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Comparative Evaluation of Multispectral UAV-Derived Vegetation Indices in Rice Fields

Hana Hanifa[1*], Zulfa Az Zahroh[2], Mohamad Zaki Alfatih[2]

[1] Land Resource Planning Study Program, Faculty of Agriculture, Universitas Jenderal Soedirman, Banyumas, Indonesia
[2] Agrotechnology Study Program, Faculty of Agriculture, Universitas Jenderal Soedirman, Banyumas, Indonesia

[*]Correspondence author email: hana.hanifa@unsoed.ac.id

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Abstract

This study presents a comparative evaluation of multispectral UAV-derived vegetation indices (VIs) in rice fields. Seven UAV-derived VIs — the Chlorophyll Index (CI), Chlorophyll Vegetation Index (CVI), Modified Soil-Adjusted Vegetation Index (MSAVI), Green Normalized Difference Vegetation Index (GNDVI), Normalized Difference Red Edge Index (NDRE), Normalized Difference Vegetation Index (NDVI), and Perpendicular Vegetation Index (PVI) were computed from UAV multispectral orthomosaics acquired over a lowland rice field in Purwokerto, Central Java. The data were collected during the late vegetative stage of rice growth. Pearson correlation analysis showed strong positive correlations between the structural indices NDVI, MSAVI, and PVI ($r > 0.93$) and the chlorophyll-related indices CI and NDRE ($r = 0.93$), whereas CVI was negatively correlated with NDRE ($r = −0.66$), indicating that biomass accumulation and chlorophyll status did not always change together. Forty-three field points, classified into rice condition categories, were used to train and test a Random Forest classifier. Both models reached the same overall test accuracy of 63.64% (Kappa = 0.42 and 0.41, respectively), and the cross-validated model reached a cross-validation Kappa of 0.48 at mtry = 7. Variable importance ranked PVI as by far the most influential predictor (importance = 100), followed at a distance by CI (18.4), NDRE (12.9), and CVI (9.5), while MSAVI, NDVI, and GNDVI contributed little. Soil-background-sensitive PVI carried the strongest discriminative signal, chlorophyll-related indices added complementary information, and GNDVI was largely redundant. These findings offer preliminary evidence that PVI, paired with CI or NDRE, is the most relevant index combination for UAV-based rice field assessment.

1. Introduction

Precision agriculture increasingly relies on unmanned aerial vehicle (UAV) remote sensing to monitor rice field conditions at spatial and temporal resolutions that satellite platforms cannot easily match. UAVs can be deployed on demand, below persistent cloud cover, and at flight altitudes that yield centimeter-scale ground sampling distance, making them well suited to field-scale rice monitoring, where crop condition can vary over just a few meters (Siegfried et al., 2023; Zhang and Kovacs, 2012). Multispectral UAV sensors extend this capability beyond the visible spectrum by capturing reflectance in the green, red, red-edge, and near-infrared bands, which are sensitive to canopy chlorophyll content, leaf area, and canopy structure properties that change measurably as rice plants respond to nutrient status, water stress, and disease (Norasma et al., 2019). From these bands, vegetation indices (VIs) are computed as band-ratio or band-difference formulas designed to isolate a particular vegetation signal, such as chlorophyll content, canopy structure, or soil-background influence, while suppressing noise from illumination or soil variation. Because different indices emphasize different biophysical properties and differ in their sensitivity to saturation, soil background reflectance, and canopy structure, no single index is universally optimal for crop monitoring (Marino and Alvino, 2021; Nitu et al., 2025). Comparative evaluation of multiple indices under identical acquisition conditions is therefore necessary before any one index or minimal combination of indices can be recommended for operational rice monitoring.

Rice (*Oryza sativa* L.) is a staple food crop that plays a critical role in food security, particularly in the volcanic lowland regions of Indonesia, where soil fertility and water availability strongly influence crop productivity. The health status of rice plants is closely linked to soil physical and chemical properties, including texture, drainage, pH, and nutrient availability; consequently, timely and accurate assessment of crop health is essential for effective soil plant management and sustainable agricultural practice. Traditional assessment methods rely heavily on visual observation and destructive sampling, which are labor-intensive, subjective, and limited in spatial coverage. These limitations hinder early detection of crop stress related to nutrient deficiency, water imbalance, or suboptimal soil conditions, motivating the development of spatially explicit, objective, and efficient field-scale monitoring approaches.

