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Research article

Estimation of Rice Chlorophyll Content in Salt-Affected Soils Using UAV-Based Multispectral Sensing

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Abstract

The decline in rice productivity in coastal areas is often associated with agricultural land salinization. Chlorophyll, as an indicator of plant health, can be monitored using remote sensing technology. This study aims to evaluate the capability of multispectral UAV imagery to estimate rice chlorophyll content and compare the effectiveness of several vegetation indices in saline coastal paddy fields. Data were collected over ±30 hectares of rice fields in Kendal Regency using a DJI Phantom 4 Multispectral UAV during the vegetative stage (30–45 days after planting). Field measurements included chlorophyll content (SPAD) and soil electrical conductivity (EC). The results showed a weak and statistically insignificant correlation between soil salinity and rice chlorophyll content ($r = 0.119$; $p = 0.571$). These findings suggest that under the specific conditions of this study, characterized by moderate salinity levels (±4.47 dS/m) and the use of rice varieties with varying degrees of tolerance (Ciherang as tolerant and IR32 as moderately tolerant), the spatial variability of chlorophyll was more strongly influenced by phenological stages and micro-environmental factors than by salinity stress. Among the evaluated indices, red-edge-based indices showed the best performance, with CIre ($R^2 = 0.831$) and NDRE ($R^2 = 0.822$) yielding the lowest estimation errors, while NDVI ($R^2= 0.297$) was limited by spectral saturation and CIg ($R^2=0.415$) was affected by its sensitivity to plant canopy structure. These results indicate that red-edge-based indices are highly effective for mapping chlorophyll variability. The limited impact of salinity observed in this study is likely due to the tolerance of the rice varieties and to salinity levels remaining below critical thresholds. Thus, CIre and NDRE are recommended as the most effective indices for estimating rice chlorophyll in coastal paddy fields using multispectral UAV imagery.

Keywords: Chlorophyll; Rice; Salinity; Multispectral UAV; Vegetation Index.

1. Introduction

Rice (Oryza sativa) is a staple crop not only in Indonesia but also globally, as more than half of the world's population relies on rice as a primary food source (Ningrat *et al.,* 2021). In Indonesia, approximately 90% of the population depends on rice as their main carbohydrate source (Fajri *et al.,* 2022), and the country ranks fourth among the world's largest rice producers, with a production of 53.9 million tons in 2023 (FAO, 2023). Despite its strategic importance to food security, rice productivity in coastal agricultural areas has been declining. In Kendal Regency, productivity in the northern coastal districts decreased from 61.8 quintals per hectare in 2019 to 58.97 quintals per hectare in 2023, representing a decline of approximately 4.59% (Badan Pusat Statistik Kabupaten Kendal, 2024). In addition, in 2018, the Regional Development Planning, Research, and Development Agency (Baperlitbang) of Kendal Regency recorded approximately 2,583 hectares of agricultural land affected by salinity stress due to seawater intrusion (Oelviani *et al.,* 2024). This condition indicates that most agricultural areas in the coastal region of Kendal have a high potential for salinity accumulation, which can lead to decreased crop yields and, in severe cases, crop failure (Saputro *et al.,* 2022). These conditions suggest significant environmental stress, particularly soil salinity resulting from seawater intrusion and uneven irrigation management, which can degrade soil fertility and reduce crop productivity in coastal agricultural systems.

Soil salinity is widely recognized as a major constraint in agricultural production, especially in coastal and irrigated areas, as it cause osmotic stress, ionic toxicity, and nutrient imbalance that ultimately inhibit plant physiological processes, including photosynthesis (Lu & Fricke, 2023). One key indicator of plant physiological response to salinity stress is chlorophyll content, which plays an important role in photosynthesis and plant growth (Chen et al., 2025). Conventional methods for determining chlorophyll content, such as laboratory-based spectrophotometric analysis, are accurate but destructive, time-consuming, and costly (Ardiansyah *et al.,* 2022; Behera *et al.,* 2022). As an alternative, the chlorophyll meter (SPAD) has been widely used as a non-destructive and practical tool, showing strong correlations with laboratory measurements and plant growth indicators (Ardiansyah *et al.,* 2022; Behera *et al.,* 2022; Kautsar *et al.,* 2024; Nasution *et al.,* 2019). However, their application is limited in terms of spatial coverage, making them less efficient for monitoring large-scale agricultural areas. To address this limitation, remote sensing technology, particularly multispectral sensors, has been increasingly used for spatial and temporal monitoring of vegetation conditions via vegetation indices.

Among various approaches, the use of multispectral Unmanned Aerial Vehicles (UAVs) has been widely used due to their ability to provide high spatial resolution imagery with flexible and cost-effective data acquisition (Dharmaratne *et al.,* 2023). Vegetation indices derived from UAV imagery, such as the Normalized Difference Vegetation Index (NDVI), have been widely applied to estimate vegetation properties, including biomass, nitrogen, and chlorophyll content (Adzima *et al.,* 2022; Agustina *et al.,* 2024; Fajri *et al.,* 2022; Dwi *et al.,* 2025; Lasaiba & Tetelepta, 2023; Widyawati *et al.,* 2023) . However, NDVI is known to suffer from saturation under high vegetation cover, reducing its sensitivity to chlorophyll variation (Rehman *et al.,* 2022). To overcome this limitation, red-edge-based indices, such as Normalized Difference Red-edge Index (NDRE) and Chlorophyll Index Red-edge (CIre), have been developed and shown to be more sensitive to chlorophyll variations due to their ability to penetrate deeper into the canopy (Boiarskii & Hasegawa, 2019; Clevers & Gitelson, 2012; Rehman *et al.,* 2022; Sah *et al.,* 2023). In addition, the Chlorophyll Index Green (CIg) has demonstrated stable performance in estimating chlorophyll content across various conditions (Clevers & Gitelson, 2012; Putra *et al.,* 2024).

Despite these advances, most previous studies have focused on estimating chlorophyll or nitrogen content under non-saline conditions, with limited attention to environmental stress factors such as soil salinity. Studies examining how salinity influences the relationship between vegetation indices and chlorophyll content, particularly in coastal paddy fields during the vegetative growth stage, remain scarce. Moreover, no study has comprehensively compared the performance of NDVI, NDRE, CIre, and CIg in detecting chlorophyll variability under saline field conditions. Therefore, this study aims to (1) analyze the relationship between soil salinity and rice chlorophyll content, (2) evaluate the performance of two conventional indices (NDVI and CIg) and two red-edge-based indices (NDRE and CIre) using multispectral UAV imagery, and (3) identify the most suitable vegetation index for crop health monitoring in salt-affected coastal paddy fields. This study contributes to improving the understanding of vegetation index performance under salinity stress and provides a practical approach for precision agriculture in coastal environments.

2. Methods

This study employed a quantitative approach integrating multispectral UAV imagery and field measurements to analyze the relationship between vegetation indices, chlorophyll content, and soil salinity in coastal rice fields. The overall research workflow consisted of three main stages: (1) study site selection based on literature review, base map analysis, and field interviews; (2) data acquisition and processing, including multispectral UAV image acquisition, field measurements, image preprocessing, and vegetation index derivation; and (3) statistical analysis and interpretation to evaluate the relationships between variables and model performance. The research framework is shown in Figure 1.

