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Multispectral UAV-Based Assessment of Vegetation Indices in Paddy Rice at Different Growth Stages: A Case Study in Sleman, Special Region of Yogyakarta

Ilham Mubarok[1], Ardan Wiratmoko[1,*], Ngadisih[1], Andri Prima Nugroho[1], Hammam Mananda Harahap[1], Faiz Ridwan Pratama[1], Mutiara Alifia Ramadhanty[1], Fahmi Arsyad[1], Fadel Arya Pradana[1], Lilik Sutiarso[1]

[1] Smart Agriculture Research Center, Department of Agricultural and Biosystems Engineering, Faculty of Agricultural Technology, Universitas Gadjah Mada. Jln. Flora No. 1 Bulaksumur Yogyakarta 55281, INDONESIA

* Email: ardan.w@ugm.ac.id

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ABSTRACT

Rice growth monitoring is essential for evaluating crop condition and supporting site-specific management in precision agriculture. This study assessed rice vegetation responses at different growth stages using multispectral unmanned aerial vehicle (UAV) imagery acquired over paddy fields in Tlogoadi, Sleman Regency, Special Region of Yogyakarta, Indonesia. The observed rice fields consisted of plots at planting, tillering, and booting stages within the same landscape. Six vegetation indices were analyzed, namely Normalized Difference Vegetation Index (NDVI), Normalized Difference Red-Edge Index (NDRE), Green Normalized Difference Vegetation Index (GNDVI), Soil-Adjusted Vegetation Index (SAVI), Chlorophyll Index Red Edge (CIRE), and Renormalized Difference Vegetation Index (RDVI). The results showed clear spatial variation in vegetation response across the paddy field area. NDVI ranged from -0.204 to 0.728, NDRE from -0.137 to 0.417, GNDVI from -0.155 to 0.589, SAVI from -0.306 to 1.092, CIRE from 1.767 to 3.572, and RDVI from -0.423 to 0.246. NDVI, GNDVI, and SAVI showed a consistent increase from planting to booting stages, indicating progressive canopy development and increased vegetation vigor. NDRE and CIRE provided complementary information related to red-edge and chlorophyll-related canopy responses, although their highest responses were observed at the tillering stage. RDVI showed a less consistent pattern, suggesting that its interpretation requires caution under heterogeneous paddy field conditions. These findings indicate that multispectral UAV imagery combined with multiple vegetation indices can effectively characterize spatial variability in rice growth stages and support precision crop management in smallholder paddy field systems.

Keywords: *paddy rice, UAV, multispectral imagery, vegetation index, growth stage, precision agriculture.*

INTRODUCTION

Rice (*Oryza sativa* L.) is a strategic food crop in Indonesia and plays an essential role in supporting national food security. In Java Island, paddy fields are commonly managed under intensive and fragmented smallholder farming systems, where differences in planting time, field management, water availability, and crop development stage may occur within a relatively small landscape (Wiratmoko et al., 2025). These conditions create substantial spatial variability in rice growth and require reliable monitoring approaches to support timely crop management decisions. Rice growth is characterized by distinct phenological stages, each associated with changes in

canopy structure, leaf area, chlorophyll concentration, and photosynthetic activity, which influence spectral reflectance properties detectable by remote sensing instruments.

Conventional rice field monitoring is commonly conducted through visual observation and periodic ground sampling. Although these methods provide direct field information, they are limited in spatial coverage, temporal efficiency, and their ability to capture within-field and between-field variability across fragmented paddy landscapes (Li et al., 2022). Such limitations are particularly relevant in smallholder rice production areas, where adjacent plots may represent different growth stages or management conditions. Therefore, spatially explicit monitoring technologies are needed to provide rapid, consistent, and high-resolution information on crop condition for precision agriculture applications (Nugroho et al., 2020, 2023; Wiratmoko et al., 2023).

Unmanned aerial vehicle (UAV) platforms equipped with multispectral sensors have become an important tool for crop monitoring because they can acquire high-resolution imagery with flexible flight schedules and relatively efficient field operation. Multispectral UAV imagery enables the acquisition of reflectance information from visible, red-edge, and near-infrared spectral bands, which are closely related to vegetation biophysical and physiological properties. From these spectral bands, vegetation indices can be calculated to describe different aspects of crop condition, including canopy vigor, greenness, chlorophyll-related response, soil background influence, and vegetation density (Xue & Su, 2017).

Several vegetation indices have been widely used for crop and rice monitoring. The Normalized Difference Vegetation Index (NDVI) is commonly used as a general indicator of vegetation vigor, green biomass, and canopy density (Chen et al., 2025). The Normalized Difference Red-Edge Index (NDRE) is more sensitive to chlorophyll-related variations, particularly in denser canopies where red-band-based indices may become less responsive (Yue et al., 2019). The Green Normalized Difference Vegetation Index (GNDVI) provides information on canopy greenness, while the Soil-Adjusted Vegetation Index (SAVI) reduces the influence of exposed soil or background reflectance in sparsely vegetated areas (Neinavaz et al., 2021). In addition, the Chlorophyll Index Red Edge (CIRE) captures chlorophyll-related reflectance using the red-edge band, whereas the Renormalized Difference Vegetation Index (RDVI) enhances vegetation contrast across different canopy densities.

Although individual vegetation indices have been widely applied in agricultural remote sensing, their responses may differ depending on canopy condition, crop stage, soil or water background, and index formulation. In heterogeneous paddy field landscapes, relying on a single vegetation index may not be sufficient to describe the full variability of rice growth conditions. A multi-index approach is therefore useful for comparing how different spectral indices respond to rice plots at different phenological stages within the same acquisition period and environmental setting. However, studies that specifically compare multiple vegetation indices across coexisting rice growth stages in smallholder paddy field landscapes remain relevant and necessary for practical precision agriculture applications.

