Rice Canopy Nitrogen Content Estimation Using UAV and XGBoost

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ABSTRACT

An operational framework for the estimation of rice Canopy Nitrogen Content (CNC) at KALRO Kirogo farm in Kenya's Mwea Irrigation Scheme is proposed in this paper. The proposed framework integrated UAV multispectral imagery with XGBoost. A DJI Phantom 2 Multispectral drone captured imagery at 50 m altitude, achieving 5 cm spatial resolution. Five Vegetation Indices (Vis) (NDRE, ReCI, GCI, NRI, GLI) were extracted from radiometrically corrected orthomosaics and paired with Soil and Plant Analysis Development (SPAD) measurements from stratified random sampling across three growth stages (Vegetative Stage (VS), Early Maturity (EM), and Late Maturity (LM)). XGBoost hyperparameters were optimized via grid search (144 combinations, 5-fold CV), achieving superior performance. SHAP analysis identified NDRE as the primary predictor with agronomically sensible contribution. High-resolution nitrogen maps enabled the detection of within-field variability at management-relevant scales for smallholder plots. The results demonstrated that UAV-XGBoost integration provides accurate, non-destructive nitrogen estimation for sub-Saharan African smallholder rice systems, offering a scalable framework for precision nitrogen management.

Keywords-rice; nitrogen; UAV; XGBoost

I. INTRODUCTION

Rice (*Oryza sativa L.*) is a significant food crop for more than half of the world's population. Over 500 million metric tons of rice are produced annually across an estimated 150 million ha of farmland worldwide [1]. Africa accounts for 10-13% of global grain output, with rice crop being currently grown in over 75% of African countries and territories [2].

In Sub-Saharan Africa (SSA), rice is the fifth most important grain by acreage and the fourth most significant by production volume. In some countries, strategic food security planning policies have gained importance due to the notable increase in rice demand. According to FAO, global paddy rice production reached 741.3 million tons in 2014, on 164 million ha, with China and India alone contributing more than half of that output [3].

The rice demand in Kenya outpaces supply, necessitating imports to meet the domestic need [4]. Only 20% of Kenya's rice requirements are met locally, and demand is expected to grow further due to population increase and rapid urbanization [5]. Specifically, the global rice market is expected to reach 517.5 million tons by 2030 [1], while Kenya is anticipated to attain rice self-sufficiency by that year. Thus, national production is expected to grow at an average annual rate of 9.3% [6].

To address this challenge, Kenya has embarked on an action-driven campaign, guided by its National Rice Development Strategy-2 (NRDS 2), which has been running from 2019 to 2030. The strategy is expected to increase the milled rice output by seven times, from 112,000 tons in 2018 to 846,000 tons in 2030 [7].

Nitrogen is essential to all life and is required for a multitude of functions [8]. A large portion of nitrogen is utilized by plants to create chlorophyll, which is necessary for photosynthesis and growth [9]. Additionally, in agricultural systems, nitrogen deficiency leads to yield loss as well as complex chemical and physiological reactions [8, 10].

Nitrogen is absorbed by plant roots as nitrate and ammonium, and then transported to leaves, where carbon assimilation occurs. Deficiency impairs photosynthesis, which can be rectified through nitrogen replenishment [11, 12]. Nitrogen significantly influences leaf size, plant height, panicle number, spikelet number, and filled spikelets, determining rice yield capacity. Adequate nitrogen during establishment and tillering ensures optimal tillers, while sufficient nitrogen before and during panicle initiation ensures robust panicle size. In Kenya, Nitrogen is the most limiting nutrient for rice production [5]. Leaf Blade Nitrogen Content (LBNC) in rice is a main indicator for assessing crop growth status, crop health, and guiding fertilization decisions [13]. Traditional chemical analysis can be accurate but is labor-intensive, while portable tools, such as Soil and Plant Analysis Development (SPAD) and GreenSeeker are impractical for large-scale monitoring. Previous studies have demonstrated strong relationships between SPAD-derived indices and Nitrogen Nutrition Index (NNI), reinforcing the diagnostic value of SPAD for predicting yield responses to nitrogen application [14].

