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Research Article

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Spatiotemporal Assessment of Rice Growth and Yield Using Remote Sensing-Derived Indices and GIS in Batticaloa District, Sri Lanka

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ABSTRACT
Rice yield is significantly influenced by climatic variability, water availability, and agronomic practices. Effective monitoring of paddy growth and yield assessment is essential to ensure food security. This study aimed to monitor rice crop growth and predict yield in the Batticaloa District, Sri Lanka, using remote sensing and Geographic Information Systems (GIS). The analysis focused on the Yala season due to frequent cloud cover during the Maha season. Sentinel-2 Level-2A imagery from the 2023 and 2024 Yala seasons was utilized to derive the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), and Red-edge index for assessing crop health and stress variations. Paddy cultivation areas were delineated through supervised classification of satellite images, supported by ground truth data collected via field surveys and farmer interviews. The relationships between vegetation indices and yield were examined using regression models. Multi-temporal analysis of NDVI, NDWI, and Red-edge indices revealed a distinct pattern, with peak values occurring approximately eight weeks after planting. The NDVI-based yield prediction model achieved an R^2 of 0.70, while the Red-edge model yielded an R^2 of 0.69, demonstrating strong correlations between vegetation indices and yield. Predicted yields for the 2024 Yala season were approximately 5046 kg/ha (NDVI) and 5005 kg/ha (Red-edge), compared to the observed yield of 4497 kg/ha. The Root Mean Square Error (RMSE) values for the NDVI and Red-edge models were 12.21% and 11.29%, respectively. These results highlight the effectiveness of remote sensing and GIS in monitoring rice growth and estimating yield, and underscore the potential of integrating such approaches with advanced technologies to promote precision agriculture in Sri Lanka. Future studies should aim to improve prediction accuracy using higher-resolution imagery, enhanced ground truth datasets, and machine learning techniques.

Keywords: Remote Sensing, Rice, Vegetation indices, Satellite imagery, Yield

Introduction

Rice is a staple food for over half of the world's population, particularly in Asia, where it serves as a primary source of nutrition and livelihood for millions [1]. In Sri Lanka, rice cultivation plays a vital role in ensuring food security and supporting rural economies, with approximately 29% of the total cultivated land allocated to paddy farming [2]. The two main cropping seasons, Maha (October–February) and Yala (April–September), depend on monsoonal rainfall and irrigation schemes [3]. However, rice production faces multiple challenges, including climate variability, water stress, pest infestations, and inefficient resource management. Timely monitoring of crop health and yield estimation is essential for efficient agricultural planning, early warning systems, and food security [4].

Estimating crop area extent is crucial for accurate yield predictions and agricultural resource planning. Traditional field-based methods, such as manual surveys and visual inspections, are time-consuming, labour-intensive, and limited in spatial

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coverage. As a result, there is an increasing need for advanced technologies to support agricultural decision-making and to optimize farm and field management [5].

Recent advancements in remote sensing and Geographic Information Systems (GIS) have revolutionized crop monitoring and yield prediction by providing large-scale, real-time, and cost-effective solutions [6]. Satellite imagery enables continuous observation of crop health, stress conditions, and biomass accumulation, thereby reducing dependence on field surveys [67-9]. Several Earth Observation (EO) satellites, including Sentinel-2, SPOT, Landsat, and MODIS, offer multispectral data that can be used for vegetation monitoring and yield forecasting.

By utilizing indices such as the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), and Red-Edge Vegetation Index, important growth factors such as plant vigour, water stress, and chlorophyll content, which are key indicators of crop health and productivity. Several studies have demonstrated the effectiveness of satellite-based crop monitoring and yield estimation models. For example, Xiao et al., (2002) developed a rice mapping model using MODIS-derived vegetation indices, while Setiyono et al. combined MODIS, Sentinel-1 SAR, and the ORYZA crop growth model to improve yield predictions [10-14]. In Sri Lanka, Bandara highlighted the potential of remote sensing in monitoring irrigation performance and paddy health, and Gunapala et al. successfully applied NDVI-based models for paddy yield estimation [15,16].

