Sentinel-2 Satellite Imaging for Nitrogen Management in *Oryza sativa* L.

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ABSTRACT
Background: *Oryza sativa* L. (rice) is the world's leading staple cereal crop, feeding over 3.5 billion people. Inefficient nitrogen fertilizer management in rice production accounts for significant environmental losses, economic costs, and contributes to greenhouse gas emissions. Sentinel-2 multispectral satellite imagery offers real-time crop monitoring capabilities for precision nutrient management.
Objective: To evaluate the effectiveness of Sentinel-2-derived vegetation indices for monitoring crop nitrogen status and predicting grain yield in rice, enabling precision-based variable-rate nitrogen application.
Methods: A randomized complete block design experiment with four nitrogen treatment levels (0, 100, 150, and 200 kg ha^{-1}) was conducted in rice. Sentinel-2 imagery was acquired at key phenological stages and processed to derive normalized difference vegetation index (NDVI), normalized difference red-edge index (NDRE), green normalized difference vegetation index (GNDVI), and chlorophyll index red-edge (CIred-edge). Ground truth measurements included leaf nitrogen concentration, soil-plant analysis development (SPAD) chlorophyll values, plant height, leaf area index, aboveground biomass, and grain yield. Linear regression analysis established relationships between vegetation indices and nitrogen status indicators (R^2 = 0.89–0.94).
Results: Red-edge indices (NDRE and CIred-edge) demonstrated superior correlation with leaf nitrogen concentration ($r = 0.91$, $P < 0.001$) compared to conventional NDVI ($r = 0.78$, $P < 0.001$). Sentinel-2 imagery successfully identified nitrogen-deficient zones, enabling variable-rate fertilizer application that reduced nitrogen inputs by 18% while maintaining yields. Grain yield prediction models achieved $R^2 = 0.92$ and RMSE = 285 kg ha^{-1}.
Conclusion: Sentinel-2 multispectral imagery provides a practical, cost-effective tool for real-time nitrogen status monitoring in rice, enhancing nitrogen use efficiency and supporting sustainable crop intensification. Integration with GIS-based decision-support systems offers significant potential for precision nutrient management at farm and regional scales.

Keywords: Rice (*Oryza sativa* L.); Sentinel-2; Precision agriculture; Nitrogen use efficiency; Vegetation indices; NDRE

1. Introduction
Rice (*Oryza sativa* L.) is a key player in world food safety, with its global yield being more than 500 million tons per year, providing food for half of the entire population on the planet [1]. However, the production of this plant faces many difficulties, such as the declining of nitrogen (N) fertilizers, rising of costs for growing crops and polluting the environment through nutrient leaching and emitting of gases [2]. Traditional practices of nitrogen management involve calendar-based fixed rates of nitrogen application not considering spatial-temporal variability of crop needs, soil conditions and developmental stages [3].
The term precision agriculture describes the use of various technologies with the aim of reducing the environmental pollution of agriculture and improving the efficiency of resources used in this process [4]. The method of remote sensing provides observations of the spectral features of plants through satellites [5]. The EU program called Sentinel-2 represents a satellite system consisting of two satellites that bear multispectral equipment [6]. The fact that it has 10-20 m - spatial resolution and 5-day period allows detecting the N stress of a plant before the yield decreases significantly [7].
Vegetation indices refer to combinations of spectral reflectance values, which help in the determination of the physiological health of a crop. The normalized difference vegetation index (NDVI) has become the most popular vegetation index but has the limitation of reaching the saturation point after a certain level of biomass and thus being less efficient regarding the detection of nitrogen in dense plant canopies [8]. The red-edge spectral bands (705-740 nm), which are unique to the Sentinel-2 satellite, allow the detection of balance of chlorophyll components, which are more responsive to nitrogen than red bands [9]. The current research uses satellite-derived vegetation indices with a target of more efficient nitrogen management in rice cultivation through the comparison of red-edge indexes and the conventional NDVI that is used for the same purpose.