Remote sensing has emerged as the most feasible approach for continuous, large-area nitrogen monitoring, due to its capacity to capture spectral signals linked to plant physiology [15, 16]. Although foliar nitrogen represents only a small fraction of leaf dry mass, hyperspectral and multispectral imagery have exhibited strong potential for retrieving nitrogen status [17]. Hyperspectral data provide fine-band sensitivity, while multispectral indices, including Normalized Difference RedEdge (NDRE), Normalized Difference Vegetation Index (NDVI), and chlorophyll-based indices, also correlate with nitrogen dynamics, though cloud interference limits satellite use. UAV-based platforms overcome these challenges by delivering high-resolution, near-real-time data at lower costs, albeit constrained by local weather conditions [18].

Vegetation Indices (VIs) are essential for nitrogen estimation, with red-edge indices outperforming the traditional ones in some contexts [19, 20]. Novel approaches using VNIR sensors [12] achieved high correlations (R = 0.93) with NDNI, offering cost-effective alternatives to SWIR-dependent methods. Machine Learning (ML) methods are increasingly being integrated to exploit complex, non-linear relationships in multi-source datasets [10]. Similarly, UAV-hyperspectral research indicated ML and PLSR provided superior performance when multiple growth stages or missing phenological data were considered [21]. Collectively, evidence confirms that UAV and satellite-based remote sensing, particularly when coupled with advanced ML techniques, provide a robust, scalable, and cost-efficient pathway for real-time monitoring of rice nitrogen status. This integration offers significant opportunities to improve fertilization strategies, enhance yield prediction, and advance precision agriculture practices.

This study aims to estimate the rice Canopy Nitrogen Content (CNC) using UAV-derived VIs and XGBoost in KALRO Kirogo farm in Mwea Irrigation Scheme, Kenya. This research departs from conventional nitrogen assessment approaches utilizing RF, SVM, or ANN by leveraging UAV-acquired multispectral data in conjunction with XGBoost utilization to develop high-resolution nitrogen maps at the plot level, thereby enabling data-driven fertilization strategies.

II. MATERIALS AND METHODS

A. Study Area

This study was conducted in KALRO Kirogo Farm in the larger Mwea Irrigation Scheme, Kenya (Figure 1). The test plots measure 5 × 5 m with varying levels of nitrogen fertilizer application.

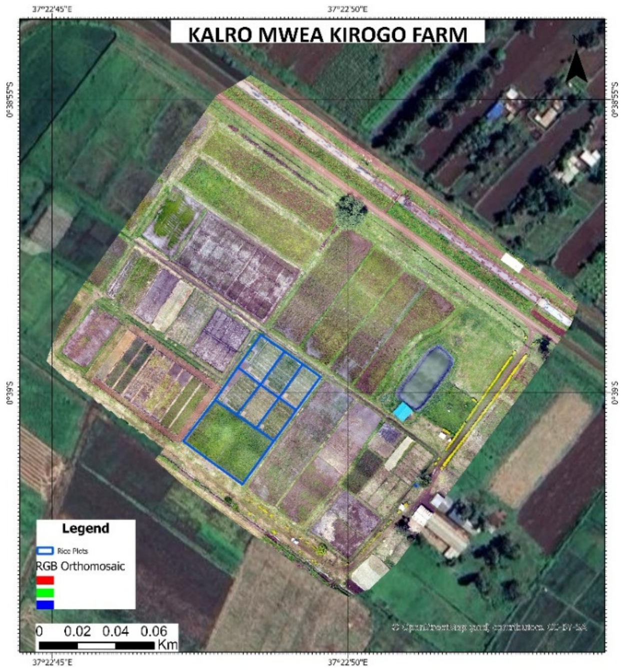

Fig. 1. Study area map.

B. Materials

This study utilized the following remote sensing tools and software:

- Chlorophyll Meter SPAD502-Plus: Used to measure the chlorophyll content of leaves in a non-destructive manner, used/and utilized as ground truth data in model calibration.

- DJI Phantom 2 Multispectral UAV: Utilized to capture high-resolution images.
- OpenDroneMap (ODM): Processing UAV imagery and generating orthomosaics of the same.
- R/Rstudio: Creating the XGBoost model.
- ArcGIS Pro: For map making and visualization.

C. Method

Figure 2 illustrates the methodology employed in this study.

