

MULTISPECTRAL IMAGING FOR RICE HEALTH IN FERTILE ALLUVIAL PLAIN OF SOUTHEASTERN FLANK MERAPI VOLCANO

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ABSTRACT

Food security is a pressing issue in Indonesia, where challenges in land suitability and crop productivity are exacerbated by rice diseases and pests. This study aims to detect and analyze rice diseases and pests in southeastern Mount Merapi, Klaten Regency, using UAV technology to support sustainable agriculture. The research establishes an integrated framework for precision agriculture by combining a region Land Potency Index (LPI) with UAV-based multispectral monitoring to address these challenges. The LPI, assessing slope, lithology, soil, water, and hazard exposure, strategically identified the central zone of Klaten Regency as the area with the highest agricultural potential, thereby optimizing the focus for subsequent detailed analysis. Within these high-potential zones, UAV-derived vegetation indices (NDVI and NDCI) served as effective early-warning indicators. The analysis revealed a clear distinction where healthy rice plants consistently exhibited $NDVI > 0.6$ and $NDCI > 0.5$, while significant clusters fell below these thresholds. Crucially, field validation confirmed that these low-value clusters were predominantly associated with leaf blast disease, demonstrating the method's efficacy in pinpointing specific physiological stress. The widespread prevalence of blast in high-potential areas underscores a direct and significant threat to regional yield. Therefore, this study demonstrates that the integration of LPI for targeting and UAVs for diagnosis provides a scalable, data-driven workflow. The findings highlight the critical need for management strategies that leverage this early detection capability to implement timely interventions, such as the use of resistant varieties and balanced fertilization, thereby enhancing the sustainability and resilience of rice production systems in Indonesia and similar agro-ecological contexts.

Keywords: Multispectral drone; LPI; NDVI; NDCI; Leaf blast.

1. INTRODUCTION

Food security is a pressing global issue that affects developed countries, developing countries, and even the very poor nations (Fada et al., 2024; Sundram and Brennan, 2024). Similarly, in Indonesia, with its diverse geography and rapidly growing population, the country faces significant challenges in ensuring a stable and sustainable food supply. Key factors in addressing these challenges include land availability and suitability, agricultural commodities and productivity, as well as food accessibility (Sundram and Brennan, 2024). The proper selection of land for agricultural effectiveness and productivity is crucial. Although Indonesia's tropical climate offers advantages for agriculture, its diverse topography requires appropriate agricultural techniques for optimal utilization (Pereponove et al., 2023; Hariyanto et al., 2025; Atapattu et al., 2025). In addition, the diversity of landforms, which are the surface manifestations of morphological units, materials, and geomorphic processes that form or transform them over time, results in varied land resources (Migoñ and Jancewicz, 2024; Jawabreh et al., 2025).

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There are two main factors causing crop losses in all regions, namely “rice diseases and pests” and “outdated equipment” (Yuan et al., 2024; Junaid and Gokce, 2025). Diseases and pests in rice agriculture have long been a concern, and they have recently gained more attention due to their increasing frequency and severity caused by climate change (Karmakar et al., 2022; Oraon et al., 2024). Rising temperatures lead to changes in the behaviour of pests and pathogens, affecting their ability to damage rice crops. Various strategies have been previously implemented to protect rice crops from diseases and pests. Integrated Pest Management (IPM) is the most ideal approach to curb the rapid increase in rice diseases and pests due to climate change, having shifted toward more sustainable and environmentally friendly method by reducing reliance of chemical pesticides (Tiwari, 2024; Abdollahzadeh and Sharifzadeh, 2024). However, its adoption in developing countries like Indonesia is hindered by financial constraints, high initial costs, and the inherent complexity and labor-intensive nature to IPM strategies compared to traditional methods. Currently, advanced technology can be used to improve the quality of agricultural yields without human presence, including disease and pest prevention (Ma et al., 2024). Remote sensing has become a powerful tool for identifying and monitoring plant diseases and pests to improve agricultural productivity. Many academics have achieved satisfactory results in mapping disease damage using satellite imagery (Ma et al., 2024; Dolatabadian et al., 2025). However, Technological solutions often face scalability issues, for instance, smart farming applications are typically limited to small areas, while satellite imagery can be constrained by its spatial and temporal resolution, leading to mismatches between field data and image pixels.

Rapid advances in remote sensing, supported by wider access to multispectral imagery and improved image processing algorithms, are enabling more complex applications in environmental monitoring and surveying, including agriculture sector (Fakriyah et al., 2023; Sabir et al., 2024; Wang et al., 2025; Nguyen et al., 2025). Remote sensing technology and Unmanned Aerial Vehicles (UAVs) offers innovative solutions in agricultural management.

Remote sensing has capability to extract spatial data rapidly over wider area. Thus, the Land Potency Index (LPI) can be generated and used for the preliminary identification of ideal agricultural land. The LPI Integrates six critical physical parameters-slope, lithology, soil type, surface water, ground water, and hazard exposure to systematically identify and map high potential agricultural zones. Meanwhile, multispectral drones provide significant advantages for monitoring rice pests and diseases. Their ability to capture images in various wavelengths beyond the visible spectrum enables early detection of plant health issues that are invisible to the naked eye. This enhanced detection capability results in more accurate assessments of pest manifestations and disease symptoms. In addition, drones can cover large areas quickly and efficiently, providing comprehensive data across vast rice fields that are difficult to inspect manually. Rapid analysis and timely decision-making can help control pest and disease outbreaks before they spread widely. The objective of this study is to identify and analyse rice diseases and pests on the southeastern flank of Mount Merapi, Klaten Regency, Central Java-a key rice producing region on a fertile alluvial plain where protecting yields is crucial for maintaining national food security.

2. STUDY AREA

Klaten Regency, located in Central Java, Indonesia, is strategically situated between two major urban centers—Yogyakarta to the west and Surakarta (Solo) to the east—making it an important transitional zone for economic, cultural, and transportation linkages in the region. Geographically, it lies between the volcanic highlands of Mount Merapi in the northwest and the extensive lowlands in the southeast. Elevation varies considerably, from over 1,000 meters above sea level on the steep volcanic slopes to less than 100 meters in the flat eastern plains. This elevational gradient produces a distinct topographic transition from rugged mountainous terrain to gently undulating hills and broad alluvial plains. Geologically, Klaten is dominated by Quaternary volcanic deposits from Merapi, including volcanic breccia, tuff, and andesite lava, which contribute to the region’s high soil fertility (Saputra et al., 2020). The uplands are characterized by Andisols with high porosity and excellent

water retention, well-suited for horticulture and perennial crops. In the lowlands, Inceptisols and Alfisols provide favorable conditions for intensive irrigated rice cultivation. The region's hydrology is shaped by river systems and irrigation channels descending from the volcanic slopes toward the plains, ensuring a reliable water supply for agriculture. These diverse physical characteristics, combined with its strategic location, make Klaten a vital agricultural and socio-economic hub in Central Java. The overview of the study area is illustrated in **figure 1**.

