ISSN 2354-9114 (online), ISSN 0024-9521 (print)
Indonesian Journal of Geography Vol 56, No 3 (2024): 387-395
DOI: 10.22146/ijg.88571 website: https://jurnal.ugm.ac.id/ijg

INDONESIAN JOURNAL OF GEOGRAPHY

RESEARCH ARTICLE

Estimation of Nitrogen Content of Rice Crops Using Sentinel-2 Data

Heni Agustina[1], Lalu Muhamad Jaelani[1]*, Hartanto Sanjaya[2,3]
[1] Department of Geomatics Engineering, Faculty of Civil, Planning, and Geo-Engineering, Institut Teknologi Sepuluh Nopember (ITS), Surabaya 60111, Indonesia
[2] Department of Civil Engineering, Faculty of Civil, Planning and Geo-Engineering, Institut Teknologi Sepuluh Nopember (ITS), Surabaya 60111, Indonesia
[3] National Research and Innovation Agency, Gedung B.J. Habibie, Jl. M.H. Thamrin No. 8, Jakarta Pusat 10340,Indonesia

Received: 2023-09-01
Revised: 2024-05-27
Accepted: 2024-08-23
Published: 2024-10-18

Key words: Generative; Nitrogen; Sentinel-2; SPAD; Vegetation Index

Correspondent email:
lmjaelani@gmail.com

Abstract Nitrogen (N) is one of the most essential nutrients for rice crops. Farmers generally provide Nitrogen requirements in rice through fertilization, but the fertilization process is only based on an estimation without calculating the amount needed first. However, neither insufficient nor excessive nitrogen content is good for rice crops, and the nitrogen needs of rice crops are different at each growth stage. The nitrogen requirement in the generative phase is relatively high because the process of panicle formation and grain filling occurs at this stage. Several methods can be used to monitor nitrogen content in rice, one of which is using remote sensing methods. With the vegetation index approach, the nitrogen content of rice plants is estimated through data analysis of the light spectrum reflected by the leaf. Sentinel-2 satellite imagery was used in this research, and several vegetation indexes such as OSAVI, GNDVI, and SRRE were applied to form an estimation model using the regression method. From the results, three vegetation indexes positively correlate with nitrogen content in rice crops. The SRRE index gives the highest correlation coefficient value of 0.692, while the correlation coefficient value for GNDVI is 0.498, and OSAVI is only 0.470. The estimation map of the nitrogen content of rice crops was obtained based on the estimation model made by linear regression between SPAD-based nitrogen content data and the best vegetation index using the SRRE index. The analysis shows that the nitrogen content of rice plants estimated in the paddy fields of Karangjati Subdistrict is dominated by nitrogen values with optimum classification.

1. Introduction

Rice is an essential staple food in many countries, especially Indonesia. The annual per capita consumption of rice-based food products exhibited a marginal decline from 94.473 kg in 2019 to 93.791 kg in 2023 (Secretariate General - Ministry of Agriculture Republic of Indonesia, 2023). But, the ~~The~~ food demand in Indonesia will continue to grow as the population increases and will reach the top three rice consumers countries in the world, as indicated by FAO (OECD-FAO, 2023). This is certainly a challenge for food suppliers. Based on data from the Central Bureau of Statistics of Ngawi Regency, East Java is the largest rice-producing province of all provinces in Indonesia in 2021, where Ngawi Regency is one of the main contributors. From January to December 2021, Ngawi Regency can produce 818,620.31 tons of milled dry grain(BPS Jawa Timur, 2022). Because of this potential, it is important to maintain the stability of rice production. One way to maintain the stability of rice production is to ensure that sufficient nutrients are provided to the rice during the growth phase. Because of this potential, rice self-sufficiency in Indonesia has been a longstanding goal, with various studies focusing on factors influencing this objective. Pratiwi (Pratiwi, 2022) highlights that achieving rice self-sufficiency in Indonesia by 2024 or 2025 with a production target of 40 million tons (in Indonesia level) is feasible through adjustments in extensification, intensification, and per capita consumption of rice per year. This aligns with the findings of Fathonah & Mashilal (Isnaeni Fathonah & Mashilal, 2021) who emphasize the importance of factors like land area, labor, and capital in reflecting rice self-sufficiency in Indonesia. Moreover, the study by Warr & Yusuf (Warr & Yusuf, 2014) underscores the historical use of agricultural input subsidies, particularly on fertilizer, to boost agricultural production and work towards rice self-sufficiency. One intensification approach is to ensure Nitrogen(N) has been highlighted as a major nutrient contributing to rice production, emphasizing its significance in achieving desirable yields.

Nitrogen (N) is one of the most essential nutrients for rice crops. Nitrogen promotes growth, grain formation, grain filling, improving grain yield and quality, increasing leaf area, and protein synthesis (Patti et al., 2018) . In general, the nitrogen needs of rice are met by fertilization applied by the farmers. However, the fertilization process is only on the basis of estimation, without any calculation of the needs before. In fact, it is important to ensure that the amount of nitrogen applied matches the needs of the rice. This is because excess or deficiency of nitrogen is not suitable for rice (Lathifah & Sukojo, 2014; Patti et al., 2018; Peng et al., 1993; Shrestha et al., 2022a; Yadav et al., 2022; Zhang et al., 2020a; Zheng et al., 2022).

Nitrogen requirements of rice crops vary at different growth stages. During the generative phase, nitrogen requirements are relatively high because of the process of panicle formation and grain filling. According to Bhupenchandra et al. (Bhupenchandra et al., 2020) , sufficient nitrogen in the generative phasis is also important in delaying leaf senescence and maintaining photosynthesis during grain filling.

Several methods can be used to measure nitrogen content, including the Kjeldahl method(Kjeldahl, 1883) and the Soil Plant Analysis Development Meter (SPAD) measurements. The Kjeldahl method is accurate for calculating nitrogen content based on laboratory analysis using biological samples, but it is tiring, time-consuming, and destructive. Another method of determining nitrogen status is by SPAD. SPAD is a measurement of chlorophyll content, which is highly correlated with leaf nitrogen content. This method is non-destructive but still time-consuming because SPAD measures only one leaf at a time (Peng et al., 1993; Rhezali & Aissaoui, 2021; Saberioon & Gholizadeh, 2016; Sharifi, 2020; Singh et al., 2022; Vishwakarma et al., 2023; L. Wang et al., 2021; Zheng et al., 2022).

