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DRONE AND SENSORS FOR NON-CONTACT ESTIMATION OF SOIL AND PLANT ATTRIBUTES

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Preface

Rice is one of the most important food crops, serving as a staple food for billions of people worldwide, particularly in India. As global population growth drives, the demand for food is increasing continuously, therefore sustainable rice management practices are essential for ensuring increased productivity along with maintaining environmental sustainability. Precision agriculture, incorporating advanced technologies such as remote sensing and machine learning algorithms, offers cost effective solutions for optimizing nutrient management by estimating soil physicochemical properties and soil nutrients for enhancing rice yield in a cost-effective and environmentally sustainable manner. In addition, the estimation of rice yield well before the crop harvest may help in policy decision and also in optimizing the management options. Currently following problems exist in real time spatial data excess and analysis. (i) Lack of high-resolution, cost-effective data for estimating soil and plant attributes (ii) Limited usage of machine learning models for providing solution at granular scale.

This research bulletin addresses several critical research gaps in sustainable rice management like limited exploration of estimation of soil parameters, particularly soil organic carbon (SOC) and plant nutrients like nitrogen (N) using multispectral imagery acquired from (Unmanned Aerial Vehicle) UAV mounted sensors combined with machine learning models.

This bulletin focuses on application of remote sensing technologies, particularly UAV-mounted sensors, to estimate rice leaf nitrogen content and soil organic carbon content and prediction of rice yield at panicle initiation stage of rice crop.

This bulletin would contribute in not only reducing the need for expensive and time-consuming methods for plant and soil nutrient laboratory analyses but also provides modelling solution for real-time site-specific N recommendation at critical stage of crop requirement for increasing the nitrogen use efficiency. Site specific N management may help in minimizing excessive fertilizer use particularly nitrogen, reducing environmental pollution and maintaining or improving yield. These developed technologies are adaptable for smallholder farms as well as large scale rice production systems. The solutions provided in the bulletin may aid in decision making for policy makers and insurance sectors through advanced machine learning models, improving yield prediction accuracy of rice crop.

We hope this research bulletin will serve as a valuable resource for researchers, policymakers and farmers in their pursuit for improving nutrient use efficiency and rice productivity while maintaining environmental sustainability.

We extend our sincere gratitude to the Director, ICAR-Central Rice Research Institute (CRRI) for providing the necessary infrastructure and resources for conducting this study. Authors would also like to express their sincere gratitude to ICAR-Network Program of Precision Agriculture (NePPA) for providing financial support for conducting the studies. Sincere thanks to The Royal Norwegian Embassy, Norway for funding RESILIENCE project through which funding support for procurement of Drones, sensors and software was provided. Special thanks to the farmers at Prahrajpur and Dakhinasailo villages for their cooperation and field support. Authors are also appreciating the assistance provided by Sasmita Samal, Biswajit Mohapatra, Sambit Kumar Mallick, Chandrasekhar Behera, Chandan Kumar Ojha and Surya Prasad Lenka in executing the field experiments and assisting for analysis of the soil and plant samples.

Authors

CONTENTS

1. INTRODUCTION

With the global population projected to reach around 9 billion by 2050, food demand is expected to rise significantly, necessitating efficient soil and nutrient management along with inclusion of advanced production technologies for higher yield productivity to ensure food security and environmental sustainability. To achieve sustainable rice production, it is essential to improve soil health and optimize the efficiency of agricultural inputs. Enhancing soil parameters, such as soil organic carbon (SOC) is important as it plays a vital role in ecosystem resilience and productivity, but human land use changes have led to significant SOC loss. Similarly, agricultural inputs like nutrient management particularly nitrogen (N) is a critical parameter in crop growth and productivity. However, improper N application can lead to inefficiencies and environmental losses. Precision management practices play a critical role in enhancing rice yields by optimizing resource utilization and minimizing inefficiencies. Traditional laboratory methods for estimating SOC and N content are costly and time-consuming (Qiu et al., 2021; Loria et al., 2024), thereby remote sensing techniques, particularly satellite remote sensing and drone-based spectroscopy, combined with machine learning models like Random Forest and Artificial Neural Networks, provide cost-effective, high-frequency monitoring and accurate yield predictions, overcoming the limitations of traditional methods (Tripathi et al., 2024a; Sun et al., 2025). Drone, with their ability for precise data acquisition and minimal atmospheric interference, are increasingly used in agricultural monitoring over satellite based remote sensing, offering a promising solution for improving crop productivity and sustainability. Drone mounted with multispectral sensors can be used for reliable estimation of soil parameters (SOC) and crop nutrient status, offering real-time, site-specific nutrient management particularly N (Tripathi et al., 2024b; Tripathi et al., 2017), enabling plot-specific N topdressing recommendations for smallholder farms to enhance rice yield in an ecologically sustainable manner. Given that rice is a staple crop for over 70% of the Indian population, accurate and timely yield forecasting is essential for effective resource allocation, informed food policy decisions and strategic crop management (Zhang et al., 2019; Tripathi et al., 2025a). Such forecasts enable policymakers and farmers to anticipate yield fluctuations, plan for optimal input application, and implement adaptive management strategies.

2. Research Gaps

- Limited exploration of non-contact estimation of soil parameters
- Less studies focusing on usage of drones and sensors for estimating plant and soil parameters
- Limited use of machine learning models combined with high resolution imageries from drone mounted sensors for non-contact estimation of soil and plant attributes
- Lack of high-resolution, cost-effective methods for spatial estimation and mapping of soil physicochemical parameters.
- Need for precise, site specific and real-time N management tools for minimizing N loss, while maximizing yield.
- Limited studies on influence of Vegetation Indices (VIs) on soil and plant attributes across varying rice growth stages.
- Limited studies focusing on scientific methods for selection of variables or indices for use in models for better estimation of soil and plant attributes. Few studies on independent variable selection techniques for development of reliable and accurate ML models.
- Lack of site-specific nutrient management protocols for small landholdings.
- Insufficient and limited use of drone and machine learning models for rice yield prediction before crop harvesting with high spatial resolution and accuracy.

3. Initiatives at ICAR-CRRI to address the above research gaps

Looking at the developments and capabilities of drones and sensors, following research works were conducted and validated to address some of the challenges mentioned in section 2.

- Estimation of Soil organic carbon using multispectral sensors mounted on drones.
- Predicting nitrogen content in rice using drone mounted multispectral imaging.
- Recommendation of nitrogen topdressing using drone mounted multispectral sensors for small holder's rice farms.
- Rice yield prediction using drone mounted sensors.
- In next sections the description about drones, sensors softwares and different methodologies adapted for above works are explained in detail.

