ARTICLE

A multispectral imaging framework for early-stage modelling and precision estimation of rice plant density using MSAVI-derived fractional vegetation cover

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ABSTRACT

Accurate early-stage estimation of rice plant density is essential for precision crop management. However, current remote sensing methods face limitations in spatial resolution, revisit frequency, and sensitivity under sparse canopy conditions, highlighting the need for scalable, high-resolution UAV-based approaches. This study presents a UAV-based multispectral imaging framework for early-stage rice plant density estimation, proposing a scalable and cost-efficient solution for precision agriculture. Fractional vegetation cover derived from the Modified Soil Adjusted Vegetation Index (MSAVI) was used as the primary predictor variable in linear regression modelling. UAV imagery was acquired across varying flight altitudes (15–30 m) and crop growth stages (14–32 DAS). Five-fold cross-validation results shows that accuracy improved with crop development, with notable gains between 14 and 20 DAS. During the early vegetative stage, RMSE ranged from 39-41 plants/m^2 and MAPE averaged ~30%, reflecting moderate predictive accuracy caused by sparse canopy cover and strong soil interference. As the crop progressed to early tillering, prediction error declined, with RMSE improving to approximately 30 plants/m^2 and MAPE decreasing to about 29%. This improvement was attributed to denser canopy structure and stronger spectral separation between vegetation and background soil. Further analysis identified 18–25 DAS as the optimal developmental window for reliable plant density estimation, wherein models achieved high coefficients of determination (R^2 = 0.9139–0.9395) and the lowest RMSE (34 plants/m^2). No significant differences were observed among flight altitudes, suggesting higher-altitude flights can maintain accuracy while improving operational efficiency and coverage.

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INTRODUCTION

Rice is a major global staple crop globally, particularly in Asia where it is a primary source of food and livelihood (Mohidem et al. 2022). As global demand for rice increases and agricultural land becomes more constrained, precision agriculture technologies are increasingly adopted to optimize crop management and improve productivity (Karunathilake et al. 2023). Among these technologies, unmanned aerial vehicles (UAVs) equipped with multispectral sensors have emerged as a powerful tool for non-destructive crop monitoring, offering the ability to rapidly assess plant growth, density, and health over large field areas (Hafeez et al. 2022; Aierken et al. 2024; Santos et al. 2025).

In rice production systems, where early detection of planting uniformity and emergence patterns can significantly influence yield outcomes, timely and scalable assessment tools are increasingly valuable (Mba et al. 2025). Early-stage estimation of rice plant density is crucial in evaluating seeding performance, diagnosing poor emergence, and guiding timely interventions (Li et al. 2024; Negi et al. 2024).

However, traditional methods such as manual plant counting and ground-based sampling are labour-intensive, time-consuming, and prone to sampling error, particularly in large or heterogeneous fields (Bai et al. 2022; Abu Bakar et al. 2017). These limitations restrict their practicality and reduce their reliability for precision management. In many rice-producing countries, including the Philippines, plant density estimation at the field level is still commonly carried out through direct human observation and visual scoring by farmers or technicians. While such practices are accessible, they are subjective, inconsistent across observers, and difficult to implement effectively on large-scale or mechanized

KEYWORDS

plant density, multispectral imaging, MSAVI, image processing

farms, further emphasizing the need for objective, technology-driven solutions (PhilRice, n.d.).

Remote sensing is scalable, but key challenges remain. Satellite-based approaches are limited by coarse spatial resolution, long revisit cycles, and cloud interference, reducing their effectiveness for early-stage monitoring (Soriano-González et al. 2022; Liu et al. 2022). While UAV-based imaging can overcome many of these constraints, existing analytical pipelines often rely on computationally intensive algorithms, advanced expertise, or later-stage canopy development for accurate results (Bai et al. 2022; Yang et al. 2025). During early crop establishment, sparse vegetation cover, soil background effects, and variability in planting patterns can reduce the sensitivity of vegetation indices and limit the accuracy of current remote sensing methods (Yang et al. 2025; Liu et al. 2023; Sun et al. 2024). Consequently, a methodological gap persists between the need for accurate, timely estimation of rice plant density and the capabilities of currently available tools.

Addressing these limitations is critical because early-stage plant density strongly influences subsequent management decisions, including replanting, nutrient management, and water allocation, all of which directly affect yield and resource-use efficiency. Without accurate and accessible monitoring approaches, farmers risk delayed interventions, suboptimal input use, and yield penalties (Bai et al. 2022; Abu Bakar et al. 2017). This underscores the need for operationally feasible, cost-effective methods that can provide reliable density estimates at the critical establishment phase of rice cultivation.