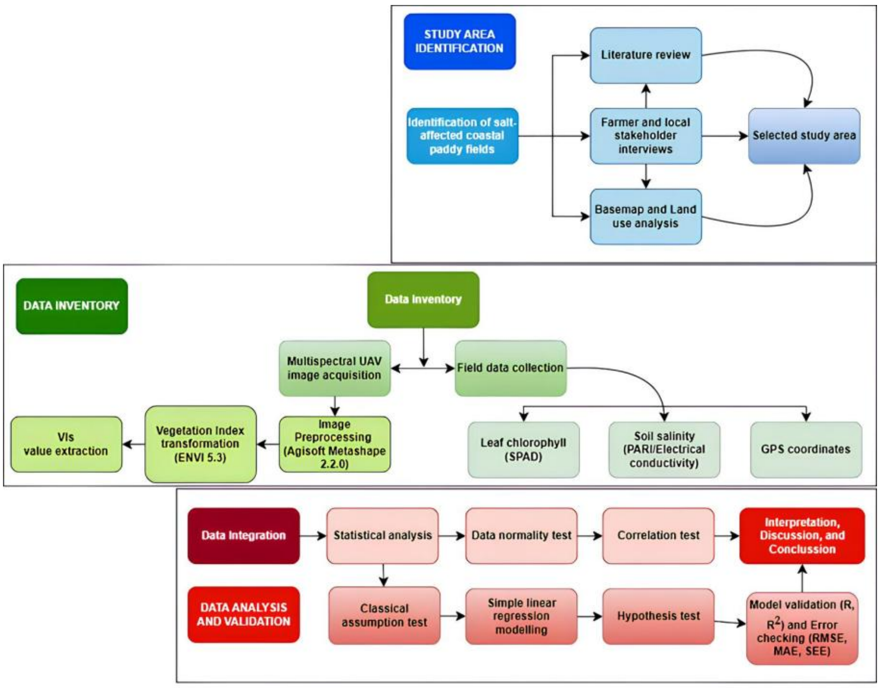

Figure 1. Flowchart of the Research Methodology.

2.1. Study Area and Data Sources

This study was conducted on approximately 30 hectares of agricultural land located in Turunrejo Village, Brangsong District, Kendal Regency, Indonesia. The site was selected based on its coastal characteristics and potential salinity exposure, identified through preliminary analyses of base maps, a literature review, and field interviews with local farmers. The study area is situated in a coastal zone directly adjacent to brackish-water fish ponds, potentially making it affected by salinity intrusion. The spatial location of the study area and the distribution of sampling points are presented in Figure 2.

Based on interviews with local farmers, the rice varieties cultivated in the study area were predominantly Ciherang and IR32. Ciherang is widely adopted due to its relatively higher tolerance to salinity, while IR32 is more sensitive than Ciherang, often showing leaf yellowing and reduced grain quality under saline conditions, although it remains popular due to its superior yield quality and seed availability. Both varieties have a similar growth cycle (approximately 115 days after transplanting), with the primordia stage (around 50 days after transplanting) identified as the most sensitive to salinity stress.

Multispectral imagery was acquired using a DJI Phantom 4 Multispectral RTK UAV, equipped with six sensors, one RGB sensor with a resolution of 20 MP and five multispectral sensors: Blue (450 ± 16 nm), Green (560 ± 16 nm), Red (650 ± 16 nm), Red Edge (730 ± 16 nm), and Near-Infrared or NIR (840 ± 26 nm), each with a resolution of 2 MP. The UAV was equipped with an RTK GNSS system connected in real time to a CORS network via NTRIP, with most image acquisitions recorded in RTK fixed solution, providing an expected horizontal accuracy of approximately ±1–3 cm. Image acquisition was conducted at an altitude of 185 m with 80% front and 60% side overlap under clear-sky conditions around 10:00 a.m. to ensure stable illumination. Automatic exposure settings were used during image acquisition to adapt to ambient lighting conditions. Ground Control Points (GCPs) were not used in this study, as georeferencing relied on RTK GNSS positioning during image acquisition.

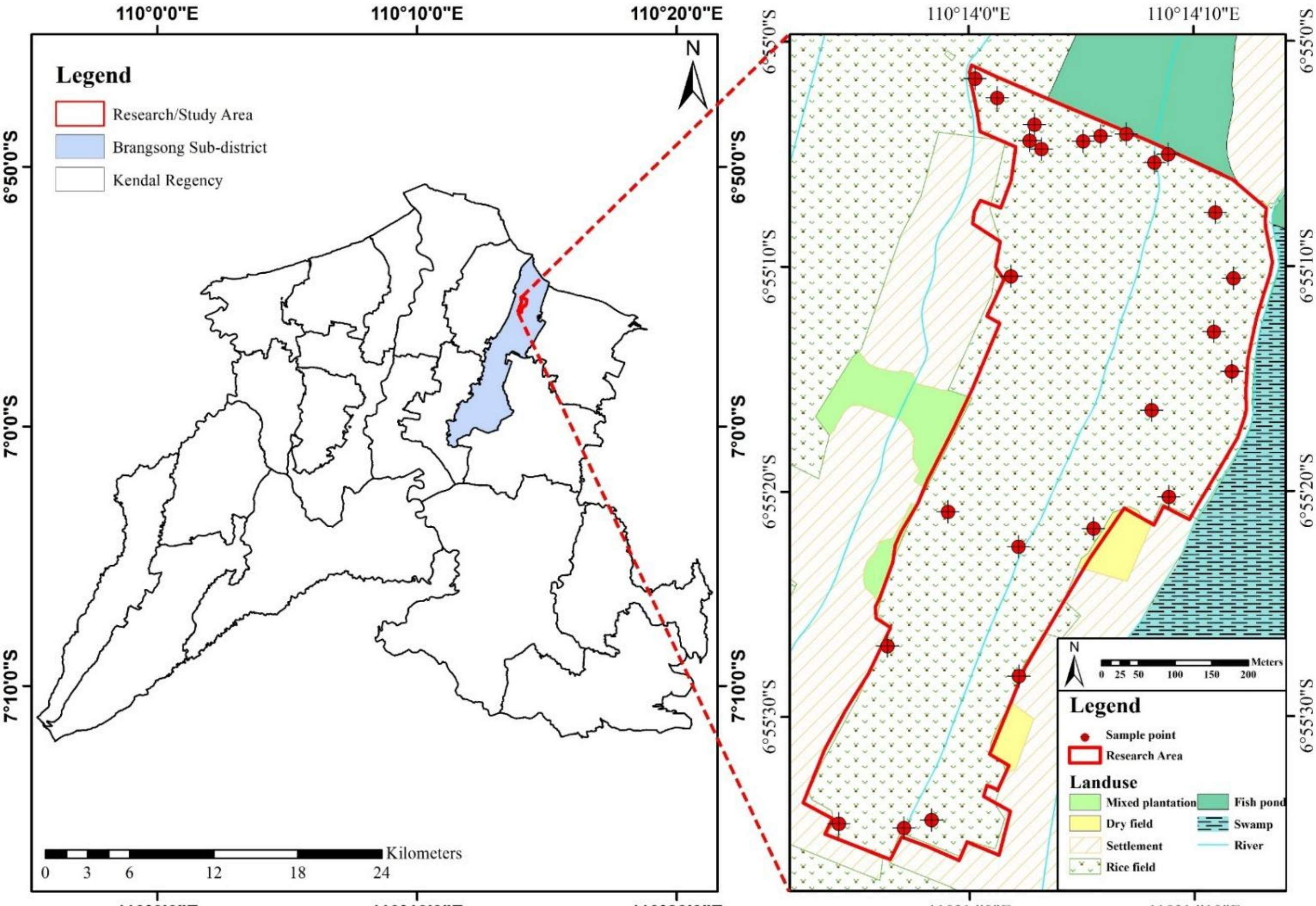

Figure 2. Map of the study area and the distribution of sampling points.

