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Knowledge-Based Vegetation Mapping Approach Using Satellite Derived Vegetation Parameters

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ABSTRACT

Chemical ecology offers a powerful framework for understanding how root-Understanding cropping patterns is essential for sustainable agricultural planning and efficient resource management, particularly in agriculturally dependent regions like India. This study aims to delineate cropping patterns in Nowpara-I Gram Panchayat, Nadia district, West Bengal, using a vegetation index–based crop event detection approach. Monthly time-series Enhanced Vegetation Index (EVI) data for 2023–2024 were derived from Sentinel-2 imagery on the Google Earth Engine platform. The data were pre-processed through cloud and shadow removal, harmonic gap filling using historical data, and Savitzky–Golay smoothing to ensure temporal continuity. Crop events were identified using a binary EVI threshold, and temporal condition classification based on a 2–3–4 pattern was applied to detect crop onset, growth, and termination stages. Cropping patterns were then extracted by counting complete and partial crop cycles at the pixel level and classified into non-agricultural, single-crop, and multi-crop areas. The results reveal that single-cropping systems dominate the study area, while multi-cropping is spatially clustered in regions with better irrigation and agricultural infrastructure. The study demonstrates that time-series EVI analysis combined with temporal rule-based classification provides a robust and scalable framework for mapping cropping patterns and can support agricultural monitoring and decision-making at local and regional scales. Future research directions include integrating machine learning and multi-sensor data fusion to enhance the approach's accuracy and applicability.

Keywords: Cropping pattern, Enhanced Vegetation Index (EVI), Optical imagery, Google Earth Engine, Time-series analysis, Crop event detection.

Introduction

Indian economic structure heavily dependable on agriculture by supporting food security provides livelihoods for over 40% of the population and significantly contributes to nation GDP around 16-18% (https://www.indiabudget.gov.in/economicsurvey). At the regional level, interaction of agriculture with multiple other activities, along with various farmers and cropping systems produce several management challenges which are directly

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linked to the type, diversity and spatial distribution of these cropping systems. To increase the production or quality of a particular crop, it is essential to be aware of the cropping system of that area (Leenhardt *et al.*, 2009). Cropping patterns are the key element of a broader cropping system which includes all essential components for crop growth (Mahlayeye *et al.*, 2022). Improper management and unsuitable cropping patterns can adversely affect water usage, soil quality, regional climate, ultimately reduce crop yields and contribute towards the degradation of natural resources (Yang *et al.*, 2020). Hence, a clear understanding of the cropping pattern is crucial for agriculture-based area.

Cropping patterns are identified by the specific spatial arrangement of crops within a field. There are two main types, monocropping (one crop in a field per year) and multi cropping (more than one crop in the same field per year) (Liu *et al.*, 2018). A developing country like India multiple cropping has been commonly practiced primarily in small farms (Mahlayeye *et al.*, 2022).

Degrading natural resources, weak eco-regional planning, climate-induced global warming etc. have emerged as major challenges to agricultural growth. Therefore, it is essential to integrating modern tools with agricultural science to achieve economically viable and environmentally sustainable crop production (Singh *et al.*, 2022).

In remote sensing research, cropping patterns have been extensively examined; however, this study specifically aims to delineate cropping patterns by vegetation index-based crop event detection.

Study Area

The study has been conducted on Nowpara Gram Panchayet (GP), Nadia district, West Bengal, India. Nadia district is bounded by 22°53" N to 24°11" N latitude and 88°09" E to 88°48" E longitude and covered an area of 3927 sq km and surrounded by Bangladesh in the east and Bardhaman district in the west, Murshidabad district to the north and South 24 Pargana and Hooghly in the south. It is the part of Ganga Brahmaputra Delta. Major soils are deep loamy soils and deep clayey loamy soils and fall under new alluvium agroclimatic zone. Main rivers are Bhagirathi, Jalangi and Mathabhanga. The area enjoys the tropical monsoon type of climate with hot humid summer and mild winter (Figure 1).