Banyumas Regency is one of the major lowland rice-producing areas in Central Java. In 2023, it ranked as the 15th-largest rice producer in the province, contributing a total production of 279,426.07 tons (BPS, 2024). Rice production in this region shows considerable spatial variability related to topography, elevation, and agroecological conditions. A key limitation is the absence of an early-warning system capable of detecting crop stress before visible symptoms appear, by which point corrective action is often already delayed (Yan et al., 2026). Conventional monitoring, being subjective, labor-intensive, and time-consuming, provides limited spatial detail on field conditions (Liu et al., 2025) and often results in uniform management practices such as blanket fertilization and pest control that disregard within-field variability, leading to inefficient input use, increased production costs, and suboptimal yields. Remote sensing, particularly UAV-based multispectral imagery, has emerged as a powerful tool for addressing these constraints (Wijayanto et al., 2023; Yao et al., 2019). Multispectral sensors capture reflectance in the visible, red-edge, and near-infrared wavelengths, enabling calculation of VIs that represent canopy structure, biomass, chlorophyll content, and plant physiological status. Structural indices such as NDVI and MSAVI are widely used to characterize canopy vigor, whereas indices such as CI and NDRE are more sensitive to chlorophyll concentration and nitrogen status (Kanke et al., 2016; Taskos et al., 2015). Understanding the relationships among these indices through correlation analysis is therefore essential for identifying which indices are redundant and which provide complementary information that can guide more efficient, non-redundant monitoring protocols.

Despite the growing number of VIs proposed for agricultural monitoring, comparative evaluation of their statistical relationships, spatial consistency, and practical contribution to crop-condition classification under identical UAV acquisition conditions remains limited, particularly for rice grown on Indonesian volcanic lowland soils (Marino and Alvino, 2021; Nitu et al., 2025; Yanti et al., 2022). This study addresses that gap by comparatively evaluating seven multispectral UAV-derived vegetation indices in a lowland rice field. Specifically, the study aims to (1) quantify the statistical relationships among the seven indices to identify redundant and complementary indices, (2) characterize their spatial distribution across the study field, and (3) assess their relative contribution to distinguishing rice-condition classes through a Random Forest classification, thereby providing evidence to support the selection of vegetation indices for UAV-based rice field assessment. This study is limited to a single lowland rice field and vegetative growing season in Purwokerto, Central Java, with a relatively small ground-truth sample; the findings are therefore intended as an initial, site-specific evidence base rather than a generalizable recommendation across rice-growing regions or seasons.

2. Research Methods

2.1. Research Location

The research was conducted in a lowland rice field in Purwokerto, Central Java, Indonesia (49S UTM: X = 109°25′17.6″, Y = −7°36′35.9″). The study area has a relatively flat topography, with an average slope of approximately 3%, suitable for intensive lowland rice cultivation. Data were acquired from August to December 2025, coinciding with the rice growing season, when variation in canopy development and physiological condition can be effectively captured through multispectral UAV imagery.

Figure 1. Location of the research site in Purwokerto, Central Java, Indonesia

2.2. UAV Data Acquisition

Data acquisition was carried out in sequential stages of preparation, flight, image processing, and validation. A preliminary field survey identified the study area boundaries, followed by flight planning to ensure optimal spatial coverage and image quality. Multispectral data were acquired using a UAV equipped with a multispectral sensor and Real-Time Kinematic (RTK) positioning to improve spatial accuracy. Flight parameters were standardized to ensure data consistency and are summarized in Table 1.

Table 1. UAV flight specifications (DJI Mavic 3M with RTK)

Parameter	Specification
UAV platform	DJI Mavic 3M RTK
Sensor type	Multispectral camera (RGB + Green, Red, Red Edge, Near Infrared)
Flight mode	Autonomous mapping flight
Positioning system	RTK (Real-Time Kinematic)
Flight altitude	80 m above ground level (AGL)
Altitude reference	Relative to takeoff point
Ground Sampling Distance (GSD)	± 0.92 cm $pixel^{-1}$
Flight pattern	Parallel grid
Forward overlap	80%
Side overlap	70%
Flight speed	5 m s^{-1}
Camera angle	90° (vertical)
Mapping area	± 1.5 ha
Estimated flight duration	± 21 minutes
Weather conditions	Clear sky, low wind
Time of flight	Daytime (10:00–14:00 local time)
Data output	Multispectral images for orthomosaic generation

2.3. Vegetation Index Calculation

The multispectral images were processed in Agisoft Metashape to generate high-resolution orthomosaics. The resulting orthomosaics were imported into QGIS version 3.32.3, where seven vegetation indices representing canopy structure, biomass, chlorophyll content, and plant physiological status were calculated (Table 2). Each index was resampled to a common grid and stacked as a set of predictor layers for subsequent analysis.