UAV-based multispectral imaging allows for the collection of high-resolution vegetation data that can be processed into vegetation indices (VIs). Recent advances have enabled these indices – such as NDVI (Normalized Difference Vegetation Index), MSAVI (Modified Soil Adjusted Vegetation Index), and others – to infer crop biophysical traits at various stages of crop development (Zhang et al. 2025; Asawapaisankul et al. 2025). Developments in precision agriculture have shown that these spectral indices are sensitive to variations in canopy structure and plant density (Bhandari et al. 2023). Nevertheless, their application during early growth stages presents specific challenges that warrant consideration. At low canopy cover, spectral signals are often influenced by background soil reflectance and surface water conditions, which can moderate the response of conventional indices (Wayal et al. 2026). In addition, the incremental changes in vegetation signal associated with small variations in plant density may be less pronounced at early growth stages, as soil background often dominates spectral responses (Ai et al. 2025; Morales-Oña et al. 2025; Zhang et al. 2025), thereby requiring indices that are more robust to soil and illumination effects. In response to these limitations, recent developments, such as soil-adjusted indices like MSAVI and the integration of high-resolution UAV data, have improved sensitivity under these conditions (Zhang et al. 2025).

Fractional vegetation cover (FVC) has been widely adopted in remote sensing applications as a practical indicator of canopy development, owing to its intuitive representation of the proportion of vegetated area within a given pixel (Ma et al. 2021). In this context, integrating FVC with MSAVI derived from UAV-based multispectral imagery provides a promising pathway for early-stage crop estimation, enhancing sensitivity under low vegetation conditions which may also reduce later-stage inaccuracies that may arise at later stages due to increased biomass and canopy overlap. This forms the basis of the study.

This study presents a multispectral imaging-based approach for the development of a linear regression model aimed at estimating rice plant density using vegetation pixels derived from UAV imagery acquired at varying altitudes. While a wide range of modelling techniques exists, linear regression remains an appealing option due to its simplicity, interpretability, and potential for integration into real-time monitoring pipelines (Teshome et al. 2023). By focusing on early growth stages, this study explores the viability of using lightweight, computationally accessible modelling strategies for early-stage field diagnostics.

The approach supports scalable assessments of seeding performance and inform precision management decisions during the critical establishment phase of rice cultivation. The results contribute to the growing body of research on remote sensing for agriculture and highlight the potential of combining UAV-based imagery with statistical modelling to improve precision management in rice production.

MATERIALS AND METHODS

Study Site and Crop Establishment

Site Selection

The study was conducted at Philippine Rice Research Institute (PhilRice) located at Maligaya, Science City of Muñoz, Nueva Ecija, Philippines. A total of forty-five (45) plots measuring 1.5 m x 1.5 m each were prepared for this research study.
The area experiences a Type I climate under the modified Corona classification, characterized by two distinct seasons: a dry season from November to April and a wet season from May to October. Average temperatures range from 22°C to 35°C, with peak rainfall typically occurring between June and September.

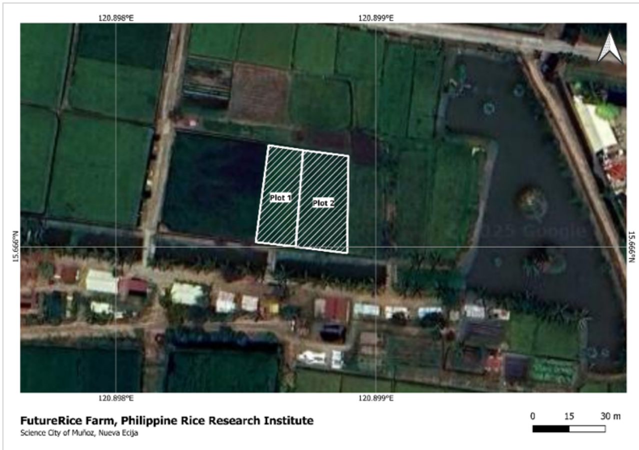


Figure 1: Location map of study site.

Experimental design

In this study, two plots were prepared to investigate the influence of key experimental factors—altitude and days after sowing (DAS)—on vegetation-based plant density estimation using UAV-acquired imagery. Plot 1 was used to evaluate whether altitude has a statistically significant effect on model performance. This initial analysis also helped identify the DAS range where plant density is most accurately and consistently captured, ensuring good canopy coverage for image-based analysis.

Based on the results of the preliminary tests, Plot 2 was then established to assess the effect of DAS in greater detail, particularly around 20 DAS range identified earlier. This allowed for a more focused investigation into how plant development over time influences model accuracy and vegetation index performance.

The experimental treatments included three sowing densities – 40 kg/ha, 60 kg/ha, and 80 kg/ha – based on the optimal ranges suggested by IRRI (n.d.). In addition to varying sowing densities, three commonly cultivated inbred rice varieties – RC 514, RC 604, and RC 622 – were included in the experiment. The inclusion of multiple varieties was essential to evaluate the model's robustness across different genotypic characteristics and to ensure that the model developed in this study can be broadly applicable and accurate regardless of the variety being grown.

Each treatment was replicated five (5) times, resulting in a total of forty-five (45) sampling units per plot, arranged in a randomized complete block design (RCBD). This replication enhances statistical reliability and ensures that findings can be generalized across different field conditions.
The study is thus structured in two main phases: a preliminary phase using altitude as a variable to aid in identifying the ideal DAS for image-based density estimation and a targeted phase examining model behaviour across DAS values close to that identified optimum.