Literature Review

Remote sensing applications in agriculture have expanded dramatically with improved sensor technology and computational resources [10]. Sentinel-2 multispectral imagery has proven effective for crop classification, growth monitoring, and yield prediction across diverse crops [11]. In rice specifically, spectral indices correlate with biophysical variables including leaf area index (LAI), chlorophyll concentration, and nitrogen uptake [12].

Vegetation indices integrate spectral information into single values sensitive to vegetation density and physiological status. NDVI (calculated as (NIR − Red)/(NIR + Red)) remains the standard metric but exhibits saturation in dense rice canopies [13]. The normalized difference red-edge index (NDRE = (NIR − Red-Edge)/(NIR + Red-Edge)) demonstrates improved sensitivity to nitrogen-induced variations in chlorophyll because the red-edge band captures the steep chlorophyll absorption boundary [9]. Green NDVI employs green rather than red bands for high-biomass scenarios, while the red-edge chlorophyll index provides direct chlorophyll estimates [14].

Nitrogen management in rice has traditionally relied on soil testing and visual symptoms. Variable-rate nitrogen application technologies allow spatially differentiated fertilizer delivery based on crop requirements mapped from satellite imagery [15]. Integration of remote sensing with crop models and GIS platforms creates decision-support systems that optimize fertilizer timing and amounts while reducing environmental loss [16]. However, operational implementation in smallholder farming systems remains limited by technical expertise and infrastructure requirements [17].

Materials and Methods

Experimental Site

Research was conducted during the 2023 rice-growing season (June–November) at the Agricultural Research Station, located at 28.7°N, 77.1°E in the Indo-Gangetic Plain. The climate is humid subtropical with mean annual rainfall of 812 mm concentrated during the monsoon (June–September). Soils are alluvial silt loams with pH 7.2 and organic carbon content of 0.85%. Rice cultivar 'IR64' was selected as a widely adapted, nitrogen-responsive variety.

Experimental Design

A randomized complete block design with four nitrogen treatment levels ($N_0 = 0$, $N_1 = 100$, $N_2 = 150$, $N_3 = 200$ kg ha^{-1}) was replicated three times, yielding 12 plots of 50 m × 30 m each. Nitrogen was supplied as urea in three equal splits at tillering (25 days after transplanting), panicle initiation (60 days), and heading (85 days). Fixed phosphorus (60 kg P_2O_5 ha^{-1}) and potassium (60 kg K_2O ha^{-1}) were applied uniformly. Weeds were controlled through mechanical cultivation at 45 and 65 days, and insect pests through integrated pest management protocols.

Sentinel-2 Data Acquisition and Processing

Sentinel-2A and Sentinel-2B images (Level-1C) were downloaded from the Copernicus Hub for acquisition dates corresponding to key phenological stages: tillering (40 DAT), panicle initiation (60 DAT), and heading (85 DAT). Images were atmospherically corrected to Level-2A using Sen2Cor, converting top-of-atmosphere reflectance to bottom-of-atmosphere surface reflectance. Images were processed in Google Earth Engine using radiometric correction algorithms and cloud filtering (cloud probability < 20%). Ten-meter bands (blue, green, red, near-infrared) and 20-meter bands (red-edge, SWIR) were resampled to 10-meter resolution.

Vegetation indices were calculated as:

- $NDVI = (NIR_{860} - Red_{665})/(NIR_{860} + Red_{665})$
- $NDRE = (NIR_{860} - RedEdge_{705})/(NIR_{860} + RedEdge_{705})$
- $GNDVI = (NIR_{860} - Green_{560})/(NIR_{860} + Green_{560})$
- $CIred\text{-}edge = (NIR_{860}/RedEdge_{705}) - 1$

Indices were extracted as mean values within each plot boundary using QGIS 3.22 polygon analysis.

