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Effect of NDVI Landsat 9 image acquisition timing on paddy productivity estimation in a single planting cycle

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Abstract: Paddy productivity is a critical component of food security and agricultural planning in Indonesia. Conventional productivity monitoring methods are often time-consuming and costly, making satellite-based remote sensing a promising alternative. This study aimed to evaluate the effect of Landsat 9 image acquisition timing on NDVI-based paddy productivity estimation and to identify the most suitable pre-harvest growth phase for productivity assessment in Kebumen Regency, Central Java, Indonesia. NDVI values derived from Landsat 9 imagery were combined with field productivity data obtained through the BPS ubinan survey and analyzed using linear regression. Three pre-harvest growth stages were evaluated: Generative 1 (52 days before harvest), Generative 2 (36 days before harvest), and Ripening (20 days before harvest). The results showed that estimated productivity declined substantially from Generative 1 to Generative 2. Regression analysis indicated that the Generative 1 phase produced the strongest relationship between NDVI and field productivity (R^2 = 0.781), reflecting peak canopy development and vegetation vigor. However, comparison with BPS production statistics revealed that the Generative 2 phase provided the highest agreement with observed production (r = 0.901; R^2 = 0.811), while the Ripening phase yielded the lowest estimation error (MAPE = 35.85%). These findings demonstrate that image acquisition timing significantly affects NDVI-based productivity estimation. Generative 1 imagery is most suitable for estimating potential productivity, whereas Generative 2 imagery provides the closest representation of actual production conditions. Therefore, phenology-based image acquisition should be considered to improve the accuracy and reliability of satellite-derived paddy productivity assessments.

Keywords: Generative phase; Kebumen; Landsat 9; paddy productivity; satellite imagery.

Abbreviations: BPS, Badan Pusat Statistik (Indonesian Central Bureau of Statistics); GEE, Google Earth Engine; NDVI, Normalized Difference Vegetation Index; NIR, near infrared; R, red.

Introduction

Rice is one of the most strategic agricultural commodities in the world because it plays a fundamental role in food security, economic development, and rural livelihoods. More than half of the global population depends on rice as a staple food, making sustainable rice production a critical concern for governments, researchers, and policymakers (Gnanamanickam, 2009; Muthayya et al., 2014; Maraseni et al., 2018). In Indonesia, rice consumption remains considerably high, further emphasizing the importance of maintaining stable rice production and productivity (Sitaresmi et al. 2023). As a result, rice productivity has become a key indicator of long-term food security, agricultural sustainability, and socio-economic stability (Sokra et al. 2026). Heightened productivity corresponds with diminished poverty rates (Ayu and Sukojo 2023). The importance of rice production is also reflected in the Sustainable Development Goals (SDGs), particularly SDG 2 (Zero Hunger), which prioritizes food security, sustainable agriculture, and improved nutrition (Arora and Mishra 2022). Consequently, ensuring adequate rice production is not only an agricultural objective but also a strategic requirement for achieving sustainable development and maintaining food availability for future generations.

The significance of rice productivity extends beyond food production and directly influences poverty reduction, farmer welfare, and regional economic development. Destiartono (2023) demonstrated that rice productivity and poverty rates are cointegrated, indicating that increases in productivity contribute to reductions in poverty levels. Similarly, Rajindra et al. (2021) reported that rice productivity significantly affects household income and food security among farming communities. Yamin et al. (2025) further showed that improvements in cultivation systems increased rice productivity from 4.5 t ha^{-1} to 6.5 t ha^{-1}, resulting in enhanced farmer welfare and food security. These findings indicate that accurate information regarding rice productivity is essential for supporting agricultural policies, food security programs, and rural development initiatives. Therefore, monitoring and estimating rice productivity have become increasingly important for both researchers and policymakers seeking to improve agricultural performance and socio-economic outcomes.

In Indonesia, one of the major rice-producing countries in the world, agricultural land conversion has emerged as a serious challenge to sustainable food production. The conversion of paddy fields into non-agricultural land threatens rice

availability and may reduce future production capacity (Sudiana et al. 2025). This issue is particularly important in regions where rice cultivation serves as the primary source of livelihood and food supply. One such region is Kebumen Regency, Central Java Province, which is recognized as an important rice-producing area characterized by fertile soils, favorable climatic conditions, and abundant water resources (BPS 2024). However, productive agricultural lands in Kebumen are increasingly vulnerable to climate change impacts, including shifts in rainfall patterns and temperature variability that influence crop growth and productivity (Sekaranom et al., 2021). In addition, the continuous reduction of paddy field areas poses a challenge to maintaining sustainable rice production. Meanwhile, some areas within the Karangsambung–Karangbolong Geopark region continue to experience food supply limitations (Harini et al. 2022). These conditions highlight the need for efficient monitoring systems capable of providing timely and accurate information regarding rice production and availability.

Despite the importance of rice productivity monitoring, detailed productivity data at the sub-district level remain limited. In Kebumen Regency, productivity statistics are generally reported at aggregated administrative levels, while detailed spatial information remains unavailable. Such limitations hinder effective agricultural planning and food security assessment. Conventional approaches for estimating productivity typically rely on field surveys and crop-cutting experiments, which require substantial time, labor, and financial resources (Berd et al., 2022). Although these methods provide reliable measurements, their application over large agricultural areas is often impractical. Consequently, alternative approaches capable of producing rapid, cost-effective, and spatially explicit productivity estimates are increasingly needed. Remote sensing technology offers considerable advantages in this regard because it enables repeated observations over extensive areas while reducing field survey requirements.

Recent advances in remote sensing have substantially improved agricultural monitoring and crop yield estimation. Remote sensing provides valuable information regarding crop growth conditions, vegetation health, and biophysical characteristics associated with productivity (Ali et al. 2022). Furthermore, remote sensing has become a fundamental component of precision agriculture by supporting efficient agricultural management and decision-making processes (Sokra et al. 2026). Among the available satellite systems, the Landsat program remains one of the most widely used due to its long-term data continuity, moderate spatial resolution, and global accessibility. The recently launched Landsat 9 mission offers consistent spectral coverage and a temporal resolution of 16 days, making it particularly suitable for agricultural monitoring applications. Nevertheless, obtaining accurate productivity estimates requires careful consideration of image acquisition timing because crop spectral responses vary substantially throughout the growing season (Du et al. 2022). Therefore, understanding the influence of acquisition timing on vegetation indices and productivity estimation models remains an important research challenge.

One of the most widely applied vegetation indicators in agricultural remote sensing is the Normalized Difference Vegetation Index (NDVI). NDVI is derived from red and near-infrared reflectance and has proven effective for representing vegetation vigor, biomass accumulation, chlorophyll concentration, and photosynthetic activity. Because these characteristics are closely related to crop growth and yield formation, NDVI has been extensively used for estimating agricultural productivity. Previous studies consistently demonstrated strong relationships between NDVI values and rice productivity. Putra et al. (2018) developed a Landsat 8-based rice productivity model with an accuracy of 89.29%, while Sekarsih and Kusuma (2024) obtained(Sekarsih and Kusuma 2024) an accuracy of 86% using NDVI-derived productivity estimation. Berd et al. (2022) also reported that NDVI effectively predicted rice productivity and identified the Generative II phase as the most suitable period for estimation. These findings indicate that NDVI is a reliable indicator for monitoring rice growth and estimating yield before harvest.

Although NDVI has proven effective for productivity estimation, the accuracy of NDVI-based models depends strongly on crop phenology and image acquisition timing. Rice growth consists of several phenological stages, including vegetative, reproductive (generative), and ripening phases, each characterized by distinct physiological and spectral properties (dela Torre et al., 2021). During the vegetative stage, active leaf development and stem elongation increase canopy greenness and NDVI values. During the reproductive stage, panicle initiation, booting, and heading processes influence biomass accumulation and photosynthetic activity, which are closely related to final grain yield. As the crop enters the ripening phase, senescence gradually reduces vegetation vigor and alters spectral reflectance patterns. Consequently, NDVI values vary throughout the growth cycle, potentially affecting their relationship with actual productivity. Previous studies demonstrated that phenological stages significantly influence estimation accuracy. Nazir et al. (2021) found that late vegetative and reproductive stages provided the strongest relationship with rice yield ($R^2 = 0.84$), while Sheng et al. (2022) showed that growth stages could be identified from satellite imagery with an accuracy of 98.77%. Similarly, dela Torre et al. (2021) concluded that booting and heading stages are among the most suitable periods for rice yield estimation.

