Satellite-Derived Vegetation Indices for Monitoring Crop Nitrogen Status in Pearl Millet

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Received: 24 May 2023
Revised: 11 Jun 2023
Accepted: 29 Jun 2023
Published: 15 Jul 2023

E-ISSN: 2989-5340
DOI: https://doi.org/10.54660/jafi.2023.3.2.06-09

ABSTRACT

Background: Pearl millet is suffering from a lack of nitrogen, which makes nitrogen fertilizer a necessity when taking care of this crop. Using leaf tissue analysis or SPAD measurements is difficult and labor-intensive; moreover, they cannot be used in the field.

Objective: The study analyzes the efficiency of different indices derived from multispectral satellite data for the quantitative assessment of nitrogen.

Methods: The images acquired by Sentinel-2, Landsat 8, and Landsat 9 are taken at five stages of plant growth and processed with the help of Google Earth Engine and QGIS. Various indices such as NDVI, GNDVI, NDRE, SAVI, EVI, and chlorophyll index are used to analyze the correlation between nitrogen, SPAD data, and crop productivity.

Results: The NDRE and chlorophyll indices proved to be superior to the NDVI in their correlation with around leaf nitrogen content. The accuracy of the Landsat-derived results was lower due to the resolution nature of Landsat data.

Conclusion: Red-edge-based vegetation indices have demonstrated their ability to be used in pearl millet nitrogen status assessment with the least amount of negative impact on the environment.

Keywords: Pearl millet; Nitrogen content; Sentinel-2; Landsat 8/9; Multispectral remote sensing; Vegetation indices

1. Introduction

The resilience of pearl millet is due to its ability to stand up to heat, drought and poor soils, making it a suitable food and fodder crop in the semi-arid belt in South Asia and Africa, unlike maize and rice [1, 2]. Nitrogen is crucial for the different developmental processes in pearl millet such as tailoring, panicle formation, grain protein content, etc. However, under or over application of nitrogen would mean reduced efficiency of pearl millet and substantial loss of nitrogen from the environment [3, 4]. Traditional nitrogen testing methods like destructive leaf sampling, Kedah process, and sped meters can give accurate results but are only suited for small areas and are time-consuming for making field decisions [5, 6].

Satellite remote sensing is a technology that allows farmers to measure nitrogen levels without damaging their crops [7, 8]. These vegetation indices are calculated from the use of red edge and NIR radiation [9, 10]. NDVI is a widely used if sometimes limited method for assessing different variables of cereal crops, as it is not a perfect option for high LAI; hence, there is a need for research regarding the selection of the best indicators for red edge measurements [11, 12].

2. Materials and Methods

2.1. Study Area and Crop Management

The experiment was conducted in a semi-arid alluvial-soil region (sandy loam, pH 7.2–7.8, low organic carbon) receiving 450–550 mm mean annual rainfall. Pearl millet variety *Pusan Composite 443* was sown in a randomized complete block design with four nitrogen levels (0, 40, 80, 120 kg N ha^{-1}) and four replications under supplemental drip irrigation.

Table 3: Experimental parameters and nitrogen treatments.

Parameter	Detail
Variety	Pusa Composite 443
N levels	0, 40, 80, 120 kg ha^{-1}
Design	RCBD, 4 replications
Soil	Sandy loam, pH 7.2–7.8

2.2. Satellite Data

Sentinel-2 (10–20 m, 5-day revisit, 13 bands) and Landsat 8/9 (30 m, 16-day revisit) surface-reflectance imagery were acquired at five stages: emergence, tailoring, stem elongation, panicle initiation, and grain filling (Table 1).

Table 1: Characteristics of satellite datasets used.