This study addressed this need by analyzing the spatial distribution of six vegetation indices derived from multispectral UAV imagery acquired over rice paddy fields in Tlogoadi, Sleman Regency, Special Region of Yogyakarta, Indonesia. The study area consisted of rice plots at planting, tillering, and booting stages coexisting within the same landscape, allowing direct comparison of vegetation index responses under similar environmental and atmospheric conditions. The objectives of this study were:

(1) to map the spatial distribution of NDVI, NDRE, GNDVI, SAVI, CIRE, and RDVI across the study area
(2) to compare vegetation index responses among planting, tillering, and booting stages
(3) to evaluate the usefulness and limitations of each vegetation index for rice growth-stage assessment and precision crop management.

MATERIALS AND METHODS

Study Area

The study was conducted in paddy fields located in Tlogoadi, Sleman Regency, Special Region of Yogyakarta, Indonesia. The study site consisted of fragmented smallholder paddy field plots with different rice growth stages occurring within close spatial proximity. Three growth stages were identified in the study area, namely planting, tillering, and booting stages. The simultaneous presence of these growth stages within a single landscape provided a suitable condition for comparing vegetation index responses under similar acquisition, environmental, and atmospheric conditions.

The study area was delineated using UAV-based RGB imagery as the visual base map, while plot boundaries and the area of interest were digitized for spatial interpretation. Representative examples of planting, tillering, and booting stages were also identified from the UAV imagery and field observation. All spatial data and vegetation index map outputs were produced using the WGS 1984 UTM Zone 49S coordinate system and displayed at a map scale of 1:4,500.

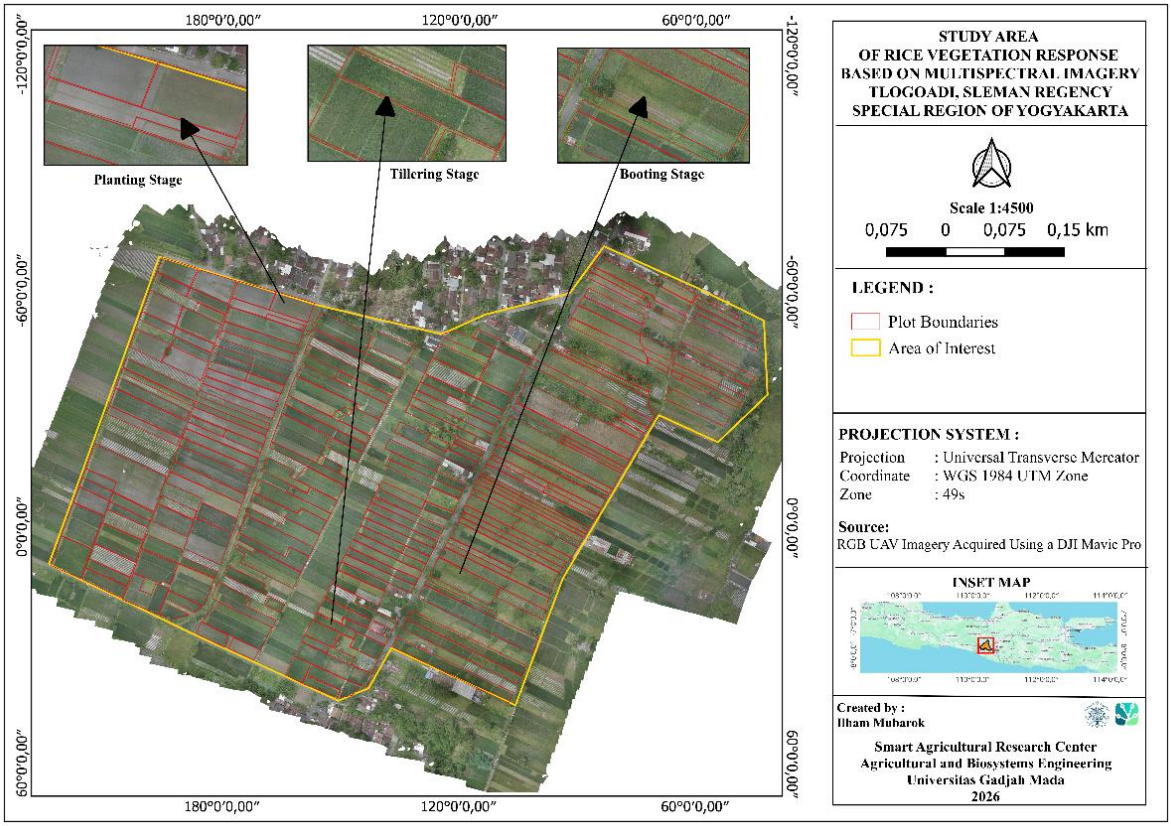


Figure 1. Study area of rice vegetation response in Tlogoadi, Sleman, Special Region of Yogyakarta, showing plot boundaries, area of interest, and representative rice growth stages. The RGB UAV orthomosaic was used as a visual base map for study area delineation.

UAV Multispectral Data Acquisition

Multispectral UAV imagery was acquired on January 31, 2026, over the paddy field study area in Tlogoadi, Sleman Regency, Special Region of Yogyakarta, Indonesia. Image acquisition was conducted using a Trinity Pro Vertical Take-Off and Landing (VTOL) UAV (Quantum Systems, Germany) equipped with a MicaSense RedEdge-P multispectral sensor (MicaSense Inc., USA). This UAV–sensor configuration was used to obtain high-resolution multispectral reflectance data required for vegetation index calculation and rice canopy condition assessment.

