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Monitoring Sugarcane Phenology Using Sentinel-1 SAR and Machine Learning in Central Lampung

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ABSTRACT

Sugarcane is a vital commodity in the national sugar industry, requiring accurate growth monitoring to support precision agriculture. In Indonesia, conventional monitoring methods remain limited in spatial and temporal coverage. This study aims to monitor sugarcane phenology using multitemporal Sentinel-1 Synthetic Aperture Radar and to develop a machine learning–based growth phase classification model. The study was conducted in Central Lampung during one complete growing season from November 2023 to December 2024. Time-series analysis of VV and VH backscatter coefficients and the Normalised Polarisation Ratio was applied to capture sugarcane growth dynamics. Growth phase classification models were developed using Random Forest (RF) and Support Vector Machine (SVM) and evaluated using the confusion matrix, overall accuracy, Kappa coefficient, coefficient of determination, and root mean square error. The results indicate that RF consistently outperformed SVM across all model configurations. The best performance was achieved using combined VV–VH polarization, yielding an R^2 of 0.929, RMSE of 0.295, and classification accuracy of 93%. In contrast, SVM models showed weak predictive performance with negative R^2 values and classification accuracy below 32%. These findings demonstrate that multitemporal Sentinel-1 SAR data combined with RF provide an effective approach for spatial and temporal monitoring of sugarcane phenology.

INTRODUCTION

Sugarcane (Saccharum officinarum) is the main commodity in the national sugar industry (Amaliya et al., 2025). In Indonesia, sugarcane is widely cultivated, especially in tropical regions such as Java, Sumatra, and Sulawesi (Sulistiyanto et al., 2021). Its production is highly influenced by cultivation management, climate conditions, and the availability of accurate and sustainable plant growth monitoring systems (Nurhadi et al., 2025; Ahmed et al., 2024).

However, sugarcane growth monitoring systems in Indonesia still highly rely on conventional methods, such as field observations and manual reporting, which are limited in spatial coverage and temporal continuity (Msomba et al., 2024). These limitations made obtaining up-to-date information on growth phases, planting schedules, and yield potential markedly problematic, particularly on large-scale plantations (Nadzir et al., 2020; Suspidayanti & Rokhmana, 2021). Therefore, a technology-based approach is needed to provide accurate and efficient spatiotemporal information.

Remote sensing, particularly radar-based imagery such as Synthetic Aperture Radar (SAR), offers a promising solution to these challenges. Unlike optical imagery, which is affected by cloud cover and lighting conditions, SAR imagery can capture surface information under all weather conditions and at any time. Sentinel-1, SAR satellites from the Copernicus program managed by the European Space Agency (ESA), provide dual-polarization data (VV and VH) with high spatial resolution (10 meters) and frequent acquisition intervals (every 6–12 days), making it well-suited for multitemporal monitoring of crop growth.

Backscatter values derived from SAR imagery can detect changes in crop structure, soil moisture, and canopy dynamics, closely related to phenological stages (Suspidayanti & Rokhmana, 2021). A time-series approach using SAR imagery enables the visualization and analysis of crop growth trends from planting to harvest with a phenology-based method, like in Brazil (Zheng, Dos Santos Luciano, et al., 2022), India (Yeasin et al., 2022), Reunion Island of France (El Hajj et al., 2009), and in China (Hong et al., 2025; Jiang et al., 2019; Zheng, Li, et al., 2022). Additionally, advancements in data analysis methods such as machine learning, particularly classification algorithms like RF and SVM, have proven effective in processing remote sensing data for vegetation classification and estimation of crop biophysical parameters (Nihar et al., 2022; Som-ard et al., 2021). In addition, algorithms such as deep learning perform well to classify sugarcane crop on SAR and optical data (Sreedhar et al., 2022).

Moreover, recent studies highlight the strategic role of multitemporal SAR data in operational agricultural monitoring, especially in tropical regions where persistent cloud cover often limits the effectiveness of optical imagery (Pott et al., 2021). The integration of SAR time-series with machine learning has also demonstrated strong performance in distinguishing subtle phenological variations in various crops, indicating its potential for sugarcane monitoring at regional scales (Hong et al., 2024).

Despite these advancements, studies focusing on sugarcane phenology in Indonesia—particularly those employing dense multitemporal Sentinel-1 SAR time-series combined with machine learning across a complete growing season—remain limited. This lack of comprehensive SAR-based phenological analysis constitutes a clear research gap in tropical agricultural monitoring.

This study aims to examine the potential of multitemporal Sentinel-1 SAR imagery for monitoring the phenological development of sugarcane (Saccharum officinarum) in Central Lampung Regency. Specifically, it analyzes temporal patterns of VV and VH backscatter throughout a single sugarcane growing season, identifies growth stages using SAR time-series analysis, and develops machine learning–based classification models using RF and SVM algorithms. Through this approach, accurate spatial and temporal information on sugarcane growth dynamics is generated to support precision agriculture, yield estimation, and improved production efficiency.

Therefore, this study provides a novel framework for sugarcane phenology monitoring by integrating dense multitemporal Sentinel-1 SAR time-series features with machine learning algorithms to classify sugarcane growth stages throughout an entire growing season under tropical agricultural conditions in Indonesia. This framework extends previous studies by emphasizing continuous SAR-based temporal dynamics rather than single-date or limited-temporal observations, enabling robust phenological monitoring in cloud-prone regions.

RESEARCH METHODS

A. Study Site

The study was conducted in Central Lampung Regency, Lampung Province, Indonesia, one of the main sugarcane production centers in Sumatra. Geographically, the study area is located approximately between 105°10′ – 105°50′ East Longitude and 4°45′ – 5°30′ South Latitude, indicated in **Figure 1**. Central Lampung is characterized by predominantly flat to gently undulating terrain, which is highly suitable for large-scale sugarcane cultivation.

The region has a tropical humid climate with a clear distinction between rainy and dry seasons, which strongly influences planting schedules, crop growth, and harvesting periods. Sugarcane plantations in Central Lampung are generally managed under monoculture farming systems with relatively uniform planting blocks, facilitating the identification of phenological stages using remote sensing techniques.