To estimate nitrogen content, remote sensing technology is now being developed. With the vegetation index approach, the nitrogen content of rice crops is estimated by data analysis of the light spectrum reflected by the leaf. A spectral index is usually used for multispectral/hyperspectral remote sensing data, which is constructed by the selection of appropriate bands in the red and near-infrared (NIR) regions (Zheng et al., 2022). The red and NIR bands are commonly used for crop monitoring due to the strong absorption in the red band and the high reflectance in the near-infrared (NIR) band (Sun et al., 2022). Several vegetation index algorithms can be used in nitrogen analysis, including the Optimized Soil Adjusted Vegetation Index (OSAVI) (Lathifah & Sukojo, 2014), Green Normalized Difference Vegetation Index (GNDVI)(Saberioon & Gholizadeh, 2016), and Red Edge Simple Ratio (SRRE) (Sharifi, 2020). (Saberioon & Gholizadeh, 2016)—Sukojo (Lathifah & Sukojo, 2014) to-

Lathifah & Sukojo (2014) utilized OSAVI indice as a valuable tool in assessing nitrogen levels in vegetation, particularly in crops like rice. The utilization of hyperspectral technology with hundreds of channels allows for a detailed spectral analysis of objects under observation, enabling the detection and monitoring of nitrogen levels in vegetation. This study reported that the indice and field nitrogen has a correlation(R^2) result of 0.776. The study by Sharifi (2020) demonstrates the effectiveness of the Spectral Ratio Red Edge (SRRE) vegetation index in predicting nitrogen uptake in maize crops in Iran using Sentinel-2 data. The research shows that SRRE outperformed other vegetation indices with an R-squared value of 0.91 and a Root Mean Squared Error (RMSE) of 11. Saberioon & Gholizadeh (2016) proposed as an alternative that can potentially provide more accurate information, especially in areas with dense vegetation or when dealing with specific types of crops like paddy fields. The experimental validation of this approach was conducted on the farmland of Universiti Putra Malaysia. The results demonstrated a standard error and coefficient of variation (CV) of 0.015 and 7.10%, respectively. In agricultural research, the nitrogen content in leaf differing across crop phases signifies a crucial aspect due to nitrogen's vital role in plant growth and development. During vegetative phase, plants absorb nitrogen through their roots and utilize it for constructing their cellular structures. During the generative phase, N stored in the vegetative parts of the plant is relocated to the developing grain(Hirel et al., 2007). However, even though some of the nitrogen is moved, there is still a certain amount of nitrogen that remains in the leaf. Therefore, nitrogen can still be detected in the leaf during this phase(Tegeder & Masclaux-Daubresse, 2018).

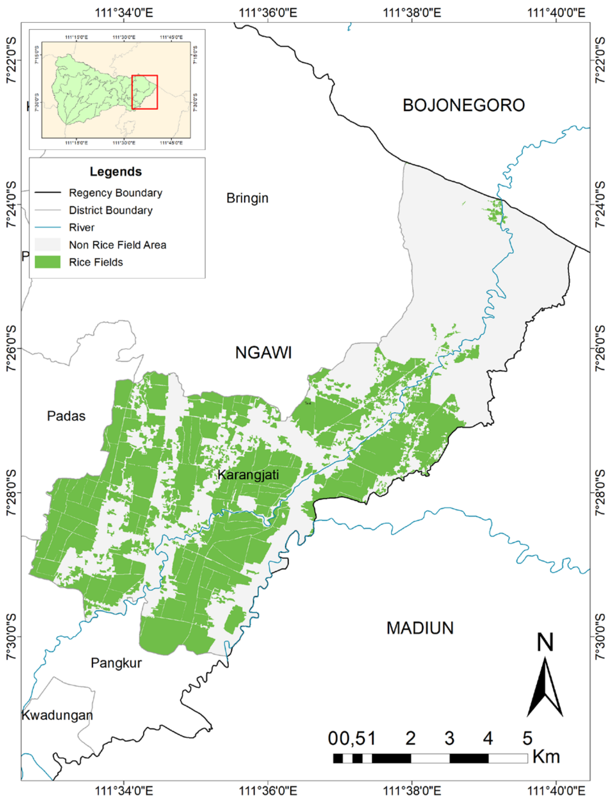

Figure 1. Study Area

Based on the description above, this study estimates the nitrogen content of rice crops, especially in the generative phase, using several vegetation index algorithms. The data used are Sentinel-2 and MODIS satellite images. Sentinel-2 was chosen because the visible light spectrum and red edge are closely related to chlorophyll and nitrogen content in plants. Meanwhile, MODIS, which is a satellite image with high temporal resolution, can be used to determine the phase of rice crops. The research results are expected to support precision agriculture efforts to increase rice production.

2. Methods

Study Areas

The research was conducted at a rice field area in Karangjati district, Ngawi Regency, East Java. Karangjati district has an area of 6,676 ha, whereas about 40 percent, or about 2,683.90 ha, are paddy fields.

Data and Equipment

The data used for this study is the Sentinel-2 Level-2A surface reflectance satellite image, which was acquired on January 13, 2023. Sentinel-2 is a moderate-resolution satellite image with 13 spectral bands, 290 km coverage, and high temporal resolution; with these capabilities, the Sentinel-2 instrument can support various studies(ESA, 2015; Gascon et al., 2014) . Sentinel-2 images are used to calculate the nitrogen content of rice crops. The next image data required is MODIS MCD43A4 - MODIS/Terra + Aqua Nadir BRDF satellite image data with an acquisition period from January 2022 to May 2023. MODIS MCD43A4 -MODIS/Terra + Aqua Nadir BRDF is a satellite image with daily temporal and 500-meter spatial resolutions. MODIS images were corrected for nadir and atmosphere (Schaaf et al., 2002). In this study, MODIS images were used to determine the threshold of the growth stage of rice crops. In addition, vector data of paddy fields from the Geospatial Information Agency (BIG) were used to delimit the study area, and SPAD reading data were used to estimate rice nitrogen in the field.