4. Materials / drones / sensors / softwares used in the study

4.1 Drones / Unmanned Aerial Vehicle (UAV) / Unmanned Aircraft System (UAS)

The terms UAV, UAS and drone are often used interchangeably, as they all refer to aerial technologies used for remote sensing and aerial data collection. Despite their similarities, they are slightly differentiated by their technological aspects. A UAV (Unmanned Aerial Vehicle) is an aircraft that operates without a human pilot onboard, controlled either remotely or autonomously. A drone is a more commonly used term that typically refers to the same flying vehicle as a UAV (Fig.1). Meanwhile, a UAS refers to the complete system that includes the UAV or drone, along with the ground control station, communication links, and any supporting equipment needed for operation. In most contexts, "drone" and "UAV" are used as synonyms to refer to the flying vehicle itself. In agriculture, drones are increasingly employed for precision farming, where they facilitate tasks such as crop monitoring, field mapping, pesticide and fertilizer application, and assessment of plant health using multispectral and thermal imaging technologies. These applications enhance efficiency, reduce resource use, and improve yield outcomes by providing real-time, data-driven insights into crop and soil conditions.

Fig. 1 UAV / drone

4.2 Softwares used in this study

4.2.1 Software for flight plan mapping

A ground control software was used for real-time flight planning, sensor calibration and data acquisition. In agricultural applications, it enables precise control of drone flight paths and ensures accurate triggering of sensors at predefined time interval for image acquisition. This ensures optimal frontal and side overlap of the captured images with a defined altitude and tolerance limit, which are essential for generating high-quality datasets used model training and development. In this study Bluefire Touch Software (version v4.2.9134.18070) was used for flight plan mapping and drone flying (Fig. 2).

Fig. 2 Generation of mapping plan using blue fire touch software

4.2.2 Remote sensing image analysis and processing software

An image processing software is used for processing of the captured raw drone imagery and transform it into digital surface models (DSMs) and 3D point clouds to generate the georeferenced orthomosaics. In agriculture, it plays an important role in aligning and stitching captured images, correcting distortions and generating spatially accurate orthomosaics, which are further used for generating vegetation indices and further geospatial analysis. In this study Agisoft Metashape Software (version 2.0.2) was used for image analysis and processing (Fig. 3).

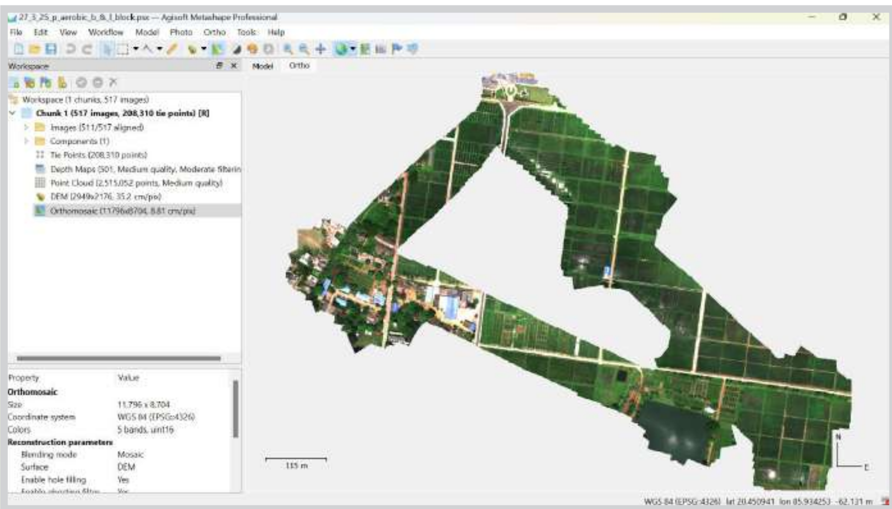

Fig.3 Image processing and generation of orthomosaics using Agisoft software

4.2.3 Spectral index computation and mapping software

Geographic information system (GIS) platforms are used for advanced spatial analysis, mapping and extraction of vegetation indices such as NDVI, NDRE, SAVI, etc. from orthomosaic image of drone mounted sensor. Users can assess spatial variability in crop health, analyze inter-field variability and integrate various spatial datasets for informed decision-making in precision farming. In this study ArcGIS Software (version 10.2.2) was used for Spectral index computation and mapping.

4.2.4 Data analytics and predictive modeling software

Data analytics softwares are used to develop and validate machine learning models like Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Networks (ANN), etc. using vegetation indices as independent variables and crop parameters such as nitrogen content, biomass, yield, etc. as dependent variables. This software also enables the application of different machine learning algorithms to predict crop parameters and different soil physio chemical properties based on drone-acquired data. In this study RStudio Software (version 2025.05.1+513) was used for data analytics and predictive modeling.

4.3 Sensors used in this study

4.3.1 Imaging sensor

Multispectral sensors were employed to acquire high-resolution remote sensing data across the visible, near-infrared (NIR) and red-edge spectral bands for various agricultural applications. These sensors enable precise monitoring of crop health, chlorophyll content and nitrogen status through vegetation indices such as NDVI, NDRE, etc. Their high radiometric accuracy and compatibility with UAV platforms make them ideal for precision agriculture, supporting site-specific management of irrigation, fertilization and pest as well as disease control. In this study MicaSense RedEdge-MX multispectral sensor (Fig. 4) was used for capturing images across five spectral bands (blue, green, red, red-edge and NIR).

Fig. 4 MicaSense RedEdge-MX sensor

4.3.2 Downwelling Light Sensor (DLS) sensor

This sensor measures the intensity and quality of ambient sunlight during flight, which is essential for radiometric calibration of the captured imagery (Fig. 5). By recording real-time light conditions across relevant spectral bands, the DLS allows for correction of illumination differences caused by changing weather, sun angle or cloud cover. This ensures that reflectance values derived from multispectral images are consistent and comparable, enabling accurate calculation of vegetation indices such as NDVI, NDRE, etc. Proper installation and orientation of the DLS sensor are also important for maximizing data accuracy and reliability.

Fig. 5 Downwelling Light Sensor (DLS) sensor

4.4 Components of the unmanned Aerial system

4.4.1 Communication Box (Comm Box)

The Communication Box acts as the central hub for data transmission between the drone and the ground control station (Fig. 6). It manages real-time communication, sending commands to the drone and receiving telemetry, sensor data and video feed. In this study drone, the Comm Box ensured secure, stable and low-latency links for efficient flight control, payload management and handling integration with peripherals like cameras and sensors, allowing synchronized data acquisition.

Fig. 6 Communication Box

4.4.2 White calibration panel / white reference panel / white balance card

White panel calibration involves capturing images of a standardized white reference panel before or during the flight (Fig. 7). This panel has known reflectance properties and is used to calibrate the drone's sensors for consistent color and spectral accuracy. It corrects sensor drift, lighting variations and ensures that the acquired images accurately represent the true reflectance of the target surfaces. Together with the DLS, white panel calibration is important for acquisition of high-quality, scientifically valid remote sensing data.

Fig. 7 White Calibration panel

4.4.3 Computer systems for automated flight planning and execution

A suitable laptop system is essential for efficient drone operation, requiring at least an Intel i5 or Ryzen 5 processor, 8 GB of RAM, a 256 GB SSD and a reliable battery for managing complex flight plans (Fig. 8), ensuring real-time responsiveness during automated missions and process large volumes of data accurately, ultimately enhancing the safety, efficiency and effectiveness of drone operations. In this study a laptop with 12 gen intel core i7 processor, 16 GB RAM and 64-bit operating system was used.