The study utilized field observations and satellite data covering one complete sugarcane growing cycle from November 2023 to December 2024, encompassing the planting, vegetative growth, maturation, and harvesting phases. The frequent cloud cover experienced in the region, particularly during the rainy season, limits the usability of optical imagery and underscores the advantage of Sentinel-1 Synthetic Aperture Radar (SAR) data, which enables continuous data acquisition under all weather conditions.

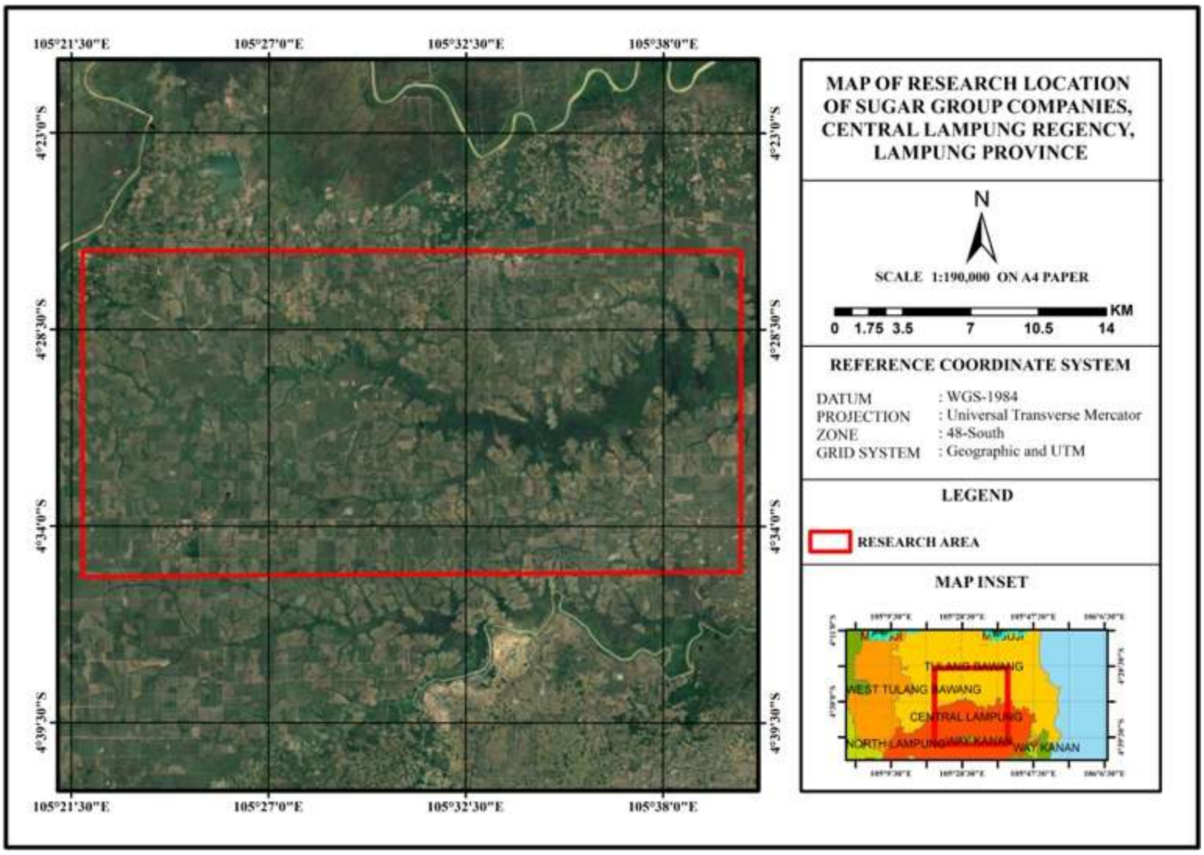


Figure 1. Map of the sugarcane research location in Central Lampung Regency, Lampung Province, Indonesia (Source: Sentinel-2, 2024)

The datasets used in this study consist of multitemporal remote sensing data and field observations. Sentinel-1 GRD SAR data were employed to extract backscatter information for phenological analysis, while Sentinel-2 multispectral data were used for visual validation of sugarcane growth stages. Field survey data were collected to provide ground reference information for model training and validation. **Table 1** presents the data sources, acquisition periods, spatial resolution, and data providers employed in this study for sugarcane phenology analysis.

Table 1. Data sources and characteristics used in this study

Data	Description	Acquisition Time	Resolution	Source
Sentinel-1 GRD	VV and VH polarimetry	2023-11-06, 2023-11-30, 2023-12-24, 2024-01-17, 2024-02-10, 2024-02-27, 2024-03-22, 2024-04-22, 2024-05-12, 2024-06-02, 2024-06-22, 2024-07-04, 2024-07-20, 2024-08-09, 2024-09-01, 2024-09-25, 2024-10-19, 2024-11-17, 2024-12-06, dan 2024-12-23.	10 m	Google Earth Engine https://earthengine.google.com/
Sentinel-2A	Blue Green Red Red Edge 1 Red Edge 2 Red Edge 3 NIR		10 m	Google Earth Engine https://earthengine.google.com/
Field Survey	planting phase, vegetative growth, ripening, and harvesting.	May- June, 2025	-	Central Lampung (Source: Field Survey Results, 2025)

B. Research Stages

The primary data were Sentinel-1 Level GRD images with VV and VH polarimetry. Supporting data included Sentinel-2 images for vegetation validation and field observation data, such as planting dates and growth phases. The research stages are presented in Figure 2, which is explained in detail in the subsequent paragraphs.