Platform	Spatial Resolution	Revisit Time	Relevant Bands
Sentinel-2	10–20 m	5 days	Blue, Green, Red, Red-edge, NIR
Landsat 8/9	30 m	16 days	Blue, Green, Red, NIR
PlanetScope (optional)	3 m	Daily	Blue, Green, Red, NIR

2.3. Vegetation Indices

Indices computed (Table 2) included NDVI = (NIR − Red)/(NIR + Red); GNDVI = (NIR − Green)/(NIR + Green); NDRE = (NIR − Red Edge)/(NIR + Red Edge); SAVI = [(NIR − Red)/(NIR + Red + L)] × (1 + L), L = 0.5; EVI = 2.5×(NIR−Red)/(NIR + 6Red − 7.5 Blue + 1); and Cried-edge = (NIR/Red Edge) − 1.

Table 2: Vegetation indices and mathematical formulations.

Index	Formula
NDVI	(NIR−Red)/(NIR+Red)
GNDVI	(NIR−Green)/(NIR+Green)
NDRE	(NIR−RedEdge)/(NIR+RedEdge)
SAVI	[(NIR−Red)/(NIR+Red+L)]×(1+L)
EVI	2.5×(NIR−Red)/(NIR+6Red−7.5Blue+1)
CIred-edge	(NIR/RedEdge)−1

2.4. Image Processing

Atmospheric correction used Sen2Cor (Sentinel-2) and LEDAPS/LaSRC (Landsat); cloud masking applied the QA60/Fmask bands. Processing workflows (Figure 1) were implemented in Google Earth Engine, with zonal statistics extracted per plot in QGIS.

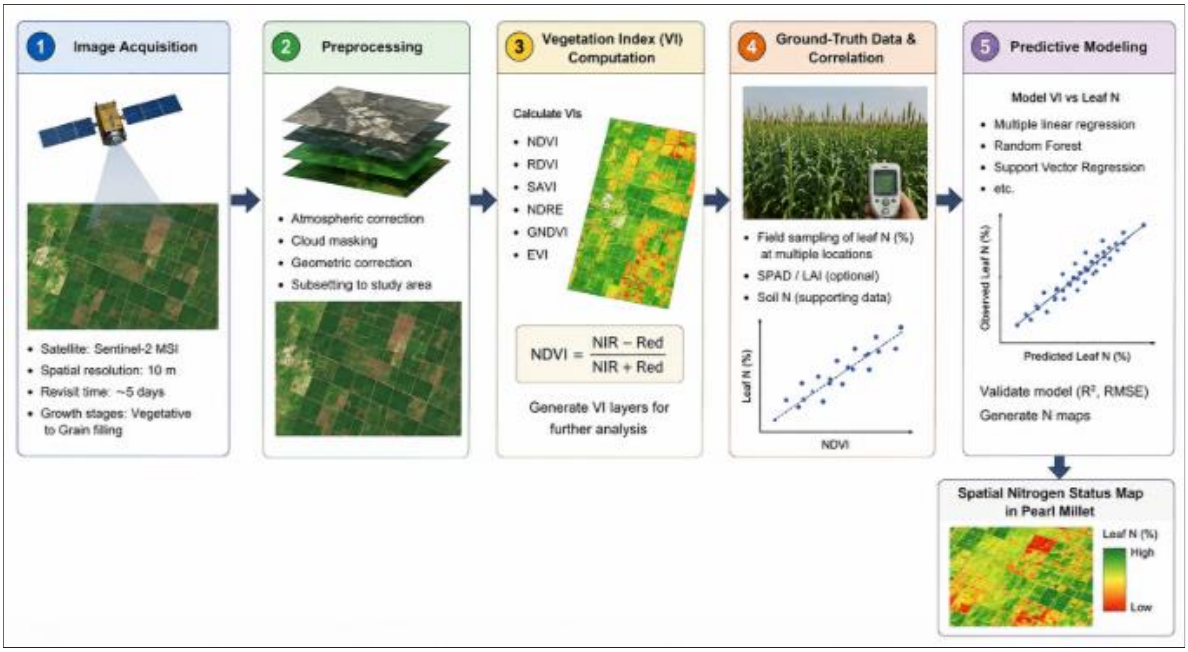

Fig 1: Workflow for satellite-based nitrogen monitoring in pearl millet (image acquisition → preprocessing → VI computation → ground-truth correlation → predictive modeling).