The MicaSense RedEdge-P sensor captures five discrete spectral bands, namely Blue at 475 nm, Green at 560 nm, Red at 668 nm, Red Edge at 717 nm, and Near-Infrared (NIR) at 842 nm. In this study, the green, red, red-edge, and NIR bands were used to calculate NDVI, NDRE, GNDVI, SAVI, CIRE, and RDVI, while the blue band was retained as part of the multispectral dataset but was not directly used in the selected vegetation index formulations. The availability of red-edge and NIR bands was important for characterizing rice canopy vigor, greenness, chlorophyll-related response, and vegetation density.

The UAV flight was conducted at approximately 100 m above ground level, resulting in a ground sampling distance of about 6–7 cm. This spatial resolution was sufficient to observe plot-level variability and canopy condition differences across the fragmented paddy field landscape. Image acquisition was carried out under relatively stable illumination conditions to reduce reflectance variability caused by changes in sunlight intensity during the flight. Radiometric calibration was applied before vegetation index calculation to convert image values into surface reflectance and improve the comparability of spectral responses among rice plots and growth stages.

The acquired multispectral images were processed through a photogrammetric workflow to generate georeferenced and radiometrically corrected orthomosaic layers for each spectral band. These reflectance orthomosaics were used as the primary input for pixel-based vegetation index calculation. The RGB UAV imagery shown in **Figure 1** was used only as a visual base map for study area presentation, plot boundary interpretation, and growth-stage identification. Therefore, the calculation of NDVI, NDRE, GNDVI, SAVI, CIRE, and RDVI was based on calibrated multispectral bands rather than RGB imagery.

Image Processing and Vegetation Index Calculation

The acquired multispectral images were processed using a standard photogrammetric workflow to generate georeferenced and radiometrically corrected orthomosaic images for each spectral band. The workflow included image alignment, orthomosaic generation, radiometric correction, and spatial referencing. The resulting reflectance orthomosaics were then used as the primary input for pixel-based vegetation index calculation.

Following orthomosaic generation and radiometric correction, six vegetation indices were calculated on a per-pixel basis from the multispectral reflectance bands. The indices used in this study were Normalized Difference Vegetation Index (NDVI), Normalized Difference Red-Edge Index (NDRE), Green Normalized Difference Vegetation Index (GNDVI), Soil-Adjusted Vegetation Index (SAVI), Chlorophyll Index Red Edge (CIRE), and Renormalized Difference Vegetation Index (RDVI). These indices were selected to represent different aspects of rice canopy condition, including general vegetation vigor, canopy greenness, chlorophyll-related response, soil background adjustment, and vegetation contrast. The mathematical formulation and main interpretation of each vegetation index are presented in **Table 1** (Vera-Esmeraldas et al., 2025).

Table 1. Vegetation indices used in this study

Vegetation Index	Abbreviation	Mathematical Formulation	Main Interpretation
Normalized Difference Vegetation Index	NDVI	$NDVI = \frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + \rho_{Red}}$	General vegetation vigor
Normalized Difference Red-Edge Index	NDRE	$NDRE = \frac{\rho_{NIR} - \rho_{RedEdge}}{\rho_{NIR} + \rho_{RedEdge}}$	Chlorophyll-related red-edge response
Green Normalized Difference Vegetation Index	GNDVI	$GNDVI = \frac{\rho_{NIR} - \rho_{Green}}{\rho_{NIR} + \rho_{Green}}$	Canopy greenness

Vegetation Index	Abbreviation	Mathematical Formulation	Main Interpretation
Soil-Adjusted Vegetation Index	SAVI	$SAVI = \frac{(\rho_{NIR} - \rho_{Red})(1 + L)}{\rho_{NIR} + \rho_{Red} + L}$	Vegetation vigor with soil background adjustment
Chlorophyll Index Red Edge	CIRE	$CIRE = \frac{\rho_{NIR}}{\rho_{RedEdge}} - 1$	Chlorophyll-related vegetation sensitivity
Renormalized Difference Vegetation Index	RDVI	$RDVI = \frac{\rho_{NIR} - \rho_{Red}}{\sqrt{\rho_{NIR} + \rho_{Red}}}$	Vegetation vigor with enhanced contrast

Growth Stage Interpretation

Rice growth stages within the study area were interpreted based on canopy appearance in the UAV imagery and supported by field observation. Three growth stages were identified, namely planting, tillering, and booting stages. The planting stage was characterized by sparse canopy cover and visible soil or water background. The tillering stage was characterized by increasing canopy density, greater leaf area development, and more continuous green cover. The booting stage was characterized by denser canopy conditions and more advanced crop development.

The growth-stage categories were used as the basis for comparing vegetation index responses across the study area. Each identified growth-stage area was interpreted consistently across all vegetation index maps, allowing direct comparison of spectral responses among planting, tillering, and booting stages.

Data Analysis

The analysis was conducted through spatial interpretation of vegetation index maps and descriptive statistical comparison among rice growth stages. Each vegetation index map was visually examined to identify the spatial distribution of rice vegetation response across the study area. The spatial patterns were then compared with the interpreted growth-stage distribution to evaluate how each index responded to planting, tillering, and booting stages.

Descriptive statistics were extracted for each vegetation index, including minimum, maximum, range, mean, and standard deviation values. Minimum, maximum, and range values were used to describe the overall spectral response across the study area, while mean and standard deviation values were used to compare vegetation index responses among growth stages. A combined comparative visualization was prepared to present representative plot examples, mean vegetation index values by growth stage, and the distribution of vegetation index values. This approach enabled simultaneous assessment of spatial pattern, central tendency, and variability of vegetation index responses across the three rice growth stages.

