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Long-Term NDVI-Based Analysis of Rice Growth Cycles in Malaysia Using Landsat Time-Series Data

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ABSTRACT

Rice is one of the key food crops in Malaysia and is cultivated under a double-cropping system that consists of a main season and an off-season. Continuous and long-term monitoring of rice growth is essential for understanding crop phenology and supporting future agricultural management and yield assessment. This study presents a long-term analysis of rice growth trends in Malaysia using the Normalized Difference Vegetation Index derived from Landsat satellite time-series data spanning January 2000 to December 2024. The study area covers approximately 10 km² of rice cultivation land located near Pekan, on the east coast of Peninsular Malaysia. Monthly NDVI composites were generated from Landsat 5 TM, Landsat 7 ETM+, Landsat 8 OLI, and Landsat 9 OLI-2 surface reflectance products, with cloud-contaminated pixels removed using quality assessment information. The results reveal a clear bimodal NDVI pattern that corresponds to Malaysia's double-cropping rice system, with peak NDVI values occurring during the off-season (May–June) and main season (October–November). Seasonal NDVI variations reflect distinct rice growth stages, including tillering, heading, and harvesting periods. The findings demonstrate the capability of long-term Landsat NDVI data to effectively capture rice growth dynamics and seasonal cycles. This study provides a quantitative baseline for future research on rice growth stage modeling, pest and disease monitoring, and yield estimation using satellite-based observations.

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1. INTRODUCTION

Rice is a major staple food crop in Malaysia and plays a central role in national food security. It is the primary carbohydrate source for the population, with per capita rice consumption remaining high compared to other staple foods [1] [2]. Malaysia cultivates rice across Peninsular Malaysia, Sabah, and Sarawak, with production concentrated in designated granary areas. Despite continuous improvements in farming practices, domestic rice production does not fully meet national demand, making Malaysia partially dependent on rice imports. This reliance highlights the importance of improving local productivity and ensuring stable rice yields to strengthen food security.

Rice cultivation in Malaysia predominantly follows a double-cropping system consisting of a main season and an off-season. The main season is largely dependent on monsoonal rainfall, while the off-season relies on irrigation infrastructure. Variability in weather conditions, water availability, and crop management practices can directly influence rice growth and yield outcomes [3] [4] [5]. As population growth and climate variability place increasing pressure on food systems, long-term monitoring of rice growth conditions has become increasingly important for sustainable agricultural planning.

Reliable and consistent data are fundamental for measuring, assessing, and eventually estimating rice yields. Yield formation is closely linked to crop growth conditions throughout key phenological stages, including tillering, panicle initiation, heading, and grain filling. Long-term growth data enable the identification of normal seasonal behaviour and provide a reference baseline for detecting anomalies associated with stress, disease, or management changes. Such data-driven understanding is essential for developing robust yield estimation frameworks and supporting evidence-based decision-making in agriculture. Satellite remote sensing has been widely adopted as an effective tool for agricultural monitoring due to its broad spatial coverage and temporal continuity. Among various vegetation indices, the Normalized Difference Vegetation Index (NDVI) has been extensively used to characterise vegetation greenness, biomass, and crop growth status. NDVI-based approaches have been successfully applied to monitor crop phenology, identify cropping calendars, and analyse seasonal and inter-annual variability in agricultural systems [6]. Compared to ground-based surveys, satellite-derived NDVI offers a cost-effective and repeatable method for large-scale crop monitoring.

The Landsat satellite series provides one of the longest continuous Earth observation records, with consistent multispectral data available for several decades. Its moderate spatial resolution and long-term data continuity make Landsat particularly suitable for analysing crop growth trends and supporting food security-related studies. Previous studies have demonstrated that time-series NDVI derived from Landsat can capture rice growth stages and seasonal cycles that are closely associated with yield performance [7] [8]. Despite the growing interest in advanced machine learning and predictive models for agricultural yield estimation, many studies rely on short-term datasets or limited observation periods. Long-term analyses spanning multiple decades remain relatively scarce, particularly for rice-growing regions in Malaysia. There is therefore a clear need for baseline studies that establish long-term growth patterns using transparent and interpretable data analysis approaches.