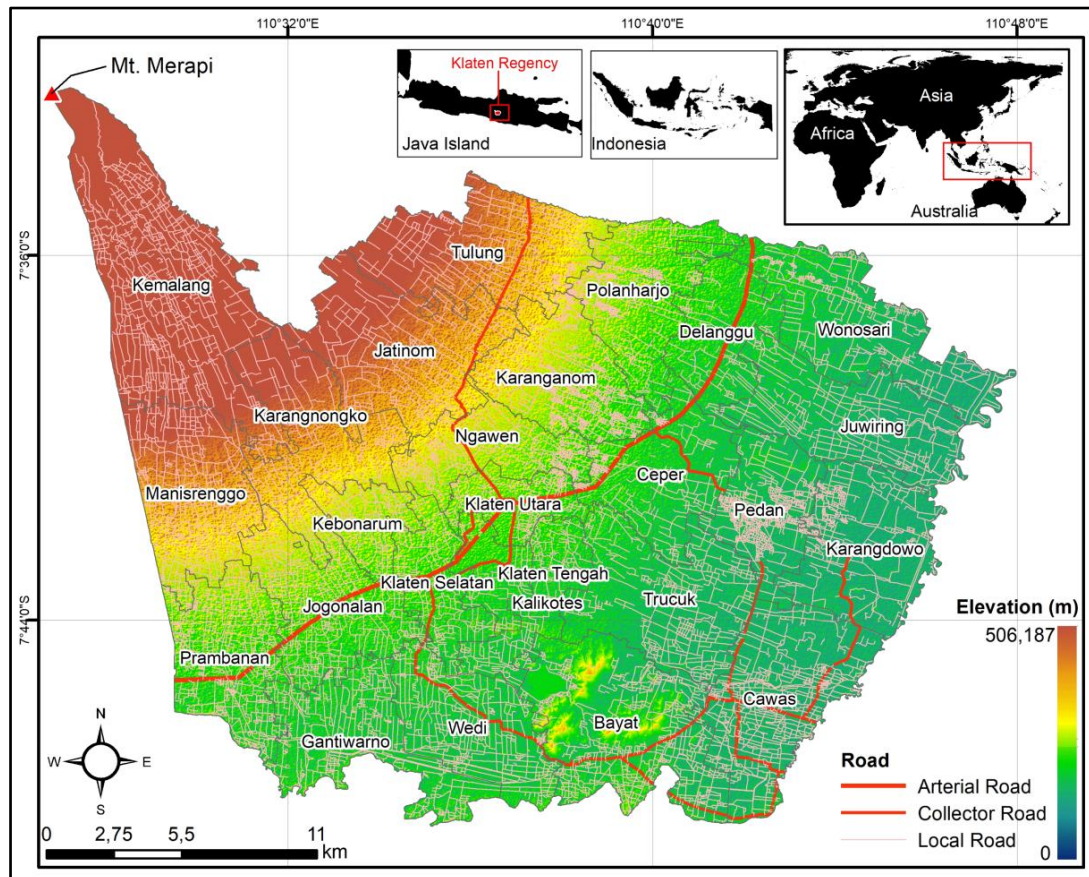


Fig. 1. Overview of Klaten Regency.

3. DATA AND METHODS

3.1. Rice Field Selection

Preliminary analysis was conducted to select the field of rice crop. The specific rice crop field was selected by using Land Potency Index (LPI). LPI was conducted in entire area of Klaten regency to identify which land has high LPI and low LPI. High LPI indicate that the land has high potency for agriculture activity, vice versa, the low LPI indicates that the land has low potency for agricultural activity due to particular factors. At least 6 parameters were used in this analysis to generate the LPI in entire Klaten Regency such as slope, lithology, soil type, surface water, ground water, and hazard condition in this case the volcano and flood hazards). The summary of the data used for extract the LPI in the study area can be seen in **table 1**.

Further analysis was conducted by applying the drone multispectral survey to obtain the level of healthiness of rice plant in study area. The high LPI area was analysed by using NDVI from multispectral drone. Additionally, physiology observation of rice plant was also conducted to identify type of disease and pests that might be found in observed paddy field.

Table 1.

The data used.

No	Data	Format Data	Scale	Source and year Provided
1	Geospatial data	Shp (vector)	1:25.000	Indonesia Geospasial Information Agency, 2010
2	Topography data	Shp (vector)	1:25.000	Indonesia Geospasial Information Agency, 2010
3	Indonesian DEM	Raster	8.3 m (Spatial Resolution)	Indonesia Geospasial Information Agency, 2022
4	Disaster data at regency level	Tabular	Regency Level	BPD P Klaten Regency, 2024

3.2. Land Potency Index (LPI)

Land potency index (LPI) was used to decide which paddy field will be observed further by using multispectral drone. LPI was obtained by overlaying 6 parameters such as slope, lithology, soil, surface water, groundwater, and hazards exposure. The general formula of LPI can be seen as follow:

$$LPI = (R + L + H) \times B \quad (1)$$

where:

LPI -Land Potency Index;

R -Slope;

L -Lithology;

H -Hydrology (Groundwater and Surface Water Condition)

B -Hazards exposure

The slope was generated from Indonesia Digital Elevation Model of known as DEMNAS. DEMNAS is an integrated elevation dataset, synthesized from multiple sources including IFSAR (5m resolution), TERRASAR-X (5m resolution), and ALOS PALSAR (11.25 m resolution). By amalgamating these diverse data sources, DEMNAS achieves a spatial resolution of 0.27 arc-seconds or approximately 8.3 m (Susetyo, 2023). The lithology of Klaten Regency was mainly extracted from the Geological Map of Yogyakarta and Surakarta Scale 1:100,000. The previous research results such as (Saputra et al., 2020) also used to obtain mode detail information of geology.

Regarding the hydrological aspect, two key factors are considered: surface water potential and groundwater potential. Surface water potential is assessed based on the abundance of surface water sources — such as rivers, lakes, and reservoirs — within a given area and the feasibility of irrigation development. Groundwater potential, conversely, is evaluated based on aquifer productivity, with data sourced from the groundwater basins of the Klaten region. Areas characterized by a high abundance of surface water, high feasibility for irrigation, high groundwater productivity, and extensive aquifer distribution are considered to have high land potential.

From a disaster aspect, volcanic activity, landslides, earthquakes, and floods were considered in determining the Land Potency Index (LPI) for Klaten Regency, given the historical occurrence of these four hazards in the region. Volcanic hazards were excluded from the overlay process because the entire Klaten area exhibits a uniform ground shaking potential, characterized by low to moderate Peak Ground Acceleration (PGA). Regarding flood susceptibility, areas prone to flooding are predominantly located in the southern part of the regency, adjacent to the rivers that form the border between Klaten Regency and Gunungkidul Regency in the Special Region of Yogyakarta.

The results of the Land Potential Index (LPI) assessment using the formula will produce a value that determines the potential of a particular land area based on the weight of each parameter. The values obtained through the calculation are classified into several land potential classes, each with different value ranges. The land potential index classes are divided into five categories as shown in **table 2** below.

Table 2.

Land Potency Index (LPI) Class.			
No	Class	LPI Class	LPI Value
1	I	Very High	32-40
2	II	High	24-31.9
3	III	Medium	16-23.9
4	IV	Low	8-15.9
5	V	Very Low	0-7.9

3.3. UAV Data Acquisition and Image Analysis

The multispectral drone mapping was conducted in rice fields with high LPI values to prioritize monitoring of high-yield potential areas. The Area of Interest (AoI) was selected based on safe flying zones, accessibility for ground validation, and a uniform late vegetative-early generative crop stage to ensure spectral variations reflected plant health. The flight mission was planned and executed using GSPRO software. In GSPRO, a double-grid (nadir) flight pattern was configured with 80% front overlap and 70% side overlap to ensure comprehensive coverage and robust data for photogrammetric processing. The mission was flown at an altitude of 80 meters AGL, achieving a ground sampling distance (GSD) of approximately 4.23 cm/pixel, a resolution sufficient for detecting intra-canopy stress. Manual pilot control, when necessary, was conducted using DJI Fly software.