Seed preparation and crop establishment
The method of sowing used was wet direct seeding via manual broadcasting. Manual broadcasting is a traditional technique in which seeds are scattered by hand over the field. While less precise than machine-assisted methods, it reflects common farmer practices and captures real-world variability in seed distribution (Nguyen et al. 2022).


Figure 2: Manual broadcasting of seeds for Plot 1.

Prior to sowing, the rice seeds underwent standard pre-germination procedures. Seeds were first soaked in clean water for 24 hours, then incubated for another 24 to 36 hours under controlled moisture conditions. Incubation continued until radicle emergence reached 2–5 mm in length, indicating readiness for field broadcasting. This ensured uniform germination and facilitated more consistent field emergence (International Rice Research Institute n.d.).

The seed quantities per sowing rate (40 kg/ha, 60 kg/ha, and 80 kg/ha) were computed based on the designated treatment levels. These amounts were initially measured before soaking and then adjusted after soaking to account for water absorption and weight changes, ensuring accurate seeding rates across all plots.

Data Collection
Image capturing
DJI Phantom 4 Multispectral was used to capture detailed data on crop development on all plots, focusing specifically on plant density from emergence through the early vegetative growth stage. To minimize illumination variability and ensure consistent image quality, all UAV flights were conducted between 10:00 a.m. and 1:00 p.m. Philippine Standard Time (PST). The captured images were utilized to monitor crop progress, with particular emphasis on detecting and assessing plant density across the field. Four variations in flight altitude (15 m, 20 m, 25 m, and 30 m) were used as treatment for the data collection, alongside the identified growth stages (14, 20, 32 DAS).

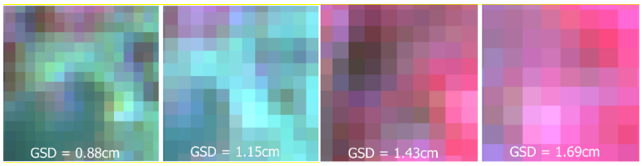


Figure 3: Image patches at increasing altitude showing reduced spatial resolution. From left to right: 15 m (GSD = 0.88 cm), 20 m (GSD = 1.15 cm), 25 m (GSD = 1.43 cm), and 30 m (GSD = 1.69 cm)

For the second phase, however, only the the altitude identified as optimal in Phase 1 was used for imaging in Plot 2, ensuring a more targeted and efficient data acquisition strategy.

To ensure accurate image stitching and orthomosaic generation, a 70% front overlap and 60% side overlap were applied during drone missions. Post-Processed Kinematic (PPK) correction was used to enhance spatial accuracy in image alignment and georeferencing. Additionally, RTK (Real-Time Kinematic) data was used to support precise ground positioning and mapping quality throughout the data acquisition process.

MSAVI (Eq. 1; Qi et al. 1994) was applied to the images to distinguish vegetation from the background and to enhance the accuracy of plant density measurements. This index is particularly useful in early crop stages when vegetation cover is minimal, providing a clearer separation of plants from non-vegetated areas (Xue and Su 2017).

$$MSAVI = NIR + \frac{1 - \sqrt{(2*NIR + 1)^2 - 8*(NIR - RED)}}{2}$$

(Eq. 1)

Figure 4: Image acquisition using DJI Phantom 4 Multispectral.

Ground Truthing
Data collection also involved manual plant density measurements, which served as the ground truth reference for UAV-based estimations. In each experimental unit, rice plants were counted manually within each plot. These measurements were conducted once during the experiment, coinciding with the first UAV image acquisition to ensure temporal alignment between aerial data and field observations. These ground-truth data served as the reference for calibrating and validating the regression models developed to estimate plant density from UAV-based multispectral imagery.

Collection frequency
To ensure accurate and timely data collection, UAV image capturing was conducted at strategically selected days after sowing (DAS), specifically at 14, 20, and 32 DAS. These time points were chosen based on key physiological developments in rice crop establishment, corresponding broadly with early vegetative growth and active tillering stages (Moldenhauer et al. 2000).

At 14 DAS, the crop typically enters early seedling establishment with around 2–3 unfolded leaves, making this stage critical for assessing initial emergence and stand uniformity. By 20 DAS, rice plants are actively expanding their leaf area (around 4–5 leaves), and early tillering may begin, allowing for the identification of gaps in planting and evaluation of early canopy closure. The 32 DAS mark aligns with the active tillering stage, approximately Biologische Bundesanstalt, Bundessortenamt and Chemical industry (BBCH) scale 25–29, which reflects significant differences in plant density due to early competition or uneven establishment (Meier, 2001). These stages were selected to facilitate early detection of areas with poor emergence or reduced density, enabling timely decision-making for potential re-seeding or management interventions.

Following the initial stage of data collection from Plot 1, a second experimental plot was monitored with UAV imaging scheduled around the DAS that showed the highest model accuracy and VI responsiveness in Plot 1. This targeted timing allowed for a more focused investigation into how the plant developmental stage affected the reliability and precision of image-based plant density estimation. By concentrating data capture within the optimal temporal window (18–25 DAS) identified from the first trial, Plot 2 strengthened the study's capacity to refine model calibration and validate UAV-based monitoring strategies under field conditions.