Several studies have attempted to identify the optimal timing for image acquisition in rice productivity estimation. Sekarsih and Kusuma (2024) reported that imagery acquired approximately one month before harvest produced reliable productivity estimates. Du et al. (2022) suggested that observations approximately two months before harvest effectively capture rice growth dynamics and improve monitoring performance. Berd et al. (2022) found that rice aged between eight and thirteen weeks provided the most accurate NDVI-based productivity predictions. Similarly, Najafi et al. (2023)(Najafi, Eftekhari, and Sharifi 2023) indicated that imagery acquired six weeks before harvest yielded the best NDVI-based productivity model. These findings collectively suggest that image acquisition timing plays a critical role in determining the accuracy of rice productivity estimation. However, the reported optimal periods differ among studies, indicating that the relationship between acquisition timing and productivity estimation remains insufficiently understood.

Previous studies have predominantly utilized Sentinel-2, Landsat 8, or MODIS imagery and have generally focused on single acquisition periods or multitemporal datasets without explicitly evaluating individual reproductive growth stages. Consequently, the influence of Landsat 9 image acquisition timing on NDVI-based paddy productivity estimation remains insufficiently understood. In particular, no studies in Indonesia have systematically compared the booting (Generative 1), panicle (Generative 2), and ripening phases using official BPS ubinan productivity data, nor have they distinguished between the growth phase that best represents potential productivity and the phase that most accurately reflects actual production conditions. To address these gaps, this study evaluates the effect of Landsat 9 acquisition timing across three reproductive stages within a single planting cycle, analyzes the relationship between NDVI and observed productivity, and identifies the most suitable phase for estimating both potential productivity and actual rice production. The findings are expected to improve the understanding of phenology-based image acquisition and support more accurate remote sensing applications for agricultural monitoring and food security planning.

Results and discussion

Rice growth phases

Rice growth is characterized by a series of phenological stages that reflect changes in plant physiology, morphology, and spectral response throughout a single cropping cycle. According to Berd et al. (2022), rice growth phases can be categorized into watery land (<3 weeks), Vegetative 1 (3–4 weeks), Vegetative 2 (4–6 weeks), Generative/Reproductive 1 (6–8 weeks), Generative/Reproductive 2 (8–13 weeks), and fallow after harvest. During the vegetative stages, rice plants experience rapid leaf development, tillering, and canopy expansion, resulting in increasing biomass and photosynthetic activity. As the crop enters the reproductive phase, physiological processes shift toward panicle initiation, booting, heading, flowering, and grain formation, which are critical determinants of final yield (dela Torre et al. 2021). These phenological transitions produce distinct spectral signatures that can be detected using satellite imagery, enabling the monitoring of crop development over time (Sheng et al., 2022). Previous studies have demonstrated that the reproductive stages are particularly important for yield estimation because vegetation indices exhibit stronger relationships with final grain production during these periods (Nazir et al., 2021). Furthermore, multitemporal satellite observations have shown that rice fields can be accurately identified and monitored by capturing changes in spectral characteristics across successive growth stages (Liao et al., 2018). Therefore, understanding the dynamics of rice growth phases is essential for determining the optimal image acquisition period and improving the accuracy of NDVI-based rice productivity estimation models (Sudiana et al., 2025). Fig. 1 shows the rice growth phases used in this study, consisting of watery land, Vegetative 1, Vegetative 2, Generative 1, Generative 2, and harvest/ripening stages.

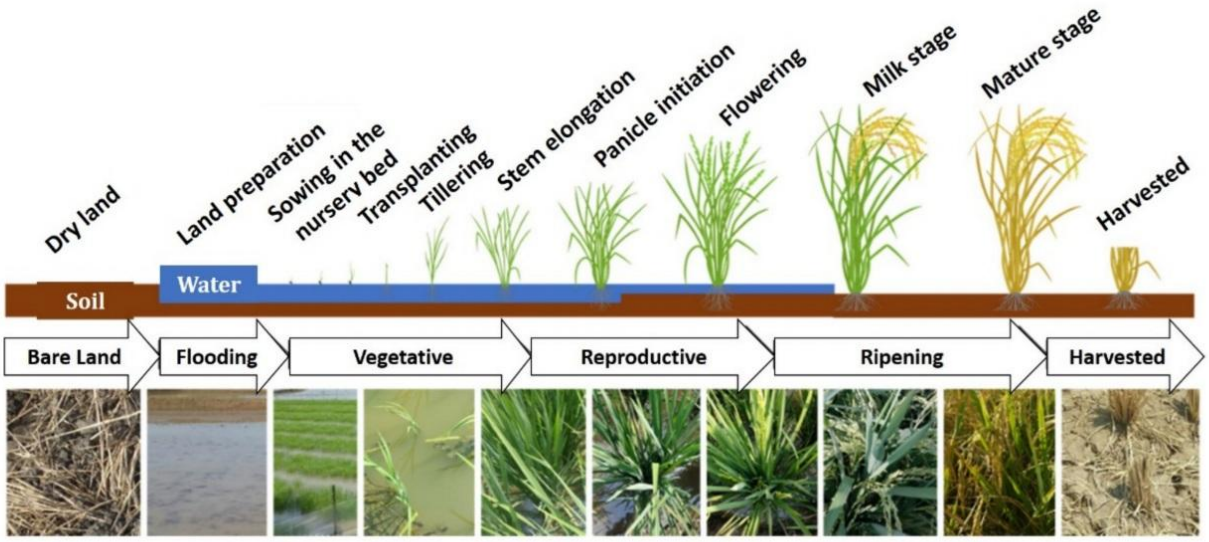


Fig. 1. Rice growth stages (Sheng et al., 2022).

Landsat data

The Landsat 9 imagery was acquired on three different dates corresponding to the Generative 1, Generative 2, and Ripening phases before harvest. The acquisition timing was selected based on rice phenology and previous studies that identified optimal periods for rice productivity estimation (Nazir et al., 2021; Berd et al., 2022; dela Torre et al., 2021). All images were obtained as Landsat 9 Surface Reflectance (SR) products and had been atmospherically corrected prior to analysis. Therefore, the spectral information and NDVI values derived from the imagery were less affected by atmospheric disturbances and more representative of actual field conditions. Table 1 shows the availability of Landsat 9 imagery used in this research.

Table 1. Landsat 9 image acquisition dates before harvest in Kebumen Regency.

Acquisition	Days before harvest	Phase
June 17, 2025	52	Generative 1 phase, also called the booting stage
July 3, 2025	36	Generative 2 phase (panicle stage)
July 19, 2025	20	Ripening phase

NDVI

Although several vegetation indices, including the Enhanced Vegetation Index (EVI), Soil Adjusted Vegetation Index (SAVI), and Red Edge Position (REP), have been reported to improve crop monitoring under specific environmental conditions, this study intentionally focused on NDVI as the primary predictor variable. The selection of NDVI was based on its widespread application in rice productivity studies, its simplicity, and its proven ability to represent vegetation vigor, canopy development, and biomass accumulation. Previous studies have demonstrated that NDVI provides reliable productivity estimates for paddy fields and often performs comparably to more complex vegetation indices, particularly during the reproductive growth stages. Moreover, the primary objective of this research was not to compare the performance of different vegetation indices, but rather to evaluate the influence of Landsat 9 image acquisition timing on productivity estimation while maintaining a consistent modeling framework across growth phases. By using a single and widely adopted vegetation index, differences in model performance could be attributed primarily to acquisition timing rather than to variations among vegetation indices. Nevertheless, future research should investigate the comparative performance of NDVI, EVI, SAVI, REP, and other spectral indicators to determine whether integrating multiple vegetation indices can further improve the accuracy and robustness of paddy productivity estimation models.

Paddy field classification

The classification of paddy fields and non-paddy fields from Landsat imagery was conducted using the Random Forest algorithm implemented in Google Earth Engine. Random Forest was selected because it is a robust machine-learning method capable of handling complex relationships among spectral variables and reducing overfitting. In this study, the classifier was constructed using 100 decision trees with a fixed random seed value of 0 to ensure the reproducibility of the classification results. A total of 351,104 samples were used in the analysis, of which 70% were allocated for model training and validation, while the remaining 30% were reserved for independent testing. After the training process, the classifier was applied to the testing dataset to generate land-cover predictions and assess its ability to distinguish between paddy and non-paddy areas. Classification performance was evaluated using a confusion matrix that compared the reference classes with the predicted classifications, providing detailed information on classification accuracy and potential errors. The validation results yielded an Overall Accuracy (OA) of 0.99 (99%), indicating that the Random Forest classifier achieved excellent predictive performance and demonstrated a high level of reliability for paddy field mapping in the study area. Fig. 2 shows the difference between the Random Forest classification results and the BPS data.