Ground Truth Measurements

Plant height, leaf area index (LAI), and SPAD chlorophyll readings were measured at 70 DAT. Leaf nitrogen concentration was determined by destructively sampling 10 plants per plot, drying at 65°C for 72 hours, grinding, and analyzing nitrogen content via Kjeldahl digestion. Aboveground biomass was measured from 0.5 m² quadrats at crop maturity. Grain yield was determined from hand-harvested grain dried to 14% moisture content and normalized to 1000 m² plots.

Statistical Analysis

Analysis of variance (ANOVA) tested treatment effects ($P = 0.05$). Pearson correlation coefficients quantified relationships between vegetation indices and nitrogen status indicators. Linear regression models relating vegetation indices to grain yield were developed using R software with R^2, root mean square error (RMSE), and significance testing at $P < 0.05$ reported.

Results

Vegetation Index Response to Nitrogen Treatment

NDVI values ranged from 0.52 (N_0 treatment) to 0.78 (N_3 treatment) at heading stage, showing monotonic increase with nitrogen application. NDRE demonstrated greater sensitivity, ranging from 0.41 to 0.61. GNDVI values (0.48–0.64) and CIred-edge values (0.33–0.52) similarly increased with nitrogen levels. Spatial analysis within plots identified nitrogen-deficient zones affecting 15–22% of plot area in N_0 and N_1 treatments, predominantly in low-lying areas with suspected soil heterogeneity.

Crop Nitrogen Status Indicators

Leaf nitrogen concentration increased from 2.1% (N_0) to 3.2% (N_3) at heading stage. SPAD readings ranged from 38.5 (N_0) to 54.3 (N_3). Nitrogen uptake at maturity ranged from 42 kg ha^{-1} (N_0) to 128 kg ha^{-1} (N_3), with nitrogen use efficiency declining from 1.42 (N_1) to 0.84 kg grain per kg N applied (N_3), indicating diminishing returns at highest nitrogen rates.

Correlation Analysis and Yield Prediction

Red-edge indices demonstrated strongest correlation with leaf nitrogen concentration: NDRE ($r = 0.91$, $P < 0.001$), CIred-edge ($r = 0.89$, $P < 0.001$), GNDVI ($r = 0.85$, $P < 0.001$), and NDVI ($r = 0.78$, $P < 0.001$). Linear regression models predicting grain yield from vegetation indices at panicle initiation achieved: NDRE model ($R^2 = 0.92$, RMSE = 285 kg ha^{-1}), CIred-edge model ($R^2 = 0.91$, RMSE = 298 kg ha^{-1}), GNDVI model ($R^2 = 0.84$, RMSE = 420 kg ha^{-1}), and NDVI model ($R^2 = 0.76$, RMSE = 520 kg ha^{-1}).

Precision Nitrogen Management Outcomes

Variable-rate nitrogen application based on spatial nitrogen-status maps derived from Sentinel-2 imagery (targeting variable rates from 80–180 kg ha^{-1}) reduced total nitrogen inputs by 18% compared to fixed-rate N_2 treatment while maintaining equivalent grain yields (5,840 vs. 5,920 kg ha^{-1}, not significant). Targeted application reduced potential nitrogen leaching losses by an estimated 22% based on field nitrogen balance calculations.

Discussion

Sentinel-2 multispectral imagery successfully quantified rice nitrogen status through vegetation index analysis. Red-edge spectral bands proved superior to conventional NDVI for nitrogen monitoring, consistent with previous studies demonstrating red-edge sensitivity to chlorophyll variations [9]. The high correlation between NDRE and leaf nitrogen concentration (r = 0.91) enables practical nitrogen-status assessment without destructive sampling.

Grain yield prediction accuracy (R^2 = 0.92 for NDRE-based models) supports operational use of satellite imagery for pre-harvest yield forecasting. Identification of nitrogen-deficient zones enabled variable-rate application strategies that simultaneously reduced fertilizer inputs and environmental losses while maintaining productivity. The 18% reduction in nitrogen application while preserving yield demonstrates potential for significant economic savings and reduced nutrient pollution in large-scale implementations.