In Sri Lanka, where rice cultivation plays a crucial role in national food security, leveraging remote sensing techniques can enhance yield predictions and resource management strategies, particularly in regions like Batticaloa, which is one of the major paddy-producing areas. The ability to assess spatial and temporal variations in crop health using remote sensing data is essential for ensuring sustainable paddy production and strengthening climate-resilient agricultural practices.

The growing challenges in paddy cultivation due to climate variability, water scarcity, and inefficient resource utilization necessitate the adoption of advanced technologies for effective crop monitoring and yield assessment. Traditional field-based monitoring methods are not scalable, making them unsuitable for large-area agricultural management.

Efficient agricultural planning and food security strategies require real-time crop monitoring to detect stress conditions early. Satellite remote sensing provides a non-destructive, cost-effective, and scalable solution for tracking paddy crop health across large areas. Predicting paddy yield with high accuracy is essential for market planning, resource allocation, and food security assessments [17]. This study integrates NDVI, NDWI, and Red-Edge Indices to monitor crop growth throughout the season and analyze their relationship with yield. The use of multi-temporal satellite imagery helps in identifying crop growth patterns, stress conditions, and water availability. Since Sentinel-2 provides medium-resolution multispectral data, it enables improved biophysical parameter estimation, which is critical for precision agriculture [18].

While remote sensing applications in rice monitoring have been widely studied in other regions, limited research has focused on Sri Lanka, particularly in Batticaloa. This research will contribute to localized methodologies for using remote sensing and GIS for paddy yield prediction.

The findings of this study will provide valuable insights for farmers, policymakers, and agricultural planners by offering timely crop health assessments to support better irrigation and fertilizer management, scalable and cost-effective methods for large-area yield estimation, integration of remote sensing with ground truth validation for enhanced precision agricultural practice. By applying remote sensing techniques, this study aims to provide scientifically validated solutions to improve rice yield estimation, ultimately contributing to Sri Lanka's agricultural sustainability and food security efforts.

In many developing countries, including Sri Lanka, agricultural management often operates in data-poor environments, where accurate and timely field-level information on crop growth, yield, and management practices is scarce due to limited financial, technical, and institutional resources [19]. In such contexts, remote sensing–based yield prediction models are particularly valuable because they provide spatially continuous, objective, and repeatable information over large agricultural areas, overcoming the limitations of fragmented or outdated ground data [17,19]. These satellite-derived predictions help bridge critical data gaps, enabling early warning of production shortfalls, improving agricultural planning, and supporting decision-making for food security and disaster preparedness [4,6]. Moreover, by integrating remote sensing with Geographic Information Systems (GIS), policymakers and farmers can generate near-real-time insights on crop health and stress conditions even in regions lacking dense observation networks, thereby enhancing the resilience and efficiency of agricultural systems under data constraints [5].

Materials and Methods

Study Area

The study was conducted in the Batticaloa District (Agro-ecological region: DL2b), Eastern Province of Sri Lanka, one of the major rice-producing regions characterized by a tropical monsoonal climate.

The district experiences two primary growing seasons;

- Maha (October–February): Dominated by the Northeast monsoon, providing ample rainfall for paddy cultivation.
- Yala (April–September): Relies mainly on irrigation schemes due to low rainfall.

The region consists of lowland paddy fields, rivers, and irrigated agricultural zones with varying soil types, predominantly alluvial soils in the paddy fields, which are well-suited for rice cultivation. a 3.5-month paddy variety, is the dominant cultivar grown in the area. Most farmers practice broadcasting, while transplanting is less common. Land preparation typically begins in the second week of March for Yala season cultivation. Planting and cultivation dates are determined during farmer organization decision making meetings (Pre and during the season meetings). This study focuses on selected paddy-growing areas within the Batticaloa District during the Yala season.

Data Collection

Data collection includes field-based ground truth data, and secondary datasets from government and research institutions and satellite imagery.