In this context, this study aims to characterise long-term rice growth dynamics in Malaysia using Landsat-derived NDVI time-series data from 2000 to 2024. Focusing on a representative rice cultivation area near Pekan, Pahang, the study applies descriptive time-series analysis combined with light statistical data analysis to quantify seasonal patterns, inter-annual variability, and phenological characteristics. The resulting NDVI-based growth indicators provide an important data foundation for future yield estimation studies, crop monitoring strategies, and AI-driven agricultural decision support systems aimed at enhancing food security in Malaysia.

2. METHOD

This study adopts a satellite-based time-series analysis framework to examine long-term rice growth dynamics in Malaysia. Landsat surface reflectance data were processed to generate a continuous NDVI time series covering the period from 2000 to 2024. The methodology consists of three main components: data sources and pre-processing, NDVI computation and time-series construction, and descriptive data analysis with phenological interpretation. This structured approach ensures consistency across multiple Landsat sensors and enables quantitative assessment of seasonal patterns and long-term variability in rice growth conditions.

2.1. Data Sources and Pre-processing

This study utilises multi-temporal Landsat satellite imagery to analyse long-term rice growth dynamics in Malaysia. The dataset covers the period from January 2000 to December 2024 and includes observations from multiple Landsat missions to ensure continuous temporal coverage. Specifically, Landsat 5 TM data were used for the period 2000–2011, Landsat 7 ETM+ data for 2000–2021, Landsat 8 OLI data for 2013–2024, and Landsat 9 OLI-2 data for 2021–2024. All datasets were obtained as Level-2 surface reflectance products, which provide atmospherically corrected reflectance values suitable for time-series analysis [9] [10] [11].

The study area is located in a rice cultivation region near Pekan, on the east coast of Peninsular Malaysia, covering approximately 10 km² as shown in Figure 1. The area was selected as it represents a typical double-cropping rice production system in Malaysia. For each Landsat scene, the study area was spatially extracted prior to further processing. Pre-processing was performed to ensure data quality and consistency across different sensors and acquisition periods. Cloud and cloud-shadow contamination were removed using the quality assessment (QA) bands provided with the Landsat Level-2 products. Pixels flagged as cloud, cloud shadow, or otherwise unreliable were excluded from the analysis. This step is essential to minimise noise and prevent erroneous NDVI values caused by atmospheric effects or surface obstructions.

Following cloud masking, only valid surface reflectance pixels were retained for NDVI computation. By using standardised Level-2 products and consistent quality filtering, the pre-processing workflow ensures that NDVI values derived from different Landsat missions are comparable over the entire 25-year study period. The resulting cloud-free reflectance data form the basis for subsequent NDVI computation, temporal compositing, and data analysis.

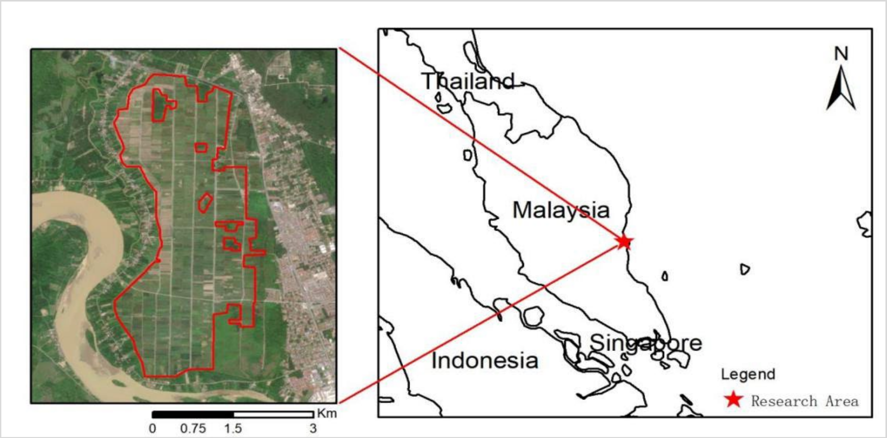

Figure 1. Location of the study area. The left panel shows the rice cultivation area near Pekan, Pahang, delineated in red over satellite imagery. The right panel indicates the geographical location of the study area within Peninsular Malaysia.