RESULTS AND DISCUSSION

Spatial Variability of Rice Vegetation Response

The vegetation index maps showed clear spatial variability in rice vegetation response across the paddy field area in Tlogoadi, Sleman, Yogyakarta. This variability was visually associated with differences in growth stage, plot boundary, canopy cover, and the heterogeneous structure of smallholder paddy fields. Planting-stage plots generally showed lower vegetation index responses because sparse rice canopy allowed stronger influence from exposed soil and water background. In contrast, tillering and booting plots tended to show higher vegetation

responses, particularly in NDVI, GNDVI, and SAVI, indicating more developed canopy structure and greater green vegetation cover.

The spatial heterogeneity observed in this study is consistent with the characteristics of fragmented paddy landscapes, where differences in planting date, water availability, and field management may occur among adjacent plots. Similar spatial variability has also been reported in complex paddy field systems, where rice phenology may vary within a single landscape due to asynchronous cultivation practices (Kania Sari et al., 2010). In the context of open-field paddy environments, microclimatic variation and water-related conditions may further influence crop development and canopy response (Wiratmoko et al., 2025). The presence of planting, tillering, and booting stages within the same UAV acquisition area provided a suitable condition for evaluating how different vegetation indices respond to rice canopy development under comparable environmental and atmospheric conditions.

NDVI Response to Rice Canopy Development

The NDVI map showed a distinct spatial gradient of vegetation vigor across the study area, with values ranging from -0.204 to 0.728 (Figure 2). Lower NDVI values were mainly observed in planting-stage plots, where soil and water surfaces were still dominant because of sparse canopy cover. Higher NDVI values were mostly distributed in tillering and booting plots, reflecting increased green biomass and canopy closure. This spatial pattern indicates that NDVI was sensitive to the contrast between early-stage plots with limited vegetation cover and later-stage plots with more developed rice canopy.

The mean NDVI increased from 0.257 in the planting stage to 0.376 in the tillering stage and 0.480 in the booting stage. This increasing trend indicates that NDVI responded consistently to the progressive development of rice canopy cover. Since NDVI is based on the contrast between red absorption and near-infrared reflectance, it is suitable for describing general vegetation vigor and green biomass condition (Adedeji et al., 2015; Chen et al., 2025). In this study, NDVI provided a clear and interpretable response for separating sparse and dense rice canopy conditions, although its sensitivity may decrease in very dense vegetation because of saturation effects.

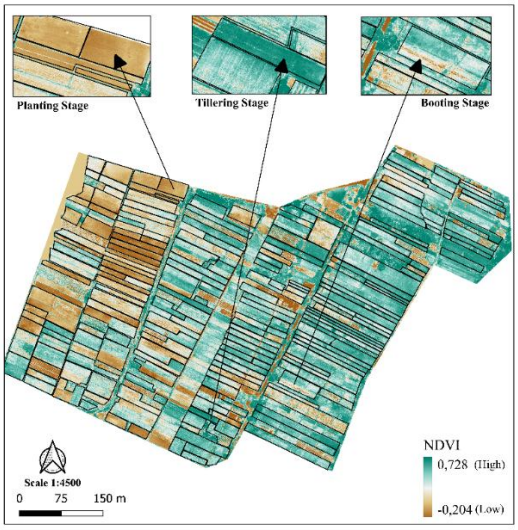


Figure 2. Spatial distribution of the Normalized Difference Vegetation Index (NDVI) across rice paddy fields in Tlogoadi, Sleman.

NDRE Response to Red-Edge Canopy Reflectance

The NDRE map produced values ranging from -0.137 to 0.417 (**Figure 3**). Compared with NDVI, the NDRE value range was narrower because NDRE uses the red-edge band rather than the red band. Spatially, higher NDRE values were generally found in plots with more developed canopy conditions, especially in the tillering stage. This pattern suggests that NDRE captured red-

edge canopy reflectance changes that were not fully represented by red-band-based vegetation indices.

The mean NDRE increased from 0.121 in the planting stage to 0.206 in the tillering stage, but decreased to 0.148 in the booting stage. This result indicates that NDRE did not increase continuously across all growth stages. The higher response during tillering may reflect greater sensitivity to active vegetative development and chlorophyll-related canopy response. The lower value at booting may be associated with canopy structure, background condition, or variation among plots. NDRE is commonly used to detect chlorophyll-related variation and may be more responsive than red-band indices in denser canopy conditions (Yue et al., 2019). Therefore, NDRE in this study should be interpreted as a complementary red-edge index rather than as a single indicator of growth-stage progression.