Table 2. Vegetation indices, formulas, and primary agronomic application

Index	Formula	Primary Application
Perpendicular Vegetation Index (PVI)	$\sqrt{(0.355NIR-0.149R)^2+(0.355R+0.852NIR)^2}$	LAI estimation; soil-background-corrected canopy signal (Zarco-Tejada et al., 2014)
Chlorophyll Index (CI)	$(\frac{NIR}{RE}) - 1$	Chlorophyll and nitrogen content (Taskos et al., 2015)
Chlorophyll Vegetation Index (CVI)	$(\frac{NIR}{G}) \times (\frac{R}{G})$	Crop growth, chlorophyll content, yield (Shang et al., 2015)
Normalized Difference Red Edge Index (NDRE)	$(\frac{NIR - RE}{NIR + RE})$	Crop vigor, biomass, nitrogen management (Kanke et al., 2016)
Modified Soil-Adjusted Vegetation Index (MSAVI)	$\frac{2NIR+1-\sqrt{(2NIR+1)^2-8(NIR-R)}}{2}$	Biomass, N-uptake, chlorophyll content, yield (Qi et al., 1994)
Green Normalized Difference Vegetation Index (GNDVI)	$(\frac{NIR - G}{NIR + G})$	Biomass, nitrogen content, water stress (Chen et al., 2020)
Normalized Difference Vegetation Index (NDVI)	$(\frac{NIR - RED}{NIR + RED})$	Crop vigor, biomass estimation (Kanke et al., 2016)

2.4. Data Analysis and Random Forest Classification

Data analysis focused on two complementary objectives: (1) quantifying statistical relationships among the seven indices, and (2) evaluating their practical utility for classifying rice-field condition using RStudio Random Forest (RF). Rather than relying on pairwise correlation to judge redundancy, the practical utility of each index was evaluated through its contribution to classifying rice-field condition. All seven indices were combined as predictor layers and extracted at 43 field-verified points, labelled into four condition classes: Non-paddy, Unhealthy, Less Healthy, and Healthy. Data were split 70/30 into training and test sets (seed = 123; stratified by class). A baseline RF classifier (500 trees) was trained on the training set and evaluated on the held-out test set using a confusion matrix and overall accuracy. A second model was trained with 10-fold cross-validation (caret: train, method = "rf"), tuning selected optimal mtry (number of variables) over three candidate values, with the best model selected by cross-validated accuracy and then evaluated on the same held-out test set. Variable importance (scaled 0–100) was extracted from the cross-validated model to rank the relative contribution of each index to classification performance, and the final tuned model was used to generate a wall-to-wall predicted rice-condition map across the full UAV raster extent.

3. Results and Discussion

3.1. Statistical Relationships among Vegetation Indices

Pearson correlation analysis among the seven UAV-derived vegetation indices revealed clear patterns of redundancy and complementarity in representing rice crop condition (Figure 2). Strong positive correlations were observed among NDVI, MSAVI, and PVI ($r > 0.93$), indices that are primarily sensitive to canopy density, leaf area, and overall vegetation vigor. This high degree of correlation indicates that the three indices capture largely overlapping spectral responses associated with dense, healthy rice canopies, consistent with the well-documented tendency of greenness-based structural indices to respond similarly to biomass and canopy-structure variation, particularly under relatively uniform crop conditions (Huete, 1988; Kanke et al., 2016; Marino and Alvino, 2021). In contrast, the two indices most closely tied to plant physiological status CI and NDRE exhibited a strong positive correlation ($r=0.93$). NDRE is particularly effective during later growth stages, when NDVI tends to saturate under dense canopies, making it more suitable than NDVI for monitoring nitrogen dynamics in high-biomass rice systems (Taskos et al., 2015; Towers et al., 2019; Zarco-Tejada et al., 2014). A more distinctive result was the moderate-to-strong negative correlation between CVI and NDRE ($r = -0.66$). This finding suggests that increased biomass accumulation, as captured by CVI, does not necessarily correspond to higher chlorophyll or nitrogen content. Such a pattern is plausible where vegetative growth is promoted by favorable water availability but constrained by limited nutrient supply in the soil — a decoupling between structural growth and physiological status that has been reported previously in nitrogen-related crop studies (Shang et al., 2015). This decoupling is agronomically important: it implies that a field can appear structurally vigorous (high CVI, high NDVI/MSAVI/PVI) while still being nutrient-limited, a condition that structural indices alone would fail to detect.