Satellite Data Acquisition

To monitor rice growth, Sentinel-2 Level-2A images were used due to their high spatial, spectral, and temporal resolution. Four time-period images were collected for analysis during 2023 and three time-period images were collected for 2024 Yala seasons to capture different crop growth stages. The study was restricted to Yala season due to heavy cloud coverage in Maha season which does not facilitate the use of satellite imagery. The selection criteria included:

- Cloud cover <15% to ensure clear images.
- Availability of multi-temporal images to analyze crop growth stages

Table 1: Details of satellite images used for the analysis

Year	Season	Acquisition Date	Sensor	Cloud cover %	Paddy Growth Stage
2023	Yala	2023.04.17	MSI	0.1%	Seedling stage
2023	Yala	2023.05.27	MSI	0.7%	Tillering stage
2023	Yala	2023.06.11	MSI	0.0%	Panicle initiation stage
2023	Yala	2023.07.16	MSI	11.8%	Heading stage
2024	Yala	2024.05.06	MSI	11%	Tillering stage
2024	Yala	2024.06.10	MSI	14%	Panicle initiation stage
2024	Yala	2024.07.10	MSI	10.38%	Heading Stage

Land Use Classification and Paddy Area Extraction

Image acquired two weeks after planting was used to identify the paddy cultivated areas, as it clearly differentiates paddy fields from other vegetation; at this early stage, the fields contain water, making them distinguishable. Supervised classification was applied to classify the image. Subsequently, a masking technique was applied to the classified image to isolate and extract paddy field pixels based on their spectral and spatial characteristics. This process effectively filtered out non-paddy land cover classes, resulting in a refined layer representing paddy fields. Finally, extracted paddy field layer was processed to generate a Paddy Base Map, which served as the foundation for subsequent spatial analyses and investigations.

Computation of vegetation Indices

In order to quantitatively assess vegetation dynamics and water content within the study area, a suite of indices was computed utilizing Sentinel-2 satellite imagery. The Normalized Difference Vegetation Index (NDVI) was calculated using the Equation

NDVI= (NIR-Red)/(NIR+Red).

This index served to measure plant vigour and overall crop health, providing insights into the photosynthetic activity and biomass of the vegetation.

Furthermore, the Normalized Difference Water Index (NDWI) was derived using the Equation

NDWI = (Green-NIR)/(Green+NIR)

This index aimed to identify and quantify water content within the field and vegetation canopy, reflecting the moisture status of the surface and plants.

Finally, the Red-Edge Index, a proxy for vegetation stress, was calculated using the Equation Red-Edge Index = (RE3-RE1)/(RE3+RE1)

Where RE3 corresponds to Red-edge band 3 and RE1 to Red edge band 1of Sentinel 2. This index was employed to detect crop stress, early drought conditions, and potential disease occurrences, leveraging the sensitivity of red-edge spectral regions to changes in plant physiology. These three indices were computed for each Sentinel-2 image for subsequent temporal analysis of vegetation characteristics.

Selection of Random Sampling Points

To analyze the temporal dynamics of vegetation indices within the paddy fields, a spatially representative sampling strategy was employed. Specifically, 100 random points were generated and distributed within the delineated paddy field boundaries. Subsequently, for each of these randomly generated points, the values of the previously computed indices—NDVI, NDWI, and the Red-Edge Index were extracted from the Sentinel-2 imagery across the entire time series of available data. This extraction process yielded a comprehensive dataset of temporal vegetation index profiles for each sampled location. Finally, a temporal analysis was performed on this extracted data, enabling the observation and quantification of how vegetation indices, and consequently, vegetation health, water content, and stress levels, varied over time within the paddy fields.

Ground Truth Data Collection & Yield Relationship Analysis

To establish a predictive model for paddy yield and to assess its accuracy, ground truth data was collected for the 2023 growing season. Specifically, 15 randomly selected points, out of the 100 previously generated within the paddy fields, were designated for detailed ground truth validation. At these locations, actual yield measurements at harvest in 2023 were obtained. In conjunction with the yield data, data were collected in the field to document sowing dates, crop management practices, fertilizer and irrigation schedules, and challenges related to climate, weeds and water availability during the season. Indices values (NDVI, NDWI, Red-Edge Index) derived from Sentinel-2 imagery for these 15 ground truth points in 2023 were then compared with the corresponding measured yield data. A regression models (simple linear models) for each index was developed using 2023 data to establish a quantitative relationship between vegetation indices and yield. These models were subsequently applied to 2024 Sentinel-2 data to predict 2024 yield. The accuracy of the prediction was then assessed by comparing the predicted 2024 yield with the actual 2024 yield data, which was collected during the 2024 harvest season, allowing evaluation of the model's performance.