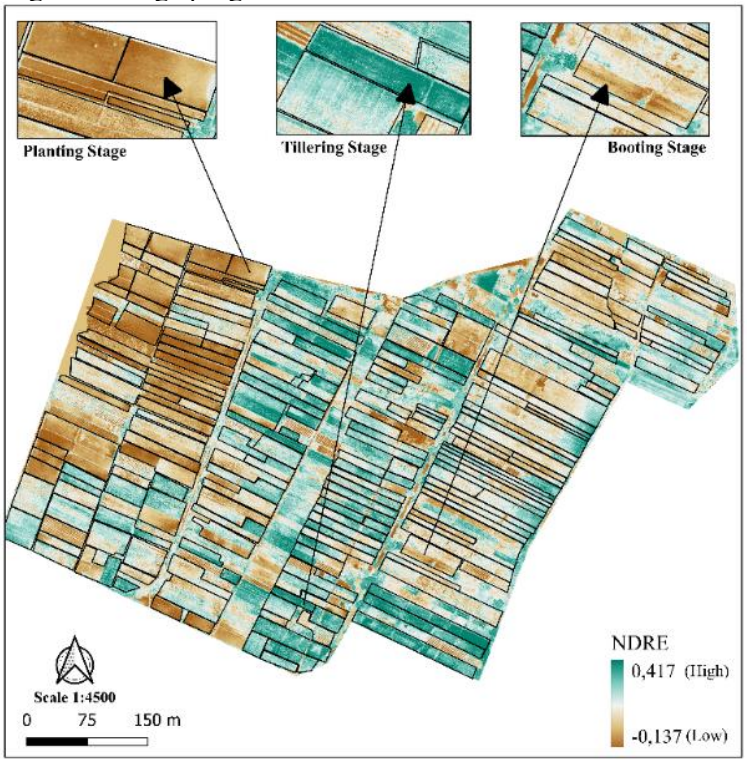


Figure 3. Spatial distribution of the Normalized Difference Red-Edge Index (NDRE) across rice paddy fields in Tlogoadi, Sleman.

GNDVI Response to Canopy Greenness

The GNDVI map showed values ranging from -0.155 to 0.589 (Figure 4). The spatial pattern of GNDVI was generally similar to NDVI, with lower values in planting-stage plots and higher values in tillering and booting plots. This pattern indicates that GNDVI was able to represent canopy greenness variation across the heterogeneous rice field area. The clearer response in more vegetated plots suggests that the green band contributed useful information for distinguishing differences in canopy greenness.

The mean GNDVI increased consistently from 0.217 in the planting stage to 0.315 in the tillering stage and 0.362 in the booting stage. This increasing trend indicates that GNDVI was responsive to the development of green canopy cover. Since GNDVI uses the green band instead of the red band, it can provide complementary information related to canopy greenness and chlorophyll-related reflectance conditions (Neinavaz et al., 2021; Xue & Su, 2017). In this study, GNDVI supported the interpretation that rice canopy greenness increased from planting to later growth stages.

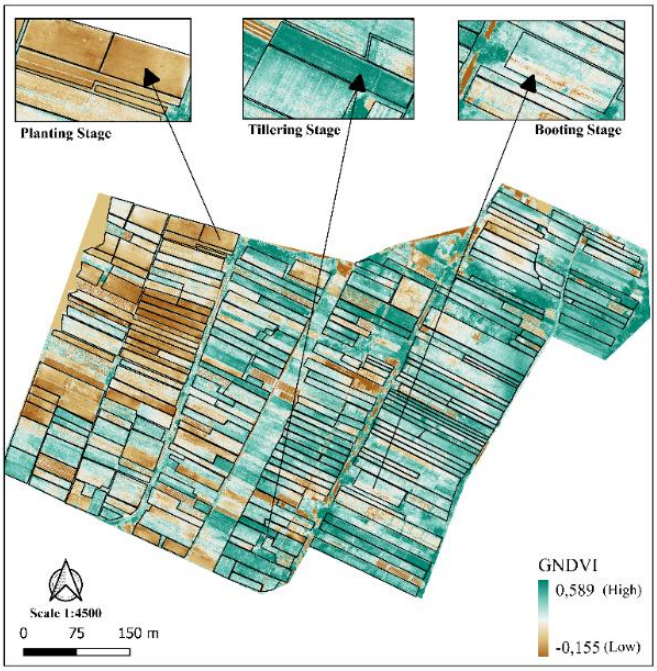


Figure 4. Spatial distribution of the Green Normalized Difference Vegetation Index (GNDVI) across rice paddy fields in Tlogoadi, Sleman.

SAVI Response to Soil–Canopy Background Variation

The SAVI map showed values ranging from -0.306 to 1.092 (**Figure 5**). Spatially, SAVI showed a clear distinction between plots with sparse canopy cover and plots with more developed rice canopy. Lower SAVI values were mainly observed in planting-stage plots, while higher values were found in tillering and booting plots. This pattern indicates that SAVI was useful for representing rice vegetation response in a landscape where exposed soil and water background were still visible in several plots.

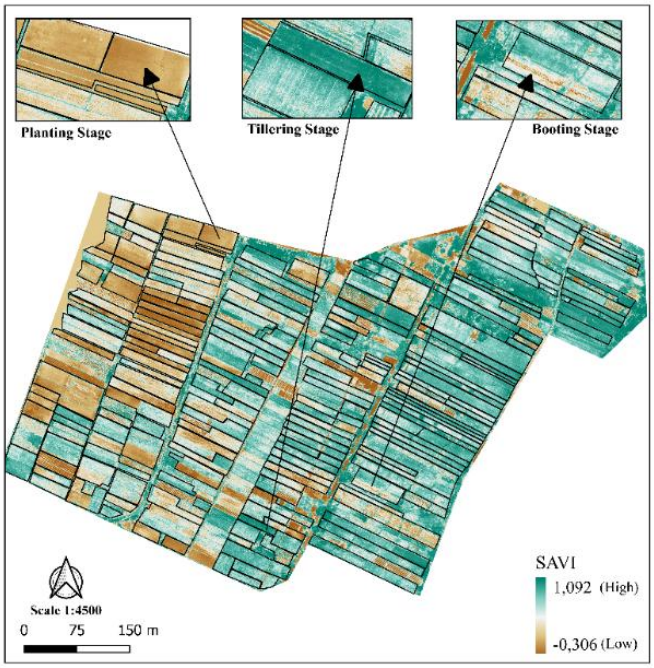


Figure 5. Spatial distribution of the Soil-Adjusted Vegetation Index (SAVI) across rice paddy fields in Tlogoadi, Sleman.