Overall, these correlation patterns show that the seven indices occupy at least two distinct interpretative domains structural indices (NDVI, MSAVI, PVI) that describe canopy development and biomass, and physiological indices (CI, NDRE) that describe chlorophyll and nitrogen status, with CVI behaving as a biomass-related index that can diverge from the physiological domain. This distinction is consistent with recent evidence that many vegetation indices, while broadly correlated with NDVI, retain meaningful differences in discriminative power depending on landscape and application context (Nitu et al., 2025). Practically, relying on a single index risks an incomplete or misleading picture of crop health; pairing one structural index with one physiological index is therefore expected to provide a more complete assessment than either alone, an expectation examined directly through the Random Forest classification in Section 3.3.

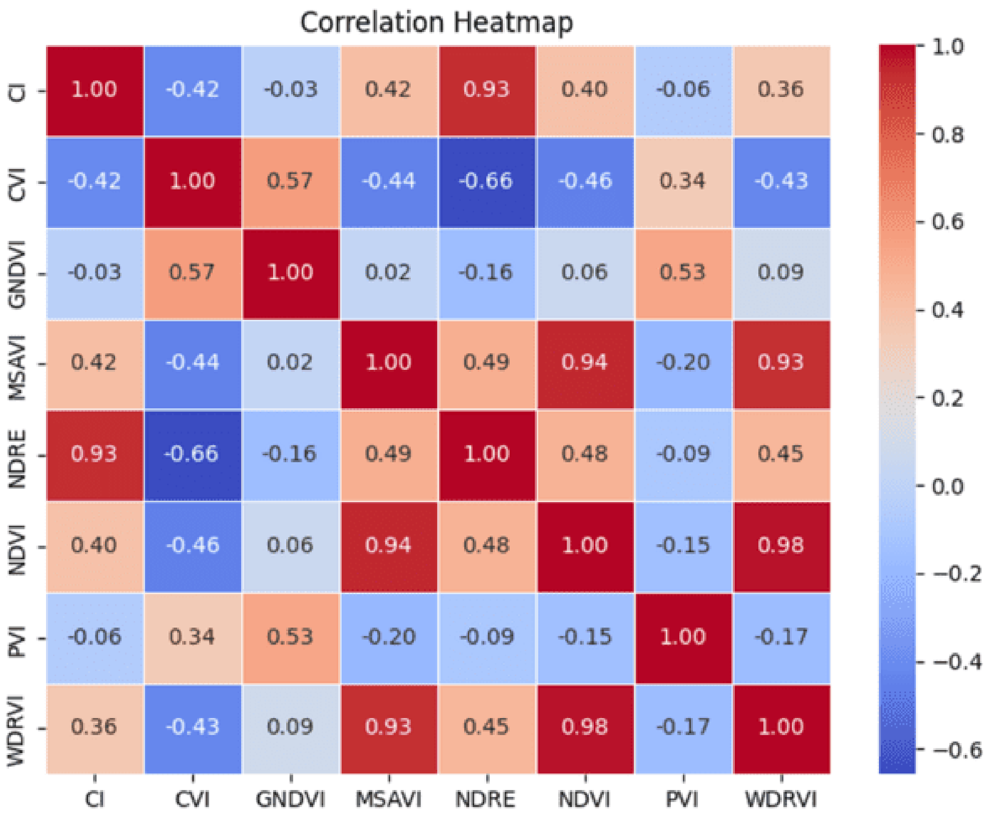
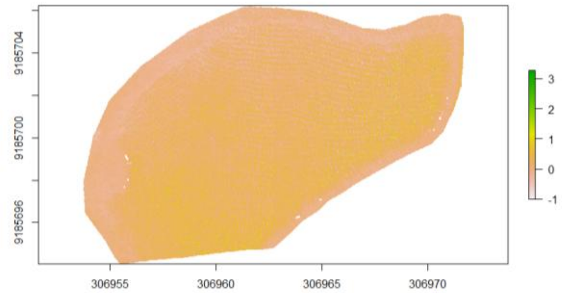