Image Processing

Image processing software plays a crucial role in analysing both multispectral images captured at various growth stages (Verrelst et al., 2018). This analysis focuses on extracting key metrics related to plant density and uniformity, which are vital for assessing the performance of both UAV seeding and manual sowing methods. To generate the stitched orthomosaic images used for analysis, Pix4Dmapper was used for image stitching and processing.

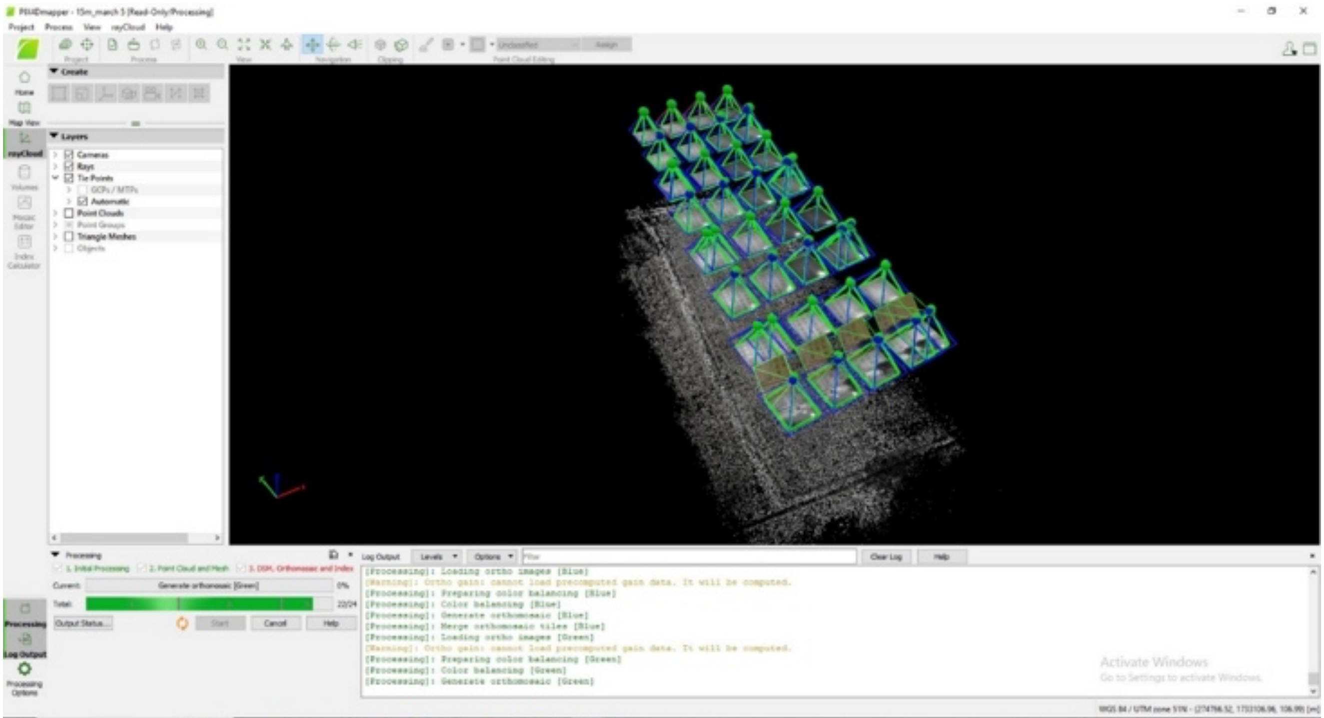


Figure 5: Sample image stitching and processing using Pix4Dmapper.

MATLAB was then utilized for advanced image analysis. Specifically, it processed the stitched UAV imagery by calculating the Modified Soil Adjusted Vegetation Index (MSAVI) – a vegetation index designed to enhance the detection of plant pixels while reducing the influence of soil background (Melnyk and Brunn 2025). MSAVI proved especially useful during early crop stages when vegetation cover was sparse, allowing for more accurate identification of plants amidst bare soil (Voitik et al. 2023; Zhao et al. 2025).

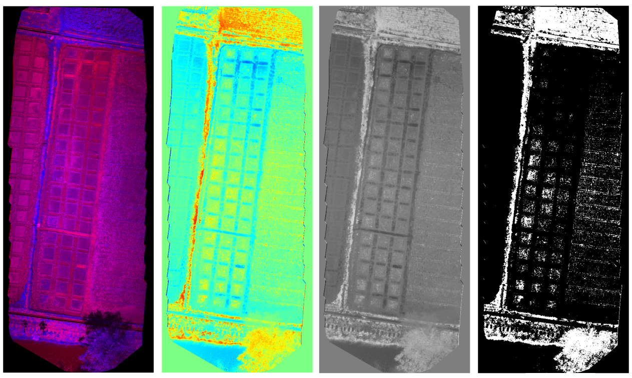
Once MSAVI was calculated and processed, MATLAB was further used to apply the Otsu method to both Plot 1 and Plot 2 datasets. This method automatically determined the optimal threshold to separate the pixels into two distinct classes: foreground (plant pixels) and background (soil pixels). The Otsu method, available in MATLAB's Image Processing Toolbox, worked by maximizing the variance between these two classes, ensuring a clear distinction between vegetation and non-vegetation areas in the images. This thresholding technique was critical for accurately segmenting the images into plant and soil components, providing a foundation for subsequent analysis (Xu et al. 2011; Castillo-Martínez 2020; Barros, Diaz, and Fernandes 2021).