Flight parameters such as altitude, overlap, and route must be set using flight planning software to ensure comprehensive coverage and high resolution. The UAV platform used was a DJI P4 Multispectral RTK, which features an integrated multispectral imaging system. This system is equipped with an integrated sunlight sensor that records solar irradiance during flight. This system captures synchronized imagery in five discrete bands: Blue (450 nm $\pm$ 16 nm FWHM), Green (560 nm $\pm$ 16 nm FWHM), Red (650 nm $\pm$ 16 nm FWHM), Red Edge (730 nm $\pm$ 16 nm FWHM), and Near-Infrared (840 nm $\pm$ 26 nm FWHM). All flights were conducted under stable, clear-sky conditions to minimize variations in illumination.

Ground Control Points (GCPs) must be placed throughout the field, with their precise coordinates recorded using high-precision GPS to improve georeferencing accuracy. A network of five (5) GCPs, constructed from high-contrast material, were distributed across the AOI's perimeter and center. Their coordinates were surveyed using a Real-Time Kinematic (RTK) GPS receiver (DRTK2) with a horizontal accuracy of ± 1 cm + 1 ppm and a vertical accuracy of ± 1.5 cm + 1 ppm. This high-precision ground truthing is essential to correct for geometric distortions in the model and achieve an absolute spatial accuracy of under 5 cm RMSE, ensuring that identified stress zones can be reliably relocated in the field.

Finally, a thorough pre-flight check of the drone must be conducted, including checking battery levels, propeller conditions, and camera functionality, as well as ensuring all software systems are working properly and there is sufficient data storage (Saputra et al., 2022). The captured multispectral imagery was processed using a standard SfM photogrammetry workflow in DJI GS PRO. The Radiometric calibration was performed to convert the raw digital numbers (DN) to reflectance values using the sunlight data. The captured multispectral imagery and the concurrent solar irradiance data from the drone's sunlight sensor were processed in Agisoft Metashape Pro 2.2.2. The 'Sun Sensor Calibration' tool was activated, which uses the irradiance data to normalize the imagery for variations in sunlight intensity, generating a calibrated surface reflectance orthomosaic for each band. This process is a core function of the integrated DJI system for achieving accurate spectral measurements without a ground reflectance panel. The key computational steps included: (1) Initial Processing for feature point matching and generation of a sparse point cloud; (2) Point Cloud Densification to create a 3D model of the terrain and canopy; and (3) Digital Surface Model (DSM) and Orthomosaic Generation. The final outputs, the 5-band orthomosaic and the DSM, were then exported for spectral

analysis in a GIS environment, where pixel-based calculations for NDVI and NDCI were performed using their standard formula. Normalized Difference Vegetation Index (NDVI) and Normalized Difference Chlorophyll Index (NDCI) was calculated as:

$$NDVI = \left(\frac{NIR-Red}{NIR+Red} \right) \quad (2)$$

$$NDCI = \left(\frac{Red_Edge-Red}{Red_Edge+Red} \right) \quad (3)$$

Addressing each of these elements carefully will lay the foundation for an effective and accurate mapping operation. In general, the workflow of this stage of research can be seen in **figure 2** below.

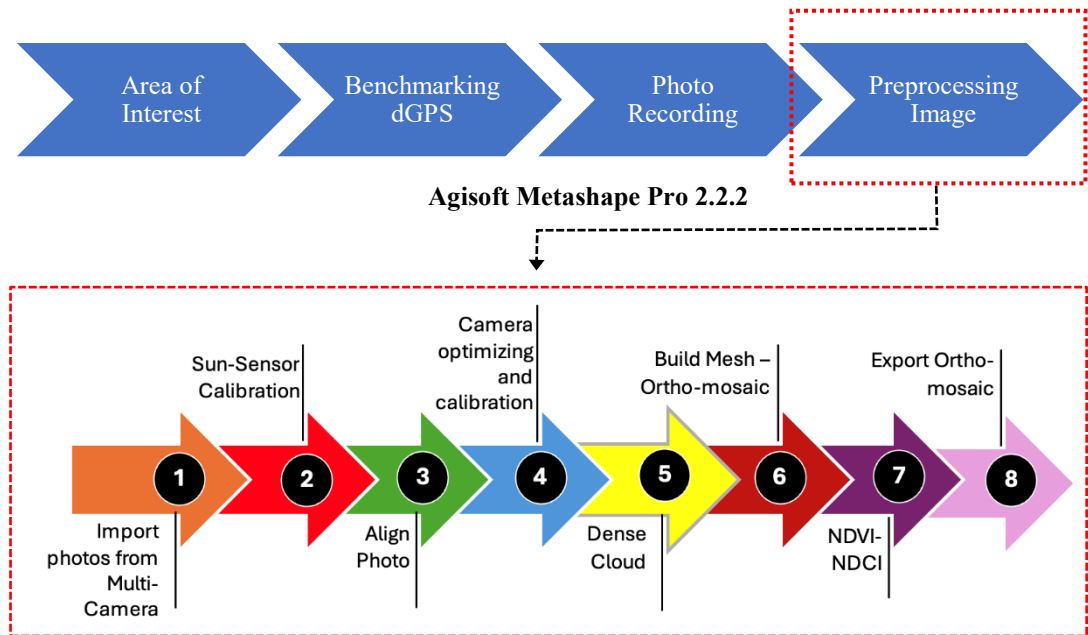


Fig. 2. The multispectral drone mapping and image analysis work flow.

3.3. Field Observation

The field observation was conducted to obtain the ground truth data. The colour stratification from the preliminary NDVI and NDCI map was used to design the sample. The field survey will be conducted using a modified version of disease identification through physiological symptoms in rice plants based on colour stratification. Disease diagnosis through physiological symptoms will be identified based on the symptoms presented in **table 3**. At least 50 georeferenced sampling points (N=50) were randomly selected, ensuring a representative spatial distribution across the entire field. The sampling unit was an individual rice plant at the specified location.

At each sampling point, the designated rice plant was visually assessed for symptoms of Leaf Blast. The assessment was based on the presence of characteristic lesion as described in Table 3 (Masnilah et al., 2020). A binary scoring system (0/1) was used. Score 1 (Diseased) was assigned if one or more typical Leaf Blast lesions such as spindle-shaped, with grey centers and brown/necrotic margins were observed on any leaf of plant. Meanwhile, score 0 was assigned if no Leaf Blast lesions were observed on any leaf, and the plant exhibited vigorous growth without signs of chlorosis or necrosis attributable to blast.

Table 3.

Symptoms and diagnosis of rice plants affected by viruses and pests.