2.2. NDVI Computation and Time-Series Construction

NDVI was used as the primary indicator to characterise vegetation greenness and rice growth dynamics in the study area. For each Landsat observation, NDVI was computed from the cloud-free Level-2 surface reflectance data using the standard formulation:

$$\text{NDVI} = (\text{NIR} - \text{Red}) / (\text{NIR} + \text{Red}) \qquad [1]$$

where NIR and Red refer to the near-infrared and red surface reflectance bands, respectively. NDVI values range from −1 to +1, with higher values indicating denser and healthier vegetation. To ensure consistency across the multi-sensor dataset, NDVI was calculated using the corresponding red and NIR bands available for each Landsat mission [12].

After NDVI computation, a monthly compositing strategy was applied to generate a continuous time series from January 2000 to December 2024. Specifically, monthly maximum NDVI compositing was used, where the maximum NDVI value within each calendar month was selected. This approach reduces residual effects from clouds, haze, and atmospheric variability, and provides a robust representation of peak vegetation condition for each month. Monthly NDVI values were then aggregated across the study area to derive representative time-series indicators for subsequent seasonal and inter-annual analysis. The output of this stage is a continuous monthly NDVI time series covering the full study period, which forms the basis for identifying seasonal growth cycles and quantifying long-term variability in rice growth conditions. The overall step-by-step workflow is shown in Figure 2.

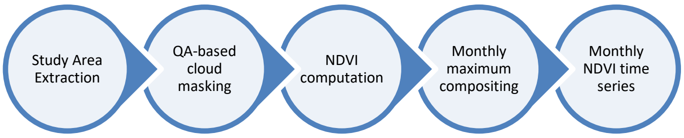

Figure 2. Workflow for NDVI computation and time-series construction using Landsat surface reflectance data. The process includes study area extraction, QA-based cloud masking, NDVI calculation, and monthly maximum compositing to generate a continuous NDVI time series from 2000 to 2024.

2.2. Data Analysis and Phenological Interpretation

Descriptive data analysis was applied to the monthly NDVI time series to quantify seasonal patterns and long-term variability in rice growth conditions. Monthly NDVI statistics, including mean, standard deviation, minimum, and maximum values, were computed across the entire study period from 2000 to 2024. These statistics provide a quantitative summary of typical vegetation conditions and the degree of variability for each month. To examine seasonal characteristics, the NDVI time series was analysed according to Malaysia's double-cropping rice system. Two cropping seasons were defined: the main season, spanning from August to February of the following year, and the off-season, occurring from March to July. For each season, seasonal mean NDVI and peak NDVI values were derived to compare growth intensity and temporal behaviour between the two cropping cycles.

Inter-annual variability was assessed by computing annual NDVI indicators, including annual mean NDVI and annual peak NDVI values. These indicators were used to examine long-term stability and potential gradual changes in rice growth conditions over the 25-year study period. Linear trend lines were applied to the annual NDVI metrics to visualise long-term tendencies without introducing complex statistical modelling. Phenological interpretation was performed by relating observed NDVI patterns to known rice growth stages. Increases in NDVI were associated with the tillering stage, while sustained high NDVI values corresponded to the panicle initiation and heading stages. Subsequent declines in NDVI were interpreted as the maturation and harvesting periods. By combining time-series analysis with phenological interpretation, the NDVI-derived indicators provide insight into rice growth dynamics and seasonal development patterns. The overall data analysis and phenological interpretation workflow is summarised in Figure 3.