The equipment used in the study consists of a SPAD502Plus to estimate the nitrogen content of rice in the fields and a GPS to determine the position of the samples. Other tools include Google Earth Engine for processing satellite image data, ArcMap for spatial data processing and map visualization, and Minitab for statistical data analysis.

Field Data Collecting

Estimates of the nitrogen content of rice in the field were obtained by measurements using the Konica Minolta SPAD-502Plus Soil Plant Analysis Development (SPAD). SPAD can be used to determine the nitrogen status of plants in the field because it measures chlorophyll content, which is highly correlated with leaf nitrogen content (Y.-P. Wang et al., 2022). The SPAD measurements provide a direct and localized assessment of chlorophyll content in individual leaf (Uddling et al., 2007). On the other hand, remote sensing data offers a broader, area-based estimate of chlorophyll content by capturing light reflectance from the surface, providing a more comprehensive view of vegetation status (Lu & He, 2021). To bridge the gap, following Coste (Coste et al., 2010) and the manual book of SPAD, in this research, SPAD measurements were conducted at 30 randomly selected observation points in the study area. At each measurement point, a rice clump with five leaves was selected and each leaf was read three times. The sampling points of the leaf parts used for measurements are located at the paddy leaves' top, middle, and base. Furthermore, the value obtained from each reading at each point is taken as an average. The coordinates of each observation point are also measured.

Based on research by Peng et al. (Peng et al., 1993), a relationship was found between SPAD values and nitrogen content at each growth stage. A regression equation can be used to calculate nitrogen content based on the predicted dry weight, as shown in Equation 1. In this equation, N represents nitrogen content (g/kg), and SPAD represents the SPAD reading.

$$N = 0.81(SPAD) - 2.35 \quad (1)$$

Data Processing

A. Determine the rice growth phase.

In the first step, Sentinel-2 and MODIS satellite images were cropped based on vector data of rice fields to constrain the study area. The cropped MODIS satellite image data were then calculated using the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI).

$$NDVI = \frac{(\rho NIR - \rho RED)}{(\rho NIR + \rho RED)} \quad (2)$$

$$NDWI = \frac{(\rho GREEN - \rho NIR)}{(\rho GREEN + \rho NIR)} \quad (3)$$

Where:

ρNIR = Near-infrared band reflectance

ρRED = Red band reflectance

ρGREEN = Green band reflectance

The generative phase threshold is obtained by extracting NDVI and NDWI spectral indexes using several sample points distributed over the study area. The results of this spectral index extraction are used to generate a time series plot for the period January 2022 to May 2023. NDVI and NDWI spectral index calculations were also performed on Sentinel-2 satellite image data. The results of the NDVI and NDWI spectral index calculations are then masked using the threshold obtained from the calculation on the MODIS image. This process produces satellite images in the generative phase.

B. Calculate Nitrogen Estimation Using Vegetation Index

The satellite images in the generative phase will be used to calculate the estimation of the nitrogen content using three vegetation indexes, which are the Optimized Soil Adjusted Vegetation Index (OSAVI), Green Normalized Difference Vegetation Index (GNDVI), and Red Edge Simple Ratio (SRRE).

OSAVI was developed by Rondeaux et al. in 1996 using reflections in the near-infrared (NIR) and red channels with optimized ground adjustment coefficients(Rondeaux et al., 1996). OSAVI can be expressed by the equation 4.

$$OSAVI = \frac{(\rho NIR - \rho RED)}{(\rho NIR + \rho RED + 0,16)} \quad (4)$$

Where:
ρNIR = Near-infrared band reflectance
ρRED = Red channel band reflectance

GNDVI was developed from the Normalized Difference Vegetation Index (NDVI). It is more sensitive to chlorophyll concentration than NDVI (Gitelson et al., 1996). GNDVI can be expressed by the equation 5.

$$GNDVI = \frac{(\rho NIR - \rho GREEN)}{(\rho NIR + \rho GREEN)} \quad \text{.....(5)}$$

Where:
ρNIR = Near-infrared band reflectance
ρGREEN = Green band reflectance

SRRE is a vegetation index that is sensitive to LAI, chlorophyll and nitrogen content, and canopy structure (Purhartanto et al., 2019). SRRE can be expressed by equation 6.

$$SRRE = \frac{\rho NIR}{\rho RED\ EDGE} \quad \text{.....(6)}$$

Where:
ρNIR = Near-infrared band reflectance
ρRED EDGE = Red Edge band reflectance (740nm). This band captures the peak of chlorophyll absorption and is often used for assessing plant biomass and nitrogen content.

The indices used 20m spatial resolution band (e.g. ρRED EDGE) has been resampled to match the spatial resolution of 10m bands.

C. Statistical Analysis

The statistical analysis used to determine the relationship between different vegetation indexes and nitrogen content is correlation and regression analysis. The index value is the independent variable (X), and the nitrogen content is the dependent variable (Y). The correlation between vegetation index and nitrogen content resulted in r and R^2 values. One of the methods often used for calculating the correlation coefficient is the Pearson correlation. Pearson correlation is used to determine the direction of the relationship, the strength of the relationship, and the significance of the strength of the relationship between two variables, provided that the two variables have a normal distribution of data (Roflin & Riana, 2022). The basic formula for Pearson correlation can be expressed in equation 7.

$$r_{xy} = \frac{\sum(X_i - \bar{X})(Y_i - \overline{Y})}{\sqrt{(X_i - \bar{X})^2}.\sqrt{(Y_i - \bar{Y})^2}} \quad \text{.....(7)}$$

In addition, the regression analysis is used to model the nitrogen content estimation based on the remote sensing data. The input for the regression analysis are the pixel values of the vegetation index from the processing of the Sentinel-2 satellite image.

D. Mapping Estimation of Nitrogen Content of Rice Crops

The estimate maps of the nitrogen content of rice plants were made based on the best regression model. The selection of the best regression model is based on the highest coefficient of determination and the lowest RMSE.

