visible spectrum made it less ideal for calculating nitrogen uptake. Stressed leaves are more compact in reflecting near- infrared light compared to healthy leaves. Therefore, combining visible light and near- infrared algorithms yielded better performance in detecting the greenness of rice plants compared to the use of only the visible light algorithm (Gnyp et al., 2014).

Figure 6 showed the comparison between the actual and the predicted leaf nitrogen content, indicating a s difference between these two. The difference in values was caused by several factors, including the background factor of inundated soil. The pixel component in the captured image also affected the index value (Huang, Tang, Hupy, Wang, & Shao, 2021) The image resolution used in this study was 10 x 10 m in size, indicating that the pixel area was 100 m^2. The diversity of objects in one pixel also affected the index value obtained (Waleed et al., 2022). Each pixel represented one sample with the desired planting age, while other lands in the same pixel had different planting ages. This discrepancy can lead to an under-representation of samples in one pixel.

The accuracy of the obtained equation model was assessed by calculating the root mean square error (RMSE) value to determine the error rate of the estimation, as presented in Table 3. Based on the RMSE values, the NDVI index had the lowest error value, although all values of RMSE are comparably similar. A smaller RMSE value indicates a better performance because the error rate is less. These results showed that the best vegetation index for estimating nitrogen uptake in rice plants was NDVI. Despite variations in leaf nitrogen content in rice, these differences do not impact the values of the vegetation indices. This aligns with the findings of (Chowdhury et al., 2024) who reported that different nitrogen treatments (120, 160, 200, and 240 kg N/ha) resulted in similar values for the vegetation indices (NDVI, RVI, NDRE, and GNDVI) throughout the rice growth stages.

3.4 Spatial Distribution of Vegetation Indices

Figure 7 illustrated the distribution of greenness obtained from the analysis of four vegetation indices for the ages of rice 10 DAP (vegetative), 40 DAP (generative), and 70 DAP (ripening). Table 4 showed the acreage (Ha) of each greenness class, where the pattern on the value of indices was in observation 2. There was also an increasing tendency of the area from very low to moderate greenness for four vegetations, indicating the canopy development of rice.

Based on direct field observations, the rice has entered the generative phase, with panicles emerging while the leaves remain green, as shown in Figure 5c. Some rice leaves have started to yellow, indicating the grain ripening stage, and a few rice plants are nearing harvest. The NDVI and SAVI vegetation indices have shown significant changes compared to the GNDVI and VARI indices.

Table 3. The accuracy of leaf nitrogen estimation

No	Vegetation Indices	RMSE
1	NDVI	0.5108
2	GNDVI	0.5175
3	SAVI	0.5299
4	VARI	0.5525