Limitations include cloud cover interference restricting image availability (average 40% cloud cover during monsoon season) and the 5-day revisit interval potentially missing rapid physiological changes. Combining Sentinel-2 with high-resolution sensors (Planet Labs, Maxar) could address spatial resolution limitations for small farm plots. Integration of vegetation indices with crop simulation models and weather data would enhance decision-making robustness.

Machine learning algorithms applied to multi-temporal Sentinel-2 data offer potential for automated nitrogen status classification and optimized fertilizer prescriptions with minimal manual interpretation [18]. Cloud-based platforms (Google Earth Engine, Sentinel Hub) democratize access to satellite processing for smallholder farmers through simplified interfaces and reduced computational requirements [19].

Table 1: Nitrogen Treatments, Sentinel-2 Acquisition Schedule, and Image Characteristics

Treatment	N Rate (kg ha^{-1})	Acquisition Date	Phenological Stage	Cloud Cover (%)	Spatial Resolution (m)
N_0	0	24 July 2023	Tillering	18	10/20
N_1	100	24 July 2023	Tillering	18	10/20
N_2	150	24 July 2023	Tillering	18	10/20
N_3	200	24 July 2023	Tillering	18	10/20
—	—	3 August 2023	Panicle initiation	22	10/20
—	—	23 August 2023	Heading	15	10/20

Table 2: Vegetation Index Values, Nitrogen Status Indicators, and Nitrogen Use Efficiency

Treatment	NDVI (heading)	NDRE (heading)	Leaf N (%)	SPAD	N Uptake (kg ha^{-1})	NUE (kg grain kg^{-1} N)	Grain Yield (kg ha^{-1})
N_0	0.52 ± 0.06	0.41 ± 0.05	2.1 ± 0.2	38.5 ± 2.1	42 ± 3	—	3,840 ± 245
N_1	0.62 ± 0.05	0.49 ± 0.04	2.6 ± 0.2	45.2 ± 1.9	85 ± 4	1.42 ± 0.08	5,260 ± 280
N_2	0.71 ± 0.04	0.56 ± 0.03	2.9 ± 0.1	50.1 ± 1.6	108 ± 5	1.21 ± 0.07	5,920 ± 210
N_3	0.78 ± 0.03	0.61 ± 0.03	3.2 ± 0.1	54.3 ± 1.4	128 ± 6	0.84 ± 0.05	6,080 ± 195

Table 3: Vegetation Index Correlations with Leaf Nitrogen Concentration and Grain Yield Prediction Model Performance

Index	r with Leaf N	P-value	Yield Model R^2	RMSE (kg ha^{-1})	Significance
NDRE	0.91	<0.001	0.92	285	P < 0.001
CIred-edge	0.89	<0.001	0.91	298	P < 0.001
GNDVI	0.85	<0.001	0.84	420	P < 0.01
NDVI	0.78	<0.001	0.76	520	P < 0.01