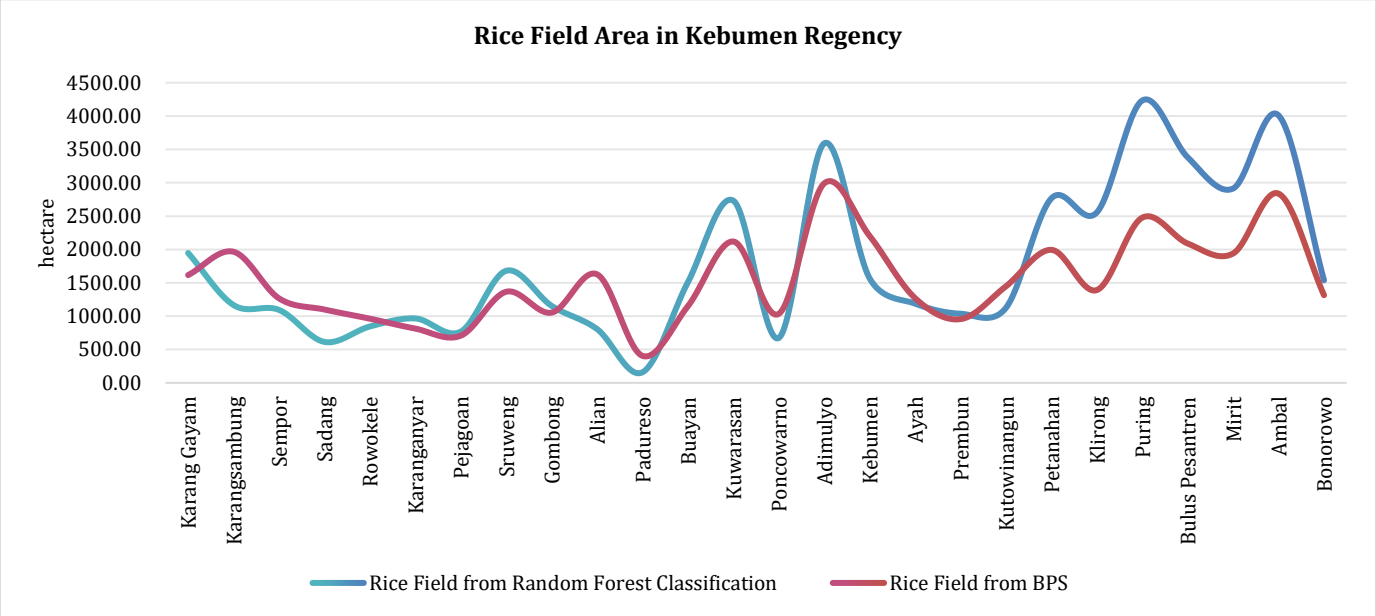


Fig. 2. Comparison of paddy field areas from Random Forest classification and BPS data. Source: Research results, 2026.

BPS ubinan field productivity data

The BPS Kebumen government collected field data on productivity. The productivity data was collected on August 8, 2025. The method used to measure crop paddy productivity was the "ubinan sampling" method. The ubinan survey is a routine survey that collects productivity data on food crops (BPS Kabupaten Kebumen, 2025). The ubinan data were collected using

a 2.5 × 2.5 m sampling plot (Fig. 3a), in which the weight of harvested dry unhusked rice was measured for each plot. The obtained data were then converted to yield per hectare. Fig. 3b is the spatial distribution of *ubinan's* samples in Kebumen Regency and Random Forest Classification for paddy yield area.

A



(Dinas Pertanian, Ketahanan Pangan 2023).

B

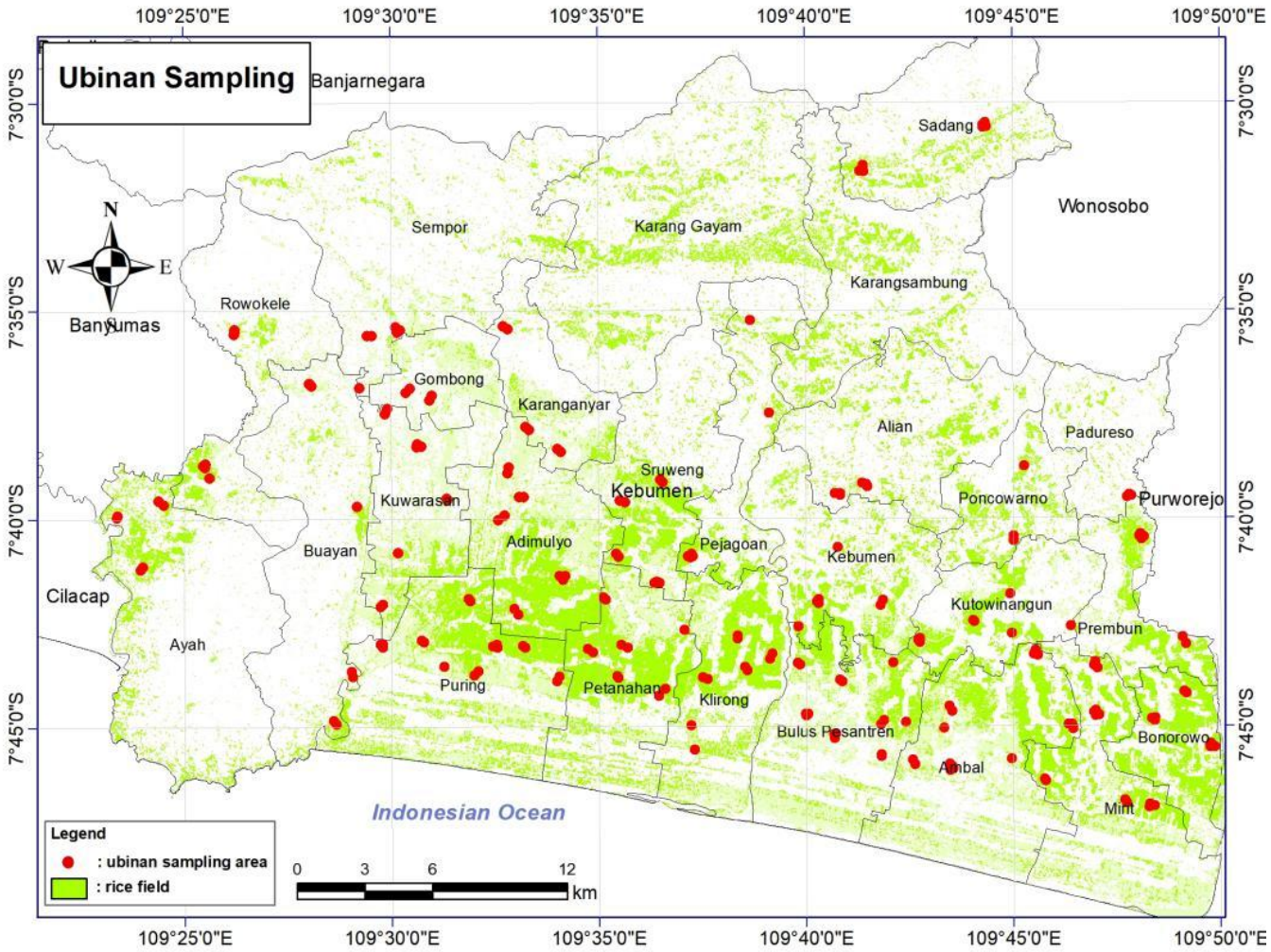


Fig. 3. Field collection of productivity data using the ubinan method (a), and spatial distribution of ubinan sampling plots in Kebumen Regency (b).

Normalized Difference Vegetation Index

Crop yield prediction plays a crucial role in supporting agricultural management, food security, and decision-making processes. The increasing availability of satellite remote sensing data, particularly vegetation indices such as the Normalized

Difference Vegetation Index (NDVI), has significantly improved the capability to estimate crop productivity across large areas. NDVI is widely recognized as an effective indicator of crop vigor, biomass accumulation, and photosynthetic activity, making it one of the most frequently used variables in yield prediction studies. Many previous studies have employed simple linear regression models to establish relationships between NDVI values and crop yield due to their simplicity, interpretability, and ease of implementation. For example, Huang et al. (2014) developed an empirical regression model using NDVI and meteorological variables for crop yield estimation, while numerous remote sensing-based yield prediction studies have relied on linear regression as a baseline approach.

However, crop growth is influenced by complex interactions among climatic, environmental, and management factors that are often nonlinear in nature. Consequently, simple linear regression may not fully capture the underlying relationships between NDVI and crop productivity. Recent studies have demonstrated that advanced modeling approaches, including multiple linear regression, support vector regression, random forest, ensemble learning, and deep learning models, can substantially improve prediction accuracy. Comparative analyses indicate that machine learning and deep learning algorithms frequently outperform conventional linear models because they can model complex nonlinear patterns and interactions among variables.

Therefore, although simple linear regression remains a useful and widely adopted approach, various simulation studies suggest that exploring alternative predictive models is essential to identify the most accurate and robust method for crop yield estimation. The development and evaluation of multiple modeling techniques can provide a more reliable framework for achieving optimal prediction performance under diverse agricultural conditions. The performance metrics of the regression analysis are shown in Table 2, and the regression parameters are shown in Table 3.