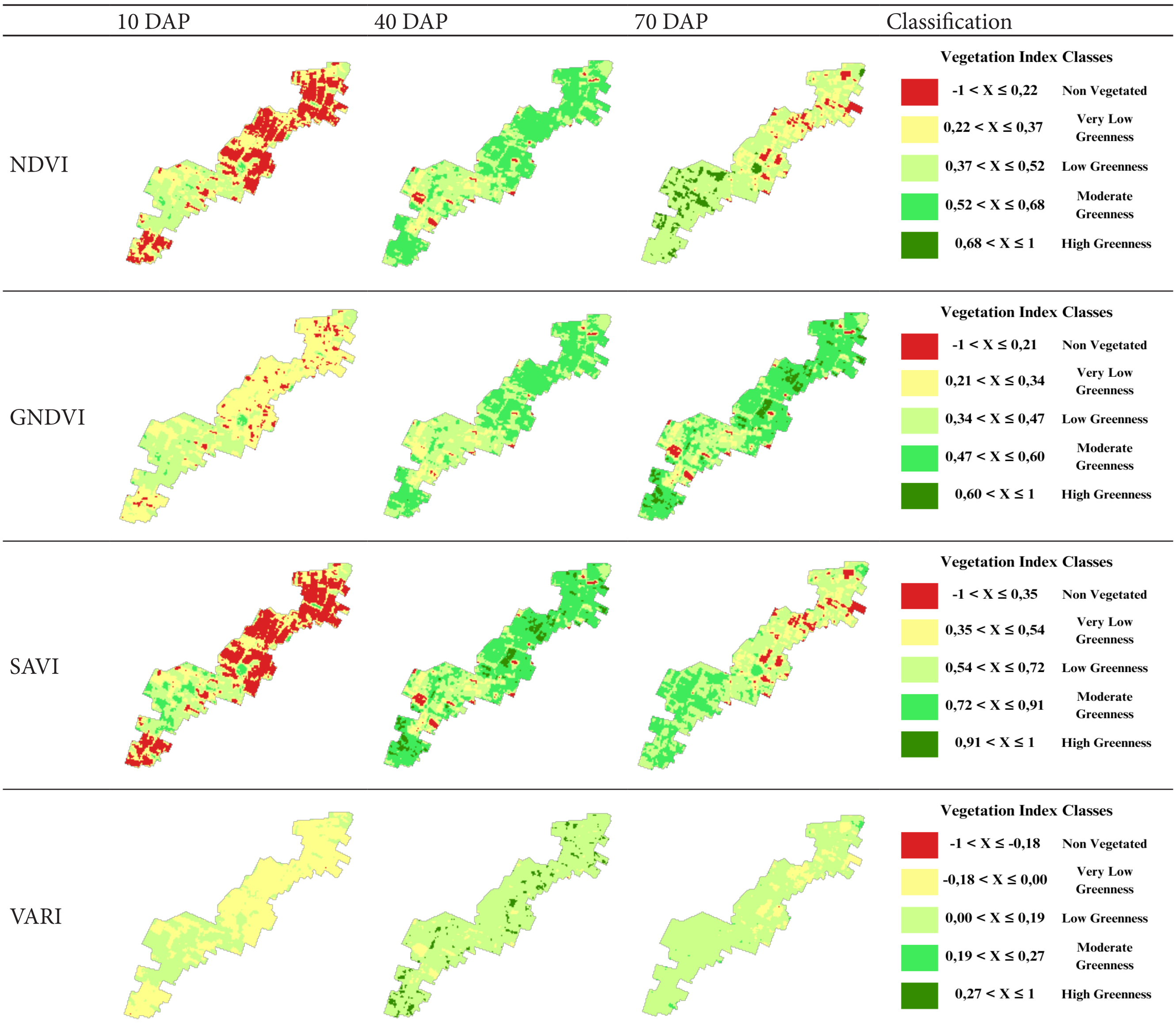

Figure 7. Spatial distribution of vegetation indices

Each index changes with each growth phase, but NDVI and SAVI more accurately reflect the field conditions. The VARI index is less indicative of these conditions because it only uses visible light, specifically Bands 2 (Blue), 3 (Green), and 4 (Red) and VARI does not incorporate Band 8 (Near Infrared). In contrast, the NDVI, GNDVI, and SAVI indices utilize Band 8 (Near Infrared) in their calculations. The Near Infrared spectrum is crucial for accurately representing vegetation conditions. According to Hisham, et al. (2022) the Near Infrared spectral effectively represents the condition of rice leaves, which is highly reflected during the generative phase, resulting in high greenness levels, while visible light is largely absorbed by plants for photosynthesis, as evidence in Table 4 in Observation 3 with the higher values of greenness.

3.4 Yield Prediction

The value used to calculate productivity was milled dry grain (MDG) in tons/ha, obtained by converting the grain weight value of each tile. The average productivity was obtained at 6.10 tons/ha MSG and the Inpari 32 variety had a general average yield of ±6.30 tons/ha. Therefore, the production was still below standard with a 98% percentage of achievement of the general average. One of the factors ccontributing to the lower percentage of productivity was due to the application of fertilizer that did not meet the standards of the Balai Penelitian dan Pengembangan Pertanian (2020). The amount of fertilizer applied in the study area with the Urea fertilizer is 250 kg/ha, which is still in below the recommended standard (300 kh/Ha) by Balai Penelitian dan Pengembangan Pertanian (2020). Considering this, lack of Urea fertilizer could be the main reason for low rice productivity in the study area.

Multiple regression analysis was used to determine the predicted yields and NDVI was used. The results showed that by considering the values NDVI from the first, second, and third observations with yield data, the correlation coefficient (r) 0.8 was obtained, indicating a very strong relationship.