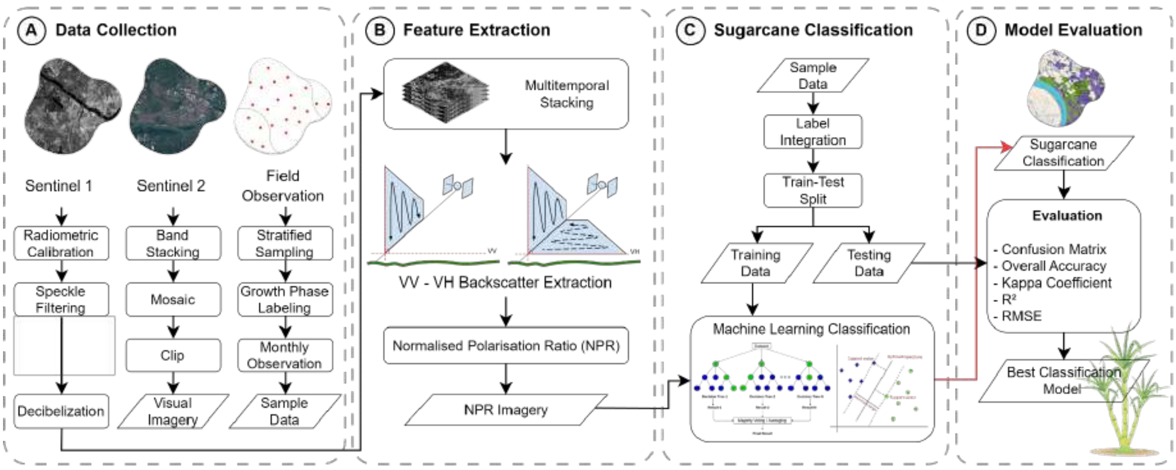


Figure 2. Feature Extraction and Classification Framework for Sugarcane (Source: Field Survey Results, 2025)

C. Pre-processing of SAR Images

Pre-processing steps for Sentinel-1 Synthetic Aperture Radar (SAR) images are carried out to ensure data quality and improve the accuracy of further analysis. This process includes several main stages, as follows:

1. Radiometric Calibration

All Sentinel-1 SAR pre-processing was performed using the Google Earth Engine (GEE) platform. Ground Range Detected (GRD) images acquired in Interferometric Wide (IW) mode were used. Radiometric calibration, thermal noise removal, precise orbit correction, and terrain correction were automatically applied using the standard Sentinel-1 processing chain implemented in GEE. These procedures ensure that the backscatter values are physically calibrated and temporally consistent, enabling reliable time-series analysis and land-cover classification

2. Speckle Filtering Using the Lee Filter

SAR images tend to have granular noise known as speckle, which can interfere with classification analysis and feature extraction (Simatupang et al., 2022). Therefore, filtering is performed using an adaptive Lee filter, which reduces noise without eliminating important spatial structures in the image. This filter preserves object boundaries so that textural information is not obscured (Baraha & Sahoo, 2022).

3. Conversion to Sigma-Nought Values (σ°)

   Backscatter values were converted to σ° in decibel (dB) units using a logarithmic transformation, enabling consistent comparison of surface scattering properties across acquisition dates.

4. Extraction of Backscatter Values from Field Observation Points

Mean σ° backscatter values were extracted from each field observation plot using polygon-based zonal statistics and subsequently used as input features for machine learning model training and validation.

D. Time-Series Analysis

Time-series analysis is conducted to observe VV and VH polarity backscatter value changes during the sugarcane growth cycle. Backscatter values are extracted temporally from Sentinel-1 images at the specified observation plot locations. This time-series data is then visualised in graph form to evaluate trends in radar signal changes over time (Den Besten et al., 2023).

The fluctuation patterns of backscatter values were used to identify the main phases in the sugarcane growth cycle, including the planting, vegetative, ripening, and harvesting phases. For example, increased VH values and the VV/VH ratio may indicate the vegetative growth phase due to increased biomass. In contrast, decreasing backscatter values may reflect the harvesting phase or loss of canopy cover (Phan et al., 2021).

E. Sugarcane Phenology Classification

A machine learning–based classification approach was implemented to identify the spatial and temporal phases of sugarcane growth using multitemporal Sentinel-1 SAR data. Two supervised algorithms, RF and SVM, were employed due to their proven effectiveness in remote sensing applications. The input feature set consisted of VV backscatter, VH backscatter, the VV/VH ratio, and planting time, which were selected to capture variations in crop structure and phenological development.

The RF classifier was constructed as an ensemble of decision trees generated using bootstrap sampling, where each tree was trained on a random subset of input features (Cera et al., 2023). The final classification result was determined through majority voting across all trees, allowing RF to handle non-linear relationships and reduce overfitting. This algorithm is particularly suitable for SAR data due to its robustness to noise and multicollinearity among input variables.

The SVM algorithm was applied to classify sugarcane growth phases using multitemporal Sentinel-1 SAR features. SVM was selected due to its capability to handle high-dimensional data and model non-linear decision boundaries (Chauhan et al., 2019). In this study, a radial basis function (RBF) kernel was employed, as it is widely used in remote sensing applications for capturing complex, non-linear relationships between SAR backscatter features and crop phenological stages.

The performance of the SVM model is strongly influenced by two key hyperparameters: the penalty parameter (C) and the kernel width parameter (gamma). The parameter C controls the trade-off between maximizing the margin and minimizing classification error, while gamma determines the influence range of individual training samples. To identify optimal parameter values, a grid search tuning strategy was implemented by testing multiple combinations of C and gamma values. The optimal parameters were selected based on classification accuracy obtained from the training dataset (Mizan et al., 2021).

Prior to model training, feature normalization was applied to all input variables (VV backscatter, VH backscatter, VV/VH ratio, and planting time) using min–max scaling. This step ensures that all features contribute equally to the classification process and prevents features with larger numeric ranges from dominating the decision function.

To address class imbalance among sugarcane growth phases, proportional class weighting was applied during model training. This approach assigns higher weights to underrepresented classes, allowing the SVM model to reduce bias toward dominant classes. Training and validation were performed using a 70% training and 30% testing split (Sovann et al., 2025), with field-observed growth phase labels serving as reference data.

F. Model Validation and Accuracy Testing

The validation design of this study was structured to ensure an objective and unbiased evaluation of the classification models. Field-observed sugarcane growth phase labels were used as reference data. A stratified sampling strategy was applied to maintain proportional representation of the four growth phases (planting, vegetative, ripening, and harvesting) in both training and testing datasets.