For each flight session, radiometric calibration was performed using the DJI-provided reflectance calibration panel both before and after data acquisition to ensure reflectance consistency. In addition, the integrated sunshine sensor onboard the UAV was used to correct for variations in solar irradiance during image acquisition. This information is essential, as changes in illumination conditions can affect vegetation index calculations.

Field data collection was conducted at the same time as UAV image acquisition to minimize temporal discrepancies between ground observations and aerial data. During each flight mission, a field team collected SPAD and soil salinity measurements at predetermined sampling points while the UAV was operating over the study area. Each sampling point was measured within a short time window (±10–15 minutes) relative to the UAV overpass to ensure temporal consistency. A total of 25 sampling points were selected using a purposive sampling approach, supported by interviews with local farmers on planting schedules, to ensure the selected rice plants were in the late vegetative stage (30–45 days after planting). Each sampling point represented a cluster of rice plants within the study area.

Chlorophyll content was measured using a SPAD chlorophyll meter (Konica Minolta SPAD-502 Plus). At each sampling point, measurements were taken from three parts of the leaf (tip, middle, and base), and the average value was used to represent chlorophyll content (Nasution et al., 2019).

This growth stage was specifically selected because chlorophyll increases rapidly before the generative phase, making it more sensitive to environmental stress, including salinity. In addition, rice plants at the vegetative stage have high water requirements, allowing saline stress conditions to be identified at an early stage (Saputra *et al.,* 2025).

Soil salinity was measured at the same sampling points using a PARI instrument to obtain electrical conductivity (EC) values (dS/m), which were subsequently interpreted as soil salinity levels based on FAO/USDA classification standards. The soil salinity levels measured in the study area ranged from 1.99 dS/m to 8.31 dS/m, with an average of 4.47 dS/m. The instrument was equipped with integrated electrodes and GPS, allowing simultaneous measurement of EC and recording of geographic coordinates. Readings were taken after the values stabilized (approximately one minute) to ensure measurement reliability.

2.2. Image Processing and Vegetation Index Derivation

Image processing was carried out through an orthomosaic generation workflow, which involves merging aerial photos into a single georeferenced image using image alignment based on feature matching (tie points). The processing stages included image import, image alignment, dense point cloud generation, and orthomosaic creation. During the photo alignment stage, Agisoft Metashape Professional 2.2.0 is used to automatically correct camera position and orientation errors, resulting in an initial point cloud. A dense point cloud was then generated from overlapping images to estimate surface elevation. In addition to geometric processing, reflectance consistency was maintained using data from the sunlight sensor and reflectance calibration panel during orthomosaic generation, ensuring consistent reflectance values across images. Based on the dense point cloud and digital elevation model (DEM), the final orthomosaic was produced. The orthomosaic represents a geometrically corrected image with uniform scale and reflectance, allowing accurate spatial analysis (Marwan *et al.,* 2021).

The corrected orthomosaic was exported and analyzed using ENVI 5.3 for vegetation index calculation, while ArcMap 10.8 was used for thematic map generation. The vegetation indices to be calculated include NDVI, NDRE, CIre, and CIg. These four indices were selected because they are commonly used to estimate plant chlorophyll content and have different spectral characteristics. NDVI represents a conventional red–NIR–based index, whereas NDRE and CIre utilize the red-edge band, which been shown in previous studies to be more responsive to chlorophyll variations under dense canopy conditions. CIg was included as a comparative index because it utilizes the green band, which is relatively stable under varying illumination conditions. The specific mathematical formulas and spectral bands utilized for each index are presented in Table 1.

Table 1. Vegetation Indices used in this study.

VIs	Formula/equation	Source	
Normalized Difference Vegetation Index (NDVI)	$\frac{NIR - RED}{NIR + RED}$	(Rouse et al., 1973)	(1)
Normalized Difference Red-edge Index (NDRE)	$\frac{NIR - Red\ edge}{NIR + Red\ edge}$	(Buschmann & Nagel, 1993)	(2)
Chlorophyll Index Red-edge (CIre)	$\frac{NIR}{Red - edge} - 1$	(Gitelson et al., 2003)	(3)
Chlorophyll Index Green (CIg)	$\frac{NIR}{Green} - 1$	(Gitelson et al., 2003)	(4)

Vegetation index values were extracted using a point sampling approach, where each sampling point was represented by a single pixel due to the high spatial resolution of the UAV imagery (9.8 cm per pixel). This approach was adopted to preserve the original spectral signal of the rice canopy and to avoid spectral mixing effects that may occur when averaging multiple pixels, particularly in heterogeneous field conditions.

2.3. Statistical Analysis

Correlation tests were conducted to determine the relationship between SPAD-based chlorophyll values and soil salinity, as well as between SPAD chlorophyll and vegetation indices. These analyses aimed to assess whether plant condition, as represented by chlorophyll values, was influenced by soil salinity levels and how well this relationship could be captured by vegetation indices derived from remote sensing data.

Data normality tests were first conducted using the Shapiro–Wilk test, with a p-value > 0.05 indicating normal distribution (Ismail, 2022). Normally distributed data were analyzed using Pearson's correlation, while non-normally distributed data were analyzed using Spearman's correlation (Sihotang *et al.,* 2024).

Simple linear regression analysis was employed to assess how well each vegetation index derived from multispectral UAV imagery can predict rice chlorophyll content. The independent variables were vegetation indices (NDVI, NDRE, CIg, and CIre), while the dependent variable was the SPAD chlorophyll value. All available field observations were used simultaneously in the regression analysis without separating the dataset into training and validation subsets, as the aim of this study was to examine the statistical relationship and how accurately each vegetation index estimates chlorophyll content, rather than to develop a general predictive model.

Prior to analysis, assumption tests were conducted to ensure model validity, including tests for normality of residuals (the Kolmogorov–Smirnov test) and heteroscedasticity (the Glejser test). Multicollinearity and autocorrelation tests were not performed because the model used a single predictor and was not based on time-series data. Regression significance was tested using the F-test and t-test. The model performance was evaluated using the coefficient of determination (R^2) and several error metrics, including the Standard Error of Estimate (SEE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). The inclusion of SEE and RMSE is important because chlorophyll estimation requires accuracy in actual values, not only in overall trends. MAE was included to evaluate the consistency of the prediction errors. All statistical analyses were conducted using SPSS 27 and Microsoft Excel 2019, with a significance level set at 5% ($\alpha = 0.05$).

3. Results and Discussion

3.1. Remote Sensing Analysis of Vegetation Indices

The multispectral UAV imagery was processed into an orthomosaic with good geometric consistency and visual clarity, allowing reliable extraction of spectral values across the study area (Figure 3). This image was used for vegetation index analysis.

The statistical characteristics of the computed indices, including the mean and variability, are detailed in Table 2. To complement these numerical values, the vegetation index transformations produced spatially explicit maps of NDVI, NDRE, CIre, and CIg (Figure 4). These maps illustrate vegetation conditions across the study area and are used for further analysis of rice chlorophyll variability.