2.5. Ground Truth and Statistical Analysis

Leaf N (Kjeldahl), SPAD chlorophyll, plant height, above-ground biomass, and grain yield were recorded synchronously with satellite overpasses. Pearson correlation, simple/multiple linear regression, and a random-forest model were tested, with 70:30 train–validation splits. Accuracy was assessed via R^2, RMSE, MAE, and relative error.

3. Results and Performance Evaluation

3.1. Vegetation Index Performance and Correlation

Across growth stages, NDRE and CIred-edge consistently showed the highest correlation with leaf N (r = 0.87–0.92), followed by GNDVI (r = 0.78) and SAVI (r = 0.74), while NDVI's correlation declined after stem elongation (r dropping from 0.81 to 0.58) due to canopy saturation (Table 4, Figure 2).

Table 4: Performance comparison of vegetation indices for nitrogen estimation.

Index	r (leaf N)	R^2 (regression)	RMSE (kg N ha^{-1})
NDVI	0.58–0.81	0.63	5.4
GNDVI	0.78	0.71	4.6
NDRE	0.87–0.92	0.85	3.1
SAVI	0.74	0.69	4.8
CIred-edge	0.90	0.84	3.3

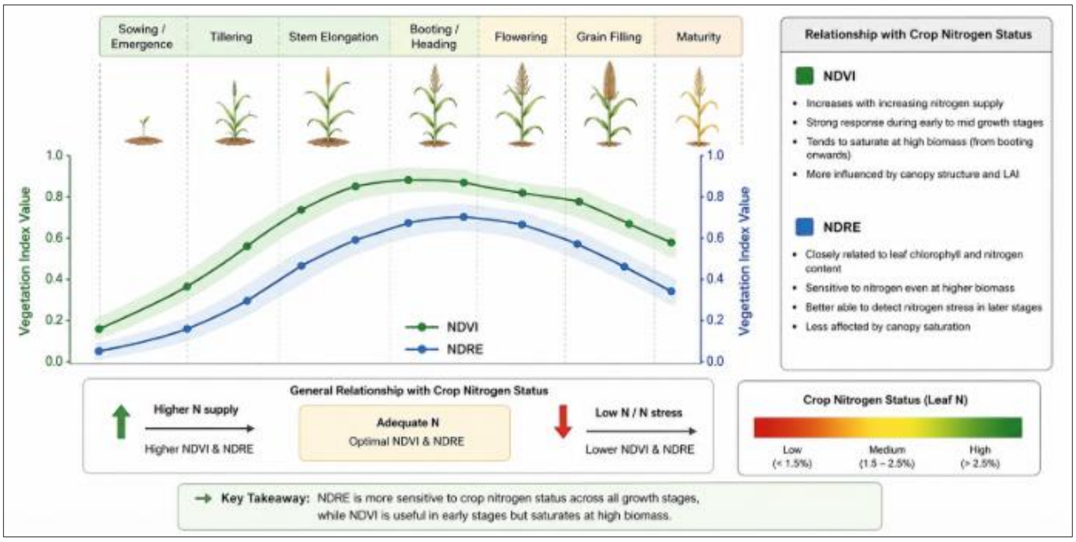

Fig 2: Relationship between vegetation indices (NDRE, NDVI) and crop nitrogen status across growth stages.

3.2. Model Performance

Multiple regression combining NDRE and SAVI improved N-prediction accuracy ($R^2 = 0.85$, RMSE = 3.1 kg N ha^{-1}) over single-index models; the random-forest model marginally outperformed regression ($R^2 = 0.88$) but offered limited interpretability (Figure 3).