(a) 10 DAP

(b) 40 DAP

(c)70 DAP

Table 4. The areal distribution of greenness in the study area

Observation	Vegetation Index	Vegetation Area (Ha)				
		Non Vegetated	Very Low Greenness	Low Greenness	Moderate Greenness	High Greenness
1	NDVI	31.25	30.23	24.79	0.98	0
	GNDVI	3.91	52.84	29.47	1.11	0
	SAVI	35.44	24.72	21.59	5.57	0
	VARI	0.01	58.45	28.90	0	0
2	NDVI	2.00	8.52	33.15	43.63	0
	GNDVI	0.78	9.14	37.19	40.13	0.01
	SAVI	2.32	7.49	22.07	49.59	5.85
	VARI	0.01	4.07	78.62	4.62	0
3	NDVI	4.85	20.34	55.36	6.71	0
	GNDVI	1.91	23.65	56.75	5.00	0
	SAVI	5.86	15.94	44.33	21.09	0.01
	VARI	0.01	10.45	76.05	0.82	0

Furthermore, the coefficient of determination (R^2) was found at the value of 0.65. The results of the multiple regression equation between the NDVI vegetation index and rice productivity were formulated as follows:

$$y=0,76x1+4,96x2-1,8x3+3,73$$

in this case

y yields prediction

x1 : NDVI Observation 1

x2 : NDVI Observation 2

x3 : NDVI Observation 3

The equation model obtained was, then used to calculate the estimated productivity of rice plants in Figure 8. The estimation results of rice productivity from the multiple regression analysis equation model were validated by calculating the RMSE value to determine the error in Table 5. Based on the results, the NDVI vegetation index had the lowest RMSE value, indicating that the closer the values to zero, the smaller the error. It is apparent form the results that by utilizing NDVI data from several observations during rice growth, accurate estimate of crop yields can be established due to the capability in capturing the complexity and diversity of vegetation dynamics. Similarly, Htun et al., (2023) stated rice productivity was more accurately predicted by using multiple regression. This indicated that the estimated values of rice productivity using the NDVI were close to the actual ones, therefore, it was considered an acceptable correlation. These results seem to disagree with that of the relationship between Nitrogen and used Vegetation Indices as shown before which may be due to the fact that rice yields are affected by other factors other than Nitrogen.

Employing machine learning techniques may produce predictions that are more accurate than those made with traditional multiple regression models as shown in this study. However, sufficient data on soil properties, climate variables, and rice plants are still lacking to provide reliable machine learning prediction. Joshua et al.'s (2021) claims that machine learning methods such as Support Vector Machines, General Regression Neural Networks (GRNNs), Radial Basis Functional Neural Networks (RBFNNs), and Back-Propagation Neural Networks (BPNNs) require a substantial amount of data in order to predict rice yields, such as rainfall, temperature, soil properties, urea, and the elements nitrogen, phosphorous, and potassium. As a result, further investigation into machine learning methodologies through comprehensive compilation of relevant data will be conducted in the future.

4. Conclusion

Studying vegetation indices in relation to chlorophyll, nitrogen, and crop yield in small areas with varied crop management is challenging. The results indicate that NDVI and GNDVI contribute more to chlorophyll content estimation than SAVI and VARI, highlighting their spectral sensitivity. Similar trends were observed for nitrogen prediction, with NDVI and GNDVI showing better RMSE values than SAVI and VARI, though the differences were small. However, yield prediction accuracy differed, with NDVI being the most accurate, followed by SAVI, VARI, and GNDVI being the least accurate. This suggests that while GNDVI is sensitive to nitrogen, its complex relationship with yield may reduce its predictive accuracy compared to the broader vegetation health captured by NDVI. If nitrogen is not the primary yield-limiting factor, NDVI might outperform GNDVI. For further study, it is recommended to investigate additional yield-limiting factors, conduct focused studies on GNDVI under varying nitrogen levels, implement long-term studies across different seasons and possbly apply machine learning techniques, and investigate spatial and temporal variability of indices.

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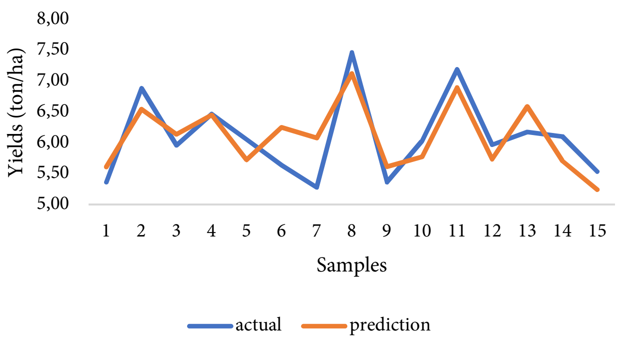

Figure 8. The relationship between actual and predicted yields

Table 5. The accuracy yield prediction

No	Vegetation Indices	RMSE
1	NDVI	0.1421
2	GNDVI	0.5258
3	SAVI	0.4701
4	VARI	0.5030

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