The dataset was divided into 70% for model training and 30% for independent testing. The data split was performed at the plot level to avoid spatial autocorrelation between training and testing samples. Model evaluation was conducted using confusion matrices to assess class-level performance, overall accuracy (OA), and the Kappa coefficient to measure agreement beyond chance (Hong et al., 2025; Simarmata et al., 2022).

In addition, regression-based metrics including RMSE, MAE, and coefficient of determination (R^2) were used to evaluate the consistency of predicted phenological stages against reference observations in a temporal context (Hakim et al., 2022). This combined validation strategy allows both spatial classification accuracy and temporal prediction reliability to be assessed comprehensively (Li et al., 2024).

G. Field Observation

The planting time and phenological stages of sugarcane are determined through systematic field data collection. The stratified sampling method is used to identify 100 sugarcane plots, representing four main growth phases, namely planting, vegetative, ripening, and harvesting, with a relatively balanced number of plots in each phase. The results of field surveys for each phase of sugarcane cultivation are presented in Figure 3.

Figure 3. (a) Planting; (b) vegetative; (c) ripening; (d) harvesting
(Source: Survey Results, 2025)

The growth phase label for each plot was determined based on the most dominant phenological condition, which was determined through visual observation of plant height, canopy density, and leaf condition during field surveys (Holman et al., 2016; Koch et al., 2007). Observations were conducted monthly and adjusted to the Sentinel-1 image acquisition schedule to ensure temporal consistency between field and satellite data (Simarmata et al., 2023). The labeled data was then used as a reference in the development of a machine learning model, with the dataset divided into 70% for training and 30% for testing, to ensure objective and unbiased model evaluation.

RESULTS AND DISCUSSION

A. Time-series graph of sugarcane backscatter values for each phase

Sentinel-1 image analysis was conducted to monitor changes in backscatter values during the sugarcane growth cycle in Central Lampung. The data was analysed temporally using the Normalised Polarisation Ratio (NPR) approach, representing the ratio between VV and VH signal polarities. NPR is used because it is sensitive to changes in plant structure and water content, making it suitable for detecting vegetation dynamics. The results are presented as time-series graphs illustrating NPR value variations throughout the observation year, differentiated by the main growth phases: planting, vegetative, maturation, and harvest. Research (Den Besten et al., 2023) shows that waterlogging causes an increase in all polarizations. Not only that, it has been found that various other factors such as crop age, weather patterns and soil type could impact reflectance, in turn changing the backscatter power (Waters et al., 2025). Figure 4 shows the time series of the Normalized Polarization Ratio (NPR) for sugarcane.

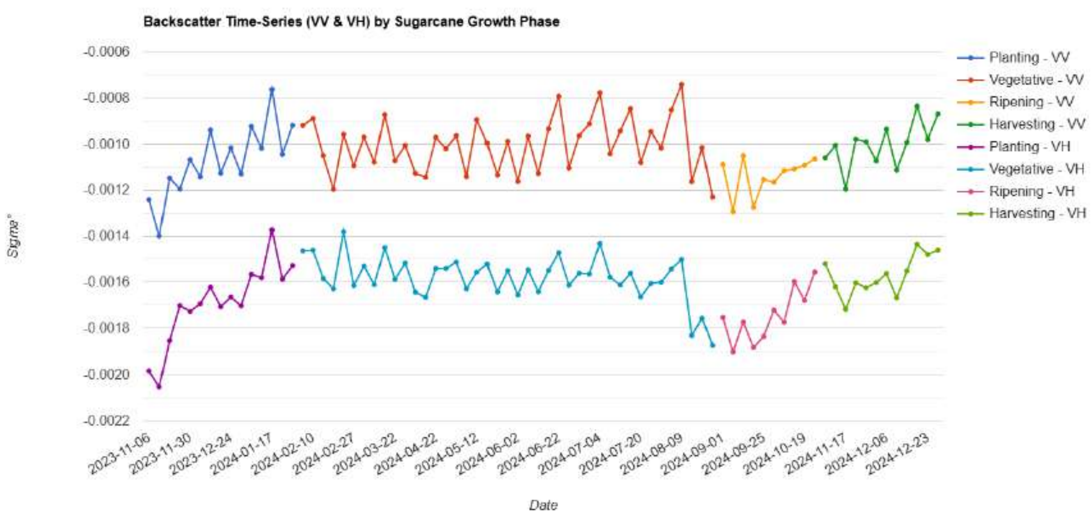


Figure 4. NPR Time Series of Sugarcane Plant (Source: Analysis Results, 2025)

The time-series graph above shows the dynamics of the Normalised Polarisation Ratio (NPR) values resulting from smoothing as a representation of the backscatter values from Sentinel-1 radar images of sugarcane phenological growth in Central Lampung during the period from November 2023 to December 2024. This graph distinguishes four main phases of sugarcane growth, namely the planting phase (blue), vegetative phase (green), ripening phase (orange), and harvesting phase (red), each of which exhibits different radar signal reflection characteristics based on the plant's biophysical conditions.

During the planting phase, the NPR values tend to be low and stable, ranging from -0.35 to -0.15. This reflects the dominant surface conditions of the soil, as the plants have not yet grown significantly, causing radar signals to be primarily reflected by open soil. During the vegetative phase, NPR values exhibit higher fluctuations, even reaching -0.5 at certain points. This increase and variation indicate the growth of plant canopies and the development of complex leaf and stem structures, causing radar signals to be more scattered and absorbed. This indicates biomass accumulation and increased water content in the vegetation.

During the maturation phase, the NPR value slightly increases and stabilises, ranging from -0.3 to -0.1. This stability indicates that plant growth has reached a physiologically mature phase, where plant structures begin to harden, and water content decreases, resulting in a more consistent radar signal reflection. Meanwhile, during the harvest phase, the NPR value drops significantly again, approaching -0.4, similar to the planting phase. This decrease indicates the loss of vegetation cover due to harvesting, causing the soil surface to once again dominate the radar signal response.