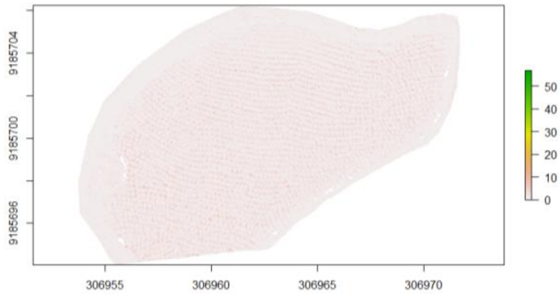
Figure 2. Pearson correlation heatmap of the seven UAV-derived vegetation indices, showing strong positive correlations among structural indices (NDVI, MSAVI, PVI) and between the physiological indices (CI, NDRE), together with the negative CVI–NDRE relationship.

3.2. Spatial Distribution of Vegetation Indices

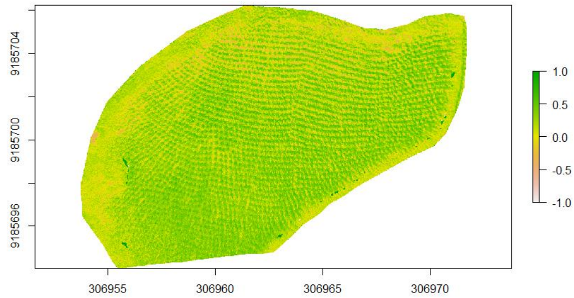
The seven UAV-derived raster maps depict spatial variation in vegetation greenness and canopy vigor across the study area, each generated from a different index sensitive to distinct plant physiological or structural properties (Figure 3). The CI map shows relatively uniform, low-to-moderate values (mostly near 0–1 on a –1 to 3 scale), suggesting a fairly homogeneous canopy chlorophyll content with limited high-chlorophyll zones. The CVI map displays predominantly low values (close to 0 on a 0–59 scale), indicating that canopy structure combined with chlorophyll concentration is generally consistent across the plot. The GNDVI map, which emphasizes chlorophyll absorption in the green band, shows a yellow-to-green pattern (values around 0.3–0.6), reflecting moderate to healthy vegetation vigor. The NDRE map, sensitive to canopy structure via the red edge band and useful for detecting subtle nitrogen or health stress in canopies, shows a similar yellow-green pattern but slightly lower values than GNDVI, hinting at localized canopy stress not always visible in standard NDVI. The NDVI map, the most widely used greenness indicator, exhibits the highest and most consistent green values across the field, confirming generally healthy, dense vegetation cover overall. The PVI, which accounts for soil background reflectance, shows a more heterogeneous orange-yellow-green pattern with a wide value range (0–35,000), highlighting greater sensitivity to soil-vegetation contrast and revealing spatial variability that vegetation-only indices may mask. Finally, the MSAVI map appears almost entirely green, indicating that after minimizing soil-background influence, the canopy across nearly the whole study area registers as dense and vigorously vegetated. Together, these seven indices provide complementary perspectives from pure chlorophyll content (CI, CVI) to canopy structure (NDRE) to soil-corrected vigor (PVI, MSAVI)—offering a more robust characterization of vegetation health than any single index alone.



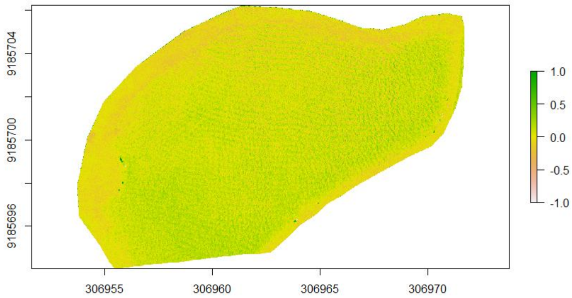
CI map of the study area.