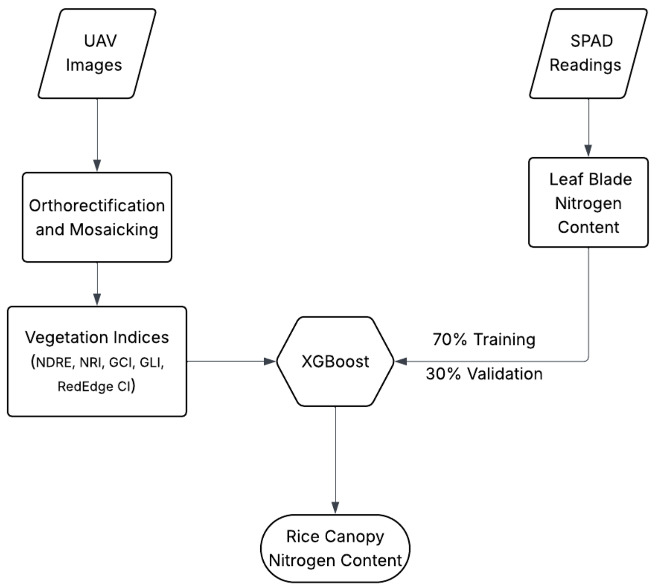

Fig. 2. Methodology.

D. Field Chlorophyll Measurements

In the KALRO Kirogo farm in Mwea, test plots of 5 × 5 m were set up by KALRO. In each plot, different levels of nitrogen fertilizers were applied. This results in rice crops having different characteristics, especially the chlorophyll content. A chlorophyll meter [SPAD-502Plus, SPAD, Minolta Camera Co., Osaka, Japan] was used for rice plant chlorophyll measurement. The chlorophyll content of plant leaves is correlated with the nutritional conditions of rice. Nitrogen is one of the nutrients closely related to the chlorophyll content. The SPAD measurements are converted to Leaf Blade Nitrogen Concentration (LBNC) using (1) - a relationship well-established in the literature (Figure 3) [14]:

$$LNBC = 0.079SPAD - 0.154 \quad (1)$$

Random sampling was used to choose the location of the measurements across rice fields representing three distinct phenological stages: Vegetative Stage (VS), Early Maturity (EM), and Late Maturity (LM), as shown in Figure 4.

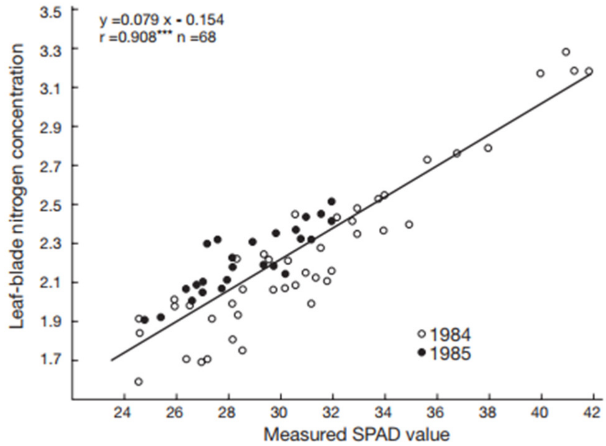

Fig. 3. Relationship between SPAD value and LBNC (Konica Minolta, 2009).

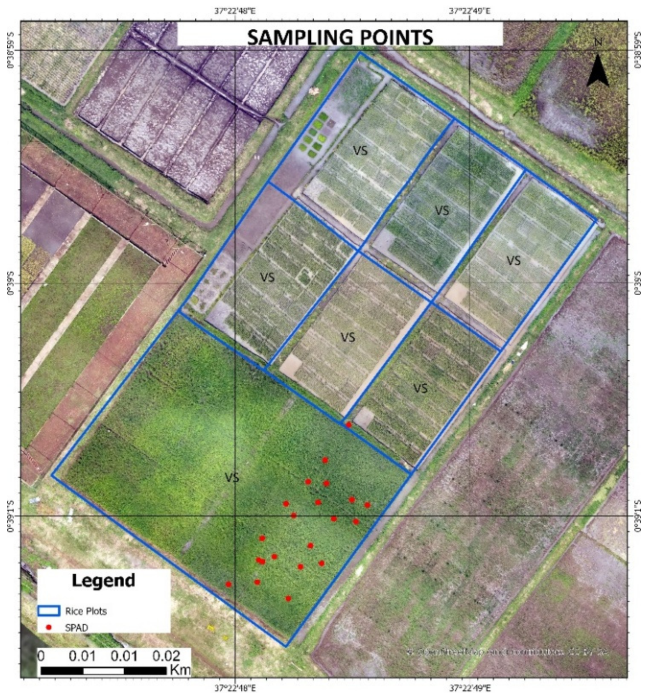

Fig. 4. Randomly sampled SPAD measuring points.