Datasets and Methodology

In the present study, optical sentinel-2 satellite data has been used to calculate monthly composite Enhanced Vegetation Index (EVI). Sentinel-2 comprises two satellites, Sentinel-2A and Sentinel-2B, with the primary mission of aiding the monitoring of vegetation, land cover, and environmental changes (Das *et al.*, 2024).

Monthly Composite EVI Generation

The time-series Enhanced Vegetation index (EVI) derived from Sentinel-2 on Google Earth Engine (GEE) by acquiring and processing imagery, removing clouds and shadows using Scene Classification Layers, creating monthly composites and filling data gaps with historical records (Das *et al.*, 2024). EVI was then calculated from the blue, red, and NIR bands. As an improved alternative to NDVI, EVI is more sensitive to vegetation density, atmospheric effects, and soil background, using corrected surface reflectance to reduce interference from clouds, aerosols, smoke, and shadows. This enables more accurate characterization of vegetation dynamics and crop growth patterns, particularly in regions with complex terrain or diverse land cover. EVI values range from 0 to 1, with higher values indicating healthier vegetation (Hu *et al.*, 2019).

$$EVI = G \frac{(\rho NIR - \rho red)}{(\rho NIR + C_1 \times \rho red - C_2 \times \rho blue + L)} \quad (1)$$

where, $\rho blue$, ρred and ρNIR represent the blue, red, near infrared band, respectively. Also, ρ values represent surface reflectance partially corrected foratmospheric effect like ozone absorption and Rayleigh scattering. Empirically determined coefficients for aerosol resistance C_1,C_2 are 6.0 and 7.5, respectively with a canopy background adjustment factor (L) set to 1.0. Additionally, again factor (G) is fixed at 2.5. The time series EVI data has been generated for the entire year of 2023-2024.

Monthly Composite EVI Gap-filling

The gap-filling method represents monthly EVI composites using a harmonic function that captures seasonal patterns, extended with historic data (e.g., using 2022 data to improve 2023 fitting). The model then generates predicted values to fill missing data, using a three-cycle-per-year harmonic setup to represent multiple annual crop cycles, thereby providing a robust and flexible framework for reconstructing incomplete time series data in agricultural applications. Detailed analysis of gap-filling method of monthly composite EVI has been explained in Das *et al.* (2024).

In the present study monthly composite EVI was further smoothened using second order and 5-window Savitzky and Golay filtering technique.

Crop Event Detection

To identify crop presence across the study area, a binary thresholding rule was applied to each pixel of the smoothed EVI time-series. Pixels with EVI values greater than 0.30 were classified as 1, indicating the presence of active vegetation or a crop event, whereas pixels with EVI values less than or equal to 0.30 were assigned a value of 0, representing no crop.

$$\text{EVI} > 0.30 \rightarrow 1 \text{ (crop present)}$$
$$\text{EVI} \leq 0.30 \rightarrow 0 \text{ (no crop)}$$

This threshold effectively distinguishes vegetated areas from bare soil or fallow fields. Applying this condition across all time steps produced a binary raster stack that clearly captures the temporal pattern of crop occurrence, enabling further analysis of cropping intensity, crop cycles, and land-use dynamics.

Temporal Condition Classification

The Temporal Condition Classification (2–3–4 Pattern) evaluates how each pixel transitions through time by examining its binary crop status across three consecutive months—previous, current, and next. By analyzing these month-to-month changes, the method identifies whether a pixel represents the beginning, middle, or end of a crop cycle, or if no crop activity is present. Each combination of temporal states (0 or 1) corresponds to a specific class (0,2,3,4) that reflects the crop growth stage or continuity of vegetation (Table 1). This sequential assessment enables the detection of cropping phases and supports the accurate delineation of cropping patterns across the landscape. In this study for every pixel, temporal transitions across consecutive layers are evaluated.