No	Disease	Symptoms	Pathogen Diagnosis	Example
1	Leaf Blight (Masnilah et al., 2020)	Leaves become gray or grayish. Disease progression causes the leaves to dry and curl along the midrib	<i>Xanthomonas campestris</i> pv. <i>oryzae</i>	
2	Leaf Blast (Masnilah et al., 2020)	A sharp spot appears at the tip of the leaf, with brown edges and a grayish or white center. The spot continues to develop, surrounded by a pale yellow area."	<i>Magnaporthe oryzae</i>	
3	Leaf Spot (Rahmawati et al., 2017)	Dark brown spots appear on the leaves, with lighter brown edges. The rice grains turn yellow, and some of them become black.	<i>Fusarium</i> sp.	
4	Sheath Blight (Rahmawati et al., 2017)	The rice plant sheath becomes rotten with elongated lesions, yellow to light brown in color, and the base of the sheath turns greenish	<i>Rhizoctonia</i> sp.	
5	Narrow Brown Leaf Spot (Rahmawati et al., 2017)	Numerous small brown spots appear on a single leaf, with dark brown centers and lighter brown edges.	<i>Cercospora oryzae</i>	
6	Grain Rot (Widarti et al., 2020)	The rice grains turn dark brown, become soft and hollow, while the edges of the leaves turn reddish, surrounded by a yellowish rot-like color	<i>Burkholderia glumae</i>	

4. RESULTS

4.1. The Land Potential Index (LPI)

The Land Potential Index (LPI) is one of the analytical tools widely used in agriculture to assess land potential. Naturally, land with a high LPI ($LPI \geq 24$) has great potential if optimized for agricultural activities. Conversely, land with a very low LPI (0–7.9) has limited potential for agricultural use due to several limiting factors. In general, the Land Potential Index (LPI) is composed of several parameters, including slope, lithology, soil type, hydrology, and hazards condition.

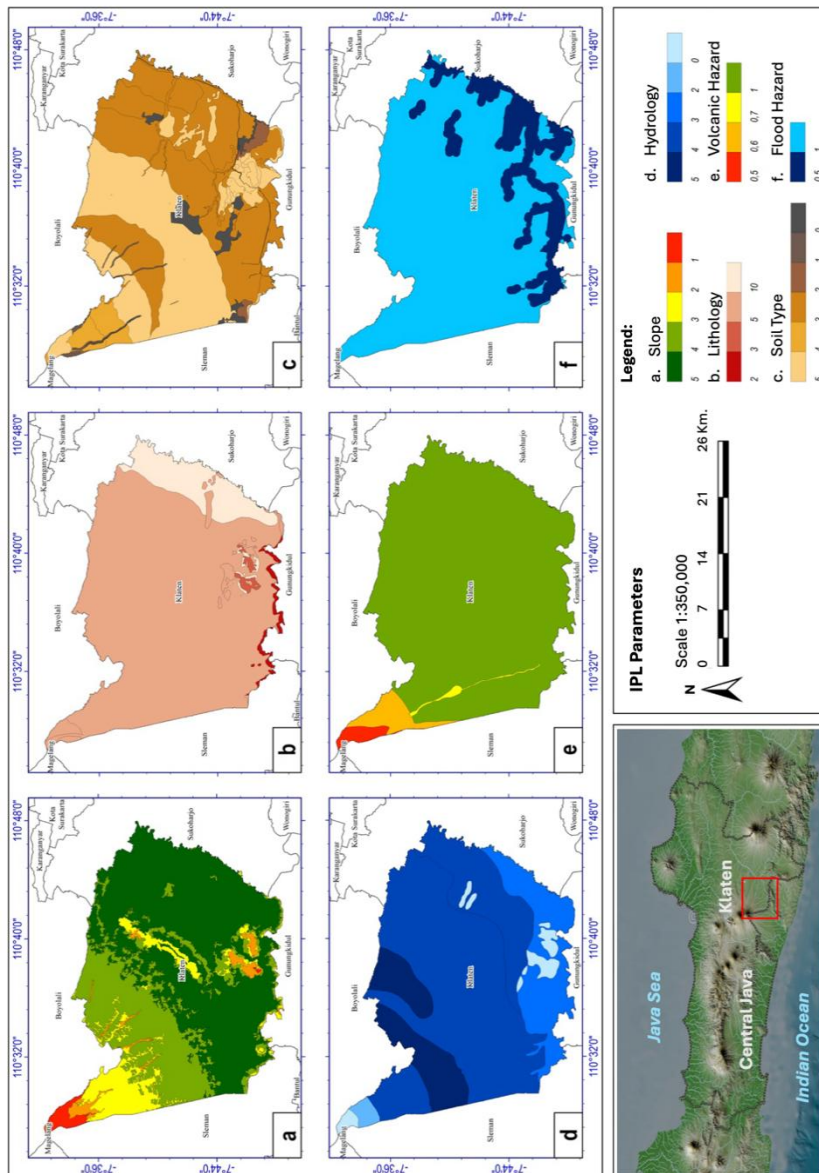


Fig. 3. The results of each parameter in term of LPI.

Gently sloping (0–5%) receives the highest score in the LPI assessment, as do alluvium-colluvium lithology, brown alluvial and Mediterranean soils, abundant surface water, highly productive groundwater, and areas free from natural hazards. The following presents the assessment results of each parameter in relation to land potential index.

Klaten Regency is predominantly characterized by an LPI slope score of 5, corresponding to slope class I with a gradient of 0–5% (flat to gently sloping). These flat-to-gently sloping areas are located in the central part of Klaten Regency, with geomorphology ranging from the volcanic foot plains of Mount Merapi to intensive alluvial plains. Steep to very steep slopes (slope > 45%) are found in the northern part of Klaten Regency, which is the cone of Mount Merapi. This area has an LPI slope score of 1. Moderately steep slopes are located in the northern and central-southern parts of Klaten Regency, namely on the upper slopes of Mount Merapi (north) and the Bayat sub-district area in the south.

Based on lithological aspects, Klaten Regency is mostly composed of volcanic rocks associated with Mount Merapi in the north. Additionally, there is a complex formation of rocks in Bayat Sub-district consisting of claystone sediments and metamorphic rocks. Alluvium and colluvium deposits are found along the narrow plains in the southern part of Klaten Regency, bordering the Baturagung Hills. The lithology or surface geology score classification of Klaten Regency can be seen in **figure 3**.

In the LPI (Land Potential Index) assessment, the soil aspect being evaluated is its texture, which refers to the ratio of sand, silt, and clay. Fine soil textures indicate that the soil is a result of denudational processes that have been accumulated and deposited. These denudational materials typically produce fine-textured deposits with high clay content. However, soils with high clay content are generally less favourable for agriculture. Similarly, soils with overly coarse textures are also less suitable for farming, as sandy soils have large pores and are unable to retain groundwater effectively. The LPI soil parameter scores for Klaten Regency can be seen in the following figure. Based on the LPI soil type scores, the highest scoring soil texture (score 5) is found in brown alluvial and Mediterranean soils, which have medium soil textures. These soil types are distributed in the central part of Klaten Regency and parts of the southern region.