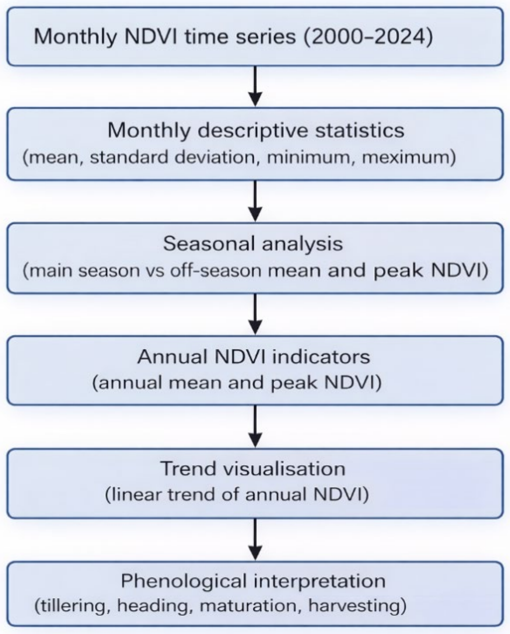

Figure 3. Flow chart of the data analysis and phenological interpretation process. Monthly NDVI time-series data were analysed using descriptive statistics, seasonal and annual NDVI indicators, and trend visualisation, followed by interpretation of rice growth stages based on NDVI patterns.

3. RESULTS AND DISCUSSION

3.1. Long-Term NDVI Temporal Patterns and Seasonal Characteristics

The long-term monthly NDVI time series from January 2000 to December 2024 exhibits a clear and repeatable seasonal pattern in rice growth within the study area. Figure 4 presents the average monthly NDVI values computed across the full 25-year period, providing an overall representation of rice growth dynamics. The temporal profile shows a distinct bimodal pattern, which is consistent with Malaysia's double-cropping rice cultivation system.

As shown in Figure 4, two pronounced NDVI peaks occur consistently each year. The first peak appears during the off-season, typically between May and June, with average NDVI values reaching approximately 0.63. The second peak is observed during the main season, between October and November, with average NDVI values of around 0.59. These peaks correspond to periods of active vegetative growth and reproductive development of rice crops. In contrast, lower NDVI values are observed during post-harvest and fallow periods. NDVI decreases to approximately 0.41 during January–February and to around 0.46 during August–September, reflecting reduced vegetation cover following harvesting activities. Seasonal characteristics further highlight the differences between the two cropping cycles. During the main season, which spans from August to February of the following year, NDVI values begin to increase in September–October, remain relatively high in November, and gradually decline during December–January as crops mature and are harvested. A similar pattern is observed during the off-season, occurring from March to July, where NDVI increases during March–April, peaks in May–June, and declines toward July–August. The off-season generally exhibits slightly higher peak NDVI values, likely due to controlled irrigation and more stable water availability during this period.

Overall, the consistent timing and magnitude of NDVI peaks across the entire study period indicate stable seasonal rice growth behaviour in the study area. Although minor fluctuations in NDVI values are present between months, the persistence of the bimodal pattern over 25 years suggests that the cropping calendar and cultivation practices have remained relatively unchanged. The long-term NDVI profile shown in Figure 4 therefore provides a reliable baseline for understanding rice growth dynamics and supports subsequent analyses of inter-annual variability and growth stage interpretation.

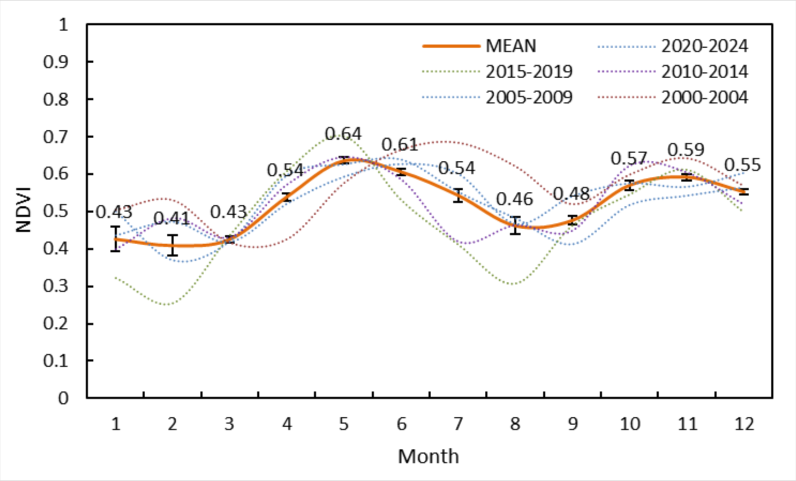

Figure 4. Long-term average monthly NDVI variation for the rice cultivation area from 2000 to 2024. The curve shows a bimodal seasonal pattern corresponding to the main season and off-season rice cropping cycles.