MSAVI Image Generation and Otsu's Thresholding

To reduce the soil background influence typical in early-stage rice imagery, the Modified Soil Adjusted Vegetation Index (MSAVI) was computed using reflectance data from the Red and NIR bands. The MSAVI was selected over traditional NDVI due to its enhanced sensitivity under sparse vegetation conditions and its robustness to bare soil noise (U.S. Geological Survey 2025.). The MSAVI was calculated in MATLAB using the standard formula as shown in equation 1.

Figure 6 presents the actual sequential image processing steps involved in extracting vegetation features at 15m altitude using MSAVI from multispectral imagery during 14 DAS. In figure 6a, a false-colour RGB composite is constructed by combining the near-infrared (NIR) band in the blue channel and the red band in the red channel. This combination enhances the spectral contrast between vegetation and non-vegetation, making vegetation appear more visually distinct. Figure 6b shows the raw MSAVI image, which directly results from applying the MSAVI formula without normalization. This image retains the full value range, highlighting subtle differences in vegetation vigour. Figure 6c displays the normalized MSAVI image, scaled between 0 and 1 to facilitate uniform visualization and subsequent thresholding. A grayscale colormap is applied to reflect the gradation in vegetation density. Figure 6d illustrates the binary thresholded image obtained using

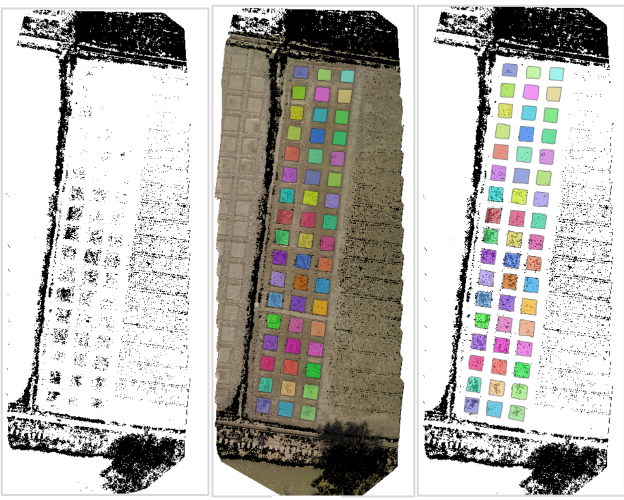
Otsu's method, where vegetation is represented in white and the background in black. However, for consistency and improved visual interpretation in QGIS, this binary scheme was inverted during further processing, with vegetation shown in black and the background in white as shown in Figure 7. This inversion aids in visually isolating vegetated areas against a neutral background for clearer delineation and vector extraction.



(a) (b) (c) (d)

Figure 6: Sample Image Processing for MSAVI-based Vegetation Detection. (**a**) False-colour RGB composite showing NIR (blue) and RED (red); (**b**) Raw MSAVI image; (**c**) Normalized MSAVI image; (**d**) Thresholded image using Otsu's Thresholding.

After applying the Otsu method in MATLAB, the images were segmented, with plant pixels and soil pixels clearly differentiated. The next step involved calculating the number of plant pixels within each subplot. QGIS software was instrumental in this aspect, wherein the images were loaded, and grids were added to identify the bounds of each plot (Figure 7b). This provided a quantitative measure of plant density, which was used to assess uniformity across the field.



(a) (b) (c)

Figure 7: Sample image processing steps for plot delineation. (**a**) Binary mask generated using Otsu's thresholding; (**b**) Overlay of the binary mask on the RGB composite to delineate plot boundaries; (**c**) Individual plots extracted based on the shapefile.

Data Analysis and Model Selection

Five-fold Cross-validation

Linear regression models were developed to relate the pixel count obtained from UAV imagery to manually counted plant density. To evaluate the reliability and generalizability of the developed models, five-fold cross-validation was applied. This method involved dividing the dataset into five equal subsets (folds). For each iteration, one fold was used as the validation set while the remaining four were used for model training. This process was repeated five times, ensuring that each data point was used once for validation and four times for training. MATLAB, through its Statistics and Machine Learning Toolbox, was used in this analysis. The toolbox enabled the development of empirical linear regression models.