The mean SAVI increased from 0.386 in the planting stage to 0.564 in the tillering stage and 0.720 in the booting stage. This consistent increase indicates that SAVI represented the progressive development of rice canopy vigor. The relatively high standard deviation in the planting stage suggests that exposed soil and water background still influenced the spectral response of early-stage plots. SAVI is designed to reduce the influence of soil background in vegetation monitoring, particularly in areas with incomplete canopy cover (Zhen et al., 2021). This characteristic made SAVI suitable for the present study because the observed paddy fields contained a mixture of sparse and dense vegetation conditions.

CIRE Response to Red-Edge Chlorophyll Sensitivity

The CIRE map produced positive values ranging from 1.767 to 3.572 (**Figure 6**). The value scale of CIRE differed from the normalized indices because CIRE is calculated as a ratio between near-infrared and red-edge reflectance. For this reason, CIRE values should not be directly compared in magnitude with NDVI, NDRE, GNDVI, SAVI, or RDVI. Its interpretation should focus on the relative response among growth stages and the role of red-edge reflectance in describing chlorophyll-related canopy conditions.

The mean CIRE was 2.380 in the planting stage, increased to 2.635 in the tillering stage, and decreased slightly to 2.410 in the booting stage. This result indicates that the highest CIRE response was observed in the tillering stage rather than in the booting stage. The increase from planting to tillering may reflect stronger chlorophyll-related canopy response during active vegetative development. The lower mean value in the booting stage suggests that CIRE response may also be affected by canopy structure, background condition, or variation among fields. Since CIRE is associated with red-edge reflectance and chlorophyll-related vegetation sensitivity, it can provide additional information that is not fully captured by general vigor indices (Hunt et al., 2011). In this study, CIRE was useful as a complementary index for interpreting red-edge and chlorophyll-related response, but it should not be interpreted as a simple linear indicator of growth-stage progression.

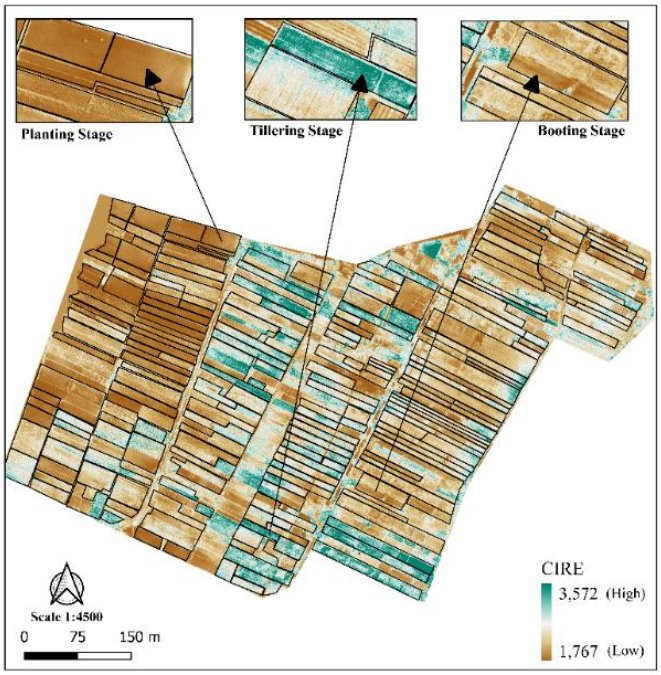


Figure 6. Spatial distribution of the Chlorophyll Index Red Edge (CIRE) across rice paddy fields in Tlogoadi, Sleman.

RDVI Response to Vegetation Contrast

The RDVI map showed values ranging from -0.423 to 0.246 (**Figure 7**). Compared with NDVI, GNDVI, and SAVI, the spatial pattern of RDVI was less consistent across the three rice growth stages. Some higher RDVI values appeared in more vegetated plots, but several areas with advanced growth stage also showed lower RDVI values. This result indicates that RDVI was more sensitive to local reflectance variation and mixed canopy-background conditions in the study area. The mean RDVI was -0.020 in the planting stage, -0.026 in the tillering stage, and -0.219 in the booting stage. This pattern indicates that RDVI did not show a consistent increase from planting to booting. The lower RDVI value in booting plots may be influenced by the mathematical structure of RDVI, local canopy reflectance variability, water background, or mixed pixels within fragmented paddy plots. RDVI has been used to improve vegetation contrast and reduce saturation effects in some conditions (Gao et al., 2023), but the result of this study suggests that its interpretation in heterogeneous paddy fields should be made carefully. Based on this dataset, RDVI was less stable than NDVI, GNDVI, and SAVI for representing rice growth-stage differences.

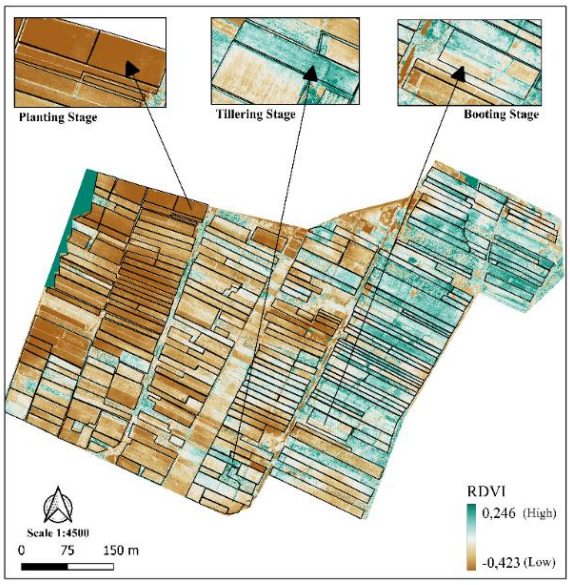


Figure 7. Spatial distribution of the Renormalized Difference Vegetation Index (RDVI) across rice paddy fields in Tlogoadi, Sleman.