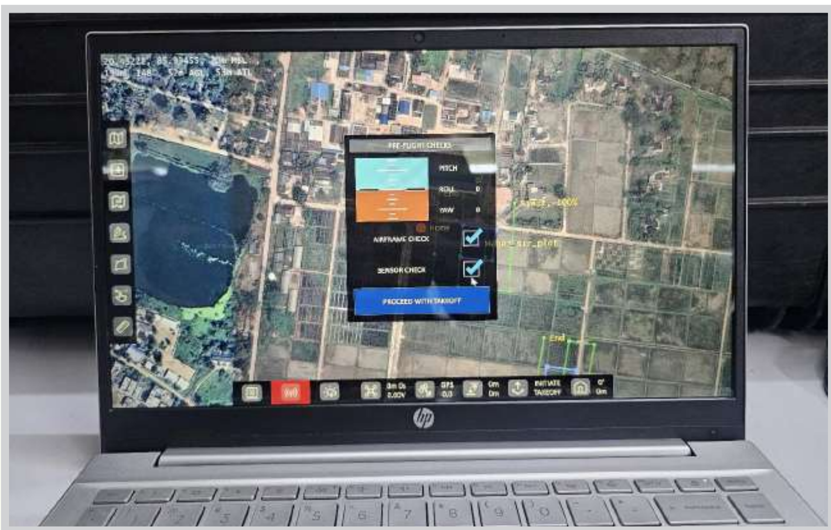

Fig. 8 Flight plan software accessed in the laptop for drone flying

4.5 Methodology of estimation of crop and soil physiochemical parameters using drone mounted sensors

Image acquisition and generation of flight plan: The Idea Forge Q4c drone equipped with a MicaSense RedEdge-MX consisting of five independent spectral bands (Table 1) was used for capturing of high-resolution multispectral images. The flight plan was planned using BlueFire Touch ground control software. Before flight the multispectral imaging sensor was calibrated using white panel reflectance calibration with a known and stable reflectance spectrum. This calibration converts raw digital numbers from the sensor into physically meaningful surface reflectance values, ensuring data comparability across different acquisition times and sensor platforms. After calibration the drone was flown under clear sky conditions with a flight altitude of 120 meters, 80% frontal overlap and 75% side overlap for acquisition of the multispectral images.

Image processing and calculation of vegetation indices: The calibrated multispectral images were processed using Agisoft Metashape Professional software to generate the orthomosaics. The orthomosaics were used to calculate Vegetation Indices (VIs) (Table 2) representing canopy traits such as chlorophyll levels and green biomass cover in ArcGIS software.

Variable selection and development of machine learning models: and The Variable Inflation Factor (VIF) technique was used to reduce multicollinearity and variable selection for model building. The selected VIs, along with ground-measured data, were used to develop and validate Machine learning (ML) algorithms in R software for estimation of Soil Organic Carbon (SOC) and rice Nitrogen (N) content as well as rice yield prediction, with datasets split into training (80%) and testing (20%) sets. Following ML models were developed.

Random Forest (RF): A machine learning algorithm that uses an ensemble of decision trees to improve prediction accuracy by averaging multiple tree outputs and reducing overfitting.

Support Vector Machine (SVM): A supervised learning algorithm that finds the optimal hyperplane to separate different classes in the feature space, aiming to maximize the margin between them.

Artificial Neural Networks (ANN): A computational model inspired by the human brain, consisting of layers of interconnected nodes (neurons) that learn complex patterns in data through backpropagation.

Model assessment: To evaluate the performance of the models, different statistical metrics like coefficient of determination (R^2), root mean square error (RMSE), mean absolute percentage error (MAPE) and mean absolute error (MAE) were used.

Table 1: Wavelength range of different bands in multi-spectral sensor mounted on unmanned arial vehicle (UAV).

Sensor	Band Number	Wavelength Range (nm)
Mica Sense Red Edge-MX Sensor	Band 1	475 - 560
	Band 2	550 - 570
	Band 3	668 - 680
	Band 4	717 - 740
	Band 5	840 - 860

Note: Band 1: Blue; Band 2: Green; Band 3: Red; Band 4: Red Edge and Band 5: Near Infra-red

Table 2: Vegetation indices and their formula

Index	Index Formula
NDVI	(NIR - Red) / (NIR + Red)
NDRE	(NIR - Red Edge) / (NIR + Red Edge)
IPVI	0.5 * (NDVI + 1)
GNDVI	(NIR - Green) / (NIR + Green)
SAVI	((NIR - Red) / (NIR + Red + 0.5)) * (1 + 0.5)
MSAVI	(2 * NIR + 1 - sqrt ((2 * NIR + 1)^2 - 8 * (NIR - Red)))/ 2
CI	(Red-Green) / (Red + Green)
CHI	(NIR/Green)-1
BI	(sqrt ((Red*Red) + (Green*Green)))/2
SRPI	B/R
SCCCI	NDRE/NDVI
TCARI	3*[(RE-R)-0.2*(RE - G) *(RE/R)]
RVI	NIR/R
RERVI	NIR / RE
RVI2	NIR/G
GRVI	(Green-red)/ (Green+red)

Note: Blue (B), Green (G), Red(R), RedEdge (RE), Near Infra-red (NIR), Normalized Differences Vegetation Index (NDVI), Normalized Difference Red Edge (NDRE), Green Normalized Difference Vegetation Index (GNDVI), Soil Adjusted Vegetation Index (SAVI), Modified Soil Adjusted Vegetation Index (MSAVI), Colour Index (Colour), Chlorophyll Index (CI), Brightness Index (BI), Chlorophyll Index (CHI), Simplified Canopy Chlorophyll Content Index (SCCCI), Transformed Chlorophyll Absorption and Reflectance Index (TCARI), Ratio Vegetation Index (RVI), Red Edge Ratio Vegetation Index (RERVI), Modified Green Red Vegetation Index (MGRVI), Ratio Vegetation Index 2 (RVI2) and Green Red Vegetation Index (GRVI).

Here are some of the case studies of utilising drone and sensors at ICAR-CRRI Cuttack as well as other districts of Odisha.

5. Estimation of Soil organic carbon using multispectral sensors mounted on drones.

Site details

The study was conducted at ICAR-Central Rice Research Institute, Odisha, India (20°25′N, 85°55′E; elevation 24 m above mean sea level). The region experiences a sub-humid tropical climate, with an average annual rainfall of 1500 mm and a mean yearly temperature of 27.6 °C during the study period. The soil in the study area is classified as Aeric Endoaquepts, with a sandy clay loam texture comprising 31% clay, 17% silt, and 52% sand and a bulk density of 1.4 Mg/m^3.

Sampling procedure

The experimental plots were ploughed with two pass of cultivator and one pass of rotavator followed by laser land levelling. A systematic grid-based sampling strategy was employed, comprising 132 sampling points that were evenly distributed across the A and B blocks of the CRRI experimental farm (as illustrated in Fig. 9). To facilitate accurate sample collection, the boundaries of each block and the coordinates of all sampling locations were digitized using ArcGIS software and physically identified in the field. At each designated point, three soil samples were collected, which were then composited into a single sample for each location. These composite samples were analyzed for soil organic carbon (SOC).