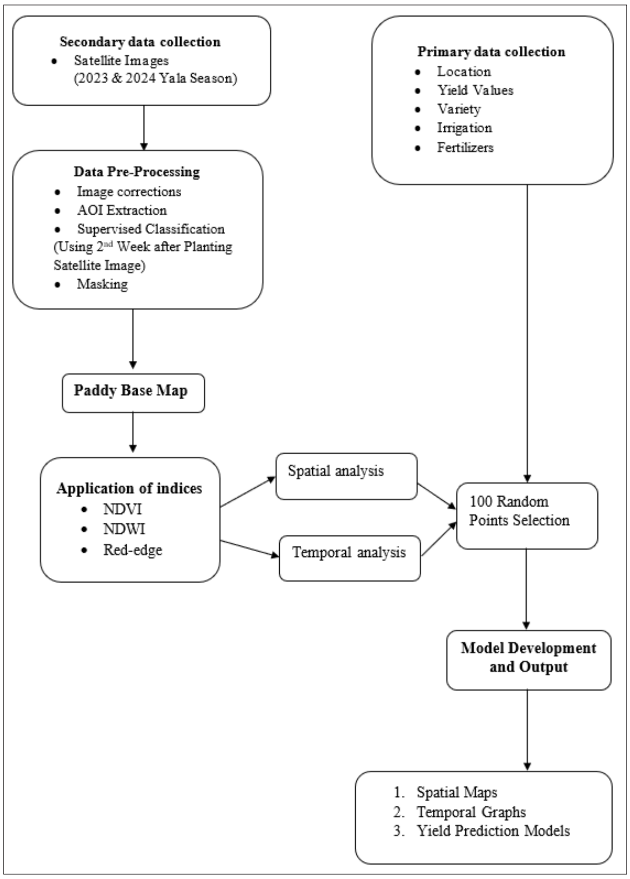


Figure 1: Flow Diagram of the Methodology

Results and Discussion

Paddy area extraction and paddy statistics of Batticaloa District

The paddy land statistics reveal significant spatial variability in cultivation practices across the Batticaloa District which include rainfed, major and minor irrigated paddy lands. Overall, rainfed cultivation accounts for the largest share of total paddy area which is 52.5%, highlighting the dependency of local agriculture on rainfall patterns and the need for improved irrigation infrastructure in many parts of the district.

Supervised classification using Sentinel-2 imagery with a 20-meter spatial resolution effectively delineated paddy fields across the Batticaloa District. The classification process identified a total of 41092 ha mapped as paddy area. When compared to the reported Yala season paddy extent of 38488 ha by the Department of Agrarian Development., the classification showed strong alignment, indicating reliable performance. An accuracy assessment yielded an overall classification accuracy of 94%, confirming the effectiveness of the methodology. The high accuracy validates the use of Sentinel-2 imagery and supervised classification as a dependable approach for mapping agricultural land use in the region.

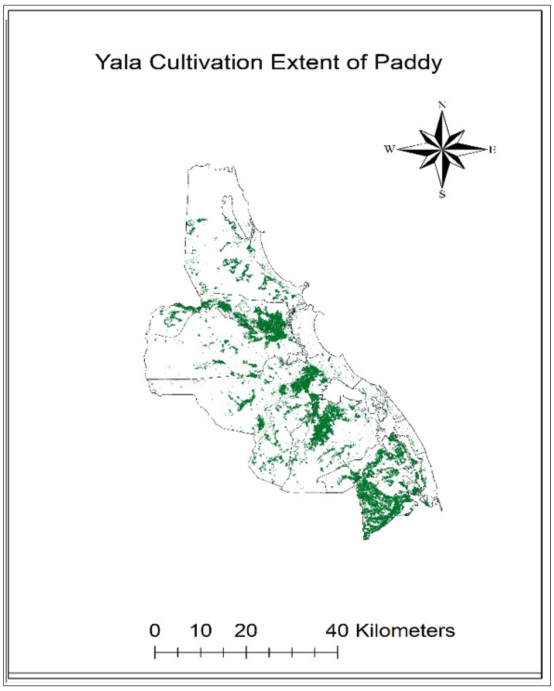


Figure 2: Yala cultivation Extent of Paddy

Spatiotemporal Distribution of Satellite Derived Indices

Normalized Difference Vegetation Index (NDVI)