3. Result and Discussion

Rice Crop Phase Identification

Nitrogen content estimation was conducted in the generative phase of rice crops. The generative phase was determined based on the threshold value of NDVI and NDWI spectral index. Satellite image data used is MODIS image from January 2022 to May 2023. In the rice fields of Karangjati district, five random sample points were selected and used to create a time series graph of NDVI and NDWI changes.

The NDVI will reach a maximum value in the generative phase before decreasing. This decrease occurs because chlorophyll begins to decrease, causing the NDVI graph to

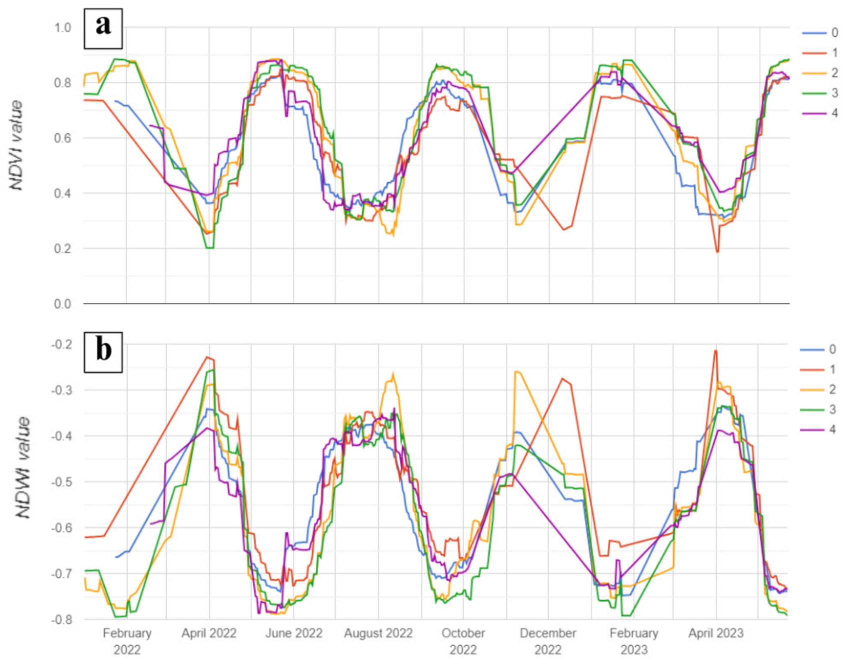

Figure 2. NDVI (a) and NDWI (b) time series MODIS January 2022-May 2023

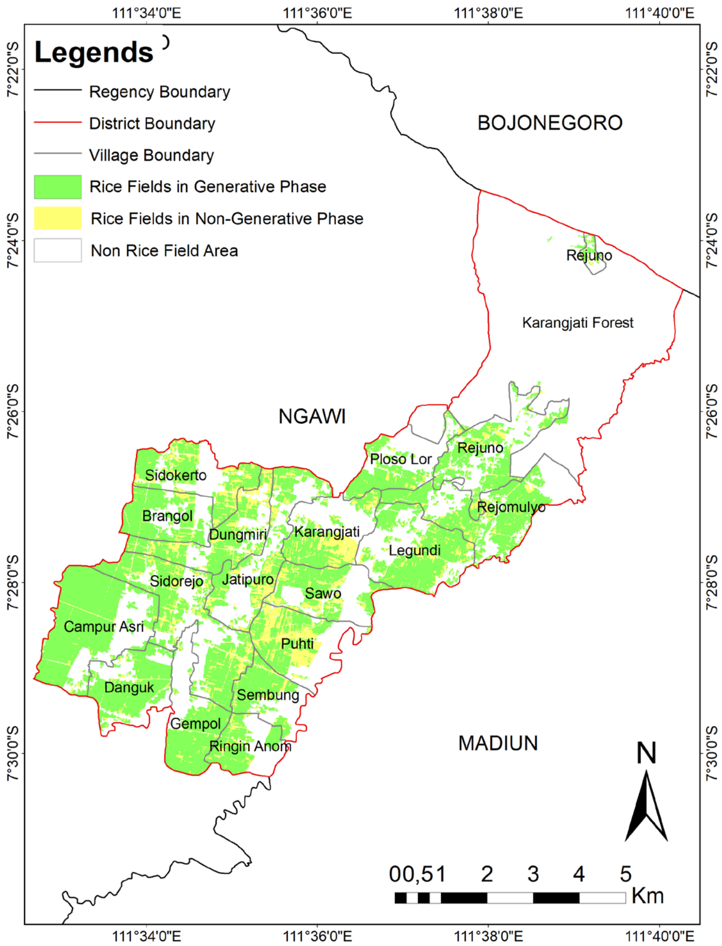

Figure 3. Rice Field in Generative Phase

Table 1. Correlation Coefficient Interpretation Guidelines (Evans, 1996)

Correlation Coefficient (r)	Strength of Correlation
0.0 – 0.19	Very weak correlation
0.2 – 0.39	Weak correlation
0.4 – 0.59	Moderate correlation
0.6 – 0.79	Strong correlation
0.8 – 1.00	Very strong correlation

decrease. Based on the graph in Figure 2, there is a decrease in NDVI values in June 2022, October 2022, and January 2023, indicating that the generative phase is in those months. Considering the range of values of both indexes and the graphs formed in Figures 2(a) and 2(b), the threshold of the generative phase can be determined when NDVI > 0.7 and NDWI < -0.4.

Sentinel-2 Satellite Image in the Generative Phase

The threshold masking process produces images in the generative phase shown in Figure 3.

Based on statistical calculations, the total area of rice fields in Karangjati district is 2881.66 ha, and that in the generative phase is 2474.2 ha. Then, using the images from the generation phase, the estimated nitrogen level was calculated using three vegetation indexes: OSAVI, GNDVI, and SRRE.

Analysis of the Relationship Between Several Vegetation Indexes and Nitrogen Content

Correlation and regression analysis determined the relationship between several vegetation indexes and nitrogen content. Correlation analysis is a method used to determine the relationship pattern and strength between two variables expressed by the correlation coefficient. Correlation can be considered unidirectional if the correlation coefficient value is positive; otherwise, it is called bidirectional correlation if the coefficient value is negative. The correlation between vegetation index and nitrogen content results gives r and R^2 values. The interpretation of the correlation coefficient is determined according to the guidelines in Table 1.