Sampling analysis

The measurement of SOC was conducted by employing the oxidation method, utilizing potassium dichromate ($K_2Cr_2O_7$) in the presence of concentrated sulfuric acid (H_2SO_4), following the procedure outlined by Walkley and Black (1934). Remote sensing data was acquired on June 6, 2023 using drone mounted with a multispectral sensor (which captures images in five independent spectral bands).

Vegetation Index generation

Nine vegetation indices were computed from drone data, based on the strength of correlation with SOC, analyzed in R software four indices NDVI, NDRE, IPVI and GNDVI were derived selected for model development.

Fig. 9 Sampling locations in experimental plots of ICAR-Central Rice Research Institute, Cuttack, India

5.1 Machine learning algorithms (ML) for SOC estimation

Random Forest (RF) and Support Vector Machine (SVM) models were developed to predict SOC. The dataset was split into 70% training and 30% testing datasets. The value of the predicted SOC from both the ML models were compared based on the accuracy parameters and the best fit model was used to generate the spatial distribution map of SOC content at the test site. The SOC estimation accuracy of the developed machine learning models was also compared using two different datasets: one generated from UAV-based imagery and the other from Sentinel-2A satellite data.

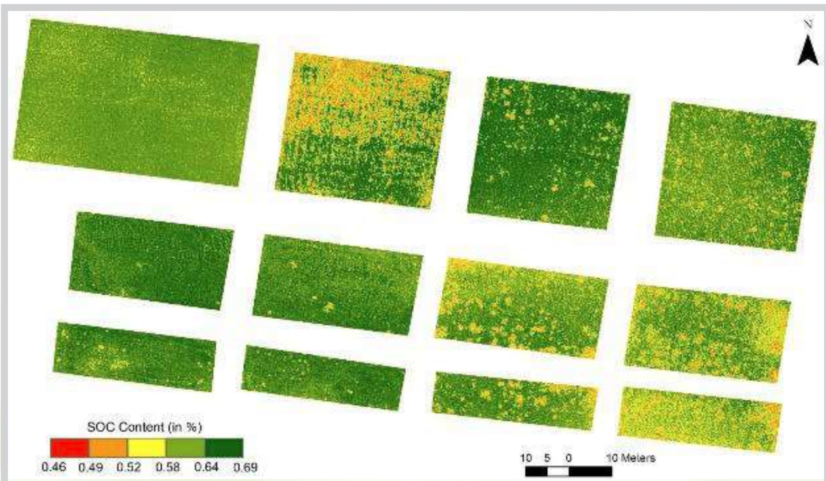

Fig.10 Soil Organic Carbon Prediction map for the study sites.

5.2 Generation of predicted SOC map

The output from both the models were compared based on the accuracy parameters and the best fit model was used to generate the spatial distribution map of SOC content in the test area.

Results

The estimated SOC content at the test site ranged from 0.405% to 0.685% as represented in Fig. 10 (Tripathi et al., 2024c). DRONE derived VIs showed stronger correlations with SOC. The Prediction accuracy for RF model (RPD = 1.09, R^2 = 0.25) was better in comparison with SVM model (Table 3).

Table 3: Accuracy parameters of Random Forest (RF) and Support Vector Machine (SVM) for estimation of SOC

Parameters	RF		SVM	
	UAS	Sentinel 2A	UAS	Sentinel 2A
RMSEcv	0.06	0.07	0.06	0.07
RPD	1.09	0.96	1.02	1.01
R^2cv	0.25	0.1	0.2	0.1
RPIQ	2.57	0.79	2.01	0.85

Note: Root Mean Square Error of Cross-Validation (RMSEcv), Ratio of Performance to Deviation (RPD), Coefficient of Determination of Cross-Validation (R^2cv), Residual Prediction Deviation Index (RPIQ), Random Forest (RF) and Support Vector Machine (SVM)

Salient findings:

- The results from the correlation matrix indicated that drone derived vegetation indices showed stronger correlation with SOC.
- This study compared the prediction accuracy of two ML models i.e. RF and SVM.
- The SOC prediction accuracy for RF model was higher in comparison with SVM model.
- UAS dataset shows higher prediction accuracy than Sentinel 2A dataset for both the ML models.
- The integration of drone-based SOC prediction techniques in precision agriculture can facilitate targeted soil management strategies which can contributes to improve resource utilization, soil health, and crop productivity.
- Drone based SOC predictions can support regulatory compliance and carbon trading initiatives

6. Predicting nitrogen content in rice using drone mounted Multispectral Imaging.

Experiment conducted for development of model.

Experiments were conducted at ICAR-CRRI, Cuttack, Odisha, in a sub-humid tropical climate with 1500 mm annual rainfall. Soil type is Eutric Gleysol. The N fertilizer was applied in three splits at basal (transplanting), active tillering (21–25 DAT) and panicle initiation (55–60 DAT) stage. Two rice varieties Pooja and Gayatri were tested across 96 subplots (4 N levels, 6 replications and 2 varieties) (Fig. 11). Leaf samples were collected at maximum tillering stage and N content was analyzed using the Kjeldahl method. Drone-mounted MicaSense Red Edge-MX sensor captured multispectral images at 120 altitude (8 cm resolution) during maximum tillering stage of rice.

Experiment conducted for validation at farmers field

Experiments in Farmers field comprised four nitrogen levels as 0, 60, 80 and 120 kg N ha^{-1} respectively. The rice varieties used for the experiment were Pooja and Gayatri. The recommended dose of phosphorus (40 kg P_2O_5 ha^{-1}) as single super phosphate, potassium (40 kg K_2O ha^{-1}) as muriate of potash were applied. N was applied through urea (Fig. 12). The experiments were conducted in the farmers field considering each farmer's plot as one Nitrogen treatment with six replications in completely randomized block design (Fig. 13).

Fig. 11 Field view of rice genotypes under different nitrogen treatments at experimental farm at ICAR-CRRI, Cuttack, Odisha

Fig. 12 Fertilizer application in farmer field

Fig. 13 Manual broadcasting of fertilizers in farmer's field

6.1 Flowchart for Model Development and Validation:

Random Forest (RF) and Artificial Neural Network (ANN) models were developed using 80% training and 20% testing data. The best RF model had optimal parameters of 650 trees (ntree) and 4 variables per split (mtry). The best architecture of ANN model had 15 neurons in the first hidden layer and 18 in the second. The developed models were validated at farmer's field (Fig. 14).