Overall, this graph demonstrates that Sentinel-1 radar imagery is highly effective in monitoring the growth dynamics of sugarcane plants based on changes in backscatter values. The NPR fluctuation pattern aligns with the biophysical changes in the plant during each phenological phase. This analysis is important for supporting precision agriculture monitoring, particularly in detecting planting time, active growth phases, and estimating harvest time. To enhance monitoring accuracy, this analysis can be combined with optical data such as NDVI from Sentinel-2 or machine learning-based classification models that were found to have an OA level of 84.5% (Singh et al., 2022) and an average of 80% for other optical sensors (Som-ard et al., 2021).

B. SAR-based classification model for sugarcane growth stages using Sentinel-1

In Model 1 RF, which uses the VV/VH ratio as the primary feature, the classification results show a good spatial distribution, although some transitions between phases appear less sharp. The vegetative and maturation phases are identified in relatively consistent block patterns, but the sharpness of the boundaries between phases is not yet optimal. Model 2 RF with the VH/VV ratio provides similar results, but with a tendency for broader harvest phase classification. This indicates that the VH/VV feature has higher sensitivity to post-harvest vegetation cover loss, although there is still some overlap between phases in some areas.

Model 3 RF, which uses the difference between VV and VH values, is superior visually and statistically. This model's classification map shows clear spatial boundaries between phases, phase distribution consistent with planting patterns, and minimal noise. The planting, vegetative, ripening, and harvesting phases are neatly divided according to actual land blocks. The high accuracy of this model (R^2 = 0.929 and OA = 93%) further reinforces its reliability in spatial classification of sugarcane phenology.

Model 4 RF, which is based on the NPR ratio, also shows good performance. Visually, the classification of the vegetative and ripening phases is relatively straightforward. Still, the boundaries between the planting and harvesting phases appear slightly blurred in some locations, especially on narrow or mixed plots. Nevertheless, this model remains representative in describing the general dynamics of vegetation. Meanwhile, Model 5 RF, which utilises multiband features, displays stable and accurate results, with classification maps like Model 3. The growth phases are well classified and follow the shape of the agricultural blocks. The advantage of this model lies in its ability to utilise a lot of information at once, making it suitable for large-scale spatial applications.

In contrast, the classification results of Model 1 SVM using the VV/VH ratio show an irregular spatial distribution pattern. Each growth phase appears randomly scattered within a single plot, without forming consistent blocks or areas. This indicates that the model cannot adequately capture vegetation's spatial structure. Model 2 SVM with the VH/VV ratio shows a slight improvement in the distribution of vegetative phases. Still, the classification remains noisy and does not match the planting block patterns. The transition between phases is blurred, and many areas are classified illogically.

Model 3 SVM, which uses the VV–VH difference, fails to provide good classification despite being based on the best features of the RF model. The results still show spatial irregularities with extreme phase mixing, indicating that the SVM algorithm cannot effectively utilise these features in a spatial context. Similarly, Model 4 SVM, which uses the NPR ratio, produces highly chaotic classifications. Growth phases appear to be distributed abnormally, even showing planting phases in the middle of the vegetative season.

Model 5 SVM, which combines multiband features, also does not show significant improvement. Instead of providing a stronger classification, the resulting map appears mosaic-like with confusing colour distribution and does not reflect the growth phase. High spatial fragmentation and dominant noise make the classification results of this model unusable operationally without additional improvements or post-processing. The results of RF and SVM-based classification are presented in Figures 5 and 6.