Once the models were developed, MATLAB's built-in functions were used to evaluate model performance. Metrics including the root mean square error (RMSE) (Eq. 2), mean absolute error (MAE) (Eq. 3), normalized root mean square error (nRMSE) based on the average plant density (Eq. 4), and mean absolute percentage error (MAPE) (Eq. 5) were computed. RMSE and MAE provide absolute measures of prediction error, while nRMSE expresses the error relative to the mean of observed values, enabling scale-independent comparison across studies. MAPE, on the other hand, reports the average deviation as a percentage, providing an intuitive measure of predictive accuracy. The metrics are computed as follows:

$$\text{Root Mean Square Error, RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2} \quad \text{(Eq. 2)}$$

$$\text{Mean Square Error,MAE}=\frac{1}{n}\sum_{i=1}^{n}|y_i-\hat{y}_i| \quad \text{(Eq. 3)}$$

$$\text{Normalized Root Mean Square Error, nRMSE}=\frac{\text{RMSE}}{\bar{y}}\ \text{x}\ 100 \quad \text{(Eq. 4)}$$

$$\text{Mean Absolute Percentage Error, MAPE}=\frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i-\hat{y}_i}{y_i}\right| \quad \text{(Eq. 5)}$$

where y_i is the observed (ground truth) values, $\hat{y}_i$ is the predicted values, n is the number of samples, and $\bar{y}$ is the mean of observed values.

The performance metrics from each fold were averaged to provide a robust estimate of model accuracy and reduce the risk of bias due to random data partitioning. This validation strategy enabled objective comparison of different modelling approaches (Zhou and Ismaeel 2021; Liu et al. 2022).

Identification of Optimum Flight Altitude and Optimum DAS for Image Capturing

To determine the optimum flight altitude for UAV-based plant density estimation, statistical comparison was performed on the RMSE values obtained from different altitudesin order to assess whether significant differences existed in model accuracy across the varying flight heights. By analysing RMSE as the dependent variable and altitude as the independent factor, the test provided insight into which altitude yielded the lowest error and thus the most reliable estimation.

Similarly, to identify the optimal window for detecting early-stage rice vegetation, regression metrics (e.g., R^2, RMSE, MAE) were computed from images captured at various Days After Sowing (DAS) around the optimal DAS (18, 21, 25 DAS) identified from Plot 1. This analysis aimed to determine the specific DAS that yielded the best model performance, allowing for more precise and timely image acquisition during early crop development.

RESULTS AND DISCUSSION

Flight altitude effect on detecting vegetation

Linear regression models demonstrated varying degrees of effectiveness in estimating rice plant density using MSAVI-derived FVC. As shown in Table 1, model performance – evaluated through cross-validated RMSE, MAE, and MAPE – varied across developmental stages (indicated by Days After Sowing, DAS) and flight altitudes.

Table 1: Cross-validated model performance across different DAS and altitudes.

DAS	Altitude	RMSE (plants/m^2)	nRMSE (%)	MAE (plants/m^2)	MAPE (%)
14 DAS	15 m	41	32.90	34	31.09
	20 m	40	32.00	33	30.57
	25 m	39	30.90	33	30.42
	30 m	41	33.00	34	30.97
20 DAS	15 m	39	31.00	32	29.18
	20 m	38	30.60	32	29.94
	25 m	38	30.10	32	30.17
	30 m	39	30.80	32	29.49
32 DAS	15 m	40	32.10	33	30.68
	20 m	40	31.70	33	30.02
	25 m	40	31.90	32	30.25
	30 m	41	33.00	34	31.84

At 14 DAS, RMSE values ranged from 39 to 41 plants/m^2, with corresponding normalized RMSE (nRMSE) of 30–33%, while MAE ranged from 32 to 34. These metrics indicate moderate predictive accuracy during early growth, as lower RMSE and MAE reflect better overall model performance (Tao et al. 2020; Ji et al. 2022). Similarly, nRMSE and MAPE values of around 30% further support the interpretation of moderate predictive capability under these conditions (Kim and Kim 2016).

These results align with expectations, as rice plants at the 2–3 leaf stage (BBCH 12–13) have sparse canopy cover, leading to lower pixel contrast and reduced accuracy in distinguishing vegetation from background soil (Zheng et al. 2020). Additionally, spectral signals are weaker due to minimal leaf area, contributing to noisier pixel–plant relationships and less stable regression fits (Cen et al. 2019). This pattern is clearly reflected in the binary masks (Figure 8), where vegetation patches are faint and less separable from the background at all altitudes.

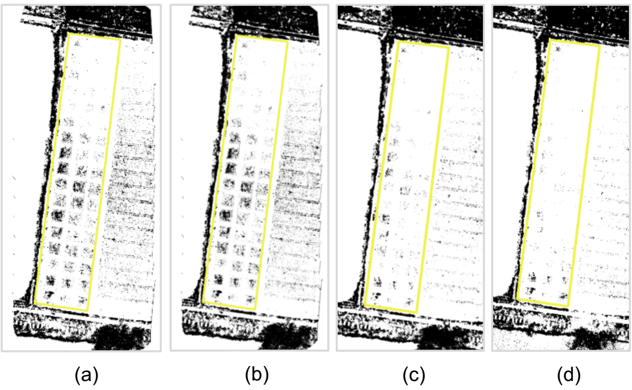


Figure 8: Binary mask generated using Otsu's thresholding across all altitudes for 14 DAS. (**a**) 15m altitude; (**b**) 20m altitude; (**c**) 25m altitude; (**d**) 30m altitude.