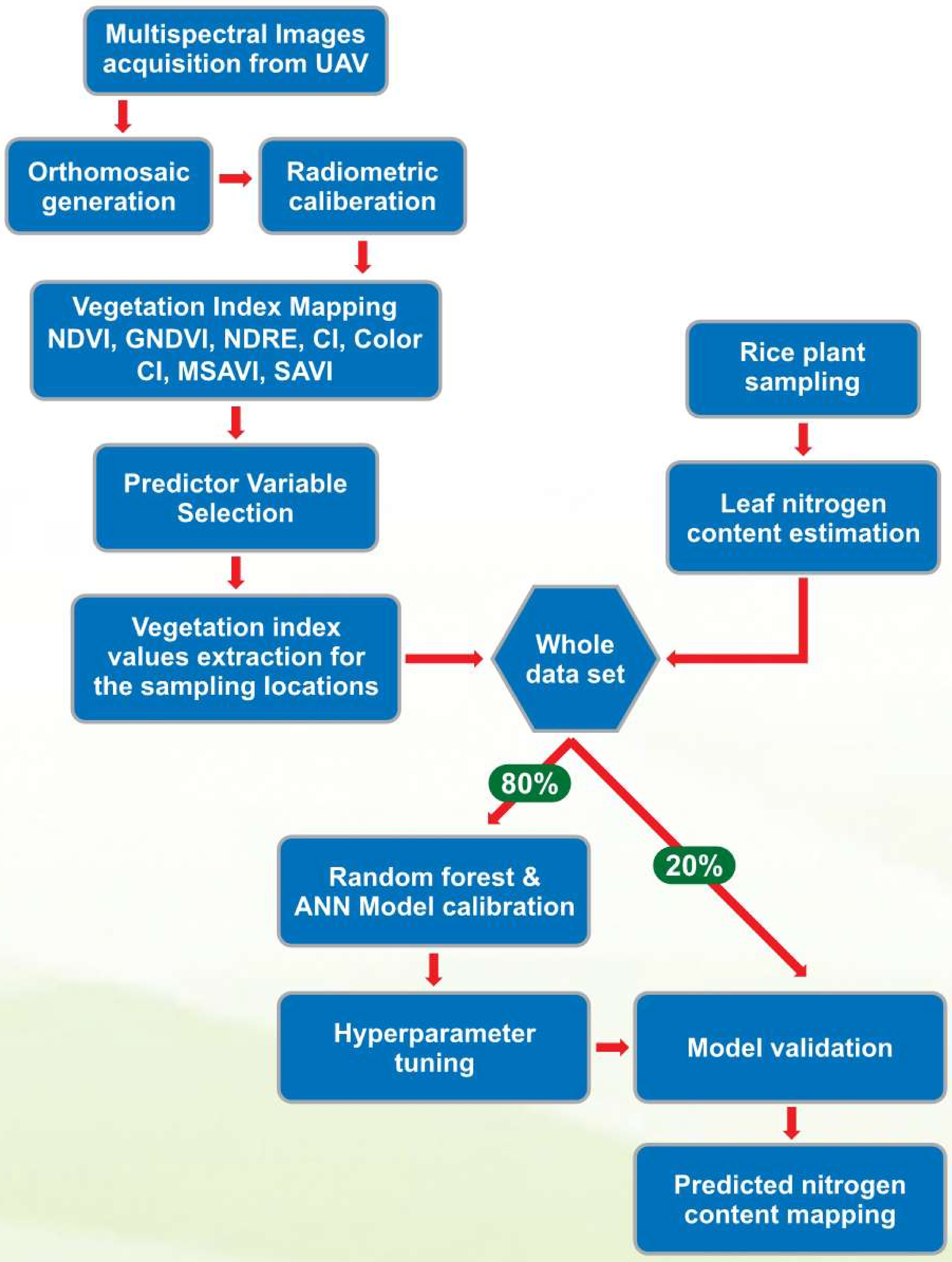

Fig. 14 Detailed methodology of rice N estimation using drone mounted sensors

6.2 Variation in estimated nitrogen in rice leaves

Vegetation indices, NDRE, NDVI and MSAVI with mean values of 0.21, 0.51 and 0.75 respectively (Table 4) were calculated from the acquired multispectral imagery. The estimated-on field rice N content ranged from 0.65% to 2.08% at the test site. RF model estimated N content with R^2 value of 0.67, while ANN achieved R^2 values of 0.55 (Fig 15). RF model had a higher N estimation accuracy across growth stages, with RMSE values of 0.03 to 0.07.Estimated N content by RF model ranged from 0.78% to 1.95%, while ANN model had a N estimated range of 0.50% to 1.78% (Fig. 16). RF demonstrated better performance in spatial N estimation compared to ANN (Tripathi et al., 2025b (Revisions submitted)).

Table 4: Descriptive statistics of the vegetation indices used in model building

Variables	Mean	Median	SD	CV	Min	Max
MSAVI	0.75	0.80	0.12	15.46	0.36	0.88
Color	-0.35	-0.36	0.08	-22.18	-0.50	-0.11
SAVI	0.96	1.00	0.15	15.83	0.61	1.19
NDVI	0.51	0.51	0.13	26.67	0.26	0.77
NDRE	0.23	0.21	0.09	40.58	0.07	0.48
CI	1.25	1.25	0.48	38.00	0.11	2.08
GNDVI	0.34	0.32	0.10	30.21	0.13	0.57
N%	1.14	1.02	0.39	33.86	0.66	2.09

Note: Modified Soil Adjusted Vegetation Index (MSAVI), Colour Index (Colour), Soil Adjusted Vegetation Index (SAVI), Normalized Differences Vegetation Index (NDVI), Normalized Difference Red Edge (NDRE), Chlorophyll Index (CI), Green Normalized Difference Vegetation Index (GNDVI), Nitrogen (N%), Standard deviation (SD), Coefficient of variation (CV), Minimum (Min), Maximum (Max), Nitrogen (N).