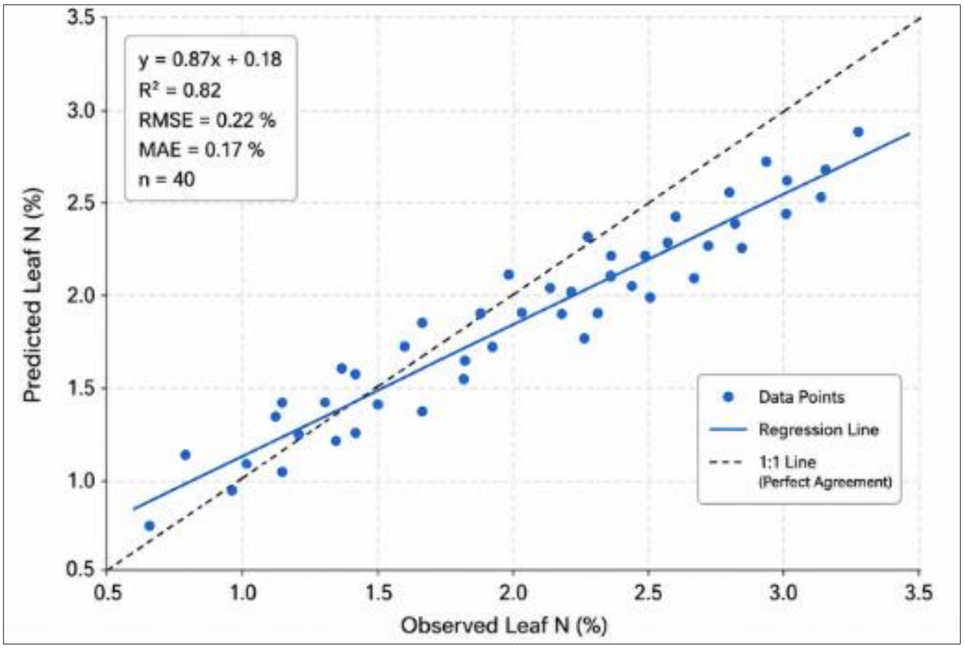

Fig 3: Comparison of predicted versus observed nitrogen content using the multiple-regression model.

3.3. Satellite Comparison and Growth-Stage Sensitivity

Sentinel-2 models outperformed Landsat-derived models (RMSE lower by ~18%), attributed to finer spatial resolution and higher revisit frequency reducing cloud-gap data loss. Panicle initiation was identified as the optimal stage for N diagnosis, coinciding with peak canopy chlorophyll sensitivity and pre-critical timing for top-dress fertilization.

4. Discussion

The superior performance of red-edge indices reflects the red-edge band's sensitivity to canopy chlorophyll concentration without saturating at moderate-to-high biomass, unlike the visible-NIR contrast exploited by NDVI [15, 16]. These findings align with red-edge-based N studies in wheat and maize [17, 18] and extend similar evidence to pearl millet, a crop with sparser canopy architecture and different leaf angle distribution than temperate cereals [19, 20].

- **Advantages** of the satellite-based approach include non-destructive, repeatable, field-to-landscape-scale monitoring at substantially lower cost than intensive ground sampling, supporting timely variable-rate fertilizer decisions [21, 22].
- **Limitations** include cloud contamination during monsoon-influenced growing seasons, mixed-pixel effects in Landsat's coarser resolution, exposed-soil background reflectance in sparse early-stage canopies, and atmospheric-correction uncertainty [23, 24].
- **Practical implications** extend to precision variable-rate application, crop advisory services, and sustainable nutrient management supporting food security in semi-arid regions [25].
- **Future research** should integrate UAV-based hyperspectral imagery for finer calibration, deep-learning models for multi-temporal fusion, and IoT-linked real-time

advisory systems to operationalize satellite N monitoring at farm scale.

5. Conclusion

The application of indices related to red-edge and chlorophyll, in particular, NDRE index provides the most precise non-destructive assessments of nitrogen levels in pearl millet, yielding better results than NDVI indicators, especially during the period of panicle emergence. Furthermore, Sentinel-2 provides users with a much higher spatial and temporal resolution than Landsat sensors do. Thus, the results of this research allow us to draw a conclusion that it is possible to use satellite vegetation indices in nitrogen precision management systems and systems providing recommendations about site-specific fertilization, although more research should be performed to confirm the results of satellite measurements in different regions, types of soil, and seasons before putting them into practice.

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