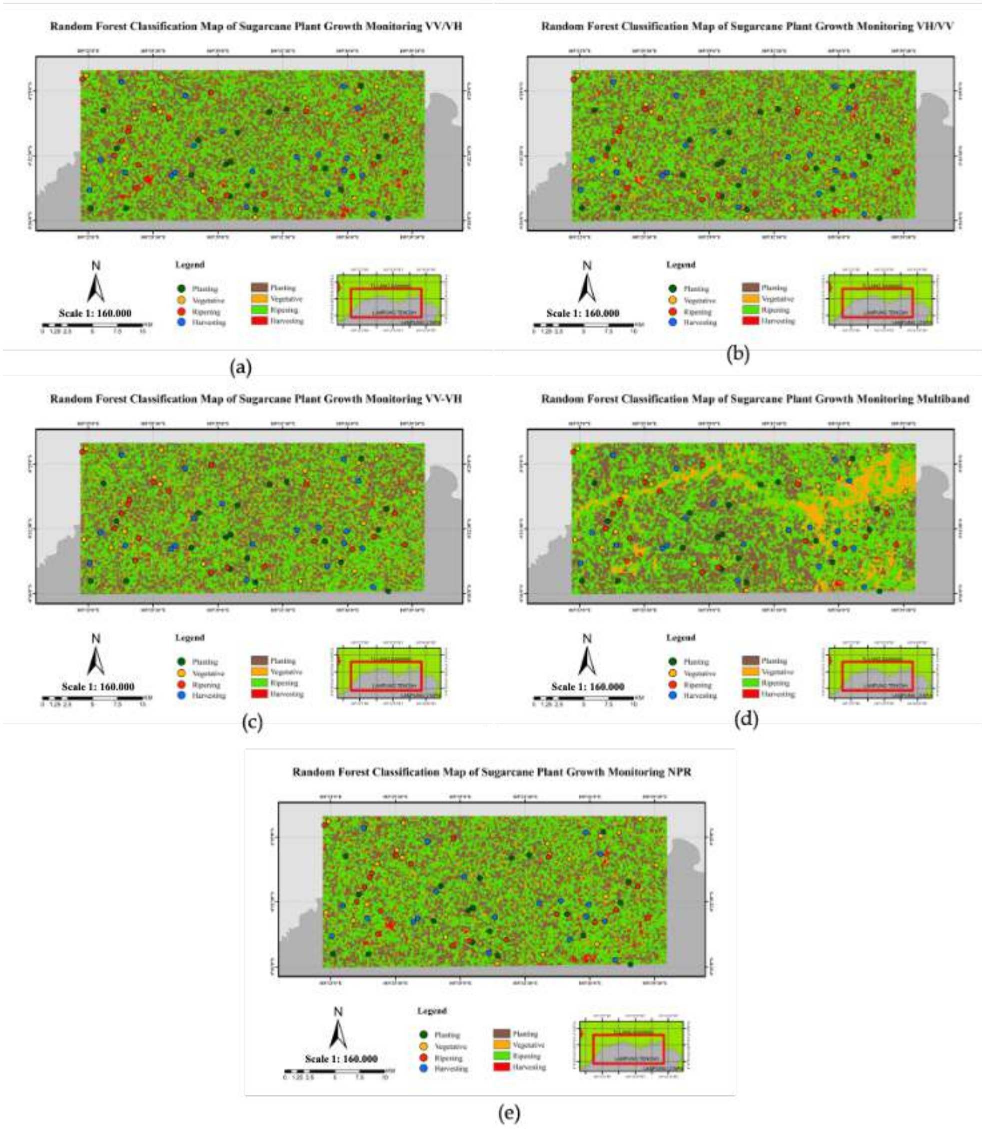
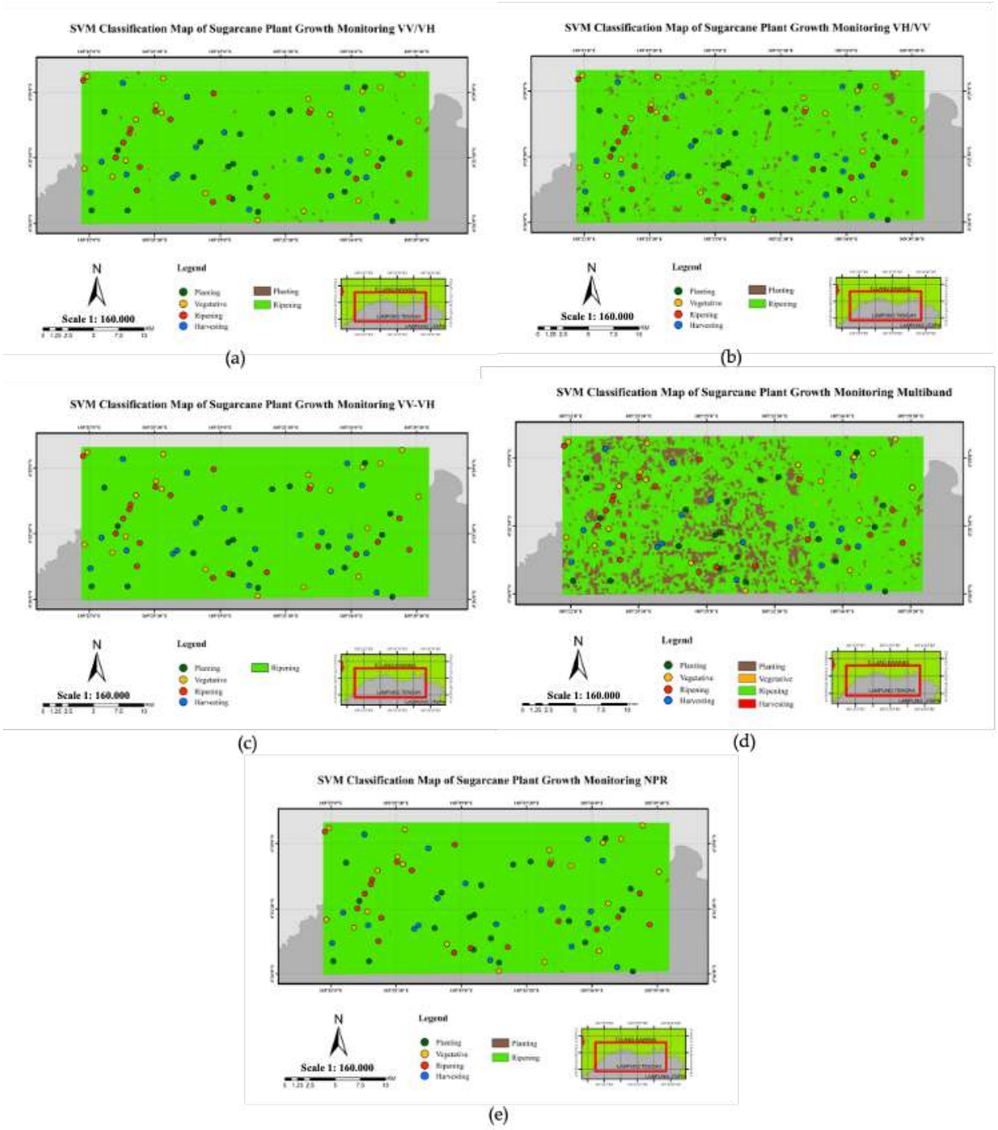


Figure 5. RF Classification Map of Sugarcane Plant Growth Monitoring (a) Model 1; (b) Model 2; (c) Model 3; (d) Model 4; (e) Model 5 (Source: Analysis Results, 2025)



Fig*ure 6.* SVM Classification Map of Sugarcane Plant Growth Monitoring (a) Model 1; (b) Model 2; (c) Model 3; (d) Model 4; (e) Model 5 (Source: Analysis Results, 2025)

C. Model Validation

As presented in the graph, the evaluation analysis of the RF model for sugarcane growth shows that the best model is [VV-VH] RF. This model performs better with the lowest RMSE and MAE, indicating the highest prediction accuracy and minimal error. Additionally, the R-squared (R^2) value for the [VV-VH] RF model is the highest, approaching 0.95, meaning this model is highly effective in explaining the variability in sugarcane growth. Although other models, such as [VV/VH] RF, [VH/VV] RF, [NPR] RF, and Multiband RF, also show good R^2 values (around 0.8), these models have higher RMSE and MAE values. This indicates that the difference between VV and VH polarisation provides the most relevant and robust information for predicting sugarcane growth compared to single polarisation ratios or other multiband combinations. In summary, based on the evaluated data, [VV-VH] RF is the optimal choice for modelling sugarcane growth. Based on research from (Sridhara et al., 2024) comparing RF, SVM, stepwise multiple linear regression (SMLR), and artificial neural networks (ANN) methods, the ANN model demonstrated superior performance. Meanwhile, a convoluted neural network

(CNN), similarly built from the neural network concept, has been found to perform reliably in combination with a field-based crowd-sourced application (Wang et al., 2020). Figure 7 illustrates the performance evaluation of the Random Forest (RF) model in classifying sugarcane phenological stages.