E. UAV Image Acquisition and Processing

UAV imagery was acquired on November 17, 2023, using a DJI Phantom 2 Multispectral drone with RGB, Red-Edge, and NIR bands. The flight mission was conducted at 50 m above ground level, achieving a Ground Sampling Distance (GSD) of 5 cm with 80% forward and side overlap. Weather conditions during the flight were optimal, characterized by calm conditions with light east-northeast winds and clear skies, ensuring minimal radiometric variations and no shadow or cloud contamination.

Orthomosaic generation and image processing were conducted using the ODM software. The Structure-from-Motion (SfM) workflow included image alignment, bundle adjustment, dense point cloud generation, Digital Elevation Model (DEM) creation, and radiometrically corrected orthomosaic production. The resulting orthomosaics maintained the 5 cm spatial resolution across all spectral bands and were georeferenced to the WGS84 UTM coordinate system. Five VIs were subsequently calculated from the calibrated orthomosaics as well as the RGB true color images.

The indices are:

- NDRE
- RedEdge Chlorophyll Index (ReCI),
- Green Chlorophyll Index (GCI),
- Nitrogen Reflectance Index (NRI),
- Green Leaf Index (GLI).

These indices are sensitive to canopy chlorophyll content, leaf area, and canopy structure, which correlate strongly with the nitrogen status in rice. NDRE and ReCI exploit red-edge reflectance patterns particularly responsive to nitrogen variation, while GCI, NRI, and GLI capture visible spectrum characteristics associated with canopy greenness and photosynthetic capacity.

$$\mathrm{NDRE} = \frac{\mathrm{RedEdge} - \mathrm{Red}}{\mathrm{RedEdge} + \mathrm{Red}} \quad (2)$$

$$\mathrm{ReCL} = \frac{\mathrm{RedEdge} - \mathrm{Red}}{\mathrm{Red}} \quad (3)$$

$$\mathrm{GCI} = \frac{\mathrm{Green} - \mathrm{RedEdge}}{\mathrm{Green} + \mathrm{RedEdge}} \quad (4)$$

$$\mathrm{NRI} = \frac{\mathrm{Red} - \mathrm{Blue}}{\mathrm{Red} + \mathrm{Blue}} \quad (5)$$

$$\mathrm{GLI} = \frac{2 * \mathrm{Green} - \mathrm{Red} - \mathrm{Blue}}{\mathrm{Green} + \mathrm{red} + \mathrm{Blue}} \quad (6)$$

F. *XGBoost for Nitrogen Estimation*

Extreme Gradient Boosting (XGBoost) regression is an ML algorithm widely employed for regression tasks. It combines the predictions of multiple weak models (usually decision trees) to create a more robust and accurate predictive model [22].

In this study, the XGBoost model for rice CNC was developed in R. The model takes the VIs (NDRE, GCI, NRI, GLI, ReCI) from the UAV orthomosaics as independent variables with LBNC values as the dependent variables. It relates the LBNC and the VIs by utilizing boosted tree regression and variable importance to get the optimum estimation model. To estimate the LBNC based on the VIs, the algorithm will build decision trees iteratively. A loss function (which measures prediction errors) and a regularization term are combined to create an objective function that must be minimized throughout the training phase. Sequential construction is used to build trees, with each new tree attempting to fix mistakes created by the previous ensemble. Gradient descent finds split points that maximize the decrease in the objective function to optimize the model parameters. Throughout the procedure, feature importance was assessed to showcase which features were the most important in outcome prediction. When the model was trained, it was used to estimate the nitrogen content for new data points or, in the case of raster data, for each pixel that contains the relevant feature values. The XGBoost model was trained using a set of hyperparameters determined through iterative tuning to balance predictive accuracy and generalization. Table I presents the considered hyperparameters. To assess the contribution of each VI to model predictions, both gain-based importance and SHAP values were computed, as displayed in Table II.