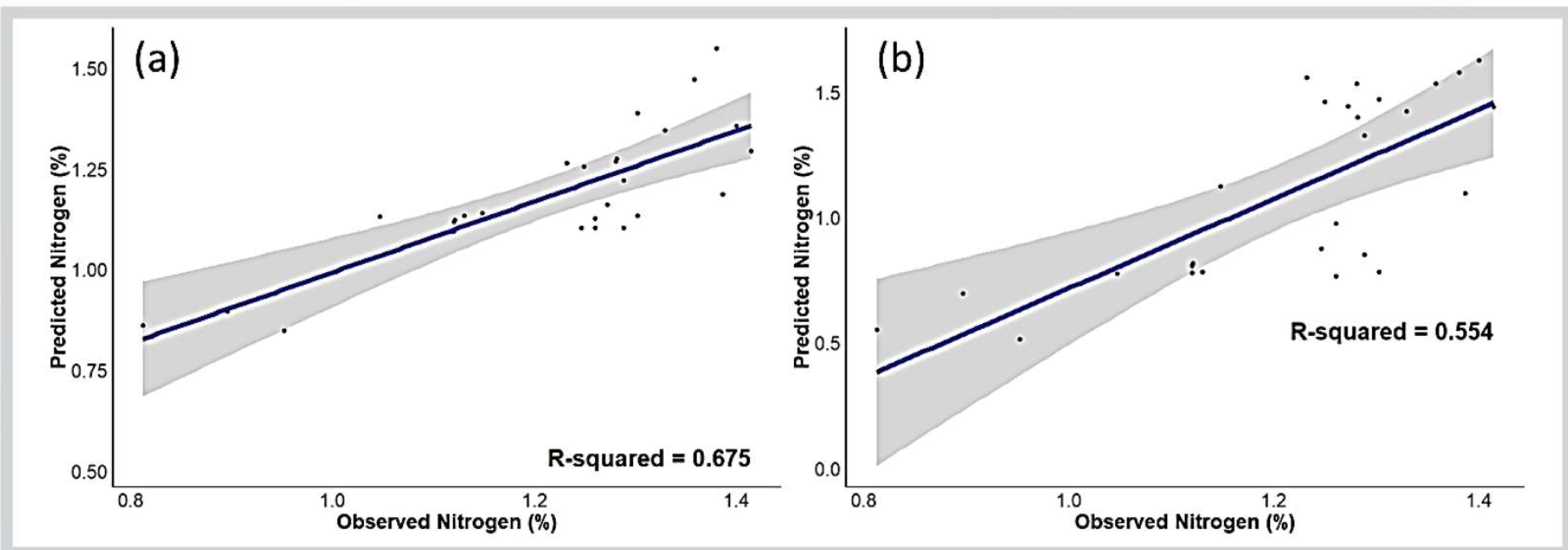

Fig. 15 Graph of Observed vs Predicted N content of rice leaf (a) RF and (b) ANN

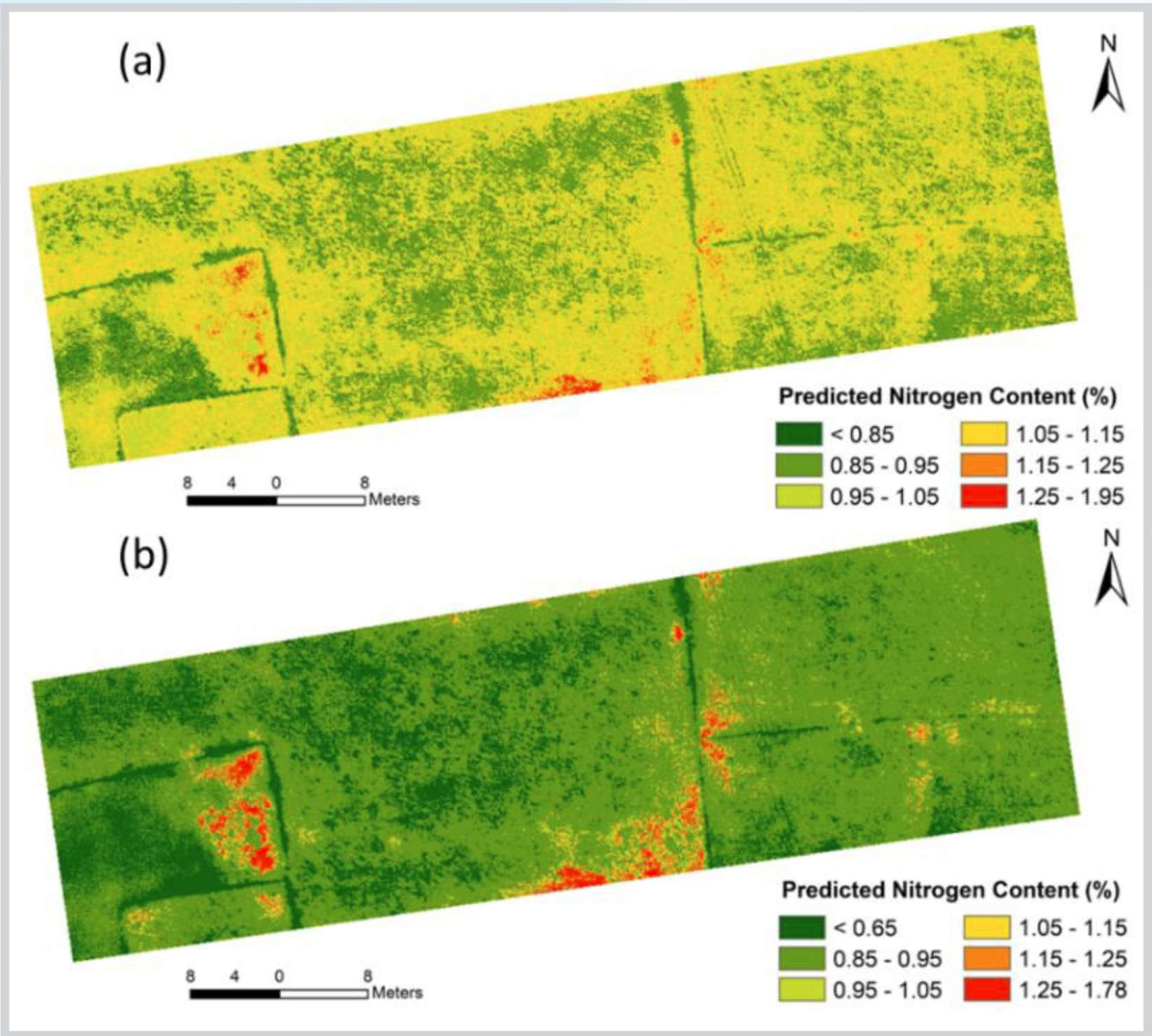

Fig. 16 DRONE-based nitrogen content (%) prediction maps for test plot at farmer's field using random forest (a) and artificial neural network modelling (b).

The variable importance graph for estimation of N content for different ML models is represented in Fig. 17. In RF model the NDRE (44.63%) index was the most important variable for predicting nitrogen content, followed by NDVI (24.73%) and GNDVI (18.68%). In ANN Model NDVI (29.89%) index was the top contributor, followed by NDRE (19.53%) and GNDVI (14.95%) (Fig. 18). In both the ML models NDRE showed the highest sensitivity to N variations, effectively predicting N content across a wider range, while NDVI was more effective in N estimation at lower concentrations.