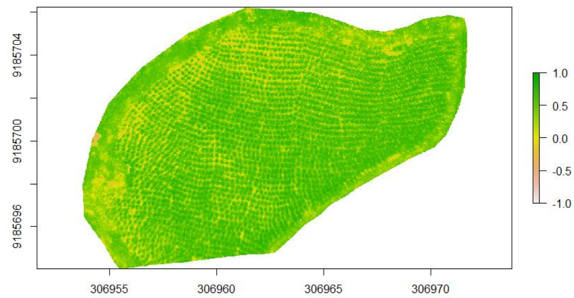
CVI map of the study area.



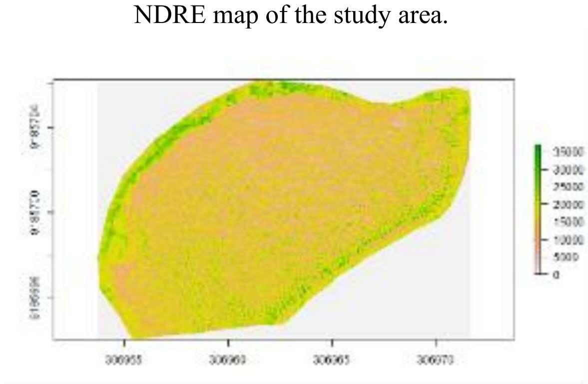
GNDVI map of the study area.



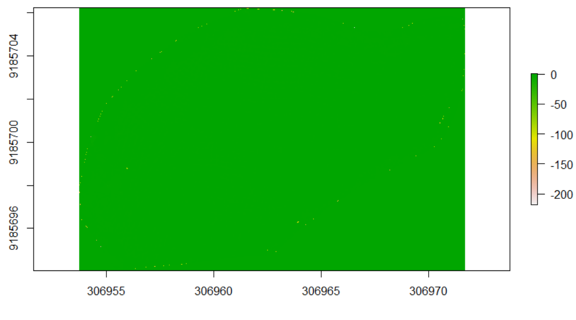
NDRE map of the study area.



NDVI map of the study area.



PVI map of the study area.



MSAVI map of the study area.

Figure 3. The seven index maps produced from the UAV orthomosaic after resampling

3.3. Random Forest Classification Performance

The baseline Random Forest model (500 trees, single 70/30 split) achieved an overall test accuracy of 63.64% (95% CI: 30.8–89.1%; Kappa = 0.421; No Information Rate = 45.45%, p = 0.18). Table 3 shows a 10-fold cross-validated model selected optimal mtry (number of variables) = 7 as optimal (cross-validation accuracy = 63.5%, Kappa = 0.477) and, when evaluated on the same held-out test set, also reached an overall accuracy of 63.64% (Kappa = 0.405).

Table 3. Comparative performance of the baseline versus cross-validated random forest models

Model	Test Accuracy	95% CI	Kappa (test)	CV Kappa
Baseline RF (500 trees, single split)	63.64%	0.308–0.891	0.421	—
RF with 10-fold CV (mtry = 7)	63.64%	0.308–0.891	0.405	0.477

Class-level performance for the cross-validated model was uneven, reflecting the small and imbalanced test set (11 points): sensitivity was high for non-paddy (0.80) and Healthy (0.67), but low for Less Healthy (0.33), while the single Unhealthy test observation could not be evaluated because the test fold contained no positive cases for that class. The close agreement between cross-validation accuracy (63.5%) and test-set accuracy (63.64%) suggests the model is not badly overfit; however, the wide 95% confidence interval (30.8–89.1%) reflects the very small test sample and warrants caution before generalizing these accuracy figures. This moderate overall accuracy is broadly consistent with the range reported for other UAV-multispectral, vegetation-index-based classification and prediction models for rice: for example, a neural-network classifier using UAV multispectral vegetation indices to distinguish rice varieties achieved 0.804 rather than near perfect discrimination (Wijayanto et al., 2023), and multi-algorithm benchmarking of remote sensing based rice yield models has likewise shown that tree-based ensembles such as Random Forest perform competitively but rarely achieve very high accuracy from spectral indices alone, particularly with limited training data (Liu et al., 2024). These comparisons should be read qualitatively rather than as a direct benchmark, since Wijayanto et al. (2023) report a discrimination metric for a variety-classification task and Liu et al. (2024) address continuous yield estimation, whereas the present study reports Kappa for a four-class condition classification; the tasks and metrics are not numerically equivalent. Taken together, this suggests that the moderate accuracy obtained here reflects a genuine ceiling on the information content of spectral vegetation indices for discrete condition classification with a small ground-truth sample, rather than a methodological shortcoming specific to this study.