TABLE I. XGBOOST HYPERPARAMETERS

Parameter	Value	Description
Learning rate (eta)	0.2	Controls learning speed (step size shrinkage)
Max depth	3	Maximum depth of each tree
Min child weight	5	Minimum sum of instance weight in a child
Subsample	0.9	Fraction of samples used for training each tree
Column sample by tree	0.8	Fraction of features used for training each tree
Gamma	0	Minimum loss reduction for split
Number of trees (*n*_estimators)	503	Final number of boosting rounds

TABLE II. FEATURE IMPORTANCE

VI	Gain	SHAP value
NDRE	0.643	0.147
GCI	0.133	0.06
NRI	0.119	0.054
GLI	0.069	0.045
ReCI	0.036	0.018

III. RESULTS AND DISCUSSION

A. *Vegetation Indices*

Five VIs (NDRE, ReCI, GCI, NRI, GLI) were derived from UAV multispectral imagery and used as inputs for modeling rice leaf nitrogen content (Figures 5-9). In all index maps, red tones indicate high values and green indicate low values.

The VIs derived from UAV imagery demonstrate clear phenological progression and provide consistent differentiation of rice growth stages. NDRE values increased during the VS and EM, where vigorous leaf expansion and active nitrogen uptake supported peak chlorophyll activity. A marked decline was evident in LM plots as nitrogen was remobilized to develop grains. Similar patterns were observed in ReCI and GCI, both of which recorded maximum values at VS and EM, and significant reductions in LM. These indices proved highly sensitive to chlorophyll content, with ReCI being particularly effective in distinguishing senescent from active canopies. The NRI closely tracked nitrogen dynamics, peaking at VS and EM, while declining and falling sharply at LM as nitrogen was redistributed. GLI followed canopy greenness and biomass distribution, with the highest values being reached at VS, sustained responses at EM, and the lowest values in LM due to soil background effects and senescence.

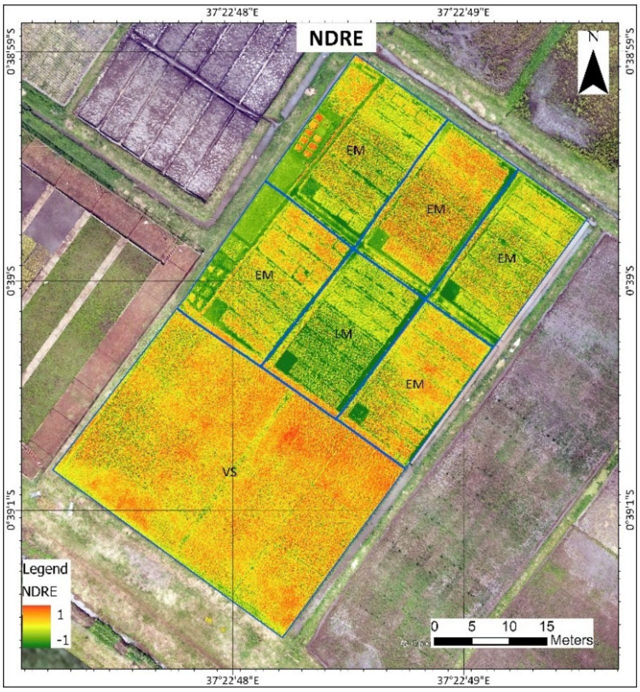

Fig. 5. NDRE distribution in the rice fields.

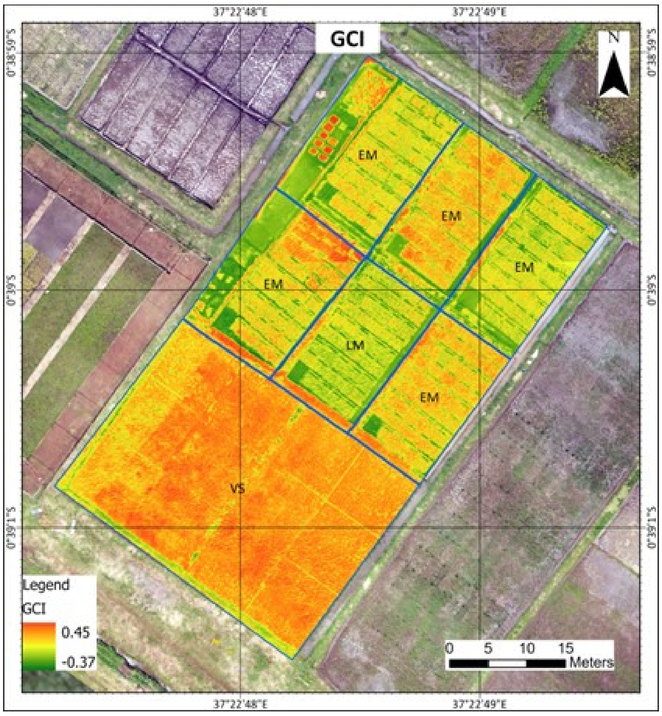

Fig. 6. Spatial distribution of the GCI across rice fields at different growth stages.