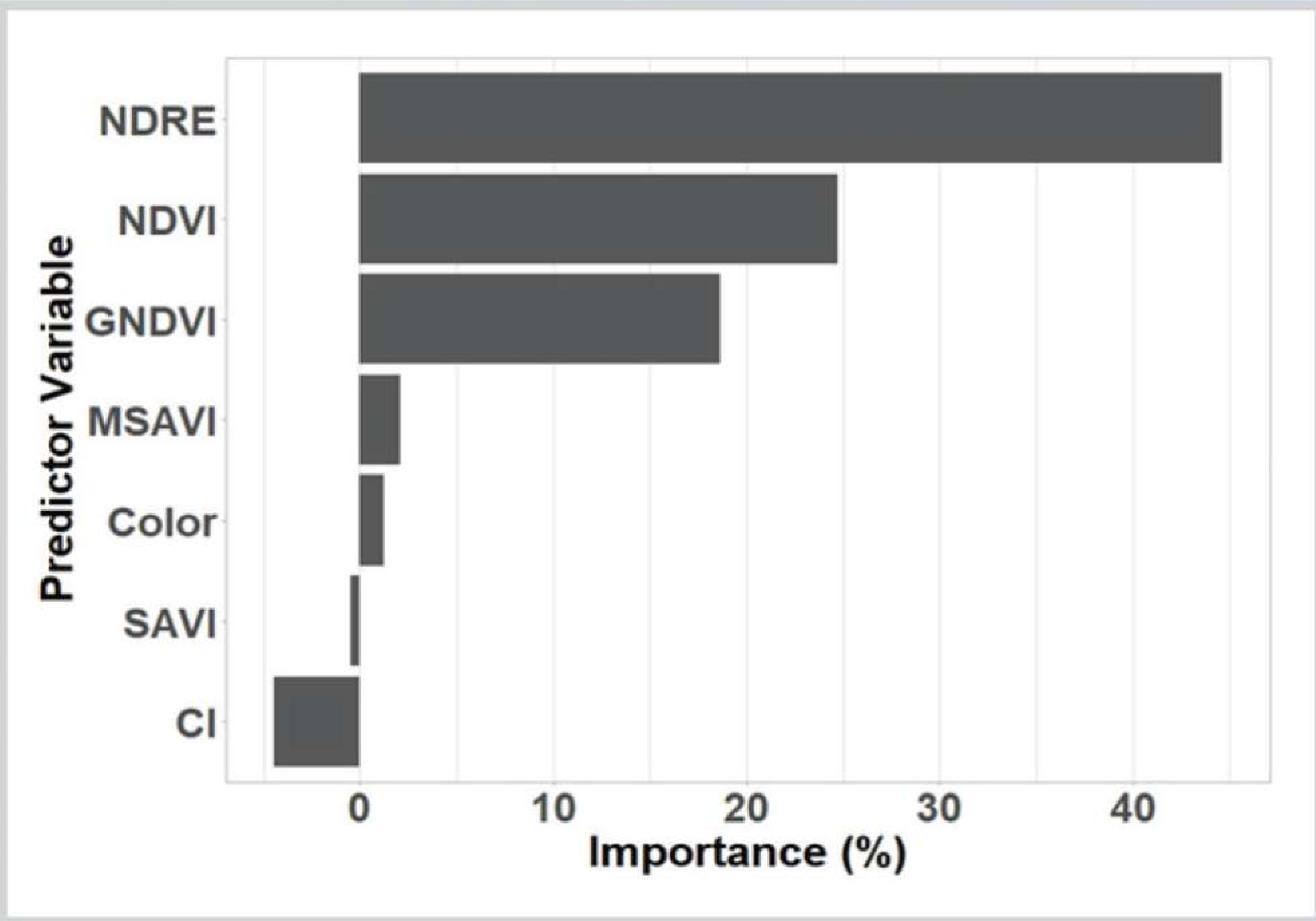

Fig. 17 Horizontal line plot representing contributions of predictor variables to the random forest model

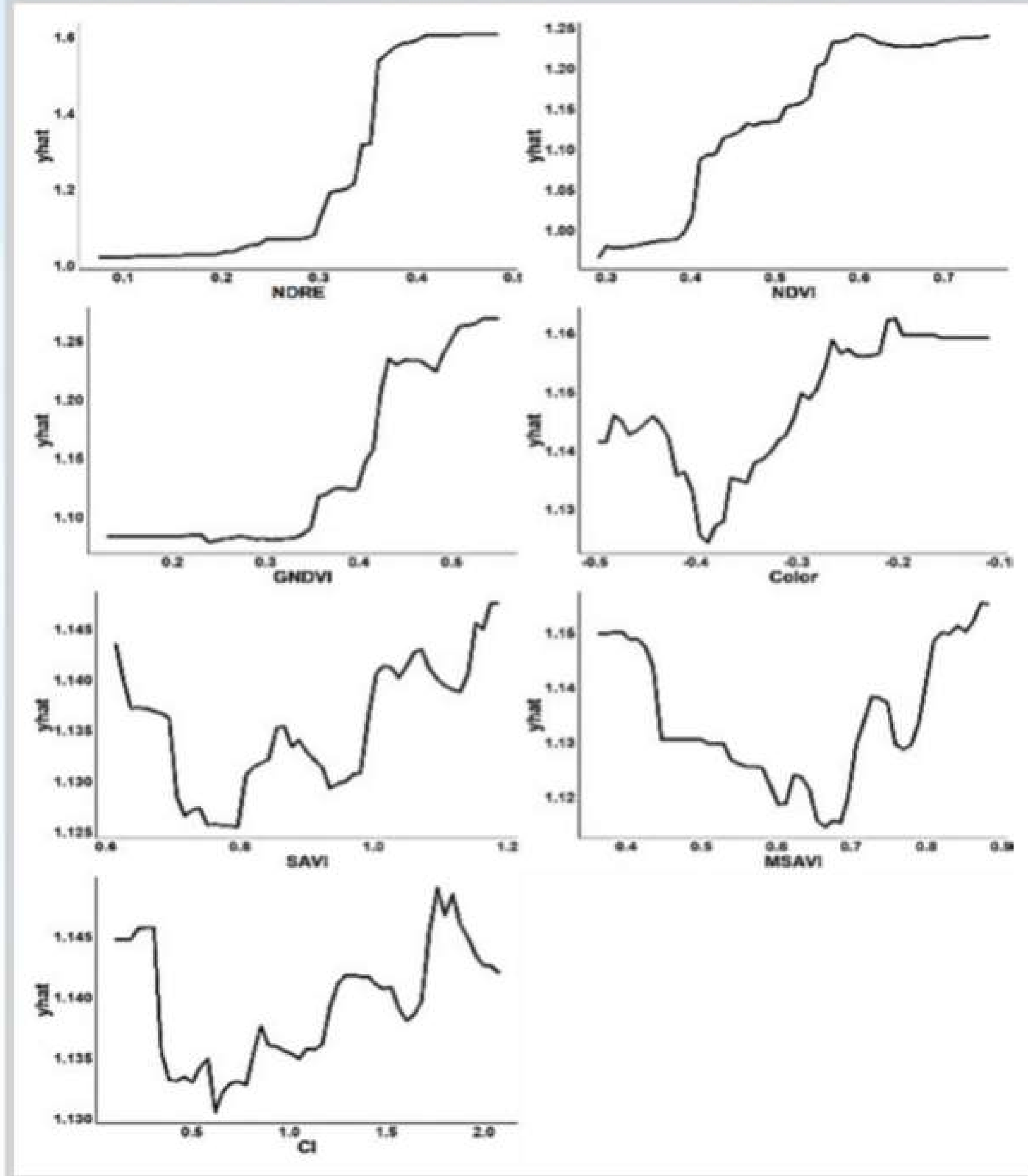

Fig. 18 Partial dependence plots visualize the relationship between each vegetation index (NDRE, NDVI, GNDVI, Color, SAVI, MSAVI, CI) and the predicted response (yhat)

Salient findings:

- Among the developed ML models RF model outperformed the ANN, achieving a higher prediction with an R^2 of 0.67 for nitrogen content (0.85% to 1.95%).
- The NDRE index was identified as the most significant vegetation index for nitrogen prediction, highlighting its sensitivity to nitrogen variations in rice.
- Both NDRE and GNDVI were highly effective in estimating nitrogen content, with NDRE exhibiting superior performance across a wider nitrogen range.
- By Incorporating data from contrasting rice varieties, growth stages, and environmental conditions will improve the robustness and generalizability of the model.
- The developed methodology has been already communicated as a research paper.