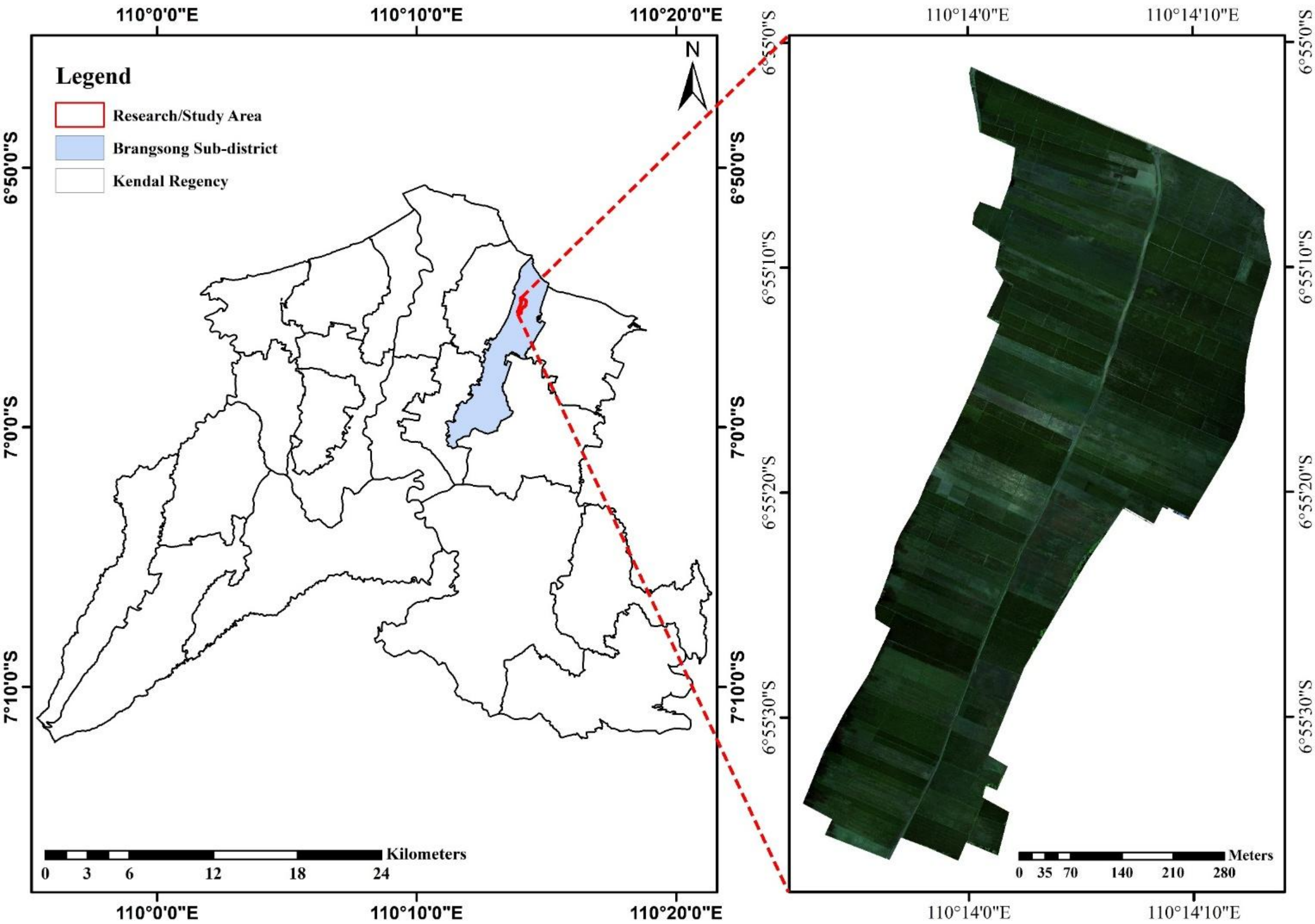

Figure 3. Orthomosaic Image Acquired from a Multispectral UAV.

Table 2. Descriptive Statistics of Vegetation Indices.

VIs	Range	Minimum	Maximum	Mean	Std. Dev	CV (%)
NDVI	0.75	0.07	0.81	0.5393	0.20002	37.09%
NDRE	0.18	0.03	0.20	0.0907	0.05129	56.56%
CIre	0.45	0.06	0.51	0.2065	0.13004	62.97%
CIg	3.29	0.11	3.40	1.2308	0.77931	63.32%

Based on Table 2, vegetation index values show varying levels of variability across parameters. NDVI has a mean of 0.5393, a standard deviation of 0.20002, and a range of 0.07 to 0.81. The coefficient of variation (CV) for NDVI is 37.09%, indicating moderate variation and more consistent values compared to the other indices. NDRE shows a lower mean value of 0.0907 with a standard deviation of 0.05129 and a range between 0.03 and 0.20. The CV of NDRE is 56.56%, indicating a relatively high level of variability and suggesting greater heterogeneity in vegetation conditions.

The CIre index has a mean of 0.2065, a standard deviation of 0.13004, and a range of 0.06 to 0.51. Its coefficient of variation is 62.97%, indicating high variability and suggesting that this index is sensitive to capturing differences in vegetation conditions in the field. Meanwhile, CIg has the highest mean of 1.2308, a standard deviation of 0.77931, and a relatively wide range from 0.11 to 3.40. The CV of CIg is 63.32%, which is the highest among all indices, indicating that this index shows the highest variability.

Overall, NDVI shows the lowest level of variability and is therefore more stable in representing vegetation conditions. In contrast, NDRE, CIre, and especially CIg show high coefficients of variation (>50%), indicating that these indices are more sensitive to changes in plant conditions in the field. This high variability may reflect their ability to detect differences in plant conditions, but it also indicates greater variation in the data.