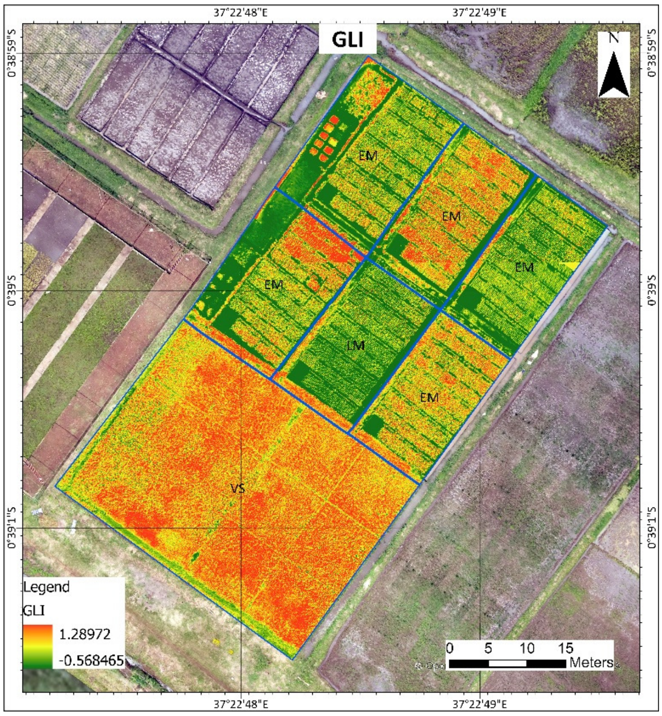

Fig. 7. GLI distribution in the rice fields.

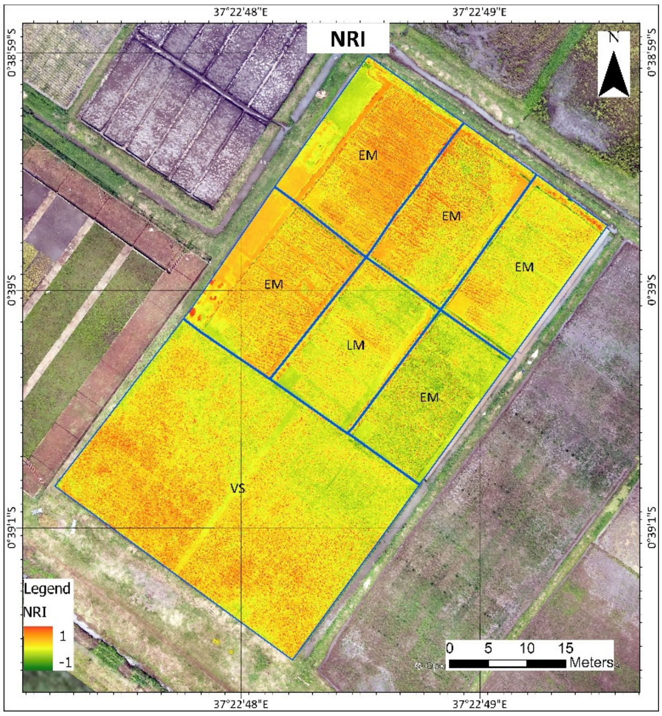

Fig. 8. NRI distribution in the rice fields.