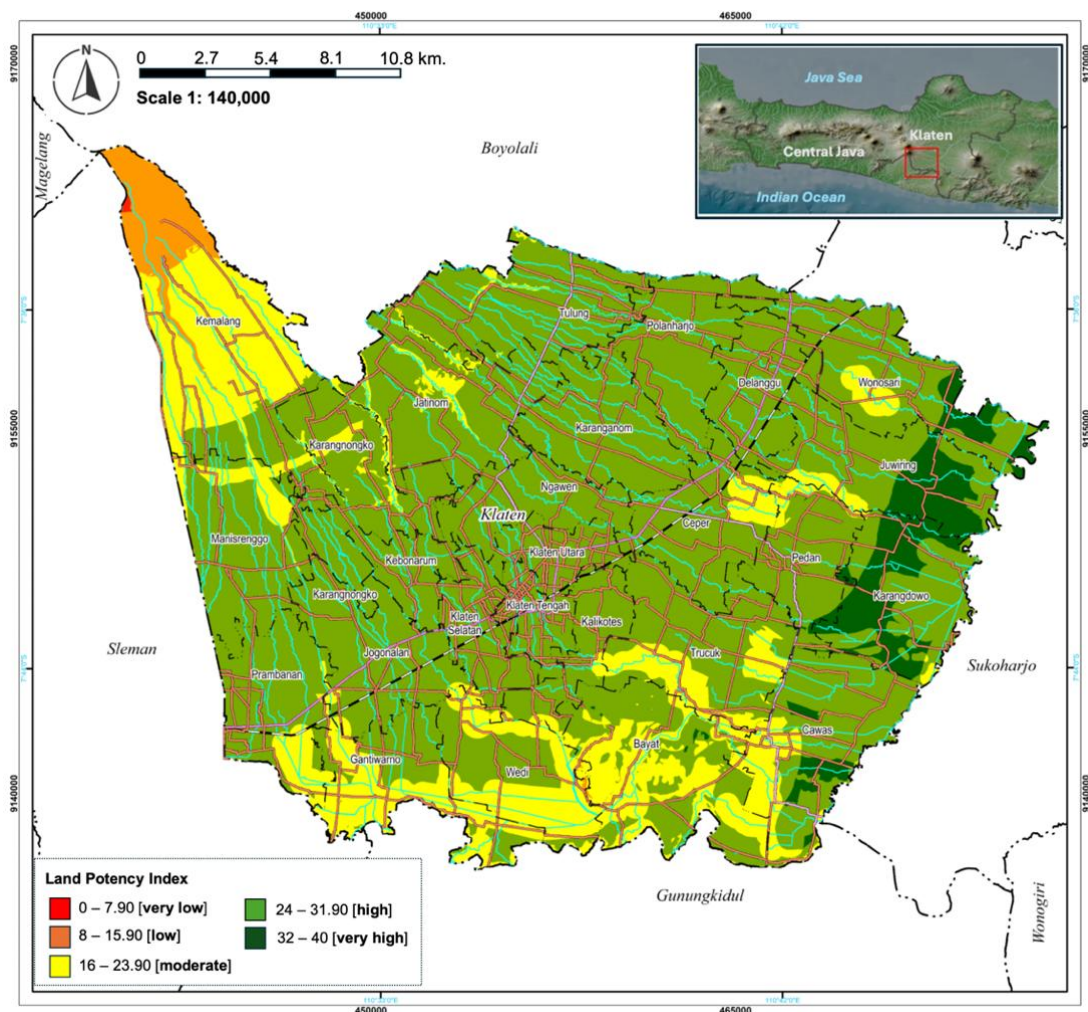


Fig. 4. LPI of Klaten Regency.

In relation to the hydrological aspect, two elements are considered: surface water potential and groundwater potential. Surface water potential is assessed based on the availability of surface water sources (rivers, lakes, and reservoirs) and the feasibility of developing irrigation. Groundwater potential is assessed based on groundwater productivity derived from the groundwater basin in the Klaten area. Characteristics that support high land potential include areas with abundant surface water resources, strong irrigation potential, and high groundwater productivity with wide distribution. The results of the hydrological assessment for LPI can be seen in **figure 3**. In terms of disaster aspects, volcanic eruptions, landslides, earthquakes, and floods are considered in determining the Land Potential Index (LPI) in Klaten Regency, as all four types of disasters have occurred in the area. Volcanic disasters were excluded during the overlay process because all areas of Klaten have similar ground acceleration (PGA) values, ranging from low to moderate. The disaster scores can be seen in **figure 3**. Areas prone to volcanic hazards are located in the northern part of Klaten Regency. These areas fall within Volcanic Hazard Zones 1 and 2. Meanwhile, the southern part of the region is prone to landslides. The central part of Klaten Regency, shown in green, is considered free from both volcanic and landslide hazards. Regarding flood hazards, flood-prone areas are located in the southern region, particularly around rivers that form the boundary between Klaten Regency and Gunungkidul Regency, in the Special Region of Yogyakarta Province.

Based on the overlay results using the formula described in Equation 1, the resulting Land Potential Index can be seen in **figure 4**. Based on the LPI Results, the drone mapping was conducted in the area which has LPI value very high in eastern part of Klaten Regency.

4.2. Multispectral drone results (NDVI and NDCI)

Multispectral drone mapping was conducted over three paddy field blocks selected specifically for their very high LPI classification, uniform late vegetative growth stage, and operational feasibility (safe flying zones, accessibility). This strategic selection ensured that spectral variations were primarily linked to plant health rather than underlying land constraints or phenological differences. The resulting NDVI and NDCI maps revealed distinct health patterns, with healthy rice exhibiting values >0.6 and >0.5 , respectively, while lower values indicated stress, corroborated by field observations of leaf blast disease.

At least three blocks of paddy field were mapped by using multispectral drone and observed further in the field. Those three blocks (**Fig. 6**, **Fig. 7** and **Fig. 8**) are belonged to very high LPI and cultivated as rice field. Based on the multispectral sensor, the drone mapping produce RGB orthophoto, Normalised Difference Vegetation Index (NDVI) and Normalised Difference Chlorophyll Index (NDCI). The Normalized Difference Vegetation Index (NDVI) is a widely used remote sensing indicator to assess vegetation health, including rice crops. In rice fields, high NDVI values (typically > 0.6) indicate dense, healthy, and photosynthetically active crops, while lower NDVI values suggest stress, disease, pest infestation, or poor growth due to insufficient nutrients or water (Liu et al., 2024; Safitri et al., 2024; Munandar et al., 2025)

The Normalized Difference Chlorophyll Index (NDCI) is a vegetation index specifically designed to estimate chlorophyll content, especially in aquatic or semi-aquatic vegetation like rice in paddy fields. This index is particularly sensitive to chlorophyll-a concentration, making it useful in monitoring crop vigour, nutrient status, and early signs of physiological stress. In rice crop health analysis, NDCI helps identify variations in chlorophyll levels that may result from nutrient deficiencies, diseases, or other stressors before these issues become visible. Compared to NDVI, NDCI can offer more nuanced insights into plant physiological conditions, especially in high-biomass or water-saturated environments (Li et al., 2024; Chen et al., 2024).

Based on the NDVI and NDCI of the observed paddy field. The NDVI of three paddy field ranging from 0-0.95.5. The lower the NDVI refers to the denser of rice crops while the lower value refers to the less dense of rice field. Several factor can affect the results of NDVI and such as, the different of plant, different rice crops ages, and land use change. In the observed rice field, low NDVI values were found due to those three factors. West Klaten famous by the extensive fertile agriculture area. Some of farmers also plant horticultural crops such vegetable, fruit, and ornament plants. Some

of theme use plastic mulch, which is widely used in horticulture to cover the soil surface for various benefits like moisture retention, weed suppression, temperature regulation, and improved crop quality. This area will likely result in relatively low NDVI values.

Different crop ages significantly influence NDVI values due to changes in plant structure, leaf area, and chlorophyll content throughout the growth cycle. In the early stages, crops are small with limited green biomass, resulting in low NDVI values. As the crops mature, the canopy becomes denser and chlorophyll levels increase, leading to higher NDVI values that reflect vigorous photosynthetic activity. However, during the senescence or harvesting phase, NDVI values decline again as leaves yellow, biomass reduces, and photosynthesis slows. Therefore, NDVI serves as a useful indicator to distinguish crop development stages and assess crop health over time.