Cropping Pattern Extraction

The cropping pattern extraction is based on analyzing temporal condition classification in a 12-month pixel-wise crop event raster data. Each pixel contains a monthly sequence of categorical values representing different crop condition states. The method identifies complete crop cycles using a 2–3–4 temporal pattern, where a pixel transitions from crop onset (2), through one or more growth stages (3), and ends with crop termination (4). A harmonic-based rule counts the number of such complete sequences within the annual time series. Based on the frequency and combination of complete and partial sequences, pixels are classified into cropping pattern classes representing no cropping activity, single cropping, or multiple cropping cycles.

Result and Discussion

The cropping pattern map of Nowpara-I Gram Panchayet, Nadia district, West Bengal revealed clear spatial differentiation between non-agricultural, single-crop, and multi-crop areas (Figure 2). Single-crop regions dominate the landscape, indicating that a large proportion of agricultural land supports only one crop cycle annually. These areas are widely distributed across the central and southern parts of the GP, reflecting dependence on seasonal rainfall, limited irrigation availability, or traditional mono-cropping practices. In contrast, multi-crop areas are spatially clustered mainly in the northern and north-western portions of the block, suggesting better access to agricultural infrastructure, favourable soil moisture conditions due to better irrigation facility, better soil fertility, and intensified agricultural management that allow multiple crop cycles within a year. Studies have shown that areas with reliable irrigation systems, fertile soils, and optimal temperature and rainfall conditions are more likely to support multiple crop cycles (Birthal *et al.*, 2013). Non-agricultural areas are interspersed throughout the block and are more prominent along settlement zones, road networks, and water bodies, reflecting land allocated to habitation, infrastructure, and other non-farming uses. The observed spatial pattern in Nowpara-I underscores the complex interplay of factors influencing cropping intensity. Variations in resource availability, such as irrigation facilities and soil quality, significantly impact agricultural productivity. Additionally, land use patterns and local agronomic practices further contribute to the heterogeneity in cropping intensity across the region.

Conclusion

This study demonstrates the effectiveness of a vegetation index–based, time-series remote sensing approach for delineating cropping patterns at the local scale. By integrating Sentinel-2–derived monthly EVI composites with harmonic gap filling, temporal smoothing, and rule-based crop event detection, the proposed methodology successfully captured the spatial and temporal dynamics of cropping systems in Nowpara-I Gram Panchayat, Nadia district, West Bengal. The temporal condition classification using the 2–3–4 pattern enabled reliable identification of crop cycles and differentiation between non-agricultural, single-crop, and multi-crop areas.

The results revealed a predominance of single-cropping systems across the study area, with multi-cropping concentrated in regions having better resource availability and agricultural infrastructure. This spatial heterogeneity highlights the influence of irrigation access, soil moisture conditions, and management practices on cropping intensity. The approach offers a scalable and cost-effective framework for monitoring cropping patterns using freely available satellite data and cloud-based platforms such as Google Earth Engine.

Overall, the findings underscore the potential of time-series EVI analysis for supporting agricultural planning, resource management, and policy formulation. The methodology can be extended to larger regions and multiple years to assess temporal changes in cropping intensity and to support sustainable agricultural development under changing climatic and socio-economic conditions.

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Table 1. **Temporal Condition Classification (2–3–4 Pattern) reflecting crop events.**

Previous Month	Current Month	Next Month	Class
0	0	0	**0** (No event)
0	1	1	**2** (Start of crop event)
1	1	1	**3** (Middle of crop event)
1	1	0	**4** (End of crop event)