The spatial distribution of NDVI across the four crop growth stages illustrates the dynamic changes in paddy crop cover and biomass accumulation. In Stage 1 (two weeks after planting), NDVI values are relatively low, predominantly at around -0.05 to 0.26, indicating sparse vegetation cover and early seedling establishment. These low values are expected during the early vegetative stage, as the leaf area index (LAI) is minimal, and photosynthetic activity is relatively low [20].

As the crop transitions to Stage 2 (six weeks after planting), NDVI values significantly increase, with a dominant shift toward 0.19 to 0.58, signifying rapid canopy development. This stage corresponds to the tillering phase, where rice plants experience exponential vegetative growth, resulting in higher chlorophyll content and biomass accumulation.

Peak NDVI values are observed in Stage 3 (eight weeks after planting), aligning with the flowering phase, where maximum canopy coverage occurs, leading to the highest photosynthetic activity. NDVI values nearing 0.6 indicate healthy crop conditions and optimal greenness, which is crucial for grain formation.

In Stage 4 (thirteen weeks after planting), NDVI values show a slight decline, which is associated with the maturity phase of the rice crop. The reduction in greenness at this stage is likely due to senescence, chlorophyll degradation, and the transition of leaves from green to yellowish shades [21].

Normalized Difference Water Index (NDWI)

The spatial distribution of NDWI reveals the changing water content of the crop and soil moisture availability throughout the growing season. In Stage 1 (two weeks after planting), NDWI values are relatively high, suggesting high soil moisture and standing water in the paddy field, which is typical for early rice cultivation under flooded conditions.

As the crop advances to Stage 2 (six weeks after planting), NDWI values begin to decline, reflecting increasing plant water uptake and evaporation. The reduction in NDWI at this stage is indicative of the shift from early vegetative to active tillering, where water requirements increase.

By Stage 3 (eight weeks after planting), NDWI reaches its lowest values, likely due to peak crop water demand during the reproductive phase. This aligns with studies indicating that NDWI tends to drop during critical growth periods, as transpiration rates are high, and the standing water level decreases [22].

In Stage 4 (thirteen weeks after planting), NDWI values show a slight increase compared to the eighth week but remain lower than in the sixth week. This increase can be attributed to the higher water content in the grain-filling phase.

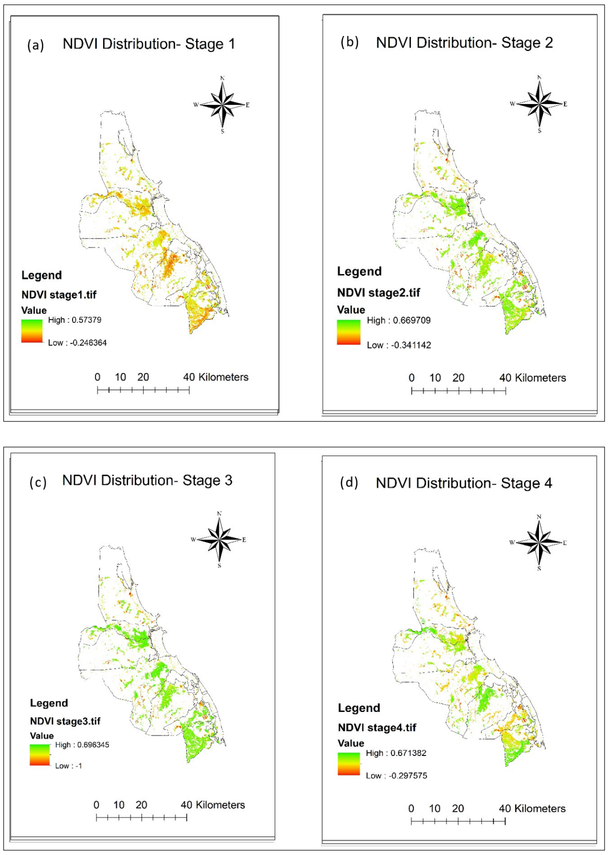
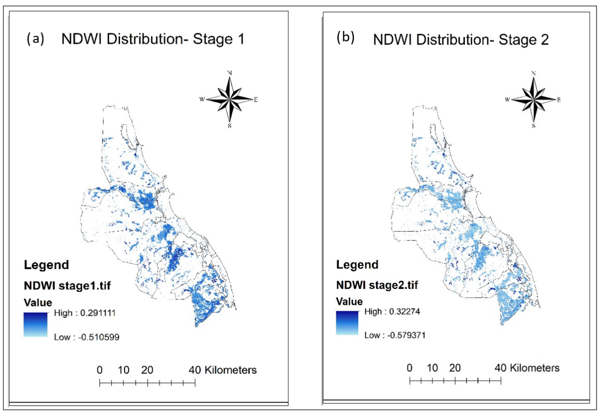