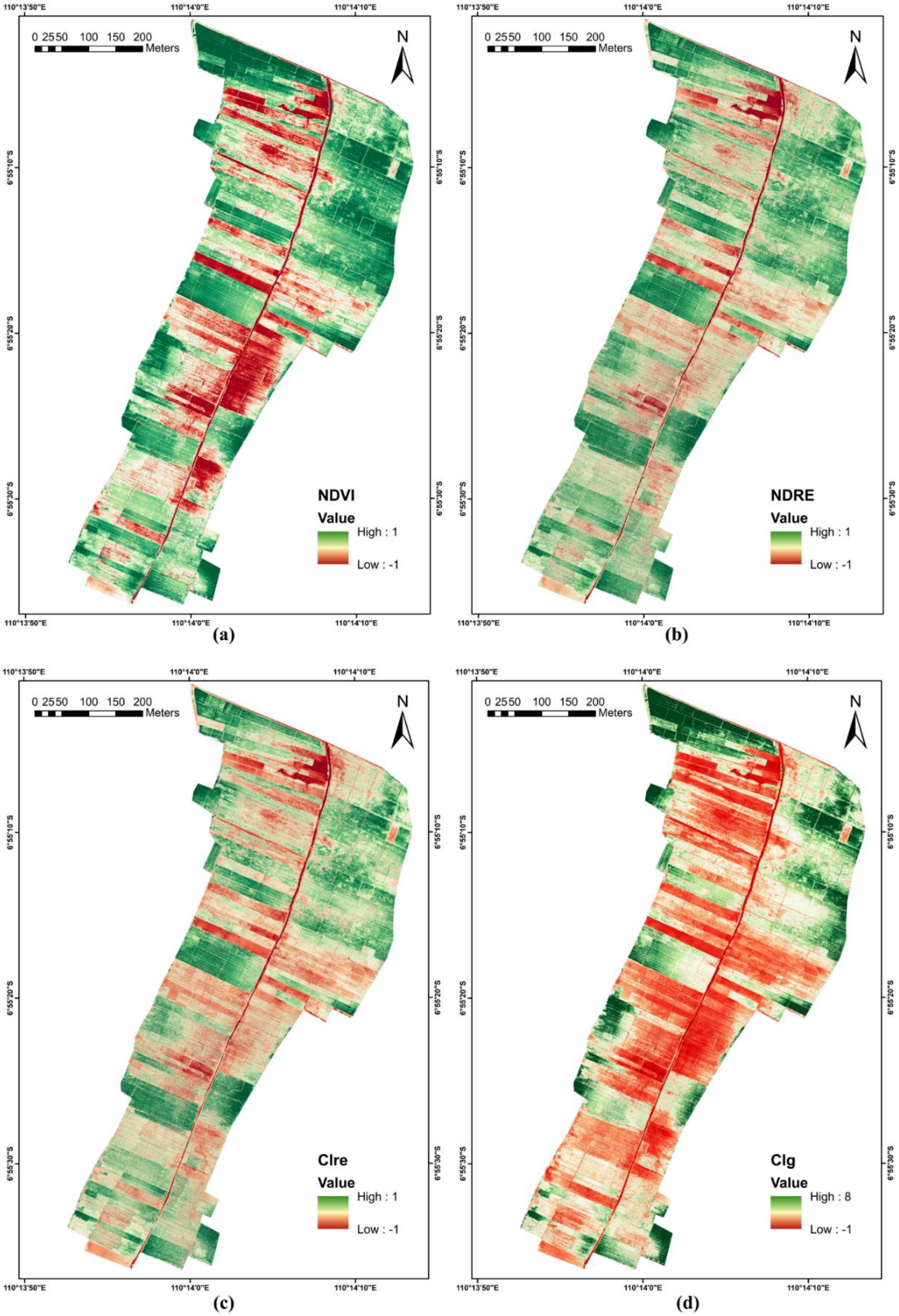

Figure 4. Results of vegetation index transformation (a) NDVI; (b) NDRE; (c) Cire; (d) Cig.

Based on Figure 4, across all vegetation index maps, greener color tones indicate higher index values, representing denser and healthier vegetation, while redder tones correspond to lower values typically associated with non-vegetated areas such as water bodies and bare soil. Overall, the four indices show similar spatial patterns, with higher values observed along the edges of the study area and lower values concentrated in the central part.

This spatial pattern is strongly influenced by the presence of a river channel crossing the site, where reflectance from rice plants is affected by water, resulting in lower vegetation index values in the central area. Despite the general similarity in spatial distribution, differences in how each index responds can be observed, particularly in areas with dense vegetation cover, indicating differences in their ability to capture chlorophyll content.

3.2. Relationship between Soil Salinity, Vegetation Indices, and Chlorophyll Content

Based on Table 3, the results of the Shapiro–Wilk test indicate that most variables are not normally distributed (p-value < 0.05), indicating non-normal data distribution in SPAD, vegetation index values and soil salinity. This condition is common in coastal paddy fields with varying local environmental conditions. Therefore, Spearman's rank correlation was used, as it does not require normally distributed data.

Table 3. Results of the Data Normality Test.

Variable	Statistic	df	p-value	Desc.
Salinity	.834	25	0.001	Not normally distributed
Chlorophyll	.916	25	0.042	Not normally distributed
NDVI	.903	25	0.021	Not normally distributed
NDRE	.907	25	0.026	Not normally distributed
CIre	.889	25	0.011	Not normally distributed
CIg	.971	25	0.678	Normally Distributed

Based on Table 4, the correlation between chlorophyll content (SPAD) and soil salinity obtained a coefficient value of 0.119 with a p-value (two-tailed) of 0.571. This indicates a very weak relationship, as the coefficient is close to zero. The p-value greater than 0.05 indicates that the relationship is not statistically significant. This suggests that the observed correlation may have occurred by chance, and there is insufficient evidence to conclude that soil salinity has a meaningful linear relationship with chlorophyll content in this dataset. In other words, changes in soil salinity do not appear to have a statistically detectable effect on chlorophyll levels of rice plants in the study area. Therefore, any variation in chlorophyll content is more likely influenced by other environmental factors or management practices rather than the measured salinity values.

Table 4. Results of SPAD chlorophyll – soil salinity correlation test.

		Chlorophyll
Saliniy	Correlation Coefficient	0.119
	p-value (two-tailed)	0.571
	N	025

The results of Spearman correlation analysis between SPAD chlorophyll values and vegetation indices are presented in Table 5. The results show strong to very strong correlations between chlorophyll content and the tested vegetation indices. NDVI shows a correlation coefficient of 0.630, while NDRE and CIre show very strong correlations, each with a coefficient of 0.894. CIg shows a correlation coefficient of 0.631. These results indicate that vegetation indices derived from UAV multispectral imagery are strongly related to chlorophyll content during the vegetative phase of rice growth, with red-edge–based indices performing better at capturing chlorophyll variation.

Table 5. Results of SPAD chlorophyll – Vegetation Index correlation test.

	Chlorophyll		
	Coefficient	p-value (two-tailed)	N
NDVI	0.630	0.001	25
NDRE	0.894	<0.001	25
CIre	0.894	<0.001	25
CIg	0.631	0.001	25

3.3. Regression Modeling for Chlorophyll Estimation

In a simple linear regression test, several assumption tests are conducted to ensure model validity. These tests assess whether the regression model satisfies key underlying assumptions (Ardiyanti *et al.*, 2024).

Table 6. Results of Classical Assumption Test.

	Residual Normality		Heteroscedasticity	
	p-value (two-tailed)	Description	p-value	Description
NDVI	0.196	Normal	0.097	None
NDRE	0.087	Normal	0.201	None
CIre	0.200	Normal	0.270	None
CIg	0.200	Normal	0.119	None

In this study, the assumption tests included tests for residual normality and heteroscedasticity. The residual normality test was performed using the One-Sample Kolmogorov–Smirnov test, with a p-value > 0.05 indicates that the residuals do not significantly deviate from normality. The heteroscedasticity test was conducted using the Glejser test, where a p-value greater than 0.05 indicates the absence of significant heteroscedasticity (Mardiatmoko, 2020). The results of these assumption tests, presented in Table 6, suggest that the residuals are approximately normally distributed and no significant heteroscedasticity was detected across all models.

Hypothesis testing in the regression analysis was conducted to assess whether the independent variables had a significant effect on the dependent variables, both individually (t-test) and jointly (F-test) (Pratiwi & Lubis, 2021). Statistical significance was evaluated at a 5% significance level ($p < 0.05$). The results of the hypothesis tests are presented in Table 7, indicating that the regression model is statistically significant and that each vegetation index shows a statistically significant relationship with SPAD-measured chlorophyll.

Table 7. The Results of the Hypothesis Test.

	t-test			**F-test**		
	t-critical value	**t-value**	**p-value**	**F-critical value**	**F-value**	**p-value**
NDVI	2.069	3.115	.005	4.28	9.702	0.005
NDRE		10.302	<.001		106.121	<0.001
CIre		10.632	<.001		113.047	<0.001
CIg		4.038	.001		16.308	0.001

Based on Table 7, all vegetation indices show statistically significant regression coefficients ($p < 0.05$). However, despite this statistical significance, the indices' estimation performance differs substantially. This finding indicates that statistical significance reflects the presence of a relationship between variables but does not necessarily represent the accuracy of the estimation.