3.2. Inter-Annual Variability and NDVI-Based Growth Stage Interpretation

Inter-annual variability in rice growth conditions was examined using grouped monthly NDVI curves for different multi-year periods between 2000 and 2024. Figure 5 presents the monthly NDVI profiles for five consecutive time intervals: 2000–2004, 2005–2009, 2010–2014, 2015–2019, and 2020–2024. These grouped curves allow for visual comparison of seasonal behaviour and assessment of long-term consistency in rice growth patterns.

As shown in Figure 5-9, the overall shape of the monthly NDVI curves remains consistent across all periods, indicating stable cropping cycles over the 25-year study duration. Each time interval exhibits a clear bimodal structure, with two NDVI peaks corresponding to the off-season and main-season rice growth phases. While minor variations in peak magnitude and timing are observed among different periods, no abrupt shifts or structural changes in the NDVI pattern are evident. This suggests that rice cultivation practices and cropping calendars in the study area have remained largely stable over time. NDVI-based growth stage interpretation further supports these observations. During both cropping seasons, the tillering stage is characterised by a gradual increase in NDVI following planting, typically occurring during September–October for the main season and March–April for the off-season. The panicle initiation and heading stages correspond to sustained high NDVI values, observed around November during the main season and May–June during the off-season. Subsequent declines in NDVI are associated with crop maturation and harvesting periods, occurring during December–January and July–August, respectively.

The consistency of NDVI transitions between growth stages across different years highlights the reliability of NDVI as an indicator of rice phenological development. Although inter-annual variability in NDVI magnitude is present, the persistence of similar growth stage timing indicates that seasonal rice development remains relatively stable.