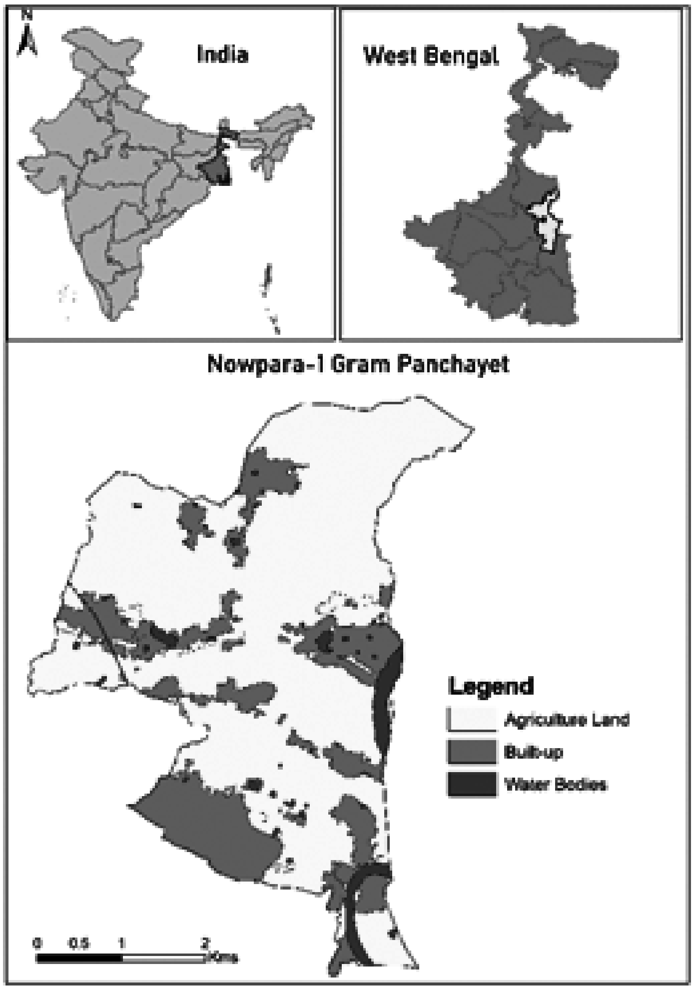

Figure 1. Study Area

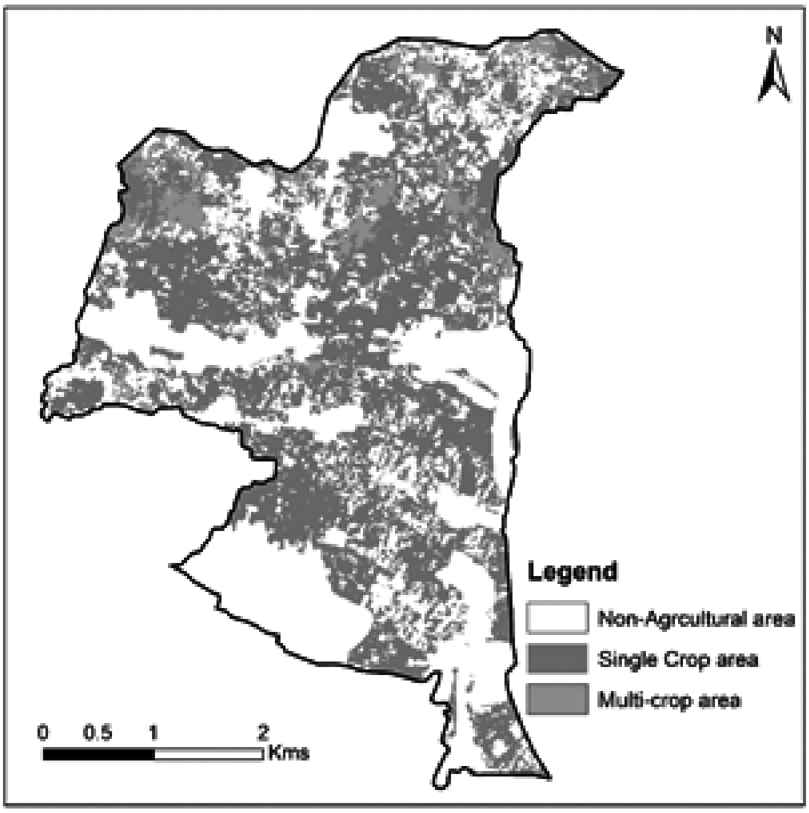

Figure 2. Spatial distribution of cropping pattern in Nowpara-1 GP, Nadia, West Bengal