Table 2. Performance metrics of NDVI-based paddy productivity estimation models across different growth phases.

Model	R^2	Adj. R^2	RMSE	MAE	MAPE (%)	MBE	CV R^2	CV RMSE
Generative 1	0.78	0.78	0.68	0.58	10.9	-9.1E-16	0.77	0.70
Generative 2	0.75	0.74	0.59	0.49	7.2	-4.5E-15	0.73	0.61
Ripening	0.77	0.77	0.65	0.57	9.1	-6.5E-18	0.75	0.68

Source: Data processing, 2026. R^2: coefficient of determination; Adj.: adjusted; RMSE: root mean square error; MAE: mean absolute error; MAPE: mean absolute percentage error; MBE: mean bias error; CV: cross-validation.

Table 3. Regression parameters of NDVI-based paddy productivity estimation models across different growth phases.

Model	Intercept	p (intercept)	CI lower (int.)	CI upper (int.)	Slope	p (slope)	CI lower (slope)	CI upper (slope)
Generative 1	-2.06	3E-05	-2.99	-1.13	22.67	<0.001	20.07	25.27
Generative 2	-0.09	9E-01	-1.24	1.06	9.66	<0.001	8.12	11.19
Ripening	1.53	4E-05	0.83	2.23	7.81	<0.001	6.77	8.84

Source: Data processing, 2026. CI: confidence interval; int.: intercept.

The regression analysis conducted during the Generative 1 phase demonstrated the strongest relationship between NDVI and rice productivity among all evaluated growth stages. The model achieved a coefficient of determination (R^2) of 0.781 and an adjusted R^2 of 0.779, indicating that approximately 78.1% of the variation in rice productivity could be explained by NDVI values. This high explanatory power suggests that vegetation conditions captured during the Generative 1 phase are closely associated with final yield formation. The regression coefficient (slope = 22.671) was highly significant ($p < 0.001$), confirming a strong positive relationship between NDVI and productivity. The 95% confidence interval for the slope ranged from 20.068 to 25.274, indicating a stable and reliable estimate. Model accuracy was further supported by relatively low prediction errors, including an RMSE of 0.675, MAE of 0.583, and MAPE of 10.98%. Cross-validation results yielded a CV-R^2 of 0.767 and a CV-RMSE of 0.697, demonstrating good model generalizability and limited overfitting. Residual diagnostics showed no evidence of autocorrelation (Durbin–Watson = 1.911) and no influential outliers (Cook's Distance = 0.334). Although the Shapiro–Wilk and Breusch–Pagan tests indicated slight deviations from normality and homoscedasticity assumptions, the model remained statistically robust and provided the highest predictive performance among all phases. These findings suggest that the Generative 1 phase is the most suitable period for estimating rice productivity using NDVI because canopy development and biomass accumulation are near their peak, making spectral responses strongly correlated with final yield.

The regression model developed for the Generative 2 phase also demonstrated a strong and statistically significant relationship between NDVI and rice productivity. The model produced an R^2 value of 0.747 and an adjusted R^2 value of 0.742, indicating that 74.7% of productivity variability could be explained by NDVI measurements. Although slightly lower than the Generative 1 model, this level of explanatory power remains substantial and confirms the usefulness of NDVI for productivity estimation during this stage. The regression slope was positive and highly significant (slope = 9.658; $p < 0.001$), with a 95% confidence interval ranging from 8.124 to 11.192. This result indicates that increases in NDVI are consistently associated with increases in rice productivity. Error metrics showed strong predictive performance, with RMSE, MAE, and MAPE values of 0.594, 0.488, and 7.22%, respectively. Notably, this phase exhibited the lowest MAPE among all models,

suggesting excellent predictive accuracy. Cross-validation analysis further supported model robustness, yielding a CV-R^2 of 0.730 and a CV-RMSE of 0.614. Diagnostic testing indicated that the regression assumptions were well satisfied. Residuals were normally distributed according to the Shapiro–Wilk test ($p = 0.777$), and no evidence of heteroscedasticity was detected by the Breusch–Pagan test ($p = 0.531$). The Durbin–Watson statistic of 2.307 suggested residual independence, while the maximum Cook's Distance of 0.124 confirmed the absence of influential outliers. Overall, the Generative 2 model demonstrated strong predictive capability and the best compliance with classical regression assumptions, making it a reliable alternative for NDVI-based productivity estimation.

The Ripening phase regression model demonstrated a strong positive relationship between NDVI and rice productivity, with an R^2 value of 0.774 and an adjusted R^2 value of 0.770. These results indicate that approximately 77.4% of the variability in rice productivity could be explained by NDVI measurements obtained during the ripening stage. The regression slope was statistically significant (slope = 7.805; $p < 0.001$), with a 95% confidence interval ranging from 6.767 to 8.843. This confirms that NDVI remained an important predictor of productivity even during the final stages of crop development. Model accuracy metrics showed satisfactory predictive performance, with RMSE, MAE, and MAPE values of 0.647, 0.567, and 9.07%, respectively. Cross-validation results produced a CV-R^2 of 0.751 and a CV-RMSE of 0.679, indicating stable predictive performance and good model transferability to unseen observations. Diagnostic analyses revealed that the model met most regression assumptions. The Breusch–Pagan test indicated homoscedastic residuals ($p = 0.853$), while the Durbin–Watson statistic of 2.123 suggested no significant autocorrelation. The maximum Cook's Distance value of 0.088 was well below the critical threshold, confirming that no influential observations affected model stability. Although the Shapiro–Wilk test suggested minor deviations from normality ($p = 0.015$), such deviations are unlikely to substantially influence model interpretation. Overall, the Ripening phase model provided reliable productivity estimates and demonstrated strong predictive performance, highlighting the continued relevance of NDVI for monitoring crop conditions and estimating yield until the final growth stage.

Productivity estimation (t ha^{-1})

The NDVI values derived from Landsat 9 imagery were transformed into rice productivity estimates (t ha^{-1}) using the regression equation obtained from the productivity model. The predicted productivity values were calculated for all paddy fields and subsequently averaged at the sub-district level to obtain the mean rice productivity (t ha^{-1}) for each administrative unit. These estimates were used to evaluate spatial differences in rice productivity among sub-districts and across different image acquisition periods. Fig. 4 shows the productivity estimation in Kebumen's sub districts.

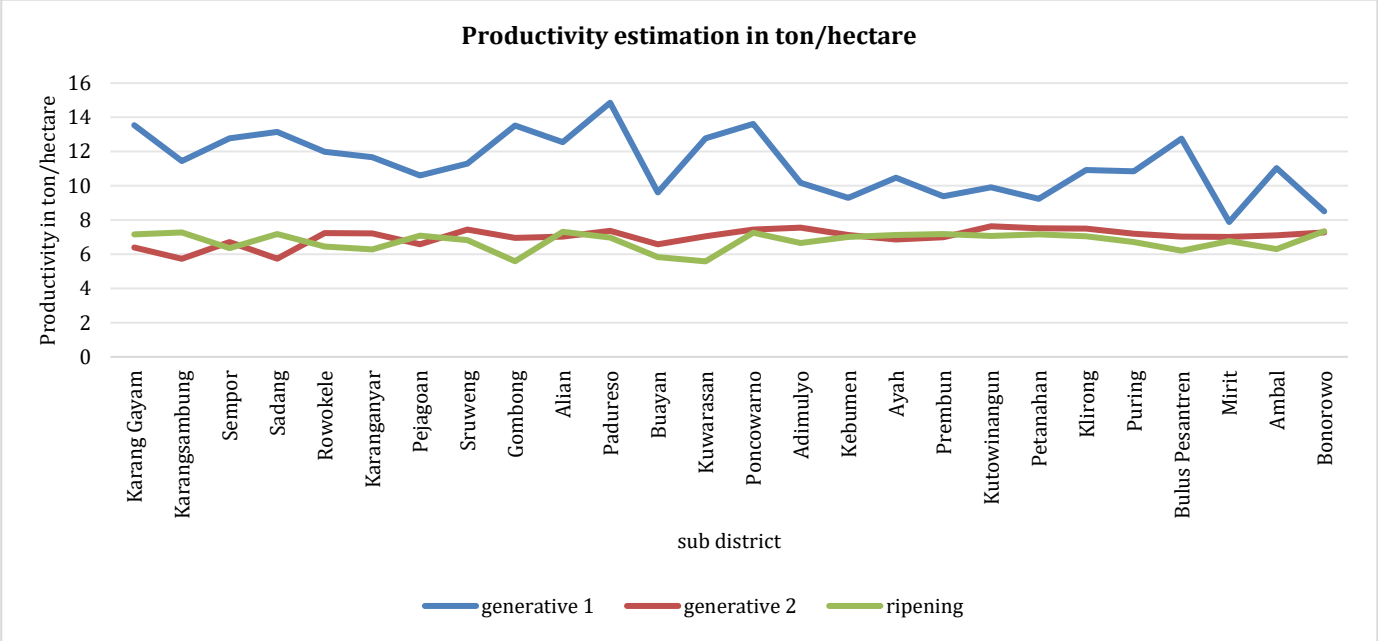


Fig. 4. Spatial variation of NDVI-based paddy productivity estimates across subdistricts in Kebumen Regency. Source: Data processing, 2026.