There were two types of observed rice plant growth stages, vegetative ages (less than 45 days) and reproduction ages (between 45-70 days) (Fig. 5). Field observation and sampling was strategically restricted to a specific window of the crop cycle: from the late vegetative stage to the early generative stage in order to minimize the confounding effect of plant phenology on spectral indices. This ensured that the observed variations in NDVI and NDCI were more likely attributable to health status rather than the natural spectral differences between very young or senescing plants.

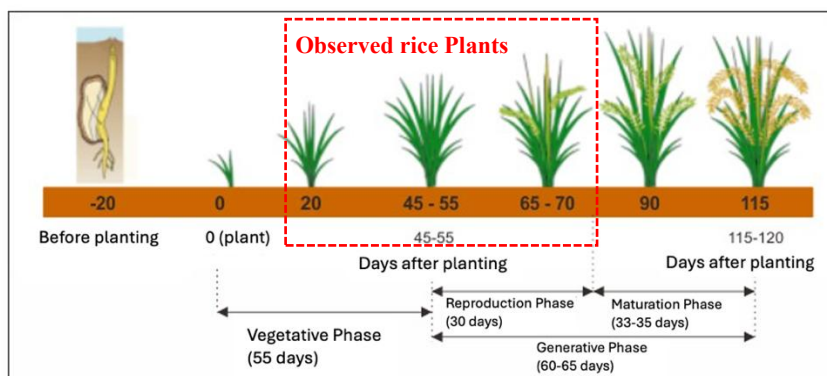


Fig. 5. Two types of rice plant phase observed in the field.

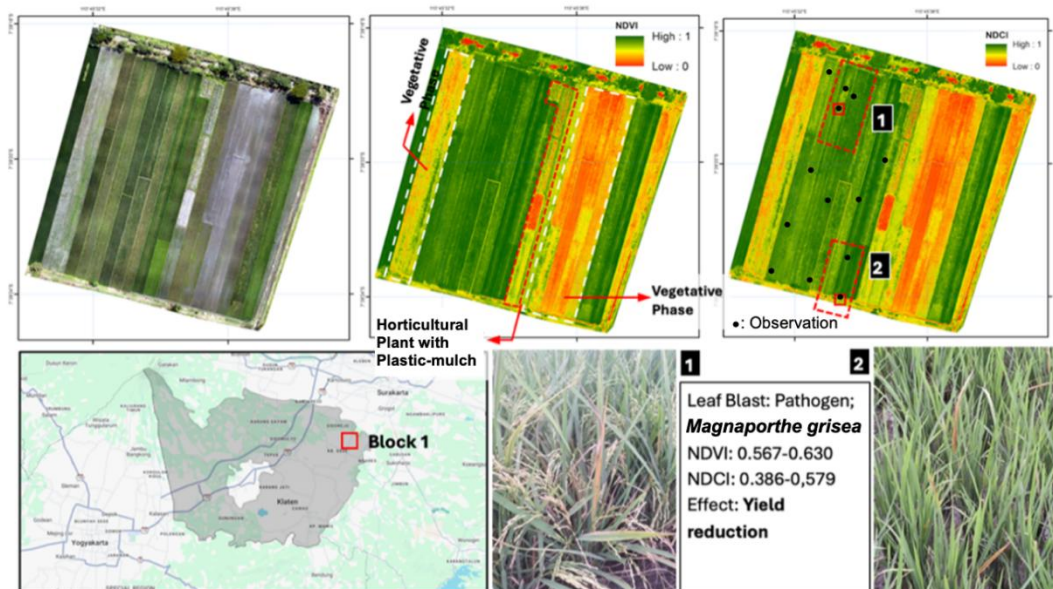


Fig. 6. The Multispectral drone results in Block 1.

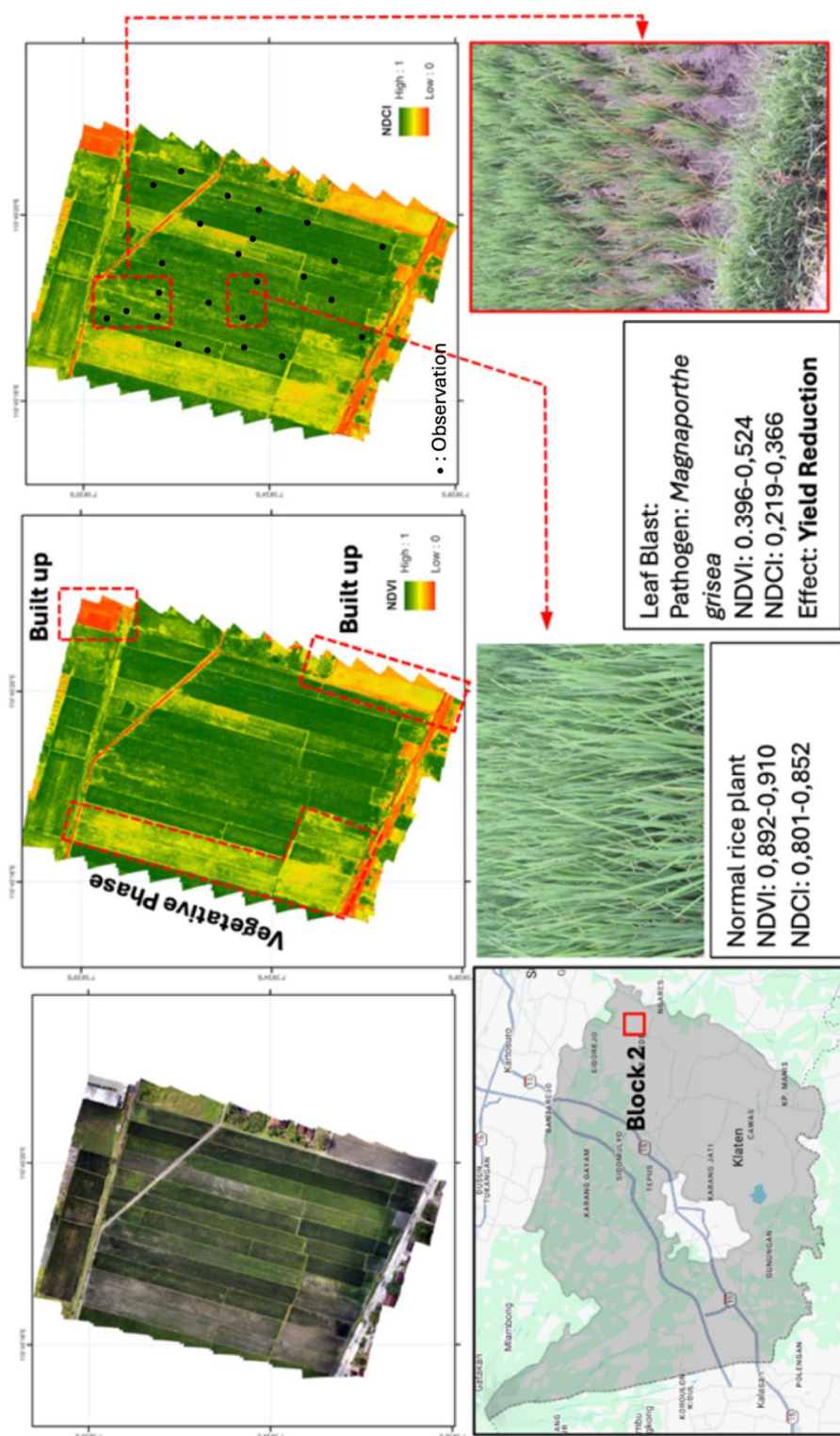


Fig 7. The Multispectral drone results in Block 2.