Furthermore, regression analysis was used to model the nitrogen content estimation of rice crops using remote sensing data. The input for the regression analysis is the vegetation index value that was processed using a Sentinel-2 satellite image. The map of the estimated nitrogen content of rice crops was created based on the best regression model of each vegetation index used. The correlation results of vegetation index and nitrogen content are shown in Figure 4(a), Figure 4(b), and Figure 4(c).

The results can be summarized in Table 2 below based on the correlation and regression calculation data.

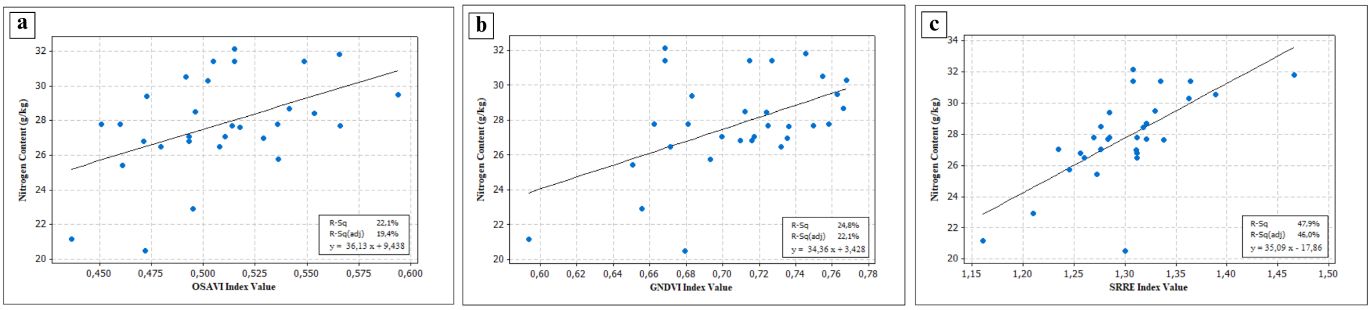

Figure 4. Correlation of OSAVI (a) GNDVI (b) and SRRE (c) Index with Nitrogen Content

Table 2. Results of the Correlation and Regression Analysis Between Vegetation Index and Nitrogen Content

Parameters (X)	Regression Model	Determination Coefficient (R^2)	Correlation Coefficient (r)
OSAVI	y = 36.13 x + 9,438	0.221	0.470
GNDVI	y = 34.36 x + 3,428	0.248	0.498
SRRE	y = 35.09 x - 17,86	0.479	0.692

Table 3. T-Test Result

Parameters (X)	The value of t count	The value of t table	P-value
OSAVI	2.82	2.04841	0.009
GNDVI	3.04	2.04841	0.005
SRRE	5.07	2.04841	0.000

The correlation analysis results showed a positive correlation between the three vegetation index and nitrogen content in rice crops. However, each vegetation index's determination coefficient (R^2) was relatively low. Several factors may cause this low R^2 value. One factor is the size of the coverage area of the Sentinel-2 satellite image, which is 10 x 10 meters in each pixel, thus, it is possible that some pixels do not fully represent rice crops in the field. Another factor is the time difference between the field measurements and the satellite image acquisition. The field measurements were conducted on February 3-5, 2023, while the Sentinel-2 satellite image acquisition was on January 13, 2023. This significant difference in measurement time may cause differences in the SPAD reading data on rice crops. The difference affects the value of the resulting determination coefficient(Sukmono et al., 2012). In addition, data collected on nitrogen estimation of rice crops in the field using SPAD instruments tends to produce variable data (arbitrary factor) compared to laboratory measurements (Darmawan et al., 2011). Several things, such as lighting conditions and measurement position, can influence this factor.

Not all regression results were used to model the nitrogen content estimation of rice crops, but the best vegetation index with the highest performance (highest R^2 and lowest RMSE) was selected. The results of the SRRE vegetation index have the highest R^2 value and the lowest RMSE when compared with other vegetation indexes (R^2=0.479, RMSE= 2.0163). It states that SRRE can explain 47.9% of nitrogen content variability with a strong relationship strength (r values = 0.692). The OSAVI and GNDVI indexes can explain 24.8% and 22.1%, respectively. These values fall into the moderate correlation category.

The SRRE index provides the best performance because of its use of the red edge band, which is sensitive to chlorophyll concentration. In general, nitrogen content is correlated with chlorophyll concentration. Chlorophyll accumulation and chloroplast construction are affected by nitrogen, which is one of the main structural elements of chlorophyll and protein molecules. The results of previous studies also show that the SRRE vegetation index has the highest performance compared to other vegetation indexes for estimating the nitrogen uptake of maize crops (Sharifi, 2020).

T-Test

After the correlation analysis, the significance test, or T-test, is carried out. T-test is a statistical calculation used to determine whether the independent variables partially affect or not the dependent variable(Lailatus Sa'adah, 2021). The following are the results of the T-test with a confidence level of 95% or a significant level of 5% (α = 0.05).

Hypothesis:
H_0: There is no relationship between vegetation index and nitrogen content.
H_1: There is a relationship between vegetation index and nitrogen content.

Test criteria:
If t count ≤ t table, then H_0 is accepted, or H_1 is rejected.
If t> t table, H_0 is rejected, or H_1 is accepted.

From the results of T-test in Table 3, it can be seen that the value of t count > t-table, so H_0 is rejected, which means that the relationship between vegetation index and nitrogen content is significant.