3.4. Variable Importance and Comparative Discussion

PVI was by far the most influential index for classifying rice-field condition, with an importance score roughly five times higher than the second-ranked index (CI). Unlike ratio-based indices, PVI measures the perpendicular distance of a pixel from a defined soil line, making it directly sensitive to the combined effect of canopy amount and soil background (Haboudane et al., 2004). This property plausibly explains its dominance in the present classification task: because the four target classes include a non-paddy category defined largely by the presence or absence of vegetated canopy over soil or water background, an index explicitly built around the soil–vegetation contrast would be expected to separate that class more cleanly than ratio-based indices that primarily track within-canopy pigment variation. The same soil-line sensitivity plausibly also helps separate classes that differ mainly in canopy cover or structure rather than in pigment concentration alone.

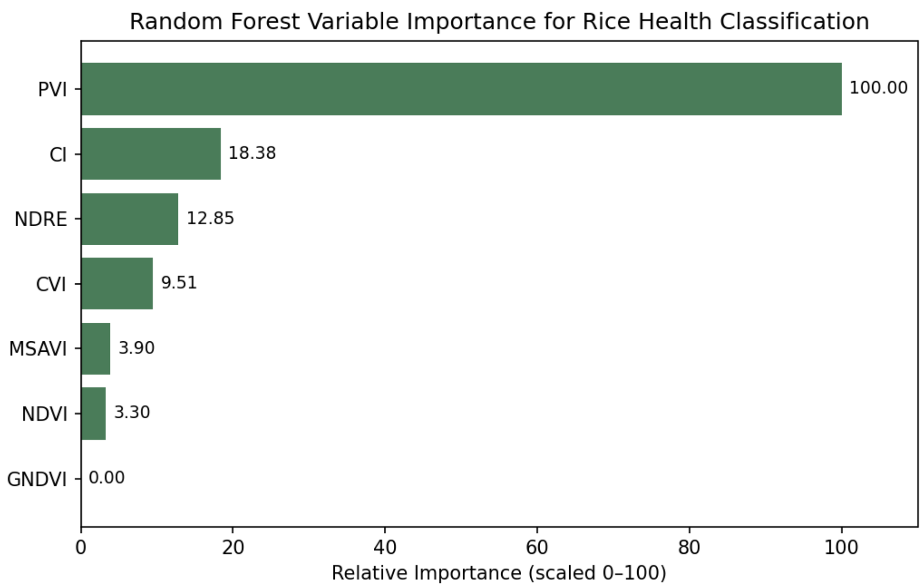


Figure 4. Random forest variable importance (scaled 0–100)

CI, NDRE, and CVI all more directly tied to chlorophyll or pigment status contributed moderately to classification accuracy, consistent with the interpretation that these indices add complementary, pigment-related information once the coarser structural separation already captured by PVI is accounted for. The model appears to rely first on structural information to separate vegetated from non-vegetated conditions, then on physiological information to differentiate condition classes within the vegetated canopy. This layered contribution supports the recommendation, following from the correlation analysis, that a single structural index combined with one physiological index is sufficient to capture most of the discriminative information available from this index set, rather than requiring all seven indices simultaneously. Two aspects of PVI's dominance warrant caution, however. First, because one of the four target classes (non-paddy) is defined largely by the presence or absence of vegetated canopy, part of PVI's importance score plausibly reflects the comparatively easy paddy-versus-non-paddy separation rather than genuine skill at distinguishing the three within-canopy condition classes (Unhealthy, Less Healthy, Healthy) that are of greatest agronomic interest; separating these effects would require re-running the classification on the vegetated subset alone, which we identify as a priority for follow-up analysis. Second, permutation-based importance measures such as those used here are known to be sensitive to correlation among predictors and to the number of correlated variables entering the model, and their ranking can be unstable when the sample size is small relative to the number of predictors, as in the present dataset (43 points, 7 indices, ~30 points in training) (Gregorutti et al., 2017; Strobl et al., 2008). The reported ranking should therefore be read as indicative of the relative information content of the two interpretative domains identified in Section 3.1 rather than as a precise, sample-independent measure of each index's standalone predictive value.