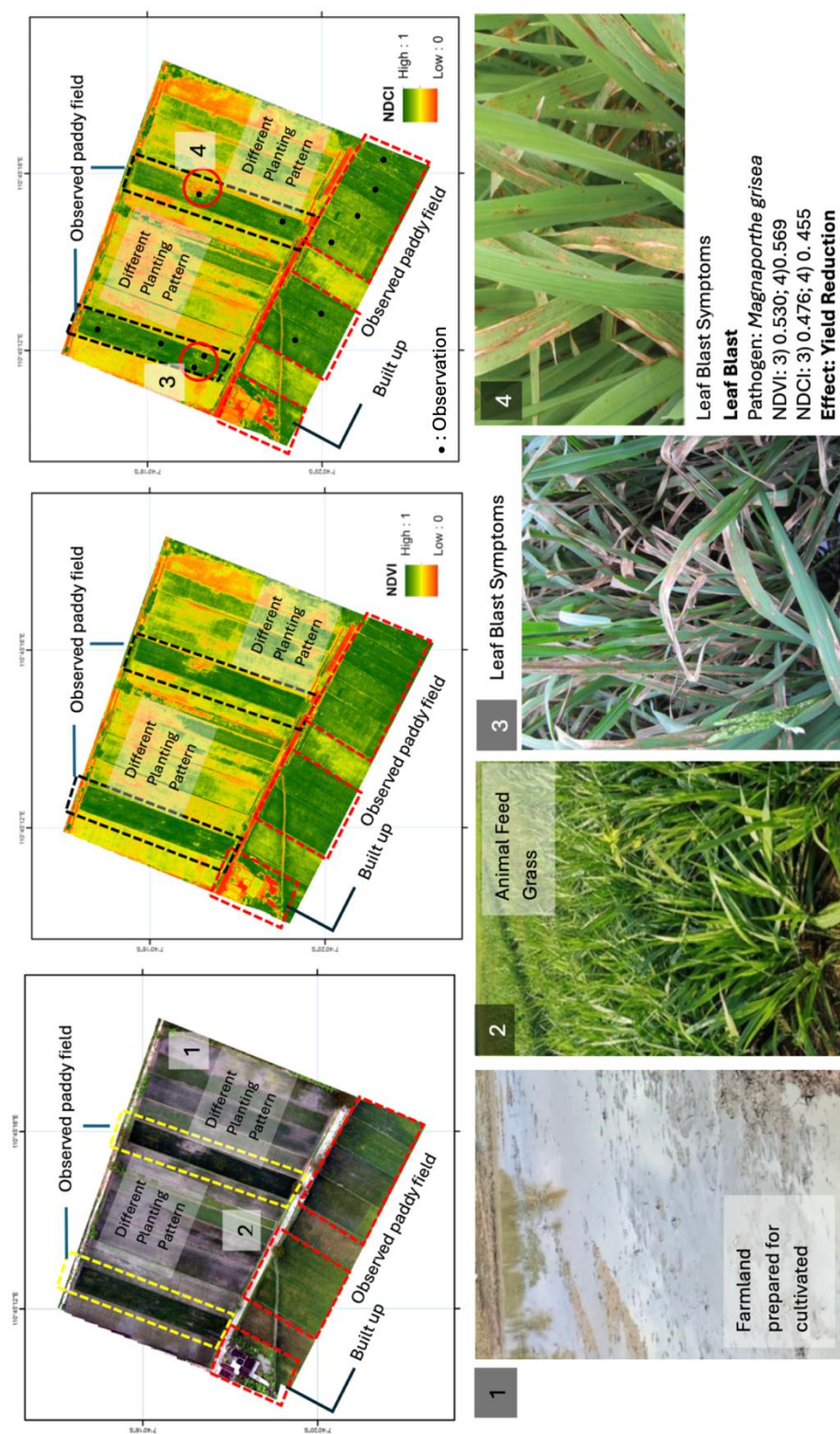


Fig. 8. The Multispectral drone results in Block 3.

Similar to NDVI, NDCI results can indicate the healthiness of rice plants. Low NDCI values, on the other hand, often point to stressed or aging crops, potentially caused by nutrient deficiencies, water stress, disease, or natural senescence. These areas may correspond with sections of the field showing poor growth or yellowing leaves. It is also possible that non-vegetated areas (e.g., bare soil, plastic mulch, or recently harvested plots) contribute to low NDCI readings. Therefore, analysing spatial patterns of NDCI across the field allows researchers to identify zones requiring further investigation or intervention, aiding in precision agriculture and crop health monitoring.

5. DISCUSSIONS

The results of this research demonstrate a clear distinction in vegetation index values between healthy and potentially diseased rice crops. Healthy rice plants generally recorded NDVI values above 0.6 and NDCI values above 0.5, reflecting vigorous growth, high chlorophyll concentration, and optimal physiological function. In contrast, certain spatial clusters exhibited NDVI values below 0.6 and NDCI values below 0.5, indicative of reduced chlorophyll content and possible physiological stress. Such reductions are commonly associated with early stages of disease, nutrient deficiency, or water stress. However, variations in NDVI may also be influenced by differences in rice growth stages across the study area. Younger rice plants in the early vegetative phase typically exhibit lower NDVI values due to incomplete canopy cover and less developed leaf area, while mature plants in the reproductive or grain-filling phases tend to reach higher NDVI values as chlorophyll concentration and biomass peak. Conversely, NDVI naturally declines in the late maturation stage as senescence begins and chlorophyll content decreases. Therefore, careful interpretation of NDVI results requires considering the crop calendar and planting synchrony to distinguish between stress-induced reductions and normal phenological variations.

A binary logistic regression was conducted to predict Leaf Blast (0/1) based on NDVI and NDCI. The model was trained on 50 observations. The model achieved an accuracy of 94.0% and an AUC of 0.976. McFadden's pseudo- R^2 was 0.676, indicating a strong relationship between the predictor and outcome (**Table 4**). The regression equation is provided as follow:

$$\text{Logit}(p) = 18.7398 - 5.4808 \times \text{NDVI} - 26.0514 \times \text{NDCI} \quad (4)$$

where:

$$\text{logit}(p) = \ln\left(\frac{p}{1-p}\right) \quad (5)$$

P is the probability of Leaf Blast = 1

Table 4.

Statistical model summary.

Statistic	Value
Pseudo R^2	0.6763
Log Likelihood	-10.58
AIC	27.15
BIC	32.89

The coefficient for NDVI (-5.4808) was not statistically significant ($p = 0.245$), suggesting that there is not enough evidence to conclude that NDVI is associated with Leaf Blast (**Table 5**). The coefficient for NDCI (-26.0514) was statistically significant ($p = 0.008$), indicating that for each one-unit increase in NDCI, the odds of Leaf Blast = 1 decrease by a factor of 0.000 (odds ratio). This means the probability of Leaf Blast = 1 decreases as NDCI increases. The intercept (18.7398) was statistically significant ($p = 0.003$). It represents the log odds when all predictors are 0, which corresponds to a probability of 1.000 for Leaf Blast = 1.

Table 5.