To explicitly present the validation of UAV-derived vegetation indices against field-measured chlorophyll values, Table 8 summarizes the validation results using SPAD measurements as ground truth. The table includes regression models and accuracy metrics, such as the coefficient of determination (R^2) and error indicators (SEE, RMSE, and MAE), to evaluate the performance of each vegetation index in estimating chlorophyll content.

Table 8. Validation Results of UAV-Based Vegetation Indices against SPAD Chlorophyll Measurements.

VIs	**Model**		**R**	**R^2**	**Field chlorophyll average**	**Estimated chlorophyll average**	**SEE**	**RMSE**	**MAE**
NDVI	28.983+29.278x	(5)	0.545	0.297	44.616	44.616	9.87	9.47	8.12
NDRE	26.134+203.777x	(6)	0.907	0.822	44.616	44.616	4.97	4.77	3.69
CIre	27.928+80.809x	(7)	0.912	0.831	44.616	44.616	4.84	4.64	3.61
CIg	33.847+8.972x	(8)	0.644	0.415	44.616	44.615	9.01	8.64	7.18

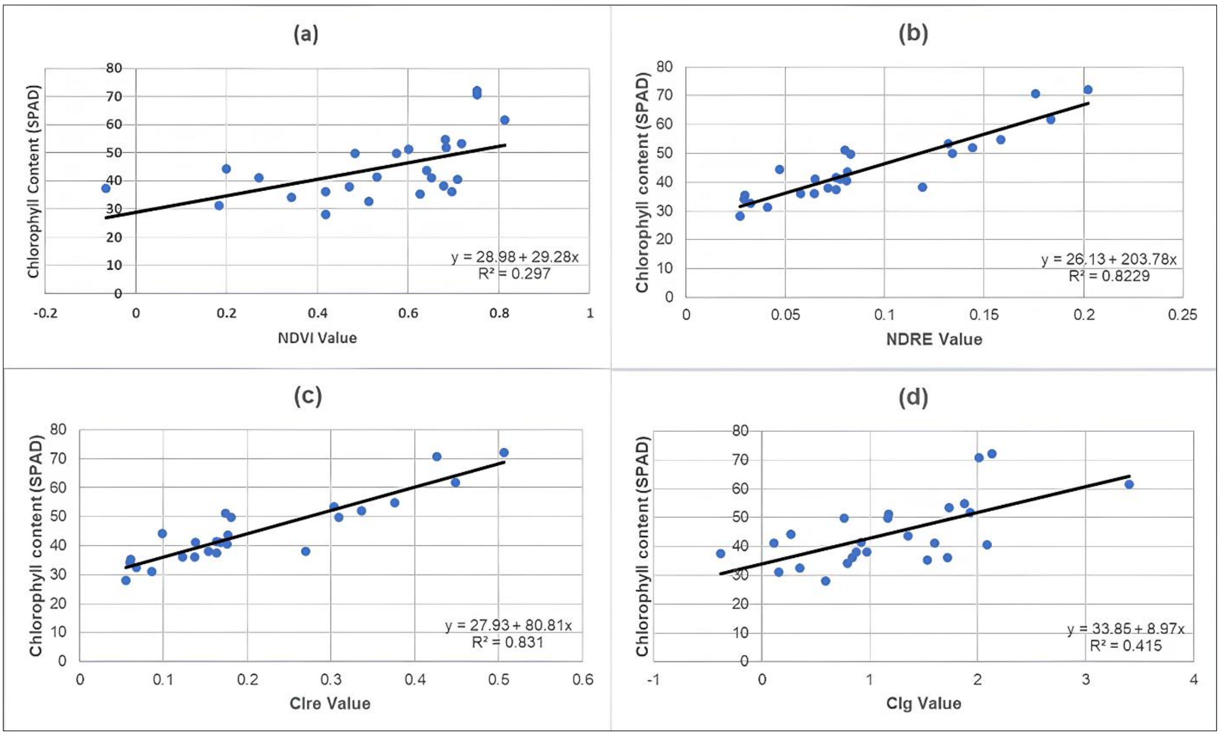

Figure 5. Scatter Plot Showing the Relationship Between NDVI (a); NDRE (b); CIre (c); and Cig (d) with Rice Chlorophyll Content (SPAD).

Based on Table 8, the validation results indicate that red-edge-based vegetation indices achieve higher accuracy in estimating rice chlorophyll content than SPAD field measurements. CIre and NDRE exhibit strong relationships with chlorophyll values, with R^2 values of 0.831 and 0.822, respectively. These indices also yield lower estimation errors (SEE, RMSE, and MAE), indicating better agreement between UAV-derived estimates and ground measurements. In contrast, NDVI and CIg show lower R^2 values and higher error metrics, suggesting weaker performance in capturing chlorophyll variability under the observed field conditions. Overall, these findings suggest that red-edge-based indices are more reliable for chlorophyll estimation, particularly under moderate to dense canopy conditions.

3.4. Discussion

In this study, two main findings were identified in relation to the research objectives. First, the correlation between soil salinity and rice chlorophyll content is very weak and non-significant (Table 4). Based on the 25 sample points analyzed, variations in soil salinity do not show a clear relationship with changes in SPAD-measured chlorophyll content. This result shows that, at the salinity levels observed in the study area, rice plants maintained relatively stable chlorophyll content without clear signs of stress.

Second, among the tested vegetation indices, red-edge-based indices, particularly CIre and NDRE, performed better at estimating rice chlorophyll content than NDVI and CIg. These indices showed stronger correlations with SPAD values and better captured variations in chlorophyll under moderate to high vegetation cover observed in the study area. This finding highlights the importance of selecting vegetation indices with higher sensitivity to changes in chlorophyll content, particularly in salt-affected coastal agricultural environments.

The weak relationship between soil salinity and rice chlorophyll content observed in this study can be explained by several factors. First, the rice varieties planted are classified as tolerant of salinity. Based on field observations and interviews with local farmers, the rice varieties cultivated in the study area were Ciherang and IR32. These varieties were selected because they are widely recognized as improved rice varieties and are commonly used in paddy field cultivation across the Kendal Regency. Ciherang, in particular, has been reported as salt-tolerant by previous studies (Hamidah *et al.,* 2025; Muttaqien & Rahmawati, 2019), and Annisa *et al.* (2015) also found that salinity (NaCl) does not significantly affect its chlorophyll content.

On the other hand, the IR32 variety is moderately sensitive to salinity. Kanawapee *et al.* (2012) classified the IR32 rice variety as moderately sensitive to salinity. However, soil salinity at the research site remained within the tolerance range of rice plants, averaging 4,47 dS/m. Furthermore, research by Hasibuan *et al.* (2026) reported that different salinity treatments (0, 4, and 8 dS/m) applied to IR32 rice did not result in significant differences, particularly in plant height at 2–9 weeks after planting (WAP). This finding indicates that the salinity conditions at the study site remained within a safe range for rice growth.

Rice plants are among the plants that are sensitive to soil salinity of 2 dS/m, which is considered optimal, but 4–6 dS/m is classified as marginal or low (Saidi *et al.,* 2020). Santanoo *et al.* (2023) also reported that salinity levels below the threshold of 6 dS/m do not have a significant negative effect on chlorophyll biosynthesis, but can still inhibit other plant processes. Therefore, both the Ciherang and IR32 varieties grew relatively well under the salinity conditions observed in the study area.