Figure 3: Spatial variation of NDVI in different growth stages of paddy (a) NDVI after 2 weeks of planting; (b) NDVI after 6 weeks of planting; (c) NDVI after 8 weeks of planting; (d) NDVI after 13 weeks of planting



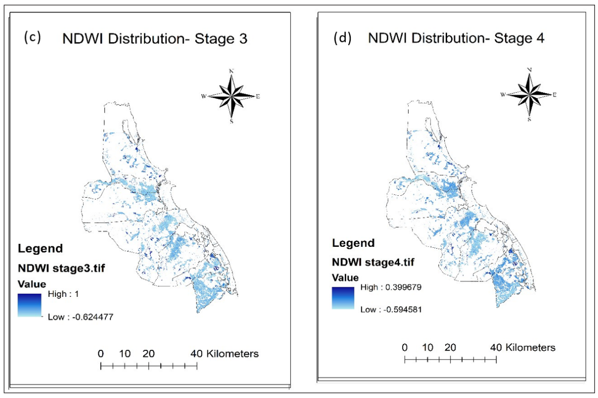


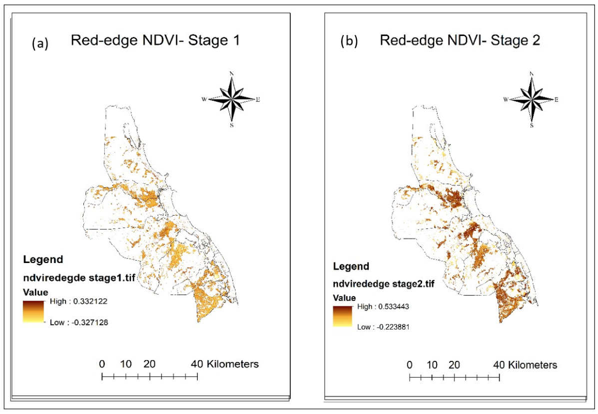
Figure 4: Spatial variation of NDWI in different growth stages of paddy (a) NDWI after 2 weeks of planting; (b) NDWI after 6 weeks of planting; (c) NDWI after 8 weeks of planting (d) NDWI after 13 weeks of planting

NDVI Red-Edge Index

The NDVI red-edge follows a similar pattern as NDVI, demonstrating a clear progression of vegetation growth and crop health status. During Stage 1 (two weeks after planting), the red-edge NDVI values are low, indicating low chlorophyll content in the early growth phase. These values gradually increase as the crop canopy develops, reaching their peak in Stage 3 (eight weeks after planting), similar to NDVI trends [21].

Red-edge NDVI is particularly useful in detecting plant stress and nitrogen availability, making it a valuable indicator for precision agriculture. The slightly higher red-edge values observed in Stage 3 suggest optimal nitrogen uptake and plant health during the flowering stage, which is crucial for grain development [23].