Regression Coefficient.					
Variable	Coefficient	Std Error	z-value	p-value	Odds Ratio
(Intercept)	18.7398	6.3646	2.9444	0.0032	137598386.2298
NDVI	-5.4808	4.7163	-1.1621	0.2452	0.0042
NDCI	-26.0514	9.7987	-2.6587	0.0078	0.0000

At the standard threshold of 0.5, the model correctly classified 94% of cases (Table 6).

Table 6.

Classification Results.	
Metric	Value
Accuracy	94.00%
Sensitivity (True Positive Rate)	88.89%
Specificity (True Negative Rate)	96.88%
AUC (Area Under ROC Curve)	0.9757

The area under ROC curve (AUC) of 0.976 suggests excellent discriminative ability (Fig. 9).

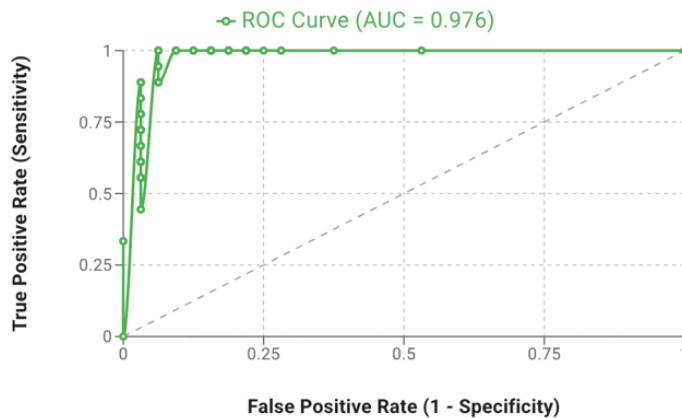


Fig. 9. ROC Curve.

Meanwhile the probability curve of each independent variable can be seen in figure 10. For multiple predictors, the probability depends on the combination of all predictor value.

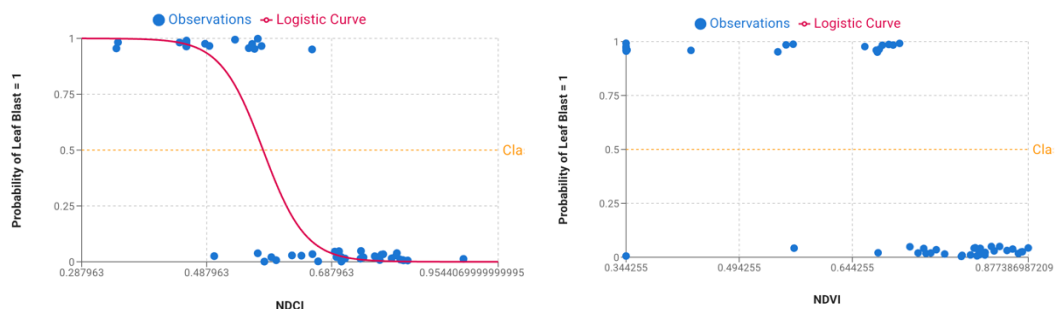


Fig. 10. (Left) Probability curve of NDCI; (Right) NDVI.

Field observations confirmed that leaf blast disease was prevalent across all paddy blocks, with visual symptoms such as elongated spindle-shaped lesions, chlorosis, and necrosis aligning closely with areas of low NDVI and NDCI values. The disease's widespread distribution suggests conducive environmental conditions—high humidity, warm temperatures, and frequent rainfall—which are characteristic of the study area during the growing season. In severe outbreaks, leaf blast can cause up to 50% yield reduction, primarily by reducing leaf area available for photosynthesis, shortening the tillering phase, and impairing panicle development (Asibi et al., 2019; Conde et al., 2025; Khadka et al., 2025; Younas et al., 2024). These physiological disruptions result in fewer spikelets, lighter grains, and ultimately lower harvest weight. The spatial pattern analysis further supports the capability of NDVI and NDCI as effective early warning indicators. Both indices are sensitive to changes in leaf pigment concentration and canopy structure, allowing detection of sub-visual symptoms before they become apparent to the naked eye. This early detection is critical because timely intervention—within days rather than weeks—can significantly reduce the spread and severity of the disease.

The study's approach, which integrates UAV-based multispectral with targeted field validation, aligns with growing trend in precision agriculture yet offer specific advantages. Unlike satellite-based studies which can be constrained by cloud cover and fixed revisit schedules (Inoue, 2020; Phang et al., 2023), UAVs Provide on-demand, high-resolution data crucial for capturing the fine-scale heterogeneity of smallholder farms. Our findings are consistent with Mandal et al. (2022) who also reported strong correlations between NDVI dan blast incidence. However, our work specifically highlights the NDCI's sensitivity to the physiological stress caused by blast, potentially offering a more direct measure of photosynthetic apparatus health than the structural focus of NDVI. A key limitation, however, is the operational scope. While highly effective for village or sub-district level monitoring, scaling this method to a provincial or national level would be logistically and computationally challenging with UAV technology. A promising hybrid solution for larger-scale monitoring would be to use satellite imagery for broad surveillance, deploying UAVs for high-resolution follow-up in areas flagged as anomalous

The identification of zones with low NDCI values should trigger a precise and integrated management response. Specific treatments for these areas must be informed by on-ground diagnosis but primarily include: (1) the immediate application of systemic fungicides effective against *Magnaporthe oryzae* (e.g., containing tricyclazole or azoxystrobin) to curb fungal growth [Cite a fungicide efficacy study]; (2) a review of nitrogen fertilization practices, as excess nitrogen exacerbates blast susceptibility, suggesting a shift to split or controlled-release applications [Cite a study on N and blast]; and (3) ensuring proper water management to avoid prolonged leaf wetness, potentially by implementing alternate wetting and drying irrigation. To mitigate the risks posed by leaf blast disease in the long term, a broader integrated management approach is essential. The use of resistant rice varieties should be prioritized to reduce vulnerability to *Magnaporthe oryzae* infection. Proper planting spacing is critical to improve air circulation within the canopy, thereby lowering humidity levels that favor disease development. Timely and targeted fungicide applications, guided by the early detection protocol established here, can suppress pathogen spread while minimizing excessive chemical use. Effective field drainage systems should be maintained to prevent prolonged leaf wetness, which supports fungal proliferation. Additionally, balanced fertilization based on soil nutrient assessments is necessary. By combining these preventive measures with regular UAV or satellite-based monitoring and on-ground validation, farmers can implement a precision agriculture strategy that minimizes yield losses and sustains long-term productivity (Zhao et al., 2024).

6. CONCLUSIONS

This study established an integrated framework for agricultural assessment in Klaten Regency by combining a regional Land Potency Index (LPI) with field-scale UAV monitoring. The LPI, which synthesizes biophysical parameters, confirmed the central zone as highly suitable for agriculture due to its flat topography and abundant water resources, while the northern and southern regions were

constrained by steep slopes and natural hazards. Within these high-potential areas, UAV-based analysis revealed that healthy rice plants exhibit NDVI > 0.6 and NDCI > 0.5, whereas lower values correlated strongly with field-verified leaf blast disease, a major threat to yields. While effective for local monitoring, the UAV-based approach faces scalability limitations. Future efforts should therefore focus on developing a hybrid system using satellites for broad surveillance and UAVs for targeted diagnosis. Future work will also aim to scale this approach by including a wider range of LPI classes and phenological stages to build a more comprehensive and robust model. Ultimately, translating these findings into practical tools for farmers will be crucial to enhance sustainable crop management and food security beyond the study area.

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