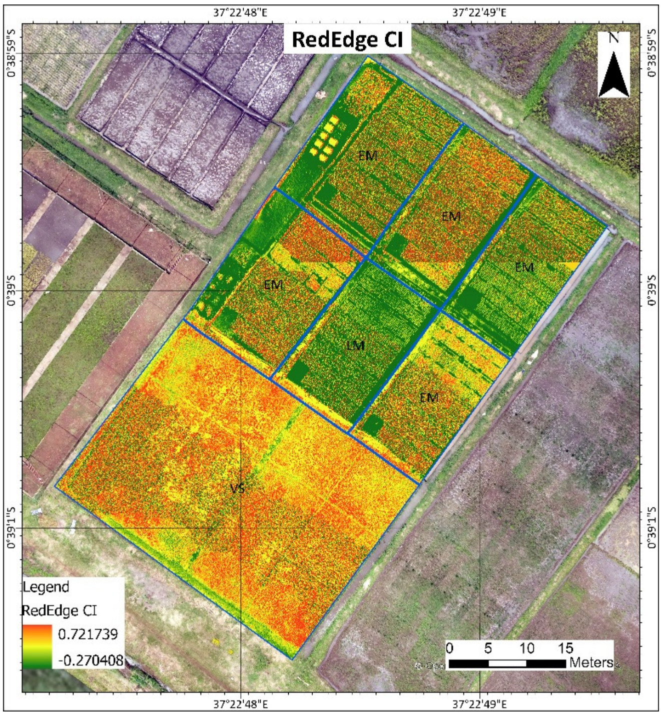

Fig. 9. ReCI distribution in the rice fields.

The above-mentioned indices revealed that VS and EM are the stages of peak nitrogen and chlorophyll status, while LM represents a phase of physiological decline. ReCI and NRI emerged as the most sensitive indices for nitrogen-chlorophyll variations, offering the clearest separation among stages, while NDRE, GCI, and GLI contributed complementary information on photosynthetic vigor, canopy greenness, and biomass accumulation. This complementarity underscores the robustness of using multiple indices simultaneously, as they capture both nitrogen concentration and structural canopy attributes across the crop cycle.

The VI maps also revealed substantial spatial heterogeneity in nitrogen and chlorophyll content. Variability was not confined to stage-level differences but extended within plots, where zones of higher and lower index values coexisted. This pattern was consistent across all indices, suggesting that the heterogeneity reflects genuine physiological and agronomic variation, such as differences in soil fertility, localized water distribution, or uneven management practices. The ability of UAV-based indices to capture both temporal (stage-wise) and spatial (within-field) variability highlights their utility as a diagnostic tool for precision agriculture, offering opportunities for targeted nutrient management and improved efficiency in rice cultivation.

B. *Nitrogen Mapping*

After running the XGBoost model (R^2 = 0.84 and *RMSE* = 0.24), a canopy nitrogen map was generated. The CNC map (Figure 10) mirrors the patterns revealed by the VIs and provides a stage-specific interpretation of nitrogen dynamics. VS and EM plots exhibited the highest nitrogen levels (red zones), which is consistent with the elevated NDRE, ReCI, GCI, and NRI values observed earlier. These indices captured peak chlorophyll content and nitrogen assimilation, explaining why the CNC model highlights these stages as nitrogen-rich. Conversely, LM plots indicated predominantly green patches, reflecting the sharp decline in NDRE and NRI values linked to nitrogen remobilization from leaves to developing grains. Three more models - RF, LASSO, and SVM - were also tested, and their performance is presented in Table III.

TABLE III. PERFORMANCE COMPARISON OF ML MODELS BASED ON R², RMSE, MAE, BIAS, AND SD ERRORS

Model	R-square	RMSE	MAE	Bias	SD_Errors
XGBoost	0.84	0.24	0.18	0.09	0.22
LASSO	0.71	0.42	0.29	0.21	0.37
RF	0.66	0.43	0.31	0.19	0.39
SVM	0.63	0.51	0.31	0.32	0.40

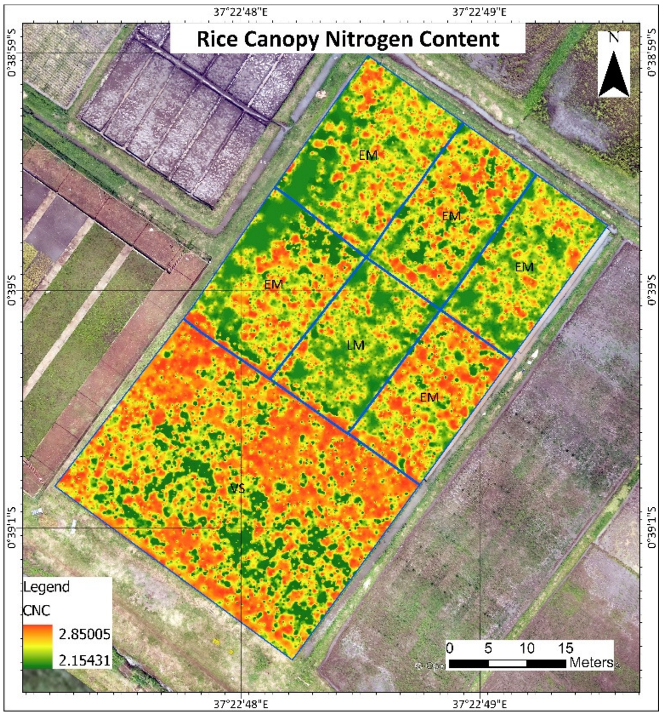

Fig. 10. Rice CNC map predicted by XGBoost model (R^2 = 0.84, *RMSE* = 0.24). Red zones indicate high nitrogen; green zones indicate low nitrogen.