Estimation of Nitrogen Content of Rice Crops

The final result obtained from the process of this research is a map of the estimated nitrogen content of rice crops in the rice fields of Karangjati district. In this research, SRRE was

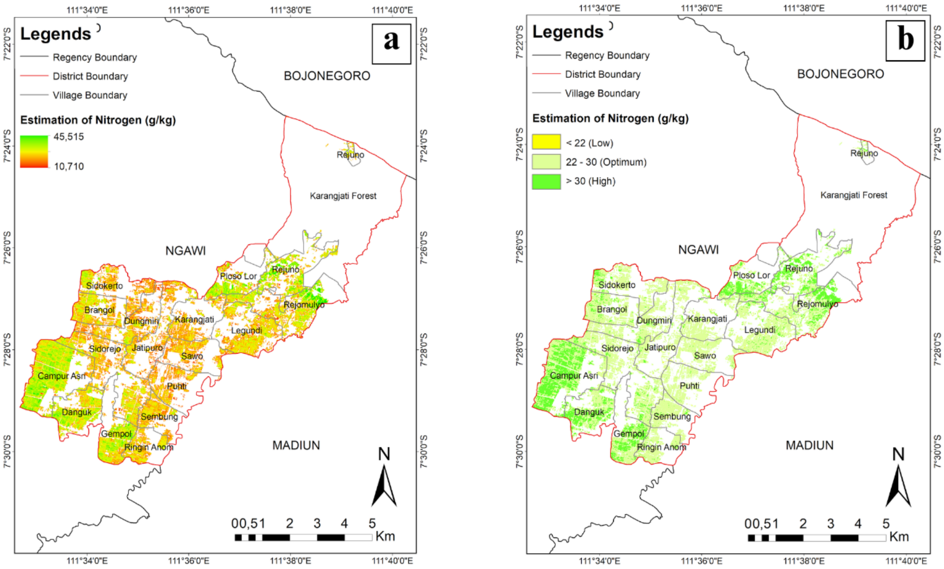

Figure 5. Map for estimation of nitrogen content (a) and classification of nitrogen content (b)

The areas of each classification are shown in Table 4.

Table 4. Areas Based on Classification

Classification	Range of Nitrogen Values (g/kg)	Area (ha)
Low	< 22	29.34
Optimum	22 - 30	1973.67
High	> 30	471.19

chosen as the best vegetation index for mapping nitrogen content estimation, the regression equation is as follows.

Where:
y = Estimated nitrogen content of rice crop (g/kg)
x = SRRE vegetation index

Map for the estimation of the nitrogen content of the rice crop is shown in Figure 5(a), and the classification of the nitrogen content is shown in Figure 5(b).

Nitrogen content in rice leaf is classified as optimum when the value is in the range of 2.2-3.0% or 22-30 g/kg (Herdiyanti et al., 2016). Based on the classification map in Figure 10, it can be seen that the research site is dominated by nitrogen content in the optimum classification (22-30 g/kg) with an area of 1973.67 ha. Furthermore, the area obtained for the low classification (<22 g/kg) is 29.34 ha, and the high classification (>30 g/kg) is 471.19 ha.

Excessive nitrogen content can cause a decrease in rice quality and attract insects and diseases in rice plants (Zhang et al., 2020, Shrestha et al., 2022). To obtain the optimum result, the correct fertilizer dose is needed. Agricultural Research and Development Center (2020) has made calculations of N, P, and K fertilizer doses. Nitrogen fertilization recommendations are based on the level of land productivity. At low productivity levels (<5 tons/ha) 200 kg/ha of urea is required. At the medium productivity level (5-6 tons/ha), urea 250-300 kg/ha is required. Meanwhile, at high productivity levels (> 6 tons/ha), urea 300-400 kg/ha is required. Applying fertilizer in accordance with the needs of plants can encourage increased agricultural production, which directly impacts food availability.

Limitation and Potential Research Improvement

This study has the potential to utilize remote sensing data through the Spectral Reflectance Ratio to Nitrogen (SRRE to N) model for estimating nitrogen levels in rice leaf without direct contact with the plant. However, the accuracy of the model may be influenced by the quality of SPAD data, which is dependent on factors such as data measurement techniques and environmental conditions, including sunlight exposure. To enhance the research, several improvements are suggested: 1) increasing the number of SPAD-based nitrogen content data points for cross-validation to ensure the robustness and reliability of the estimation model, 2) exploring the development of new or enhanced vegetation indices that could establish stronger correlations with nitrogen content, 3) experimenting with various regression models, including non-linear models or machine learning algorithms, 4) conducting longitudinal studies to monitor changes in nitrogen content over time to understand the dynamics of nitrogen uptake and its relationship with crop growth stages, and 5) replicating the research for different crop plants.

4. Conclusion

Based on the results, it is known that all three vegetation indexes have a positive correlation with nitrogen content. The SRRE index had the highest correlation coefficient of 0.692, while the correlation coefficient for GNDVI was 0.498, and OSAVI was only 0.470. The estimated map of the nitrogen content of rice crops is obtained based on the estimation model made from linear regression between SPAD-based nitrogen content data and the best vegetation index using the Red Edge Simple Ratio (SRRE) index. The regression equation is as follows.

$$y = 35.09\,x - 17.86$$

Where y is the estimated nitrogen content of rice crops (g/kg), and x is the SRRE index value. The estimated nitrogen content of rice plants in rice fields of Karangjati District is dominated by nitrogen values with an optimum, low, and high classification with an area of 1973.67 ha, 29.34 ha, and 471.19 ha, respectively.

Acknowledgment

The authors gratefully acknowledge the PT. Aria Agri Indonesia for the contribution to the field data collection work.

References

Balai Penelitian dan Pengembangan Pertanian. (2020). *Rekomendasi Pupuk N, P dan K Spesifik Lokasi untuk Tanaman Padi, Jagung, dan Kedelai pada Lahan Sawah (Per Kecamatan)*. Kementerian Pertanian.