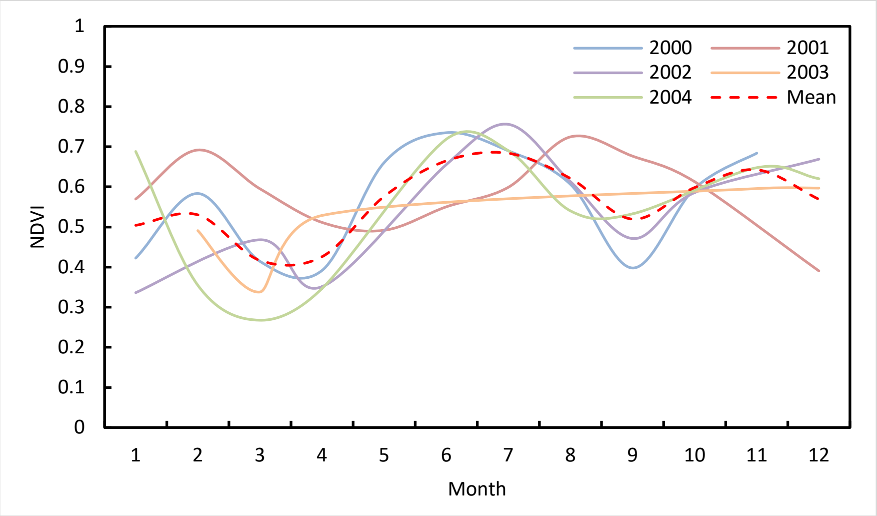

Figure 5. Monthly NDVI curve chart for each year from 2000 to 2004

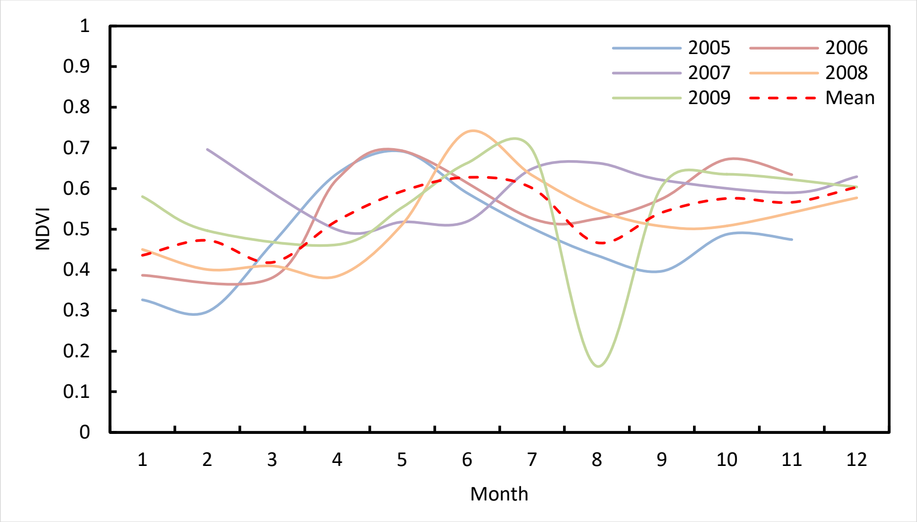

Figure 6. Monthly NDVI curve chart for each year from 2004-2009

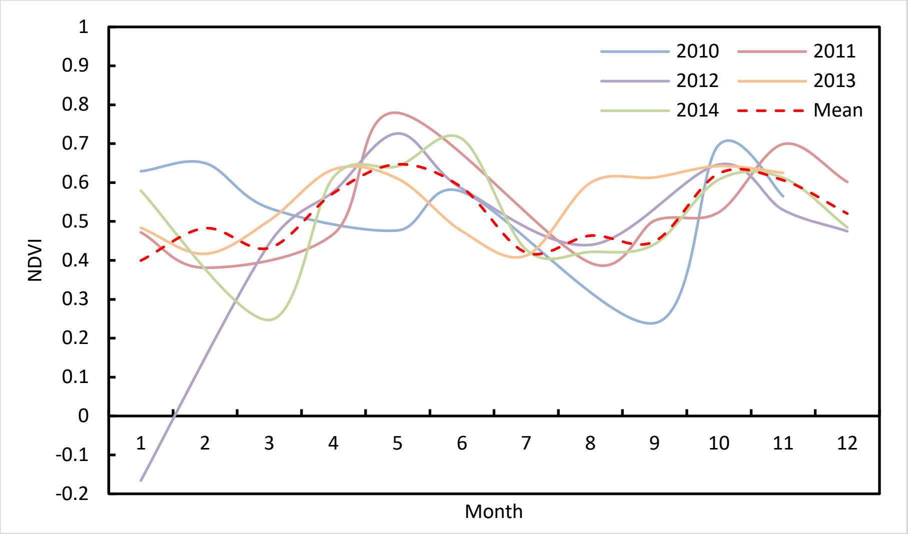

Figure 7. Monthly NDVI curve chart for each year from 2010-2014

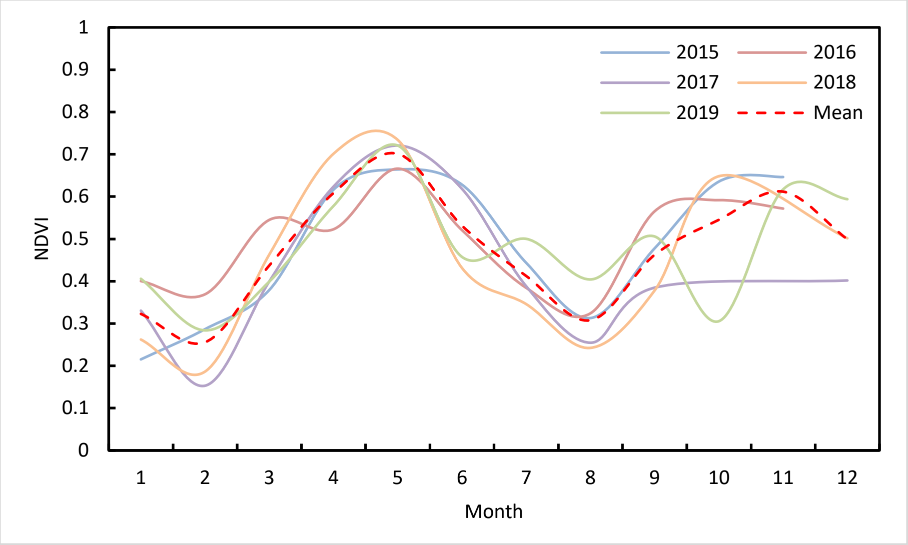

Figure 8. Monthly NDVI curve chart for each year from 2015-2019

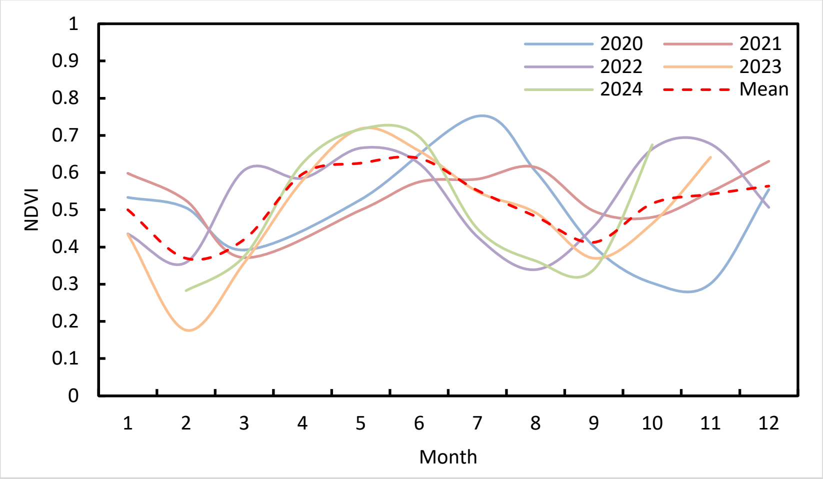

Figure 9. Monthly NDVI curve chart for each year from 2020-2024

4. DISCUSSION AND CONCLUSION

This study demonstrates the effectiveness of long-term Landsat-derived NDVI time-series data for monitoring rice growth dynamics in Malaysia. Analysis of monthly NDVI from 2000 to 2024 reveals a clear and persistent bimodal seasonal pattern that closely reflects Malaysia's double-cropping rice cultivation system. The presence of two consistent NDVI peaks each year corresponds to the off-season and main-season growth cycles, confirming the suitability of NDVI as an indicator of rice growth behaviour at a regional scale.

The long-term temporal analysis shows that both the timing and magnitude of NDVI peaks have remained relatively stable over the 25-year study period. Although minor inter-annual fluctuations are observed, no abrupt shifts or long-term degradation trends are evident. This indicates that rice cultivation practices and cropping calendars in the study area near Pekan, Pahang, have been largely maintained over time. The grouped NDVI curves further support this observation, showing consistent seasonal profiles across different multi-year periods. NDVI-based phenological interpretation reveals clear transitions between rice growth stages. Increases in NDVI correspond to the tillering stage, sustained high NDVI values indicate panicle initiation and heading, and subsequent declines reflect crop maturation and harvesting. The consistency of these transitions across years highlights the reliability of NDVI for capturing rice phenological development. While NDVI does not directly measure yield, it serves as an effective proxy for crop vigour and biomass development, which are closely related to yield formation. From a data and food security perspective, the findings emphasise the importance of long-term, consistent satellite observations for agricultural monitoring in Malaysia. Given that domestic rice production does not fully meet national demand, maintaining stable and productive rice-growing systems is critical. The NDVI-based growth indicators derived in this study provide a quantitative baseline that can support future yield estimation, anomaly detection, and risk assessment efforts. Such baseline information is particularly valuable for developing AI-driven decision support systems and data-informed agricultural policies.

In conclusion, this study provides a comprehensive long-term assessment of rice growth dynamics in Malaysia using Landsat NDVI time-series data. The results confirm stable seasonal and inter-annual growth patterns over the past two decades and establish a reliable data foundation for future research. Future work will focus on integrating additional datasets, such as weather variables, soil information, and field-based yield records, to strengthen yield estimation capabilities and enhance data-driven approaches for improving rice productivity and national food security.

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