Value Ranges of Vegetation Indices

Table 2 summarizes the minimum, maximum, and range values of each vegetation index across the study area. CIRE produced the widest numerical range, followed by SAVI. The wider range of CIRE should be interpreted carefully because its formula differs from normalized difference indices. NDVI, GNDVI, and SAVI showed clear spatial variation related to canopy development, while NDRE and CIRE provided additional information from the red-edge band. RDVI showed a narrower and less consistent response in relation to growth-stage differences.

Table 2. Vegetation index value ranges across the study area

Index	Minimum	Maximum	Range
NDVI	-0.20381	0.728088	0.931894
NDRE	-0.13702	0.416809	0.553832
GNDVI	-0.15525	0.588741	0.743994
SAVI	-0.30570	1.092119	1.397823
CIRE	1.76730	3.571818	1.804518
RDVI	-0.42319	0.246282	0.669471

The differences in value ranges among indices were mainly caused by their mathematical formulations and spectral band combinations. Therefore, the values of different vegetation indices should not be compared only based on numerical magnitude. Each index should be interpreted according to its spectral sensitivity and intended biophysical meaning. This interpretation is important in UAV-based crop monitoring because different sensor-derived variables may represent different aspects of crop condition, as shown in previous studies using imaging, soil moisture, thermal, electrical, and macronutrient sensing approaches (Afif et al., 2025; Nugroho et al., 2020, 2023, 2025, 2026).

Comparative Response Across Rice Growth Stages

Figure 8 presents the comparative response of vegetation indices across planting, tillering, and booting stages using mean values and distribution patterns. NDVI, GNDVI, and SAVI showed consistent increases from planting to booting stages. This pattern indicates that these indices were more directly related to the increase in green canopy cover and vegetation vigor during rice development. The boxplot also showed that the distributions of these indices shifted upward as the canopy became denser.

NDRE and CIRE showed their highest mean values at the tillering stage. This result suggests that red-edge-based indices may capture chlorophyll-related canopy response differently from general vegetation vigor indices. The tillering stage is characterized by active vegetative growth and increasing canopy development, which may explain the stronger NDRE and CIRE responses. The decrease in NDRE and CIRE at the booting stage indicates that these indices should not be interpreted as continuously increasing indicators across all rice growth stages. This pattern is consistent with the idea that vegetation index responses may vary depending on canopy structure, chlorophyll condition, and background reflectance.

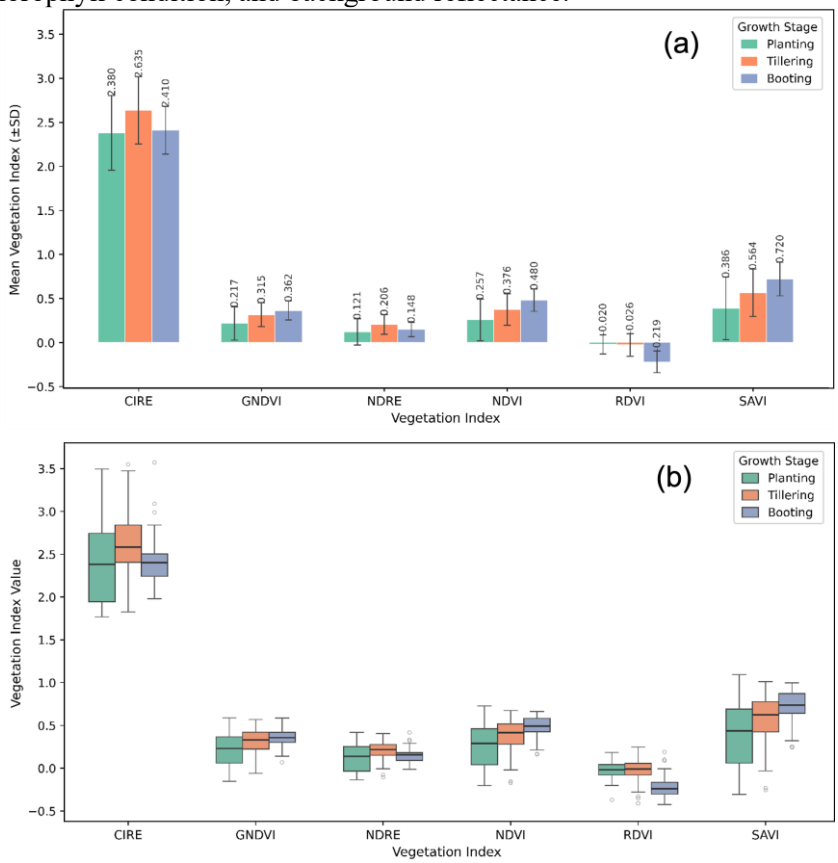


Figure 8. Comparative vegetation index response across rice growth stages: (a) mean vegetation index values with standard deviation; and (b) boxplot distribution of vegetation index values by growth stage.

RDVI showed the least consistent response among the evaluated indices. The mean RDVI decreased at the booting stage, which did not follow the pattern observed in NDVI, GNDVI, and SAVI. This result suggests that RDVI may be more sensitive to local reflectance variability, water background, or mixed canopy-background conditions in the study area. Similar to other sensor-based crop monitoring approaches, index interpretation should consider field condition, background effects, and the specific parameter being measured (Nugroho et al., 2020, 2023). In practical applications, RDVI may still provide useful complementary information, but it should be interpreted together with other vegetation indices.