Similar findings have been reported in wheat, wherein tillering-stage plots exhibited moderate RMSE and MAE values that improved markedly as canopy density increased (Peng et al 2022). Similarly, a recent rice plant density study based on UAV RGB imagery across lower flight altitudes (4m, 6m, 8m, and 10 m) found that accuracy (RMSE and MAE) significantly improves as rice enters the tillering stage and canopy becomes more uniform, consistent with the performance trends observed between 14 and 20–32 DAS in this study. (Luu et al. 2025).

By 20 DAS, model performance improved across all metrics. RMSE values declined (38–39 plants/m^2), nRMSE was around 30–31%, and MAPE dropped slightly to around 29–30%, indicating better model consistency. This improvement is likely due to enhanced canopy development during early tillering (BBCH 21–25), which provides more complete and more uniform vegetation cover, improving the reliability of fractional cover estimates (Ma et al. 2021). The best results at this stage were observed at 25 m altitude, which achieved the lowest RMSE (38 plants/m^2) along with competitive MAE, nRMSE, and MAPE values. The binary masks at this stage (Figure 9) demonstrate more distinct vegetation patches and reduced background noise compared to 14 DAS, particularly at 25 m altitude. Overall, 20 DAS appears to be the most balanced stage, yielding reliable estimates across all altitudes.

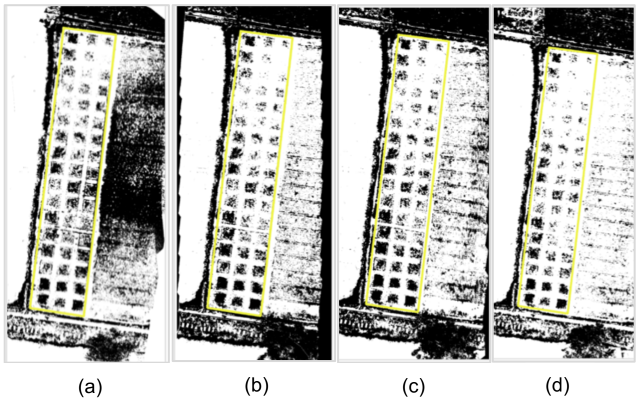


Figure 9: Binary mask generated using Otsu's thresholding across all altitudes for 20 DAS. (**a**) 15m altitude; (**b**) 20m altitude; (**c**) 25m altitude; (**d**) 30m altitude.

At 32 DAS, models continued to perform well, with RMSE values ranging from 40–41 plants/m^2, nRMSE between 31–33%, MAE around 73–77, and MAPE between 30–31%. Despite strong model fits, the slight increase in error values may be attributed to canopy saturation, overlapping tillers, and increased structural complexity (BBCH 29–30), which can reduce segmentation accuracy and weaken the direct relationship between fractional cover and discrete plant counts. The binary masks (Figure 10) illustrate this complexity, showing dense, contiguous vegetation cover with reduced within-plot contrast, making individual plant separation more challenging.

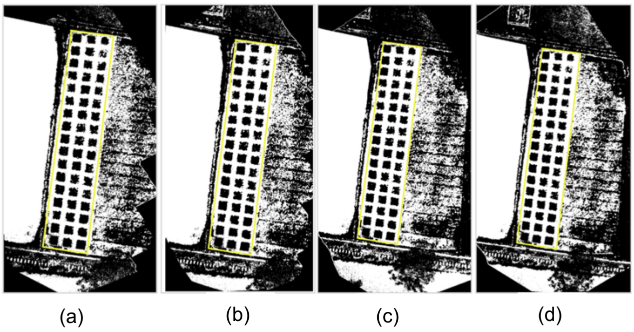


Figure 10: Binary mask generated using Otsu's thresholding across all altitudes for 32 DAS. (a) 15m altitude; (b) 20m altitude; (c) 25m altitude; (d) 30m altitude.

This trend is corroborated by Jiang et al. (2019), reporting a decline in predictive performance during advanced vegetative phases, attributed to spectral saturation and increased canopy heterogeneity—closely paralleling the 32 DAS behaviour observed in the present study.

In terms of flight altitude, no consistent pattern was observed across DAS levels. Although models at lower altitudes (e.g., 15 m) occasionally yielded slightly better results—particularly at 25 and 32 DAS—the differences were marginal. Importantly, a pairwise statistical comparison using Tukey's Honest Significant Difference (HSD) of mean RMSE values across altitudes indicated no significant differences, confirming that all tested altitudes (15–30 m) provided sufficiently accurate estimates of plant density. Recent studies have shown similar patterns. For example, Adedeji et al. (2024) observed only marginal reductions in plant height estimation accuracy when comparing UAV flights at 40 m and 80 m over cotton fields, despite the considerable altitude gap. Likewise, Luu et al. (2025) conducted rice plant density estimations using UAVs flown at very low altitudes (4, 6, 8, and 10 m) and reported that, once canopy development had progressed, differences in RMSE and MAE across flight heights were minimal. Furthermore, studies on leaf area index (LAI) estimation in rice using UAVs flown at 50–60 m found only slight variations in accuracy near canopy closure. These findings are consistent with the results of the present study, where no consistent trend was observed across DAS levels, and all tested altitudes yielded comparable predictive performance once sufficient vegetation cover was established. This suggests that higher altitudes may be preferred for operational efficiency, as they offer broader field coverage without significantly compromising accuracy.