The within-field variability evident in the CNC map also validates the sensitivity of the UAV-derived indices to nitrogen and chlorophyll heterogeneity. NDRE and NRI were most effective at capturing differences in nitrogen status, while ReCI and GCI highlighted changes in chlorophyll concentration, and GLI tracked canopy greenness. Together, these indices predicted the spatial patterns now quantified in the CNC map: nitrogen-rich zones (red) correspond to high-index areas identified during VS and EM, while nitrogen-deficient zones (green) overlap with low-index values recorded in LM. This demonstrates that VIs not only differentiate rice growth stages but also serve as reliable predictors of spatial nitrogen variability, making them powerful tools for guiding precision nutrient management.

The current XGBoost model (R^2 = 0.84, $RMSE$ = 0.24) achieved performance comparable to or exceeding recent studies on UAV-based rice nitrogen estimation. For instance, in [23], an R^2 = 0.94-0.96 was achieved for calibration but only 0.61-0.79 for validation using RF with fixed-wing UAV multispectral data in Northeast China. Authors in [24] combined digital RGB and multispectral UAV imagery with Gaussian Process Regression to estimate rice leaf nitrogen content, achieving R^2 = 0.68 and $RMSE$ = 11.45%.

Conversely, the present study is among the first to apply this methodology in Kenya's smallholder systems, addressing a research gap as the existing literature predominantly focuses on Asian commercial farms. The integration of SHAP interpretability and systematic four-algorithm comparison (XGBoost, RF, SVM, LASSO) distinguishes this research from prior studies. The 5 cm spatial resolution enabled within-field nitrogen mapping at management-relevant scales for smallholder plots, substantially improving upon coarser resolution approaches ($\geq$ 10 m) that cannot capture fine-scale heterogeneity in plots typically smaller than 0.5 ha. However, there are two primary limitations that should be considered when interpreting the results:

- Data collection was confined to a single site (KALRO Kirogo farm, Mwea Irrigation Scheme), which may limit the generalizability of the XGBoost model to other rice-growing regions with different soil types, climatic conditions, or cultivar characteristics.
- The relatively small dataset size constrains the model's ability to capture the full spectrum of nitrogen variability across all possible combinations of growth stages, soil conditions, and canopy architectures. Expanding the training dataset through multi-seasonal data collection would strengthen model robustness and improve prediction reliability under extreme nitrogen stress or excess conditions.

IV. CONCLUSION

This study successfully demonstrated the effectiveness of UAV-derived Vegetation Indices (VIs) for the non-destructive assessment of the rice nitrogen status across different growth stages. The comprehensive analysis of five VIs (NDRE, ReCI, GCI, NRI, and GLI) revealed distinct spectral signatures corresponding to nitrogen and chlorophyll dynamics throughout rice phenology, with Vegetative Stage (VS) and Early Maturity (EM) exhibiting peak index values, whereas Late Maturity (LM) displayed a significant decline due to senescence and nitrogen remobilization. Consistent spatial variability patterns observed across all indices validated their reliability for capturing both temporal and spatial variations in rice nitrogen dynamics. By integrating these indices with SPAD measurements through an XGBoost model, nitrogen can be accurately modeled across rice fields.

The findings indicated that the combination of UAV-based VIs and Machine Learning (ML) algorithms offers a robust, scalable solution for precision nitrogen management in rice production systems. The ability to generate detailed nitrogen content maps across different growth stages provides farmers with critical decision-making tools for optimizing fertilizer timing and application rates. This non-destructive, high-throughput approach to nitrogen assessment represents a practical step toward sustainable intensification of rice agriculture, enabling more efficient resource utilization and improved crop management strategies that can enhance both economic returns and environmental sustainability.

DECLARATION OF COMPETING INTERESTS

The authors declare no competing interests.

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DATA AVAILABILITY

Data and code are available upon reasonable request from the corresponding author.

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