GNDVI's zero importance is the most striking secondary finding of the classification analysis. Conceptually, GNDVI is closely related to NDVI — both are difference-based indices contrasting near-infrared reflectance against a visible band sensitive to chlorophyll and canopy vigor — and this conceptual overlap is consistent with recent evidence that GNDVI often shares substantial explanatory overlap with NDVI and other structural indices in mixed-index feature sets, reducing its marginal, non-redundant contribution once those other indices are already present (Marino and Alvino, 2021; Nitu et al., 2025). Because Random Forest tends to distribute importance unevenly among strongly correlated predictors, favoring whichever correlated index the algorithm happens to split on first, GNDVI's near-total redundancy with NDVI and PVI in this dataset (Section 3.1) offers a parsimonious explanation for why it received essentially no marginal importance here, even though GNDVI is a widely used index in other rice-monitoring contexts (Chen et al., 2019).

Compared with previous UAV-based rice studies that emphasize a single "best" index, the present results argue instead for an index-combination strategy tailored to the monitoring objective: PVI (or another soil-line-based structural index) for detecting the presence and extent of the rice canopy itself, paired with NDRE or CI for characterizing physiological condition within that canopy, while GNDVI can likely be omitted without meaningful loss of information in a similar UAV-based, soil-heterogeneous lowland setting. This is consistent with prior recommendations that combining structural and chlorophyll-sensitive indices provides a more complete basis for site-specific nutrient management than any single index used alone (Kanke et al., 2016; Khose and Mailapalli, 2024).

4. Conclusion

This study comparatively evaluated seven multispectral UAV-derived vegetation indices CI, CVI, GNDVI, MSAVI, NDRE, NDVI, and PVI for assessing rice field condition in a lowland rice system in Purwokerto, Central Java. Correlation analysis showed that the seven indices are not statistically independent: NDVI, MSAVI, and PVI form a highly redundant structural group ($r > 0.93$), CI and NDRE form a highly redundant physiological group ($r = 0.93$), and CVI diverges from the physiological group ($r = -0.66$ with NDRE), indicating that biomass accumulation and nutrient/chlorophyll status can change independently within the same field. A Random Forest classifier combining all seven indices achieved a moderate, consistent overall accuracy of 63.64% (Kappa ≈ 0.41–0.48) for distinguishing four rice-condition classes, with PVI emerging as by far the most influential single predictor, followed at a distance by CI, NDRE, and CVI, while GNDVI contributed no measurable discriminative value in this dataset. Together, these results directly address the study's aim: they show that the evaluated indices occupy at most two or three non-redundant information domains canopy/soil-background structure (best represented by PVI) and pigment/nitrogen status (best represented by NDRE or CI) — rather than seven independent sources of information. The principal contribution of this study is empirical evidence, from a UAV-based classification task rather than correlation analysis alone, that a parsimonious combination of one structural and one physiological index can likely retain most of the discriminative power of the full seven-index set for rice-condition monitoring on volcanic lowland soils, while indices such as GNDVI may be redundant in similar settings.

These conclusions should be interpreted with appropriate caution given the limitations of the dataset: the ground-truth sample comprised only 43 points across four imbalanced classes, single-site and single-season sampling, and the wide confidence interval around the reported accuracy. The predictor-to-sample ratio (seven indices evaluated against roughly 30 training points) is itself a limitation, since permutation-based variable importance is known to become less stable as this ratio increases, particularly among correlated predictors (Strobl et al., 2008; Gregorutti et al., 2017); the resulting importance ranking should accordingly be treated as a first indication rather than a precise or final ordering. In addition, the cross-validated model's test-set accuracy and the baseline model's test-set accuracy were both evaluated on the same held-out partition rather than on independent samples, so their numerical agreement demonstrates consistency on this particular split rather than independently replicated performance; repeated or nested cross-validation would provide a more robust estimate. Future research should therefore validate these index-redundancy and importance patterns using larger and multi-temporal ground-truth datasets spanning multiple rice growth stages and additional sites with contrasting soil types, incorporate direct field measurement of leaf chlorophyll and nitrogen content (e.g., SPAD readings) to confirm the physiological interpretation of CI and NDRE, re-evaluate variable importance on the vegetated-only subset to disentangle PVI's canopy-detection role from its within-canopy discriminative power, and test whether a reduced two- or three-index model achieves classification accuracy statistically comparable to the full seven-index model. Such validation would strengthen the evidence base for adopting minimal, non-redundant vegetation-index sets in operational UAV-based rice field monitoring.

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