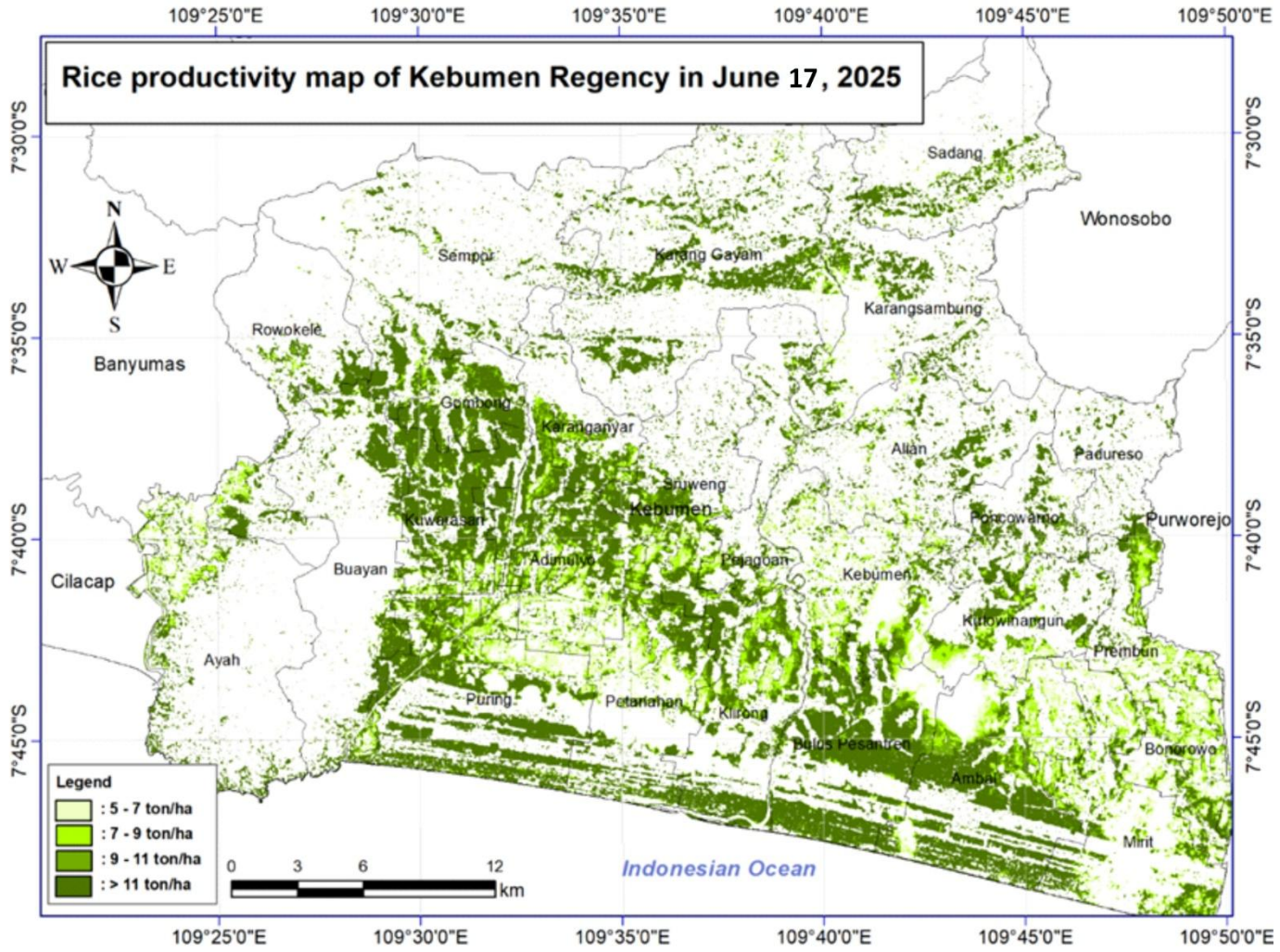
The estimated rice productivity decreased significantly from 11.30 t ha^{-1} during the Generative 1 phase to 7.01 t ha^{-1} during the Generative 2 phase, representing a reduction of approximately 37.98%. This decline is primarily associated with physiological changes in rice plants during the reproductive stage. During Generative 1, rice plants exhibit high chlorophyll content, active photosynthesis, and maximum canopy development, resulting in higher NDVI values and productivity estimates. As the crop progresses into Generative 2, assimilates are increasingly allocated to grain filling rather than vegetative growth, while leaf senescence gradually begins. These changes reduce canopy greenness and near-infrared reflectance, leading to lower NDVI values captured by Landsat 9 imagery. In addition, the saturation effect of NDVI at high biomass levels may contribute to the decline in estimated productivity. Previous studies have shown that spectral responses vary considerably across growth stages, influencing the strength of the relationship between NDVI and crop yield. Therefore, the results indicate that image acquisition timing has a substantial impact on NDVI-based rice productivity estimation.

Paddy productivity estimation in Kebumen

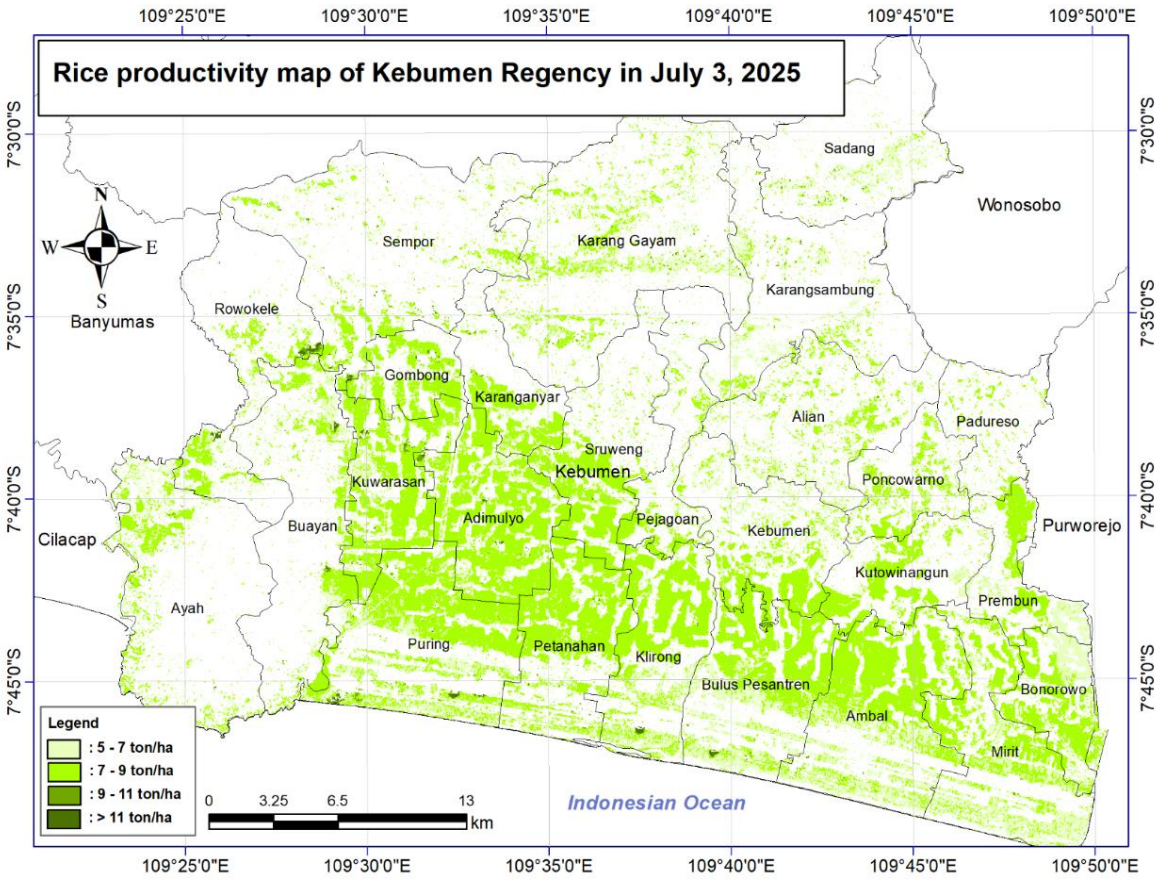
The results of this study indicate that differences in the timing of Landsat 9 image acquisition prior to harvest significantly affect estimates of paddy productivity. A 16-day difference in acquisition (generative 1 to generative 2 phase) led to lower estimated values. The productivity map (Fig. 5) shows that the transition each phase.