In Stage 4 (thirteen weeks after planting), red-edge NDVI values show a slight decline, mirroring the trend observed in NDVI. The reduction is attributed to senescence, where chlorophyll breakdown reduces the plant's reflectance in the red-edge spectral region [24,25]. The consistency between NDVI and red-edge NDVI trends confirms their strong correlation in monitoring crop growth and health dynamics.



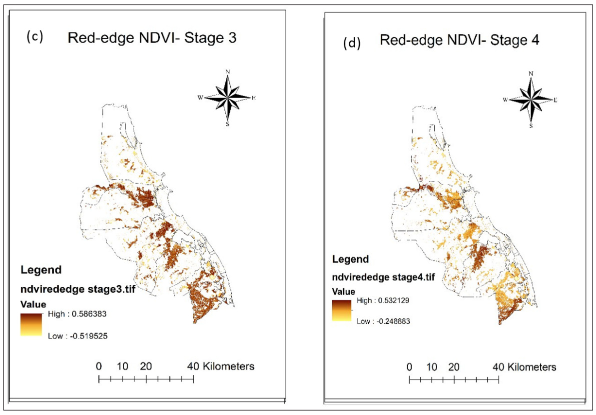


Figure 5: Spatial variation of Red Edge NDVI in different growth stages of paddy (a) Red-edge index after 2 weeks of planting; (b) Red-edge index after 6 weeks of planting; (c) Red-edge index after 8 weeks of planting; (d) Red-edge index after 13 weeks of planting

Distribution of Indices During Paddy Growth Cycle

Figure 9 presents the distribution of NDVI, NDWI and Red-Edge NDVI values during the crop growth stages during 2023 and Figure 10 presents the distribution of NDVI, NDWI and Red-Edge NDVI values during the crop growth stages during 2024 at 100 random locations of paddy.

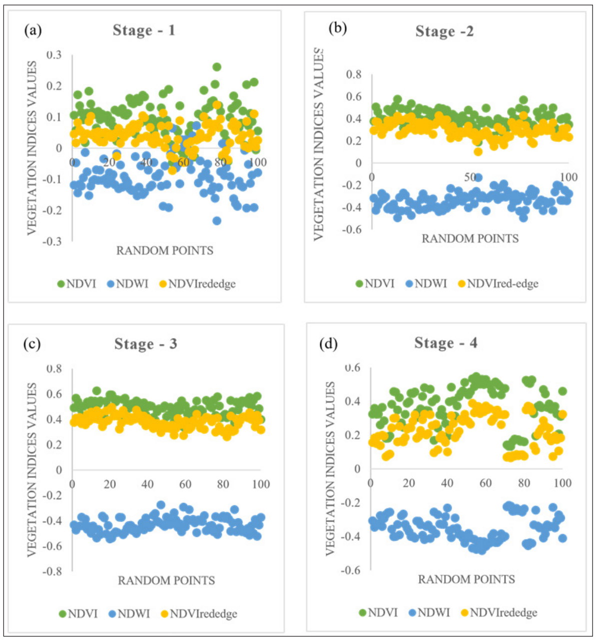


Figure 6: Distribution of indices along random locations- 2023 Yala Season (a) 2 weeks of planting; (b) 6 weeks of planting; (c) 8 weeks of planting; (d) 13 weeks of planting

Temporal variation of Indices

Temporal Change of NDVI

In years 2023 and 2024, NDVI increased gradually during the early vegetative stage, peaking at around the 8th week after planting. The peak NDVI values, around 0.5, indicate maximum canopy coverage and chlorophyll content, as reported by Shi et al. (2025). The 2023 season showed a steady increase from week 2 to 8, whereas the 2024 season exhibited a more rapid increase between weeks 6 and 8. The slight decline after the peak suggests the transition from reproductive to maturity stage.

Temporal NDVI patterns are important as they help identify the period of maximum vegetative vigour, which is strongly correlated with final grain yield. Detecting the peak NDVI stage enables early assessment of crop performance and supports timely management decisions such as fertilizer application and water scheduling. Understanding these trends therefore enhances the ability to predict yield under data-limited conditions.