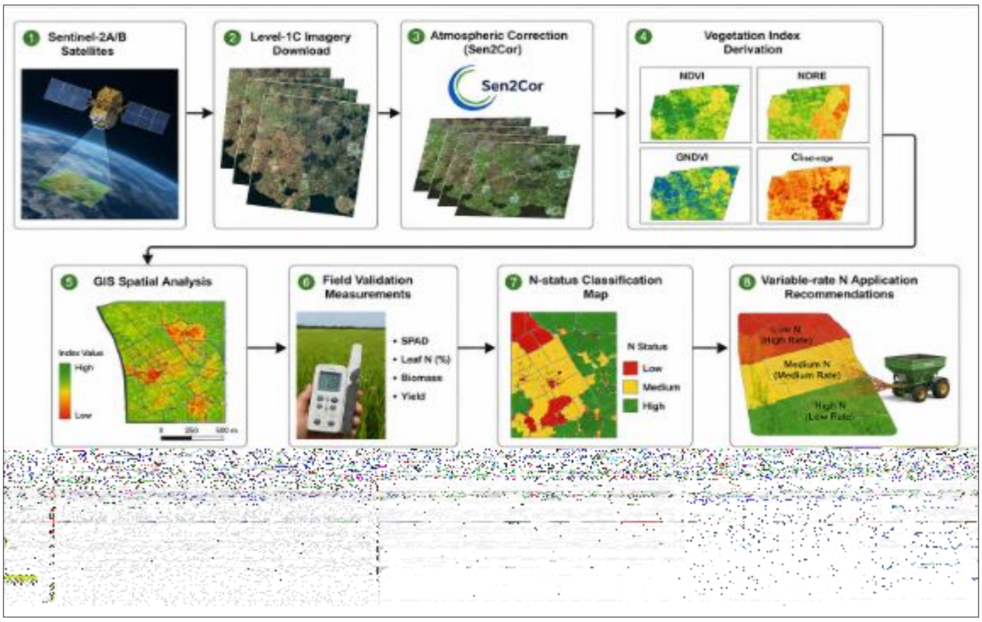

Fig 1: Sentinel-2 Image Processing Workflow for Nitrogen Management in Rice

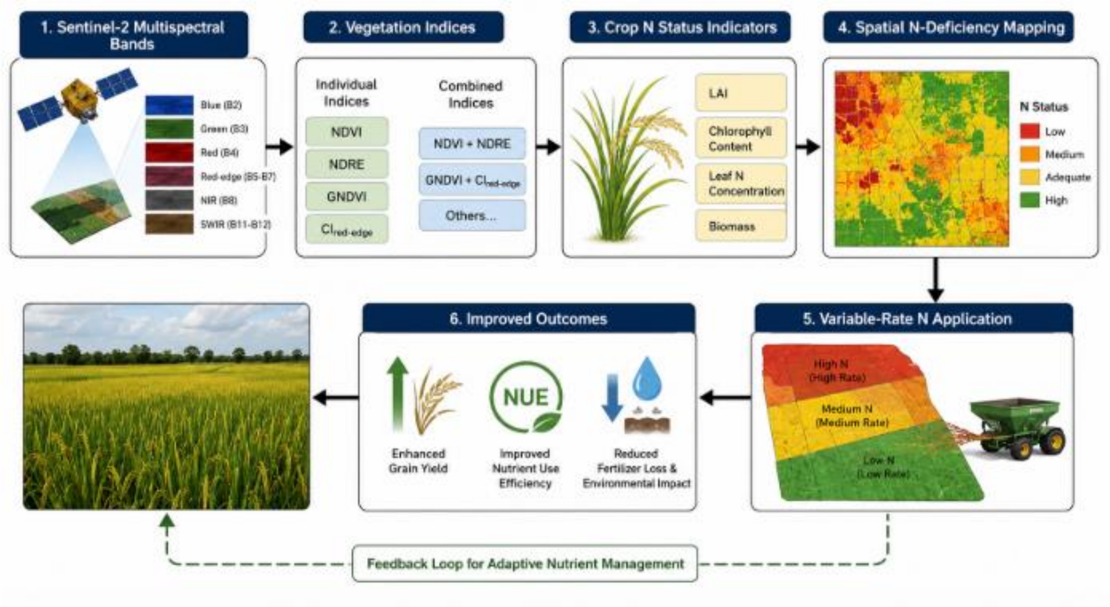

Fig 2: Integration of Remote Sensing, Crop Status Assessment, and Precision Nutrient Management

Conclusion

Images from Sentinel-2 satellites can effectively and easily be used to monitor nitrogen levels of rice crops and plan variable nitrogen rates in a timely manner. Red-edge bands perform better than the conventional NDVI method in discovering nitrogen-related developments of crop physiology. Implementing this model of satellite nitrogen management could lead to an 18% cut in input of fertilizers, with stable crop production. Using this method will bring additional advantages in terms of reducing the levels of nutrients leaking from crops, cutting production costs, and boosting farm efficiency. When integrated with GIS systems and advanced AI technologies, this method can provide significant advantages for rice cultivation around the world.

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