Fig. 5 illustrates the spatial distribution of rice productivity estimates derived from NDVI-based regression models using Landsat 9 imagery acquired at three different growth stages. The Generative 1 phase (17 June 2025) produced the highest productivity estimates, with large areas classified within the 9–11 t ha^{-1} and >11 t ha^{-1} categories. This pattern indicates that NDVI values were strongly influenced by maximum canopy development, resulting in an overestimation of actual yield. In contrast, the Generative 2 phase (3 July 2025) showed a reduction in the extent of the highest productivity class and a more balanced distribution of productivity levels. The Ripening phase (19 July 2025) further reduced the proportion of high-productivity areas, with most rice fields falling within the 5–7 t ha^{-1} and 7–9 t ha^{-1} classes. This trend reflects the decline in NDVI associated with leaf senescence prior to harvest. Overall, the maps demonstrate that satellite image acquisition timing substantially affects productivity estimation results. The Generative 2 and Ripening phases produced spatial patterns that more closely resembled observed field productivity, suggesting that imagery acquired closer to harvest provides more reliable productivity estimates than imagery acquired during peak vegetative growth.

A



B



C

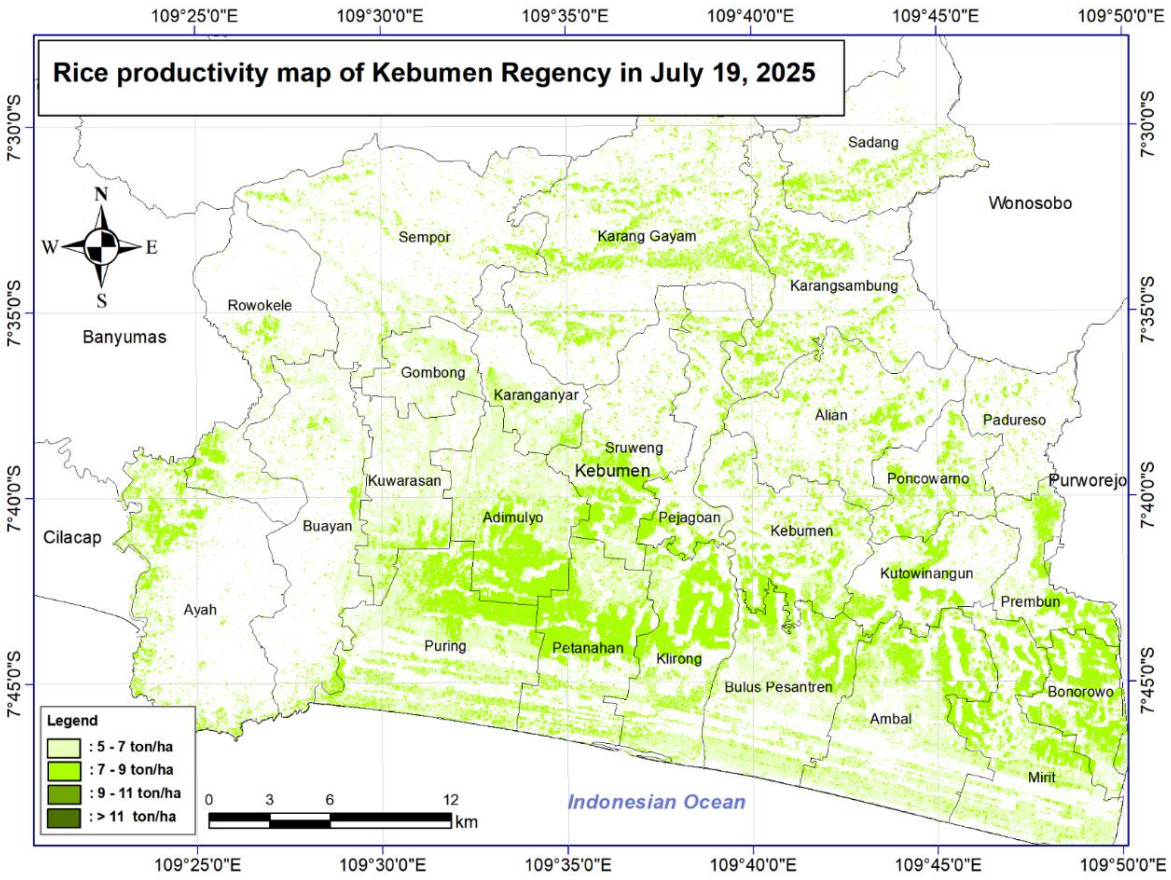


Fig. 5. Paddy productivity maps for Kebumen Regency at different image acquisition dates: (a) Generative 1; (b) Generative 2; and (c) Ripening. Source: Data processing, 2026.

Rice production for each subdistrict in Kebumen Regency

Fig. 6 shows the estimated rice production for each subdistrict in Kebumen Regency derived from NDVI-based models using satellite images acquired during three growth stages and BPS data. Overall, the Generative 1 phase produced substantially higher production estimates than the Generative 2 and Ripening phases across nearly all subdistricts. The highest production values were consistently observed in Puring, Bulus Pesantren, Ambal, Adimulyo, and Petanahan, reflecting their extensive irrigated rice-growing areas. In contrast, Padureso, Sadang, Ayah, and Alian exhibited the lowest estimated production levels throughout the study area. Although the magnitude of production estimates varied considerably among acquisition dates, the spatial ranking of subdistricts remained relatively stable. Generative 1 imagery tended to overestimate production due to the influence of maximum vegetative biomass on NDVI values. Meanwhile, the Generative 2 and Ripening phases produced more comparable estimates and better represented actual production conditions. These findings indicate that image acquisition timing strongly affects production estimation magnitude, while the overall spatial pattern of rice production remains largely consistent across growth stages. The next analysis estimates paddy productivity in Kebumen Regency for each phase and compares the results with data from the Central Statistics Agency (BPS). The data are shown also in Fig. 6 and the analysis shows in Table 4

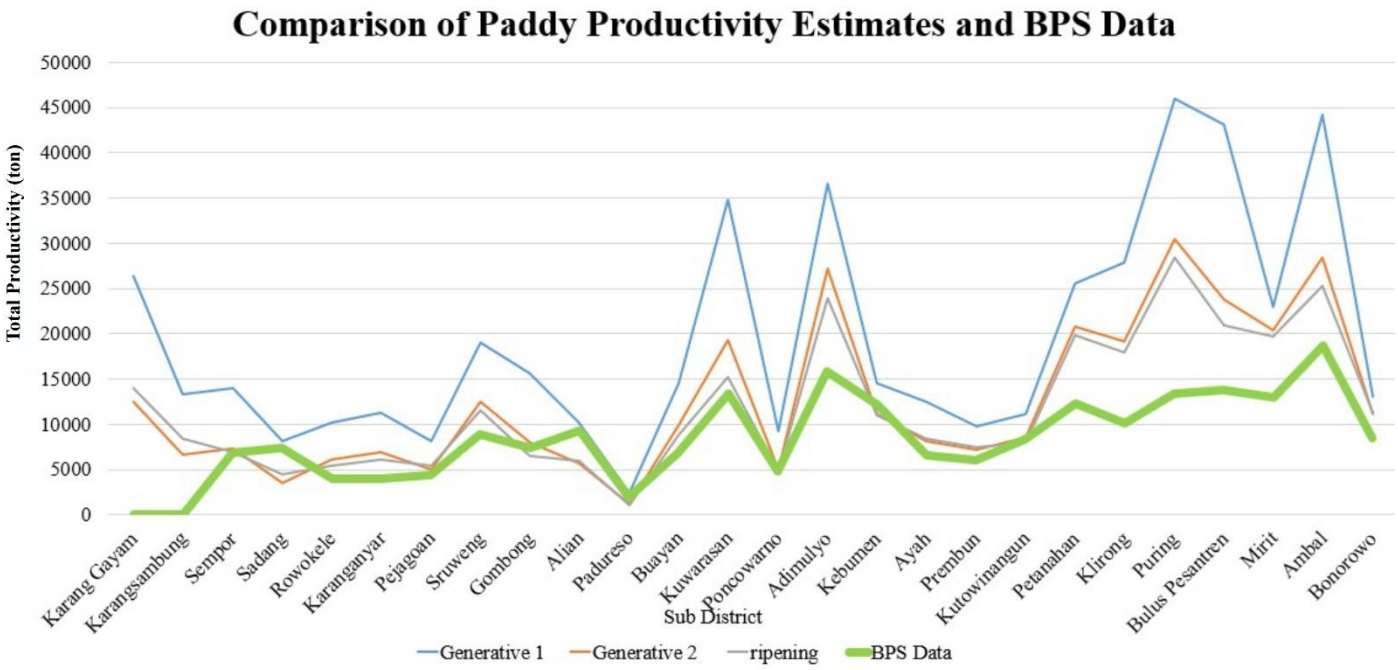


Fig. 6. Comparison of NDVI-derived paddy production estimates and BPS data. Source: Data processing, 2026.