Another possible explanation for the weak correlation is the growth stage at the time of observation, during which rice plants tend to be more tolerant to salinity stress. Previous studies have reported that rice tolerance increases during the vegetative phase but declines again during the reproductive phase (Saidi *et al.,* 2020). The study by Santanoo *et al.* (2023) demonstrated that rice plants at the vegetative stage are relatively more tolerant to salinity, as shown by the photosynthetic rate (Pn), which did not decrease significantly and, in some cases, even increased compared to non-saline conditions. In contrast, during the reproductive stage, a clearer decline in Pn was observed, particularly under high salinity levels, making this stage the most sensitive to salinity stress. On the other hand, salt-tolerant rice varieties such as Pokkali show unique responses to salinity, with photosynthetic rate remaining stable or even increasing under saline conditions. Although this study did not use such varieties, it is possible that the varieties used possess a certain level of tolerance, resulting in similar or comparable response patterns. This may explain the low correlation with chlorophyll content in this study, as under tolerant conditions, increased or stable chlorophyll content does not always reflect a decline in plant performance. Furthermore, the intensive nutrient management practiced by local farmers during the observation period may have masked the physiological impact of salinity. According to the Integrated Crop Management (ICM) guidelines issued by the Indonesian Directorate General of Food Crops, urea application is recommended in three stages: basal fertilization at 1–14 days after transplanting (DAT), the first top-dressing at 21–28 DAT, and the second top-dressing at 35–50 DAT (Siregar *et al.,* 2017). Meanwhile, based on interviews with several local farmers, urea is commonly applied approximately 1 week after transplanting for basal fertilization, followed by the first top-dressing at 21 DAT and the second at around 40 DAT. The increase in nitrogen supply during these periods, particularly during the second top-dressing, likely enhanced chlorophyll production, which may have reduced the effects of salinity at levels of 4.47 dS/m. As a result, this additional nutrient input may have contributed to the weak correlation observed between salinity and SPAD values in this study.

However, these findings do not mean that salinity has no effect on rice plant physiology. Previous studies have shown that an increase in salinity beyond the tolerance limit of the variety can have serious effects, including a decrease in chlorophyll content, disruption of the photosynthesis process, and a decrease in crop yield (Lu & Fricke, 2023; Oelviani *et al.,* 2024; Sah *et al.,* 2021; Widyawati *et al.,* 2023). Therefore, the results of this study clearly show that the effect of salinity on chlorophyll is greatly influenced by plant variety and the severity of the salinity conditions encountered. Accordingly, future studies are recommended to include areas with a wider range of salinity levels, for example, 6-12 dS/m, to allow clearer identification of the effects of salinity stress on rice chlorophyll content.

In addition to the salinity–chlorophyll relationship discussed above, this study also evaluated the performance of different vegetation indices in estimating rice chlorophyll content. Based on the regression analysis results (Table 8), the tested vegetation indices demonstrate varying levels of accuracy. The relatively low coefficient of determination (R^2) for NDVI and CIg in predicting chlorophyll content variation is due to their limited spectral sensitivity. NDVI and CIg, which rely on a combination of red, green, and NIR bands, tend to experience saturation at high levels of vegetation cover or chlorophyll content (Liu *et al.,* 2024; Wang *et al.,* 2025)

When vegetation cover changes from moderate to high, near-infrared band reflectance continues to increase, while red band reflectance continues to decrease, causing NDVI to gradually approach saturation (Liu *et al.,* 2024). This condition makes it difficult to distinguish chlorophyll levels in plants with moderate to high concentrations, thereby reducing the index's sensitivity to chlorophyll variation. The plants in this study were aged between 30 and 45 days after planting (DAP), at which age rice experiences an increase in chlorophyll content and density until it reaches its peak (Sivagnanam *et al.,* 2015; Sukojo & Kurniawan, 2021). At this age, the vegetation index also reaches its peak (Pratiwi *et al.,* 2017; Yanti *et al.,* 2023).

The spatial pattern of CIg in Figure 4(d) differs from red–edge–based indices, particularly in plots with moderate-to-low vegetation cover. While CIg can capture chlorophyll variations in dense canopies, it often misclassifies less dense areas as non-vegetation (indicated by red and white tones). This suggests that CIg sensitivity is heavily compromised by plant canopy structure (i.e., the overall arrangement and density of leaves in the upper part of the plant) and leaf orientation. At 45 DAP, where canopy closure was nearly complete, CIg values remained stable. However, in earlier stages, the more erect leaf orientation allowed background features, such as standing water or exposed soil, to interfere with green-band reflectance, leading to inconsistent chlorophyll estimation.

This behavior aligns with Wu *et al.* (2012), who noted that background reflectance and canopy architecture (i.e., the arrangement and orientation of leaves, including leaf angle) often weaken the relationship between green-band indices and plant properties. Similar findings by Zhou *et al.* (2026) In spring barley, it was confirmed that CIg is less reliable during early growth stages due to background interference, only becoming effective as biomass increases. Ultimately, while CIg resists saturation better than NDVI, it remains less precise than red-edge indices. As reported by Gitelson *et al.* (2005) Green-band indices are inherently more sensitive to plant canopy architecture, whereas red-edge indices provide a more stable estimation of chlorophyll under dense conditions.

Furthermore, the spatial patterns indicate that red-edge–based indices, namely NDRE and CIre, as shown in Figure 4(b) and 4(c), respectively, appear relatively smoother (i.e., less noisy) than NDVI and CIg, particularly in areas with dense vegetation cover. As shown in Figure 4(a), NDVI exhibits saturation in areas with dark green tones, which commonly occurs during the mid-to-late vegetative stages of rice. In contrast, NDRE and CIre maintain clear value gradients within the same locations, indicating a better ability to distinguish variations in high chlorophyll content. This finding is consistent with Boiarskii and Hasegawa (2019) and Liu *et al.* (2024), who reported that the red-edge band is highly effective for detecting chlorophyll variability because it represents the transition region between chlorophyll absorption in the red band and cellular reflectance in the near-infrared (NIR) band.

In this study, the red-edge index performed significantly better at estimating rice chlorophyll content. The regression models are shown in Table 8, where both indicate strong correlation, with coefficients of determination of 0.822 and 0.831, respectively. This performance is likely due to the red-edge spectral band (680–750 nm) having a steep increase in reflectance from the red absorption region towards the NIR. This characteristic makes the red-edge band much more sensitive to chlorophyll variations, while reducing the saturation effect that typically arises when plant chlorophyll content is high (Zhang *et al.,* 2022). In addition, the advantages of red-edge-based indices are supported by previous research showing that the red-edge band is highly sensitive to biomass, nitrogen uptake, and crop yield (Kanke *et al.,* 2016).

Although the results of this study confirm the dominance of red-edge-based indices (CIre and NDRE) in estimating chlorophyll content, these findings also clarify the limitations of using conventional vegetation indices such as NDVI and CIg, certainly under certain conditions. The weakness of both indices is not only limited to spectral saturation issues, but also shows that the accuracy of chlorophyll estimation cannot be separated from the plant growth phase and local environmental conditions. This study confirms that NDVI is not very suitable for use in high vegetation cover, and is more suitable for low and medium vegetation cover, such as in the early stages of growth (Liu *et al.,* 2024).

In the late vegetative growth phase observed in this study, rice was in a condition with high chlorophyll content, so only indices with high sensitivity in the red-edge region were able to capture these variations consistently (Al-Shammari *et al.,* 2025). The results of this study also support previous findings, such as (Boiarskii & Hasegawa, 2019; Rehman *et al.,* 2022; Sah *et al.,* 2023) which found that red-edge-based indices are better at monitoring rice plants than conventional indices such as NDVI.