Bhupenchandra, I., Devi, S. H., Basumatary, A., Dutta, S., Singh, L. K., Kalita, P., Bora, S. S., Devi, S. R., Saikia, A., Sharma, P., Bhagowati, S., Tamuli, B., Dutta, N., & Borah, K. (2020). Biostimulants: Potential and Prospects in Agriculture. *International Research Journal of Pure and Applied Chemistry*, *21*(14), 20–35. https://doi.org/10.9734/irjpac/2020/v21i1430244

BPS Jawa Timur. (2022). *Produksi Padi Jawa Timur Selama Tahun 2021 Sebesar 9,789 Juta Ton Gabah Kering Giling*. https://jatim.bps.go.id/pressrelease/2022/03/01/1312/produksi-padi-jawa-timur-selama-tahun-2021-sebesar-9-789-juta-ton-gabah-kering-giling.html

Coste, S., Baraloto, C., Leroy, C., Marcon, É., Renaud, A., Richardson, A. D., Roggy, J.-C., Schimann, H., Uddling, J., & Hérault, B. (2010). Assessing Foliar Chlorophyll Contents With the SPAD-502 Chlorophyll Meter: A Calibration Test With Thirteen Tree Species of Tropical Rainforest in French Guiana. *Annals of Forest Science*, *67*(6), 607. https://doi.org/10.1051/forest/2010020

Darmawan, A., Hariyanto, T., Sukojo, B. M., & Sadly, M. (2011). Prediksi Parameter-parameter Biofisik Tanaman Padi Dari Data Groundspectrometer dan Hyperspectral Pesawat Terbang Dengan Menggunakan Teknik Partial Least Square Regression (PLSR) dan Normalized Difference Spectral Index (NDSI). *J. Tek. Ling*, *12*(1), 93–101.

ESA. (2015). *SENTINEL-2 User Handbook Sentinel-2 User Handbook SENTINEL-2 User Handbook* (Issue 1, pp. 1–64).

Gascon, F., Cadau, E., Colin, O., Hoersch, B., Isola, C., López Fernández, B., & Martimort, P. (2014). Copernicus Sentinel-2 mission: products, algorithms and Cal/Val. In J. J. Butler, X. (Jack) Xiong, & X. Gu (Eds.), *Proceedings Volume 9218, Earth Observing Systems XIX; 92181E* (p. 92181E). https://doi.org/10.1117/12.2062260

Gitelson, A. A., Kaufman, Y. J., & Merzlyak, M. N. (1996). Use of a green channel in remote sensing of global vegetation from EOS-MODIS. *Remote Sensing of Environment*, *58*(3), 289–298. https://doi.org/10.1016/S0034-4257(96)00072-7

Herdiyanti, T., , S., & Aswidinnoor, H. (2016). Tanggap Tiga Varietas Padi Sawah terhadap Kombinasi Pemupukan dengan Sistem Pembenaman Jerami. *Jurnal Agronomi Indonesia (Indonesian Journal of Agronomy)*, *43*(3), 179. https://doi.org/10.24831/jai.v43i3.11242

Hirel, B., Le Gouis, J., Ney, B., & Gallais, A. (2007). The challenge of improving nitrogen use efficiency in crop plants: towards a more central role for genetic variability and quantitative genetics within integrated approaches. *Journal of Experimental Botany*, *58*(9), 2369–2387. https://doi.org/10.1093/jxb/erm097

Isnaeni Fathonah, F., & Mashilal. (2021). Rice Production Analysis in Reflecting Rice Self-sufficiency in Indonesia. *E3S Web of Conferences*, *316*, 02041. https://doi.org/10.1051/e3sconf/202131602041

Kjeldahl, J. (1883). Neue Methode zur Bestimmung des Stickstoffs in organischen Körpern. *Fresenius' Zeitschrift Für Analytische Chemie*, *22*(1), 366–382. https://doi.org/10.1007/BF01338151

Lailatus Sa'adah. (2021). *Statistik Inferensial*. LPPM Universitas KH. A. Wahab Hasbullah. https://books.google.co.id/books?id=o5kwEAAAQBAJ

Lathifah, R., & Sukojo, B. M. (2014). Hasil Analisa Kadar Nitrogen Vegetasi Padi Dengan Data Hyperspectral Menggunakan Index Vegetasi (Studi Kasus: Karawang). *Geoid*, *9*(2), 158. https://doi.org/10.12962/j24423998.v9i2.760

Lu, B., & He, Y. (2021). Assessing the Impacts of Species Composition on the Accuracy of Mapping Chlorophyll Content in Heterogeneous Ecosystems. *Remote Sensing*, *13*(22), 4671. https://doi.org/10.3390/rs13224671

OECD-FAO. (2023). *OECD-FAO Agricultural Outlook 2023-2032*. OECD. https://doi.org/10.1787/08801ab7-en

Patti, P. S., Kaya, E., & Silahooy, C. (2018). Analisis Status Nitrogen Tanah Dalam Kaitannya Dengan Serapan N Oleh Tanaman Padi Sawah Di Desa Waimital, Kecamatan Kairatu, Kabupaten Seram Bagian Barat. *Agrologia*, *2*(1). https://doi.org/10.30598/a.v2i1.278

Peng, S., García, F. V., Laza, R. C., & Cassman, K. G. (1993). Adjustment for Specific Leaf Weight Improves Chlorophyll Meter's Estimate of Rice Leaf Nitrogen Concentration. *Agronomy Journal*, *85*(5), 987–990. https://doi.org/10.2134/agronj1993.00021962008500050005x

Pratiwi, D. (2022). ANALYSIS OF NATIONAL RICE AVAILABILITY TOWARDS SELF-SUPPORT WITH A DYNAMIC MODEL APPROACH. *Economic Management and Social Sciences Journal*, *1*(3), 91–101. https://doi.org/10.56787/ecomans.v1i3.15

Purhartanto, L. N., Danoedoro, P., & Wicaksono, P. (2019). Kajian Transformasi Indeks Vegetasi Citra Satelit Sentinel-2a Untuk Estimasi Produksi Daun Kayu Putih Menggunakan Linear Spectral Mixture Analysis. *Jurnal Nasional Teknologi Terapan*, *3*(1), 47–70.