Temporal Change of NDWI

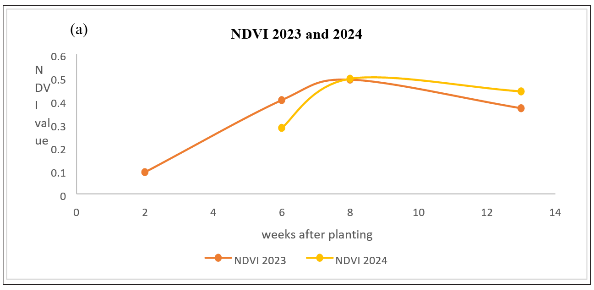
NDWI values reflect the water content in the rice field and soil moisture conditions. In both years (2023 and 2024), NDWI showed a declining trend, reaching the lowest point around 8 weeks after planting. The sharp decline corresponds to the transition from the vegetative to reproductive stage when water requirements change significantly (Triscowati et al., 2020). After week 8, a slight increase in NDWI is observed, this increase can be attributed to the higher water content in the grain-filling phase.

The temporal behaviour of NDWI is crucial for monitoring field water availability, which directly influences rice growth stages and stress levels. These insights are valuable for anticipating water-related yield reductions and improving irrigation management, particularly when ground-based moisture data are limited.

Temporal Change of NDVI Red-Edge

The NDVI red-edge variation (Figure 13) follows a pattern similar to NDVI, with a gradual increase until week 8, followed by a decrease. The red-edge index is particularly useful in detecting crop stress and chlorophyll variations, which influence rice yield (Delegido et al., 2013). Compared to NDVI, the red-edge index is more sensitive to changes in plant stress and nitrogen content, which might explain slight differences between the 2023 and 2024 curves. The slightly higher red-edge NDVI values in 2024 suggest better plant health or improved nitrogen uptake compared to 2023. This agrees with the findings of Clevers & Gitelson (2013), who demonstrated the effectiveness of red-edge indices in monitoring crop health.

The temporal red-edge response is especially important because it provides early indications of crop stress, nitrogen status, and chlorophyll changes that may not be fully captured by traditional NDVI. Identifying these patterns improves the accuracy of yield prediction models and supports early intervention to reduce stress-related yield losses. This sensitivity makes red-edge indices highly valuable for monitoring paddy growth in environments with limited field observations.



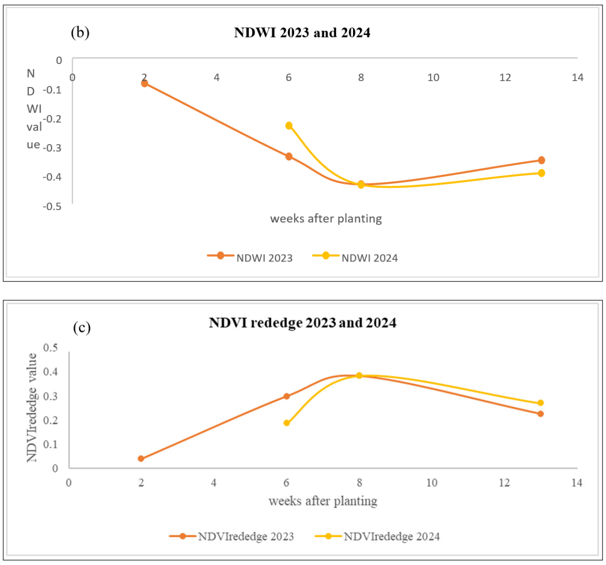


Figure 7: (a) NDVI during 2023 and 2024 Yala Season; (b) NDWI during 2023 and 2024 Yala Season; (c) NDVI red-edge during 2023 and 2024 Yala Season

Ground Truth Collection and Yield Prediction Modelling

Yield data collected from 15 ground locations was compared with corresponding NDVI, and Red-edge values (at 8 weeks after planting) (Table 4.1).

- Correlation Analysis:
- NDVI and yield showed a strong positive correlation (R^2 = 0.70). Similar results have been obtained by Noureldin et al., (2013).
- Red-Edge Index also showed a strong positive correlation (R^2 = 0.69), proving its effectiveness in estimating yield.
- 8 weeks after planting, which is the maximum tillering stage of paddy is used in correlation analysis.