Furthermore, the superior performance of CIre and NDRE suggests that plant health monitoring in coastal areas with salinity stress should not rely solely on popular vegetation indices such as NDVI. Instead, there should be an emphasis on indices that are truly sensitive to changes in plant condition, particularly those related to chlorophyll, a vital indicator of photosynthesis. Thus, this study not only confirms previous findings but also underscores the importance of selecting vegetation indices appropriate to the ecological context and plant growth phase.

These findings are consistent with previous studies that highlight the effectiveness of UAV-based remote sensing for estimating rice chlorophyll content. Several studies have demonstrated that hyperspectral UAV data combined with advanced modeling approaches, such as support vector regression, extreme learning machines, and ensemble learning frameworks, can achieve high accuracy in chlorophyll estimation, often involving specific spectral features in the green and red-edge regions (An *et al.,* 2020; Cao *et al.,* 2020; Mu *et al.,* 2026; Wang *et al.,* 2026). In addition, studies incorporating machine learning and multi-feature analysis across various genotypes have shown that spectral features, vegetation indices, and temporal dynamics play an important role in improving estimation performance and understanding yield potential (Gu *et al.,* 2024).

However, unlike these studies, which primarily rely on hyperspectral data with many variables and complex nonlinear modeling techniques, this study demonstrates that reliable chlorophyll estimation can be achieved using multispectral UAV imagery and relatively simple linear regression. This finding suggests that, under certain conditions, red-edge-based vegetation indices alone may be sufficient to capture chlorophyll variability, providing a more cost-effective and accessible methodology for routine agricultural monitoring, particularly in field-scale applications under moderate salinity conditions.

Overall, these findings contribute to the growing body of research on UAV-based crop monitoring by demonstrating that red-edge-based vegetation indices, particularly CIre and NDRE, provide more reliable estimates of chlorophyll under moderate salinity and dense canopy conditions. The results also reinforce the theoretical understanding that spectral sensitivity in the red-edge region is crucial for capturing chlorophyll variability, especially where conventional indices such as NDVI tend to saturate. From a practical perspective, this study suggests that multispectral UAV imagery combined with relatively simple regression models can serve as an effective and accessible approach for monitoring rice health in salinity-prone coastal areas.

However, several limitations of this study should be acknowledged. First, the analysis was conducted only during a single growth stage (late vegetative phase), which may limit the applicability of the results to other stages where plant structure and chlorophyll content differ. Second, the study focused on salt-tolerant rice varieties (Ciherang and IR32) under relatively low to moderate salinity conditions, which may have reduced the salinity's observable impact on chlorophyll content. Consequently, the findings should be interpreted within the context of these specific varietal and environmental conditions.

Furthermore, the number of field sampling points was relatively limited, which may affect the consistency of the statistical relationships and reduce the model's ability to be applied in other areas. The regression analysis was designed to evaluate estimation performance under observed conditions and did not include independent training and validation datasets, which may further constrain the model's transferability beyond the study area. In addition, salinity measurements were limited to soil electrical conductivity, while irrigation water salinity was not assessed, potentially limiting a more comprehensive understanding of salinity dynamics in coastal agricultural systems.

In relation to the methodological approach, this study relied on multispectral UAV imagery and linear regression models, which, although practical and cost-effective, may not fully capture the complex and nonlinear relationships between spectral responses and chlorophyll content compared to hyperspectral data and advanced machine learning approaches reported in previous studies (An *et al.,* 2020; Cao *et al.,* 2020; Mu *et al.,* 2026; Wang *et al.,* 2026).

These limitations indicate important directions for future research. Further studies should include a larger number of field sampling points and cover a wider range of salinity conditions, including both soil and irrigation water measurements, to better capture salinity variability. Expanding observations across multiple growth stages and incorporating different rice varieties with varying tolerance levels would improve the model's consistency and applicability.

In addition, future research could explore integrating multispectral and hyperspectral data, as well as applying advanced modeling approaches such as machine learning and ensemble methods, to improve prediction accuracy and better capture nonlinear relationships in chlorophyll estimation. Incorporating observations over time and across multiple growth stages may also improve the understanding of changes in chlorophyll content under different environmental conditions. Therefore, this study provides a foundation for the development of more reliable and applicable methods for detecting salinity stress in rice using multispectral UAV data.

4. Conclusion

The results of this study indicate that the chlorophyll content of rice plants in coastal paddy fields in Kendal Regency did not show a significant relationship with soil salinity variation at the time of observation ($r = 0.119$; p-value = 0.571). This result is likely influenced by several key factors, including the use of relatively salt-tolerant rice varieties (Ciherang and IR32), the salinity range at the study site, which remained within a moderate level (±4.47 dS/m) and below the threshold known to affect chlorophyll biosynthesis. In addition, the observations were conducted during the vegetative growth stage (30–45 days after planting), a phase in which rice plants tend to exhibit higher tolerance to salinity stress. Intensive nitrogen fertilization practices by local farmers may have further enhanced chlorophyll production, potentially masking the effects of salinity. Under these conditions, soil salinity at mild to moderate levels did not significantly affect rice chlorophyll content, while chlorophyll variability was more strongly associated with differences in growth stage, tiller density, and micro-environmental factors such as nutrient availability and field conditions. Nevertheless, these findings do not imply the absence of salinity effects, as higher salinity levels beyond the tolerance threshold may still negatively impact plant physiology and yield. Therefore, further studies that include a wider range of salinity levels are recommended to better understand the effect of salinity on rice chlorophyll content.

Additionally, regression analysis reveals that red-edge-based vegetation indices, namely NDRE and CIre, show better performance in estimating rice chlorophyll content compared to conventional vegetation indices, such as NDVI and CIg. These two indices showed the highest correlation (R) and coefficient of determination (R^2) values, with $R = 0.912$ and $R^2 = 0.831$ for CIre, and $R = 0.907$, $R^2 = 0.822$, along with lower error values (RMSE, MAE, SEE). In contrast, NDVI and CIg exhibit lower explanatory power, with R^2 values of 0.297 and 0.415, respectively, due to saturation effects and sensitivity to plant canopy structure, particularly during the vegetative phase. These findings provide empirical support that red-edge-based indices are more sensitive to chlorophyll variation under mild salinity conditions, suggesting their suitability for UAV-based crop health monitoring in coastal agricultural areas.

Future research should incorporate multi-temporal observations across different growth stages to better capture the dynamics of salinity stress and chlorophyll variation. Expanding the range of salinity conditions, including both soil and irrigation water measurements, as well as incorporating rice varieties with varying tolerance levels, would further improve the robustness of the analysis. In addition, increasing the number of sampling points and incorporating independent training and validation datasets would enhance model reliability and generalizability. The integration of multispectral and hyperspectral UAV data, along with advanced modeling approaches such as machine learning and nonlinear regression, is also recommended to better capture complex relationships between spectral responses and chlorophyll content.

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Author Contributions

Conceptualization: Handoko, F. D., Juhadi; **methodology**: Juhadi, Sanjoto, T. B; **investigation**: Handoko, F. D., Husna, V. N, Banowati, E; **writing—original draft preparation**: Handoko, F. D., Juhadi ; **writing—review and editing**: Banowati, E , Sanjoto, T. B ; **visualization**: Handoko, F. D., Husna, V. N. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

All authors declare that they have no conflicts of interest.

Data availability

Data is available upon Request.

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