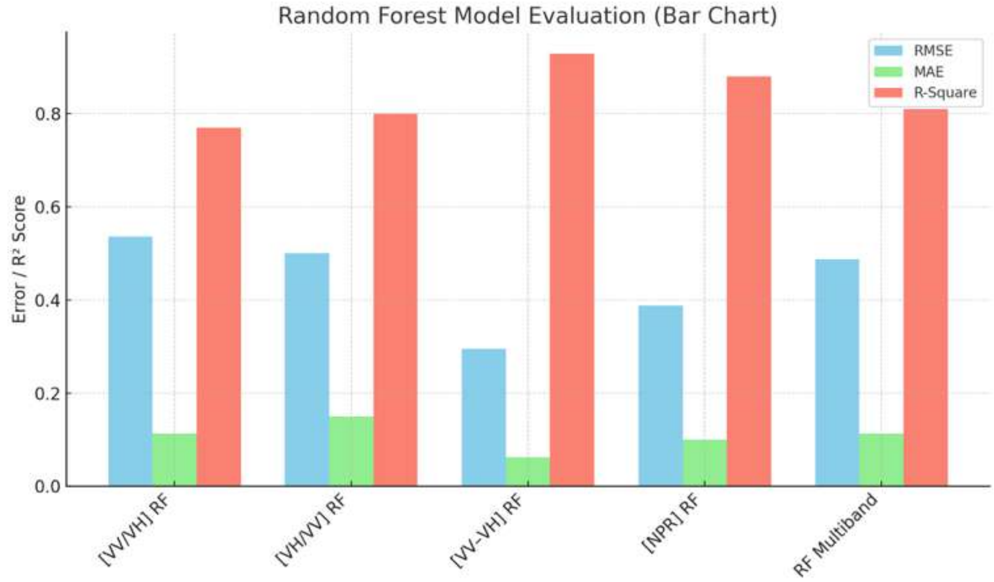


Figure 7. RF Model Evaluation (Source: Analysis Results, 2025)

The evaluation of the SVM model for predicting sugarcane growth yielded highly unsatisfactory results. All SVM model configurations tested, regardless of the polarisation combination used, produced high RMSE and MAE values and negative R-squared values. This indicates that the SVM model cannot effectively capture patterns or relationships between radar image features and sugarcane growth. Therefore, based on these evaluation results, the SVM model is not recommended for use in predicting sugarcane growth, and it is suggested that more in-depth parameter optimisation, different feature selection, or switching to a more suitable alternative model algorithm be considered. Figure 8 shows the Support Vector Machine (SVM) model evaluation results.

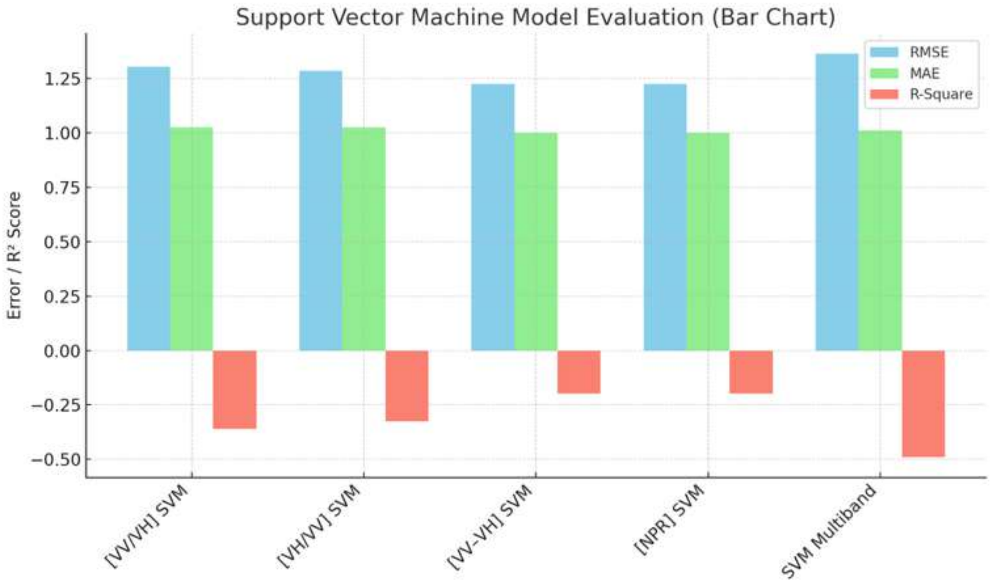


Figure 8. SVM Model Evaluation (Source: Analysis Results, 2025)

The RF model demonstrated excellent performance in predicting sugarcane growth, with high accuracy (low RMSE and MAE) and superior explanatory power (R-squared approaching 0.95), particularly in the [VV-VH] RF configuration. In contrast, the SVM model performed poorly, with high RMSE and MAE values and negative R-squared values for all configurations, indicating the model's inability to make accurate predictions. Table 2. Performance metrics (RMSE, MAE, and R^2) were used to evaluate the predictive accuracy of the models.

Table 2 RMSE, MAE and R-Square Value

Classification	RMSE	MAE	R-Square
[VV/VH] RF	0.5361	0.1125	0.77
[VH/VV] RF	0.5	0.15	0.8
[VV–VH] RF	0.295	0.0625	0.929
[NPR] RF	0.3872	0.1	0.88
RF Multiband	0.4873	0.1125	0.81
[VV/VH] SVM	1.3038	1.025	-0.361
[VH/VV] SVM	1.2845	1.025	-0.326
[VV–VH] SVM	1.2247	1	-0.199
[NPR] ASVM	1.2247	1	-0.199
SVM Multiband	1.3647	1.0125	-0.49

(Source: Analysis Results, 2025)