Rhezali, A., & Aissaoui, A. El. (2021). Feasibility Study of Using Absolute SPAD Values for Standardized Evaluation of Corn Nitrogen Status. *Nitrogen*, *2*(3), 298–307. https://doi.org/10.3390/nitrogen2030020

Roflin, E., & Riana, F. (2022). *Analisis Korelasi dan Regresi*. Penerbit NEM. https://books.google.co.id/books?id=evp7EAAAQBAJ

Rondeaux, G., Steven, M., & Baret, F. (1996). Optimization of soil-adjusted vegetation indices. *Remote Sensing of Environment*, *55*(2), 95–107. https://doi.org/10.1016/0034-4257(95)00186-7

Saberioon, M. M., & Gholizadeh, A. (2016). Novel approach for estimating nitrogen content in paddy fields using low altitude remote sensing system. *ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLI-B1*, 1011–1015. https://doi.org/10.5194/isprsarchives-XLI-B1-1011-2016

Schaaf, C. B., Gao, F., Strahler, A. H., Lucht, W., Li, X., Tsang, T., Strugnell, N. C., Zhang, X., Jin, Y., Muller, J.-P., Lewis, P., Barnsley, M., Hobson, P., Disney, M., Roberts, G., Dunderdale, M., Doll, C., D'Entremont, R. P., Hu, B., … Roy, D. (2002). First operational BRDF, albedo nadir reflectance products from MODIS. *Remote Sensing of Environment*, *83*(1–2), 135–148. https://doi.org/10.1016/S0034-4257(02)00091-3

Secretariate General - Ministry of Agriculture Republic of Indonesia. (2023). *Statistics of Food Consumption 2023* (Mas'ud & S. Wahyuningsih, Eds.). Center for agricultural data and information system. https://satudata.pertanian.go.id/assets/docs/publikasi/Buku_Statsitik_Konsumsi_Pangan_2023.pdf

Sharifi, A. (2020). Using Sentinel-2 Data to Predict Nitrogen Uptake in Maize Crop. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *13*, 2656–2662. https://doi.org/10.1109/JSTARS.2020.2998638

Shrestha, J., Karki, T. B., & Hossain, M. A. (2022a). Application of Nitrogenous Fertilizer in Rice Production: A Review. *Journal of Nepal Agricultural Research Council*, *8*, 16–26. https://doi.org/10.3126/jnarc.v8i.44815

Shrestha, J., Karki, T. B., & Hossain, M. A. (2022b). Application of Nitrogenous Fertilizer in Rice Production: A Review. *Journal of Nepal Agricultural Research Council*, *8*, 16–26. https://doi.org/10.3126/jnarc.v8i.44815

Singh, A., Sarkar, S., Jaswal, A., & Sahoo, S. (2022). On-farm Evaluation of Leaf Colour Chart and Chlorophyll Meter for Need-based Nitrogen Management in Kharif Maize (Zea mays L.). *LEGUME RESEARCH - AN INTERNATIONAL JOURNAL*, *Of*. https://doi.org/10.18805/LR-4972

Sukmono, A., Handayani, H. H., & Wibowo, A. (2012). ALGORITMA ESTIMASI KANDUNGAN KLOROFIL TANAMAN PADI DENGAN DATA AIRBORNE HYPERSPECTRAL. *Geoid*, *8*(1), 47. https://doi.org/10.12962/j24423998.v8i1.707

Sun, H., Feng, M., Yang, W., Bi, R., Sun, J., Zhao, C., Xiao, L., Wang, C., & Kubar, M. S. (2022). Monitoring Leaf Nitrogen Accumulation With Optimized Spectral Index in Winter Wheat Under Different Irrigation Regimes. *Frontiers in Plant Science*, *13*. https://doi.org/10.3389/fpls.2022.913240

Tegeder, M., & Masclaux-Daubresse, C. (2018). Source and sink mechanisms of nitrogen transport and use. *New Phytologist*, *217*(1), 35–53. https://doi.org/10.1111/nph.14876

Uddling, J., Gelang-Alfredsson, J., Piikki, K., & Pleijel, H. (2007). Evaluating the Relationship Between Leaf Chlorophyll Concentration and SPAD-502 Chlorophyll Meter Readings. *Photosynthesis Research*, *91*(1), 37–46. https://doi.org/10.1007/s11120-006-9077-5

Vishwakarma, M., Kulhare, P. S., & Tagore, G. S. (2023). Estimation of Chlorophyll Using SPAD meter. *International Journal of Environment and Climate Change*, *13*(11), 1901–1912. https://doi.org/10.9734/ijecc/2023/v13i113348

Wang, L., Chen, S., Li, D., Wang, C., Jiang, H., Zheng, Q., & Peng, Z. (2021). Estimation of Paddy Rice Nitrogen Content and Accumulation Both at Leaf and Plant Levels from UAV Hyperspectral Imagery. *Remote Sensing*, *13*(15), 2956. https://doi.org/10.3390/rs13152956

Wang, W., & Lu, Y. (2018). Analysis of the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE) in Assessing Rounding Model. *IOP Conference Series: Materials Science and Engineering*, *324*, 012049. https://doi.org/10.1088/1757-899X/324/1/012049

Wang, Y.-P., Chang, Y.-C., & Shen, Y. (2022). Estimation of nitrogen status of paddy rice at vegetative phase using unmanned aerial vehicle based multispectral imagery. *Precision Agriculture*, *23*(1), 1–17. https://doi.org/10.1007/s11119-021-09823-w

Warr, P., & Yusuf, A. A. (2014). Fertilizer subsidies and food self-sufficiency in Indonesia. *Agricultural Economics*, *45*(5), 571–588. https://doi.org/10.1111/agec.12107

Yadav, T. K., Singh, S. P., Singh, M. K., & Singh, M. K. (2022). Influence of Nitrogen Levels and Weed Management Practices on Soil Quality of Wetland Rice. *International Journal of Plant & Soil Science*, *34*(20), 394–400. https://doi.org/10.9734/ijpss/2022/v34i2031167

Zhang, J., Tong, T., Potcho, P. M., Huang, S., Ma, L., & Tang, X. (2020a). Nitrogen Effects on Yield, Quality and Physiological Characteristics of Giant Rice. *Agronomy*, *10*(11), 1816. https://doi.org/10.3390/agronomy10111816

Zhang, J., Tong, T., Potcho, P. M., Huang, S., Ma, L., & Tang, X. (2020b). Nitrogen Effects on Yield, Quality and Physiological Characteristics of Giant Rice. *Agronomy*, *10*(11), 1816. https://doi.org/10.3390/agronomy10111816

Zheng, J., Song, X., Yang, G., Du, X., Mei, X., & Yang, X. (2022). Remote Sensing Monitoring of Rice and Wheat Canopy Nitrogen: A Review. *Remote Sensing*, *14*(22), 5712. https://doi.org/10.3390/rs14225712