Table 3. Summary statistics of vegetation index values by rice growth stage

Index	Growth Stage	Mean	SD	Interpretation
NDVI	Planting	0.2573	0.2363	Low canopy vigor
NDVI	Tillering	0.3757	0.1800	Increasing canopy development
NDVI	Booting	0.4800	0.1264	Denser canopy condition
NDRE	Planting	0.1206	0.1497	Low red-edge response
NDRE	Tillering	0.2056	0.1099	Higher chlorophyll-related response
NDRE	Booting	0.1477	0.0833	Moderate red-edge response
GNDVI	Planting	0.2171	0.1893	Low canopy greenness
GNDVI	Tillering	0.3150	0.1356	Increased canopy greenness
GNDVI	Booting	0.3623	0.1076	Higher canopy greenness
SAVI	Planting	0.3859	0.3544	Sparse canopy with soil or water background influence
SAVI	Tillering	0.5636	0.2700	Intermediate canopy vigor
SAVI	Booting	0.7201	0.1895	Higher canopy vigor
CIRE	Planting	2.3804	0.4245	Lower chlorophyll-related response
CIRE	Tillering	2.6346	0.3821	Higher chlorophyll-related response
CIRE	Booting	2.4097	0.2725	Moderate to high chlorophyll-related response
RDVI	Planting	-0.0204	0.1084	Low vegetation contrast
RDVI	Tillering	-0.0264	0.1282	Variable vegetation contrast
RDVI	Booting	-0.2190	0.1244	Lower RDVI response, possibly affected by canopy-background conditions

Implications for UAV-Based Rice Growth Assessment

The results indicate that multispectral UAV imagery can characterize spatial variability in rice vegetation response across different growth stages in fragmented smallholder paddy fields. Among the six indices, NDVI, GNDVI, and SAVI showed the most consistent increase from planting to booting stages. These indices were suitable for describing general canopy development and vegetation vigor in the study area. NDRE and CIRE provided additional information related to red-edge and chlorophyll-related canopy response, but both indices reached their highest mean values at the tillering stage rather than at the booting stage. This finding highlights the importance of interpreting red-edge-based indices according to canopy condition and spectral behavior rather than using them as standalone indicators of crop stage.

RDVI showed a less consistent pattern across the three growth stages. Although RDVI can enhance vegetation contrast in some conditions, its response in this study was more variable and should be interpreted with caution in heterogeneous paddy fields. This finding supports the use of a multi-index approach rather than relying on a single vegetation index for rice growth assessment. A multi-index approach is useful because each index emphasizes different spectral

information, such as greenness, canopy vigor, red-edge response, soil background adjustment, or vegetation contrast. The interpretation of these indices should be linked to field conditions, especially in paddy fields where water surface, soil exposure, and mixed canopy-background pixels may influence spectral response.

From a practical perspective, UAV-based vegetation index mapping provides useful spatial information for identifying differences in rice canopy condition among adjacent plots. Such information can support field observation, crop condition assessment, and site-specific management decisions. Previous studies have shown that sensor-derived agricultural information becomes more useful when combined with field interpretation, decision-support systems, and digital monitoring frameworks (Nugroho et al., 2026; Wiratmoko et al., 2023). In plantation and agricultural management contexts, remote sensing imagery, big data, and machine learning have also been used to support object counting, production prediction, and data-driven decision-making (Muna et al., 2022; Syarovy et al., 2022, 2023). Although these studies differ in commodity and sensing approach, they support the broader relevance of image- and sensor-based monitoring for precision agriculture.

The findings suggest that UAV multispectral mapping can be used as a practical tool for assessing rice growth-stage variability within a single acquisition period. The approach is particularly useful for smallholder paddy field landscapes where different growth stages may coexist in adjacent plots. Further studies should include multi-temporal UAV flights and ground-truth measurements such as chlorophyll content, leaf area index, soil moisture, biomass, or yield data. These additional measurements would strengthen the interpretation of vegetation index responses and improve their relevance for operational crop monitoring. Integration with environmental and plant-based sensors, such as microclimate, thermal, soil moisture, and plant signal monitoring systems, may also provide a more complete understanding of crop condition under field conditions (Afif et al., 2025; Nugroho et al., 2025; Wiratmoko et al., 2025).

CONCLUSION

This study assessed rice vegetation responses across planting, tillering, and booting stages using multispectral UAV imagery acquired over fragmented paddy fields in Tlogoadi, Sleman Regency, Special Region of Yogyakarta. Six vegetation indices, namely NDVI, NDRE, GNDVI, SAVI, CIRE, and RDVI, were mapped and analyzed to characterize spatial variation in rice canopy condition. The results showed that vegetation index responses varied among growth stages, with planting-stage plots generally associated with lower index values due to sparse canopy cover and stronger soil or water background influence. NDVI, GNDVI, and SAVI showed consistent increases from planting to booting stages, indicating their suitability for describing general canopy development and vegetation vigor. NDRE and CIRE provided complementary information related to red-edge and chlorophyll-related canopy responses, with the highest mean values observed at the tillering stage. RDVI showed a less consistent pattern across growth stages, suggesting that its interpretation should be made carefully under heterogeneous paddy field conditions. These findings indicate that multispectral UAV imagery combined with multiple vegetation indices can support high-resolution assessment of rice growth variability in smallholder paddy field landscapes. Further studies involving multi-temporal UAV observations and ground-truth measurements such as chlorophyll content, leaf area index, biomass, soil moisture, and yield are recommended to strengthen the interpretation and operational use of vegetation indices for precision rice management.

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