D. Accuracy Test

Based on overall accuracy and the Kappa coefficient, the bar graph compares classification performance between the RF and SVM algorithms. It is clear that RF consistently outperforms SVM in this classification task. For all input feature configurations (such as [VV/VH], [VV/(VV)], [VV-VH], [NPR], and Multiband), RF achieves accuracy above 90% and a Kappa Coefficient above 0.9, indicating very high accuracy and excellent agreement between classification results and reference data. Similar research also yielded excellent classification results for sugarcane and non-sugarcane for all years, with an overall accuracy (OA) exceeding 90% (Suwanlee et al., 2025). Meanwhile, research (Virnodkar et al., 2021) using RF achieved a higher overall accuracy (88.61%) compared to SVM, which had an overall accuracy of 81.86%. The confusion matrix of the sugarcane phenological phase classification results using RF and SVM is presented in Figure 9. It can be seen below that the general behavior of RF results is markedly better than the SVM, where the former displays diagonal heat, indicating that most of the prediction classes agree with the actual classes. Conversely, the heatmap of SVM shows a column-like matrix, evidently unable to correctly predict classes other than Maturation. Yet, this differs from previous research on an arid environment that shows SVM performs better than RF (Baccari et al., 2025). This difference could be attributed to the usage of different types of datasets (SAR compared to optical image) and differing climate conditions (humid in the tropics versus desert-induced arid locations).

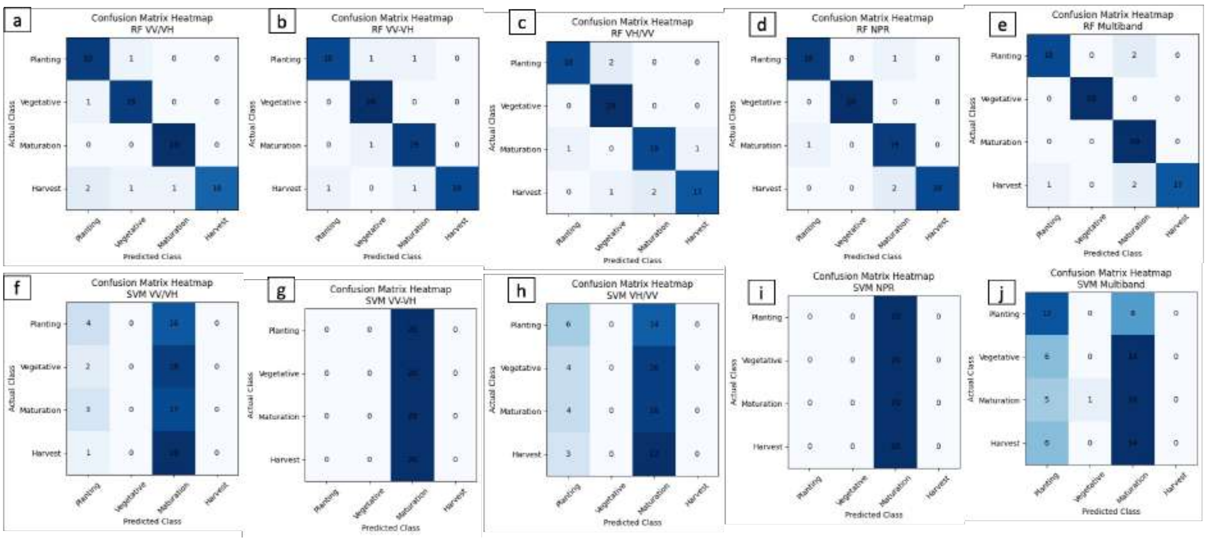


Figure 9. Confusion matrix of sugarcane phenological phase classification results using RF and SVM (Source: Analysis Results, 2025)

The table below confirms that the RF model is highly effective and reliable. In contrast, SVM shows abysmal performance, with accuracy generally below 30% and a Kappa Coefficient close to 0.0. Table 3. Comparison of classification performance based on overall accuracy and kappa coefficient values.

Table 3. Overall Accuracy And Kappa Coefficient Values

Classification	Overall Accuracy	Kappa Coefficient
[VV/VH] RF Accuracy	93%	0.916
[VH/VV] RF Accuracy	90%	0.866
[VV–VH] RF Accuracy	93%	0.916
[NPR] RF Accuracy	92%	0.9
RF Multiband Accuracy	93%	0.916
[VV/VH] SVM Accuracy	26%	0.016
[VH/VV] SVM Accuracy	27%	0.033
[VV–VH] SVM Accuracy	25%	0
[NPR] SVM Accuracy	25%	0
SVM Multiband Accuracy	32%	0.102

(Source: Analysis Results, 2025)

The classification results presented in Table 2 show that the RF algorithm performs significantly better than the SVM in classifying sugarcane growth stages based on multitemporal Sentinel-1 SAR imagery. These results indicate that RF is far more effective and reliable in processing complex and non-linear SAR backscatter data than SVM. Therefore, using the RF algorithm is recommended for sugarcane phenological phase classification, as it can better capture the spatial-temporal variations of the plants and provide accurate and consistent classification results (Suwanlee et al., 2025).

CONCLUSION

This study successfully demonstrated that multitemporal Sentinel-1 radar imagery is highly effective for monitoring the phenological growth dynamics of sugarcane (Saccharum officinarum) in Central Lampung. Time-series analysis of backscatter values (VV and VH) and the Normalised Polarisation Ratio (NPR) revealed distinct patterns across each growth phase: planting, vegetative, maturation, and harvest. The NPR values effectively represented changes in plant biophysical characteristics, reflecting biomass accumulation and canopy structure changes.

A machine learning-based growth stage classification model showed that the RF algorithm performed significantly better than the SVM. The [VV–VH] RF model achieved the highest accuracy with an RMSE of 0.295, MAE of 0.0625, and R^2 of 0.929, with overall accuracy reaching 93% and a Kappa coefficient of 0.916. Conversely, all SVM model configurations performed poorly, with negative R^2 values and classification accuracy below 32%.

Thus, the SAR Sentinel-1-based monitoring approach and RF algorithm have proven reliable for identifying and mapping sugarcane growth phases spatially and temporally. These results can potentially support the development of precision agriculture systems, particularly regarding growth monitoring, fertilisation scheduling, and harvest time estimation. For future development, integration with optical imagery such as NDVI from Sentinel-2 and improved resolution of field observation data could further enhance model accuracy and generalisation.

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