The comparison between NDVI-derived production estimates and BPS production data revealed that the Generative 2 phase provided the strongest relationship with observed production, with a correlation coefficient of 0.901. Although the Generative 1 phase exhibited high NDVI values due to maximum canopy greenness, it tended to substantially overestimate production, resulting in an average relative error exceeding 100%. In contrast, the Ripening phase produced the lowest estimation error (35.9%), indicating that spectral conditions closer to harvest better represent actual grain yield. These findings suggest that NDVI acquired during the Generative 2 phase is most suitable for explaining spatial variability in paddy production, whereas NDVI from the Ripening phase is more appropriate for estimating absolute production values. The results further indicate that maximum vegetation vigor does not necessarily correspond to final yield, emphasizing the importance of image acquisition timing in paddy productivity assessment.

Table 4. Accuracy assessment of paddy production estimates derived from different Landsat 9 acquisition phases against BPS data.

Phase	r versus BPS	R^2	RMSE	MAPE (%)
Generative 1	0.873	0.763	2,006.08	103.83
Generative 2	0.901	0.811	1,790.38	43.68
Ripening	0.894	0.799	1,844.14	35.85

Source: Data processing, 2026.

Statistical analysis demonstrated that all NDVI-based production estimates exhibited a strong positive relationship with BPS production data, with correlation coefficients exceeding 0.87 across all growth phases. Among the evaluated phases, Generative 2 produced the strongest correlation ($r = 0.901$) and the highest coefficient of determination ($R^2 = 0.811$),

indicating that approximately 81.1% of the variation in observed production could be explained by the model. Furthermore, Generative 2 yielded the lowest RMSE value, suggesting superior predictive performance compared to the other phases. In contrast, the Generative 1 phase generated the highest average production estimates and showed a tendency to overestimate actual production, resulting in the largest prediction errors. This outcome is likely because NDVI during Generative 1 primarily reflects peak canopy greenness and biomass accumulation rather than final grain yield. Although the Ripening phase exhibited a slightly lower correlation than Generative 2, it produced the lowest MAPE value (35.85%), indicating better agreement with actual production values. These findings suggest that image acquisition during the Generative 2 phase is most suitable for modeling spatial variability in paddy production, whereas imagery acquired during the Ripening phase provides more accurate estimates of absolute production. Overall, the results highlight the importance of selecting an appropriate acquisition period to improve the accuracy and reliability of NDVI-based paddy productivity estimation.

Data evaluation

To evaluate the robustness of the regression model, the dataset was randomly divided into 70% training data and 30% testing data. The training dataset was used to develop the regression model, while the testing dataset was used to assess its predictive performance on unseen observations. The validation results indicate that the model performs consistently across all growth phases. In the Generative 1 phase, the model achieved an R^2 value of 0.796 for the training dataset and 0.730 for the testing dataset, indicating strong predictive capability with limited overfitting. For the Generative 2 phase, the model obtained an R^2 value of 0.765 on the training data and 0.679 on the testing data. Although the predictive performance was slightly lower than that of Generative 1, the model still explained more than 67% of the variability in rice productivity. In the Ripening phase, the model showed the best generalization performance, with an R^2 value of 0.770 for training and 0.773 for testing, demonstrating excellent agreement between observed and predicted productivity values. The relatively small differences between training and testing R^2 values across all phases suggest that the regression models are stable and do not suffer from significant overfitting. Therefore, the developed NDVI-based regression models can be considered sufficiently reliable for estimating rice productivity within the study area. The evaluation results are shown in Table 5.

Table 5. Evaluation of the NDVI-based paddy productivity models using training and testing data.

Phase	R^2 training	R^2 testing	RMSE testing	MAE testing
Generative 1	0.796	0.73	0.773	0.627
Generative 2	0.765	0.679	0.629	0.551
Ripening	0.77	0.773	0.685	0.576

Source: Data processing, 2026.

This study has several limitations that should be considered when interpreting the results. First, the analysis was conducted using data from a single planting season, which may not fully capture interannual variations in climatic conditions, crop management practices, and rice growth dynamics. Second, the study was limited to Kebumen Regency, Central Java, Indonesia; therefore, the findings may not be directly transferable to other rice-growing regions with different environmental and agricultural characteristics. Third, productivity estimation was based solely on the Normalized Difference Vegetation Index (NDVI), while other vegetation indices such as EVI, SAVI, or red-edge-based indices may provide additional information and potentially improve estimation accuracy. Finally, the study relied on Landsat 9 imagery with a spatial resolution of 30 m, which may not adequately represent small and fragmented paddy fields and could introduce mixed-pixel effects. Future studies should incorporate multi-season observations, larger geographic extents, additional vegetation indices, and higher-resolution satellite data to improve the robustness and generalizability of rice productivity estimation models.

Future research should explore the use of higher spatial resolution satellite imagery, such as Sentinel-2, which provides 10 m spatial resolution and may improve the detection of small and fragmented paddy fields. In addition, the incorporation of time-series vegetation indices throughout the entire growing season could better capture crop phenological dynamics and improve productivity estimation accuracy compared to single-date observations. Future studies should also evaluate advanced predictive approaches, including machine learning regression algorithms such as Random Forest Regression, Support Vector Regression, and Extreme Gradient Boosting (XGBoost), which have demonstrated superior performance in modeling complex nonlinear relationships between vegetation characteristics and crop yield. Furthermore, multi-season and multi-year analyses are recommended to assess the temporal stability and generalizability of productivity estimation models under varying climatic conditions, cultivation practices, and environmental settings. Such improvements would contribute to the development of more robust and transferable remote sensing-based frameworks for paddy productivity monitoring and food security assessment.

Materials and methods

Study area

This study was conducted in Kebumen Regency, Central Java, Indonesia (Fig. 7). Kebumen is located in 7°27′–7°50′ Latitude and 109°22′–109°50′ Longitude. The regency consists of 26 sub-districts and is bordered by Banjarnegara Regency to the north, Purworejo Regency to the east, Cilacap Regency to the west, and the Indian Ocean to the south. Kebumen is one of

the major rice-producing areas in the Central Java Province (BPS, 2024). The research period covered a single paddy cropping cycle, focusing on the generative phase from June to August in 2025.

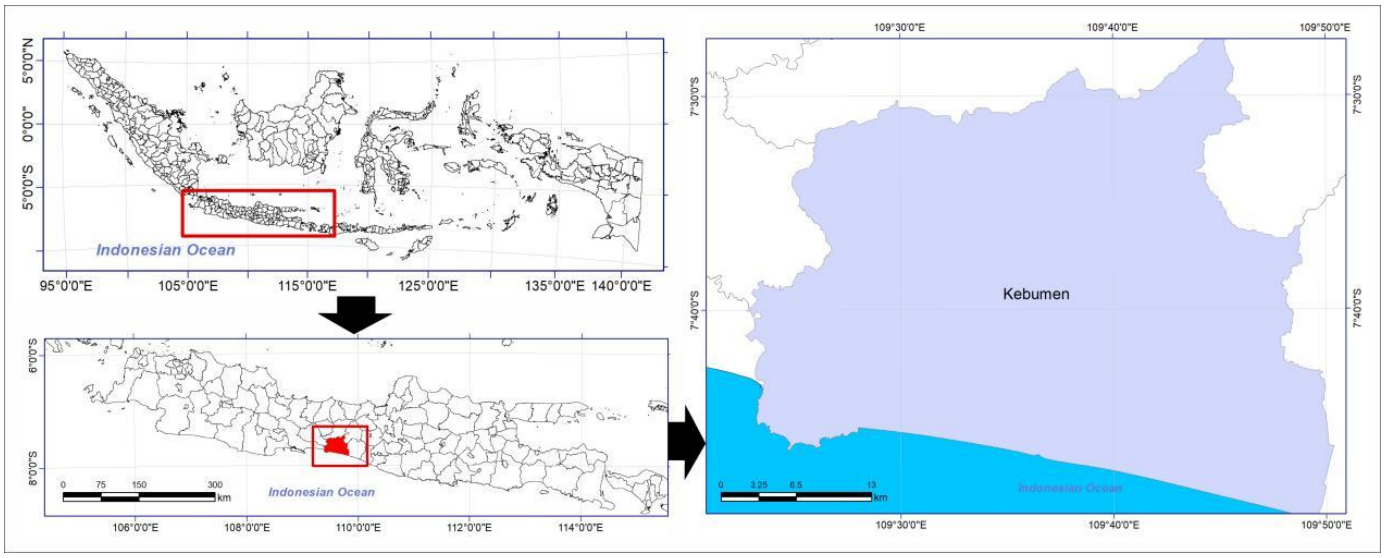


Fig. 7. Study area.