Optimum DAS window for density estimation using multispectral imaging

In the context of UAV-based estimation of rice plant density, 20 DAS was a strong single time point, delivering consistent and accurate results across all flight altitudes while minimizing prediction error based on the previous discussion. This makes it a reliable DAS for remote sensing applications in early rice crop monitoring.

To further validate this observation, model performance was compared across different DAS around the identified optimal DAS value (20 DAS) and altitude (30 m). In particular, the selected DAS values were chosen as representative stages close to the optimal 20 DAS identified in the first study, ensuring that performance stability and consistency could be assessed within the immediate developmental window. The results are summarized in Table 2.

Table 2: Cross-validated model across different DAS at 30m altitude.

DAS	Altitude	RMSE (plants/m²)	MAE (plants/m²)	MAPE (%)	R^2
18	30m	35	31	23.91	0.9139
21	30m	35	28	25.72	0.9279
25	30m	34	31	24.02	0.9395

As shown in Table 2, the models yielded high R^2 values across all three stages, ranging from 0.9139 at 18 DAS to 0.9395 at 25 DAS, indicating excellent correlation between fractional vegetation cover and actual plant density. The high R^2 values observed during this period validate MSAVI's sensitivity to canopy structure and confirm its suitability for early-stage monitoring. This supports its potential as a decision-support tool for replanting or input management strategies. Among the stages, the lowest RMSE was observed at 25 DAS (34 plants/m^2), followed closely by 21 DAS (35 plants/m^2) and 18 DAS (35 plants/m^2), suggesting consistent prediction accuracy throughout this developmental window. MAE values also remained within an acceptable or within moderate range (Liu et al. 2022), further supporting the model's reliability. As shown in Figure 11, the binary vegetation masks exhibit minimal visual variation across the evaluated stages, indicating consistent canopy detection and stable segmentation performance. This visual consistency supports the reliability of vegetation-based density estimation during this developmental window.

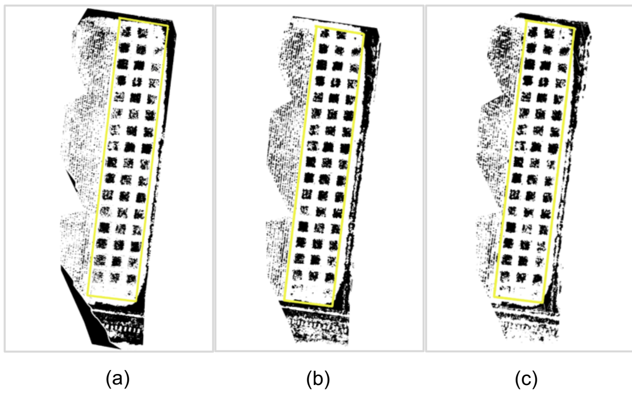


Figure 11: Binary mask generated using Otsu's thresholding across an altitude of 30m. (a) 18 DAS; (b) 21 DAS; (c) 25 DAS.

These results confirm that the period between 18 and 25 DAS provides an optimal window for accurate and robust plant density estimation using UAV-derived vegetation indices. The improvement in performance from 18 DAS onward likely reflects denser canopy development and reduced background soil interference, leading to more consistent pixel-level segmentation and prediction. This supplementary analysis supports earlier findings and reinforces the selection of this time window for operational field monitoring, as vegetation cover is both dense and uniform enough for accurate pixel-based measurement, while canopy saturation has not yet introduced substantial segmentation noise.

CONCLUSION

In summary, the findings demonstrate that UAV-based multispectral imaging, modelled using linear regression, can effectively estimate rice plant density with strong consistency and accuracy, particularly within the 18 to 25 DAS window. This aligns with PhilRice (2022), which recommends gap filling or replanting around the 21 to 28 DAS. Consequently, UAV-derived plant density estimates can directly inform timely management interventions. This period represents a critical phenological stage where vegetation cover is sufficiently developed for reliable pixel-based segmentation, yet not overly saturated to introduce noise or overlap. Among all configurations tested, flights conducted at 25–30 m altitudes yielded comparable results to lower altitudes, suggesting that higher altitudes can be strategically preferred for operational efficiency without significantly compromising predictive performance. While linear regression provided adequate accuracy, future work could explore non-linear or machine learning models to improve prediction under high canopy complexity or across different soil backgrounds. Moreover, validation in larger-scale, farmer-managed fields would support wider adoption. Overall, this study highlights a practical and scalable remote sensing approach for early-stage crop monitoring, contributing to precision agriculture applications in rice production systems.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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