Data

This study utilized Landsat 9 OLI/TIRS Level-2 Surface Reflectance imagery obtained through the Google Earth Engine (GEE) platform. Surface Reflectance products are atmospherically corrected, making them suitable for vegetation monitoring and NDVI-based analysis. The satellite data were combined with field productivity measurements obtained from the ubinan survey conducted by the Indonesian Central Bureau of Statistics (BPS). The ubinan method measures rice yield using standardized sampling plots, and the results are expressed in tons per hectare (t ha^{-1}). The harvest period in Kebumen Regency occurred on 8 August 2025; therefore, multi-temporal Landsat 9 imagery acquired prior to harvest was selected to evaluate productivity during different reproductive growth stages. Three image acquisition dates were used in this study: 17 June 2025 representing the Generative 1 phase (52 days before harvest), 3 July 2025 representing the Generative 2 phase (36 days before harvest), and 19 July 2025 representing the Ripening phase (20 days before harvest). These acquisition dates were chosen to capture temporal variations in vegetation conditions and assess their influence on paddy productivity estimation.

Data processing

Landsat 9 imagery was processed using the Normalized Difference Vegetation Index (NDVI), which is one of the most widely applied vegetation indices for crop productivity estimation. Previous studies have shown that NDVI provides better performance for paddy productivity estimation than other vegetation indices, such as the Enhanced Vegetation Index (EVI), Soil-Adjusted Vegetation Index (SAVI), and Red Edge Position (REP) (Nazir et al. 2021). NDVI values range from −1, representing non-vegetated surfaces, to +1, indicating dense and healthy vegetation. Furthermore, NDVI has been identified as an effective indicator for predicting rice yield before harvest (Najafi et al., 2023). NDVI was calculated using Equation 1, where NIR represents the Near-Infrared band and R represents the Red band of Landsat 9 imagery.

$$\text{NDVI} = \frac{NIR - R}{NIR + R} \quad (1)$$

Following NDVI calculation, paddy field areas were extracted using a Random Forest classification algorithm implemented in Google Earth Engine. The resulting paddy field map was used to mask non-paddy areas, ensuring that subsequent analyses were conducted exclusively within rice cultivation zones. The NDVI layers corresponding to the Generative 1, Generative 2, and Ripening phases were then overlaid with the paddy field classification map and extracted at the locations of the BPS ubinan sampling plots. The ubinan dataset, obtained from the Indonesian Central Bureau of Statistics (BPS), represents field-measured rice productivity expressed in tons per hectare (t ha^{-1}).

Simple linear regression analysis was performed to evaluate the relationship between NDVI values and rice productivity measured from the ubinan survey. The resulting regression equations were subsequently applied to estimate paddy productivity across the study area. To identify the most suitable image acquisition period, Pearson's correlation coefficient (r) and the coefficient of determination (R^2) were calculated for each growth phase. The phase exhibiting the strongest relationship between NDVI and field productivity was considered the optimal period for productivity estimation.

In addition, productivity estimates derived from the Generative 1, Generative 2, and Ripening phases were compared to assess the influence of image acquisition timing on estimation results. This comparison was used to quantify temporal differences in productivity estimates and evaluate the consistency of NDVI-based productivity models across different reproductive growth stages. The overall research workflow is presented in Fig. 8.

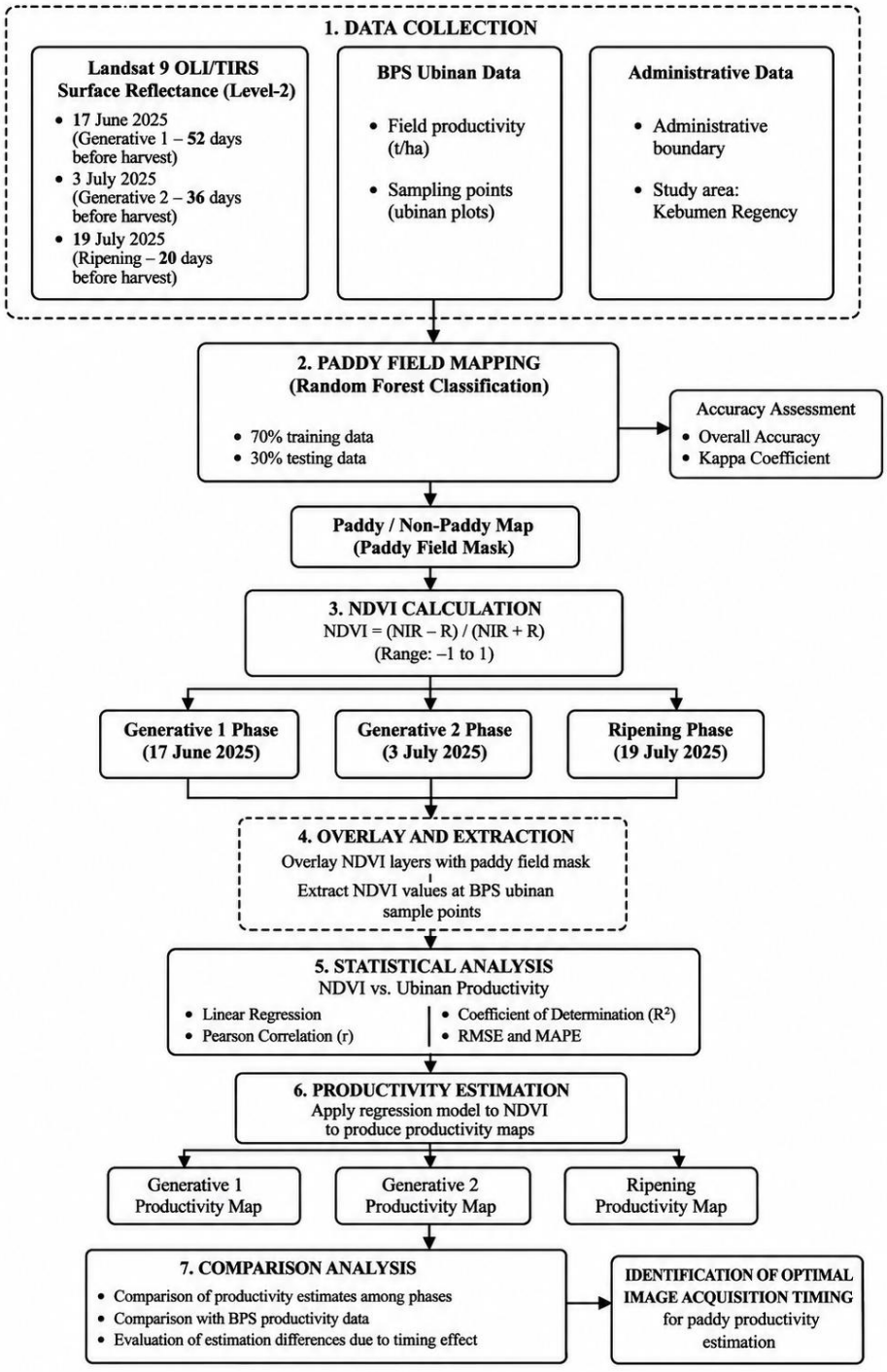


Fig. 8. Research workflow.

Conclusion

This study demonstrates that the timing of Landsat 9 image acquisition significantly influences NDVI-based paddy productivity estimation in Kebumen Regency. Analysis of three pre-harvest growth stages, namely Generative 1, Generative 2, and Ripening, revealed substantial differences in estimated productivity values resulting from temporal variations in crop phenology. The regression models showed strong relationships between NDVI and field-based productivity measurements, with R^2 values ranging from 0.747 to 0.781, indicating that NDVI is an effective indicator for rice productivity estimation. Among the evaluated phases, the Generative 1 stage provided the strongest relationship with field productivity data and produced the highest productivity estimates, reflecting maximum canopy greenness, chlorophyll content, and biomass accumulation. However, comparison with BPS production statistics showed that productivity estimates derived from the Generative 2 phase exhibited the strongest agreement with observed production ($r = 0.901$; $R^2 = 0.811$), while the Ripening phase generated the lowest estimation error (MAPE = 35.85%). These findings indicate that maximum vegetation vigor does not necessarily correspond to final grain yield because physiological changes during grain filling alter the relationship between NDVI and productivity. Therefore, image acquisition timing should be carefully selected according to the objective of the analysis. Generative 1 imagery is most suitable for estimating potential productivity, whereas Generative 2 and Ripening imagery provide more reliable estimates of actual production. Overall, this study highlights the importance of

phenology-based image acquisition for improving the accuracy and reliability of satellite-based paddy productivity assessment.

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