7. Recommendation of nitrogen topdressing using drone mounted multispectral sensors for small holder's rice farms.

The experiments were conducted at ICAR - Central Rice Research Institute for generating the model for nitrogen topdressing in rice (Fig. 19). The model was validated in farmers field in dakhinsailo village Cuttack, India, during the 2023-24 monsoon season. The study area categorized as sub-humid tropical climate. Two on-station experiments were conducted with different doses of N fertilizer application to create the variation in the canopy greenness. Two rice varieties viz. Pooja and Swarna and eight nitrogen levels (0, 20, 40, 60, 80, 100, 120 and 140 kg ha^{-1}) were implemented in a Randomized Block Design (RBD) with four replications. In another experiment, six rice varieties were taken along with six nitrogen levels in a Randomized Block Design (RBD) with three replications. But for this study we utilized the data of only two rice varieties i.e. Pooja and Swarna.

Fig. 19 Transplanting of rice at ICAR-CRRI experimental farm, Cuttack, Odisha

7.1 Drone image acquisition and processing

The drone used in this study was an Idea Forge Q4c UAV equipped with a MicaSense RedEdge-MX sensor capable of capturing high-resolution multispectral images across five independent spectral bands. The UAV had a flight time of approximately 30 minutes and featured advanced capabilities for adjusting and compensating for pitch and roll shifts during flight. To generate the N recommendation multispectral images were captured from 35 days after transplanting till flowering stage. The drone was flown under clear sky conditions with a flight altitude of 120 meters, 80% frontal overlap and 75% side overlap. The flight plan was planned using BlueFire Touch ground control software. The multispectral images were processed using Agisoft Metashape Professional. The orthomosaics were generated and exported in GeoTIFF format.

7.2 Normalized Difference Vegetation Index (NDVI) generation

The orthomosaic images were processed using ArcGIS software to compute the Normalized Difference Vegetation Index (NDVI). The NDVI was utilized for calculating the In-Season Estimate of Yield (INSEY), which was further utilized for developing the plot wise N recommendation model.

7.3 Methodology of N top dressing Recommendation model

NDVI Calculation: NDVI index was derived from multispectral drone imagery and the INSEY formula was modified for the region by dividing NDVI by the number of days from transplanting to image acquisition.

INSEY and Yield Relationship: INSEY was calculated and a power function was developed to establish a relationship between INSEY and actual grain yield to derive the value of a and b which are input parameters for N recommendation model development (Fig. 20).

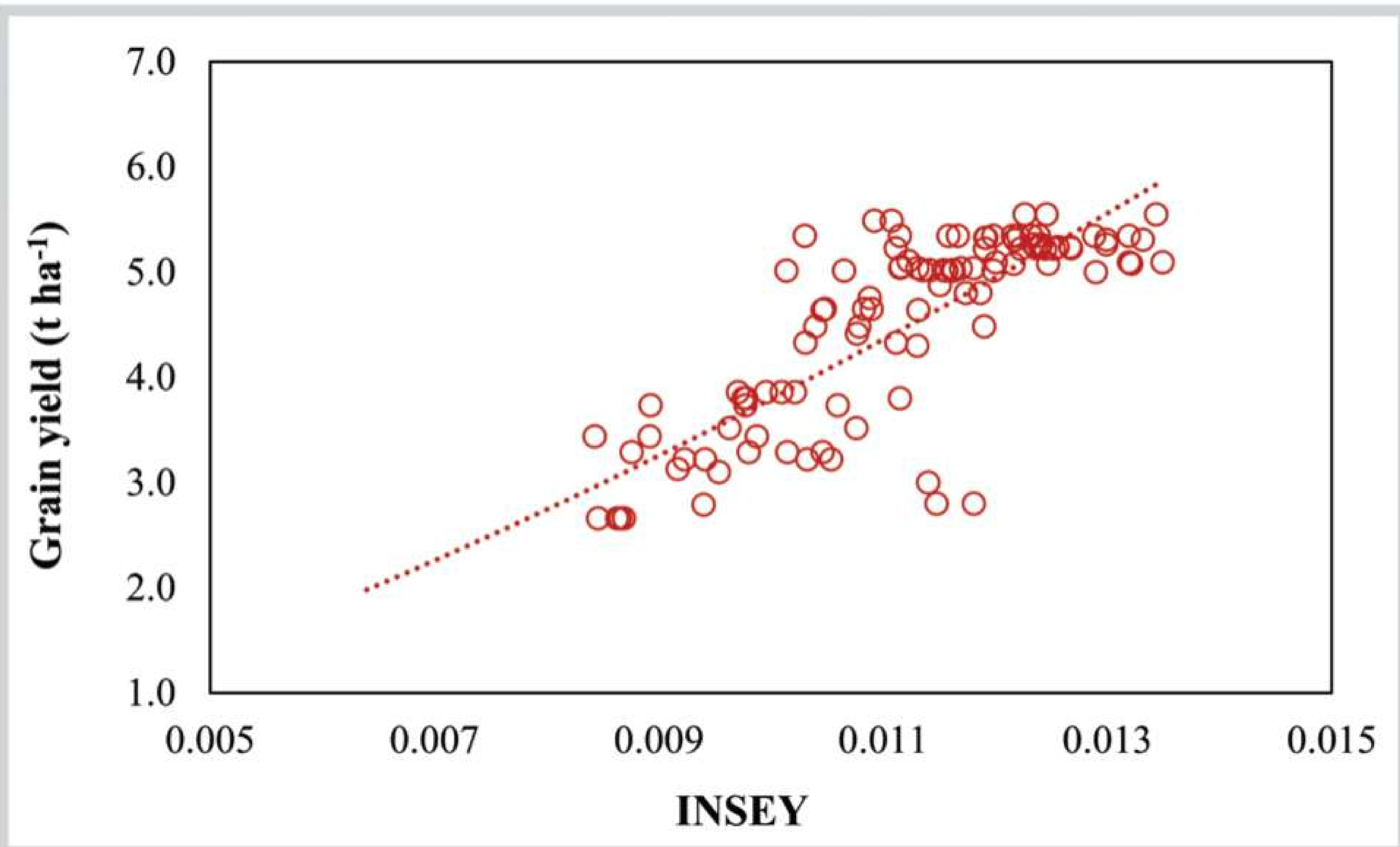

Fig. 20 Power equation fitted using actual rice grain yield vs INSEY (In-season Estimate of Yield) to generate the model parameters

RI_{NDVI} Calculation: The Response Index to Fertilizer Nitrogen (RI_{NDVI}) was calculated by dividing NDVI from a nitrogen-rich strip by the NDVI from the test plot.

Yield Prediction: Achievable yield (YPn) was calculated by adjusting the potential yield (YP_0) using RI_{NDVI} and N recommendations are generated with the formula:

$$Fertilizer\ N\ dose\ (kg\ N\ ha^{-1}) = \frac{1.2 * (YP_n - YP_0)}{(100 * 0.5)}$$

Development of N Recommendation model in R Software: The c ode f or t he N recommendation model was written in R software using raster and terra packages for processing images. The sf and sp libraries were used for shapefile transformations. Zonal statistics was performed and calculated using Exactextractr, and maps are generated with ggplot2.

Plot boundary delineation: Plot boundaries in the farmers field were updated using cadastral maps, Google Earth imagery and drone data. Transplanted plots were identified using Green Red Vegetation Index (GRVI) from drone imageries (Fig. 21).

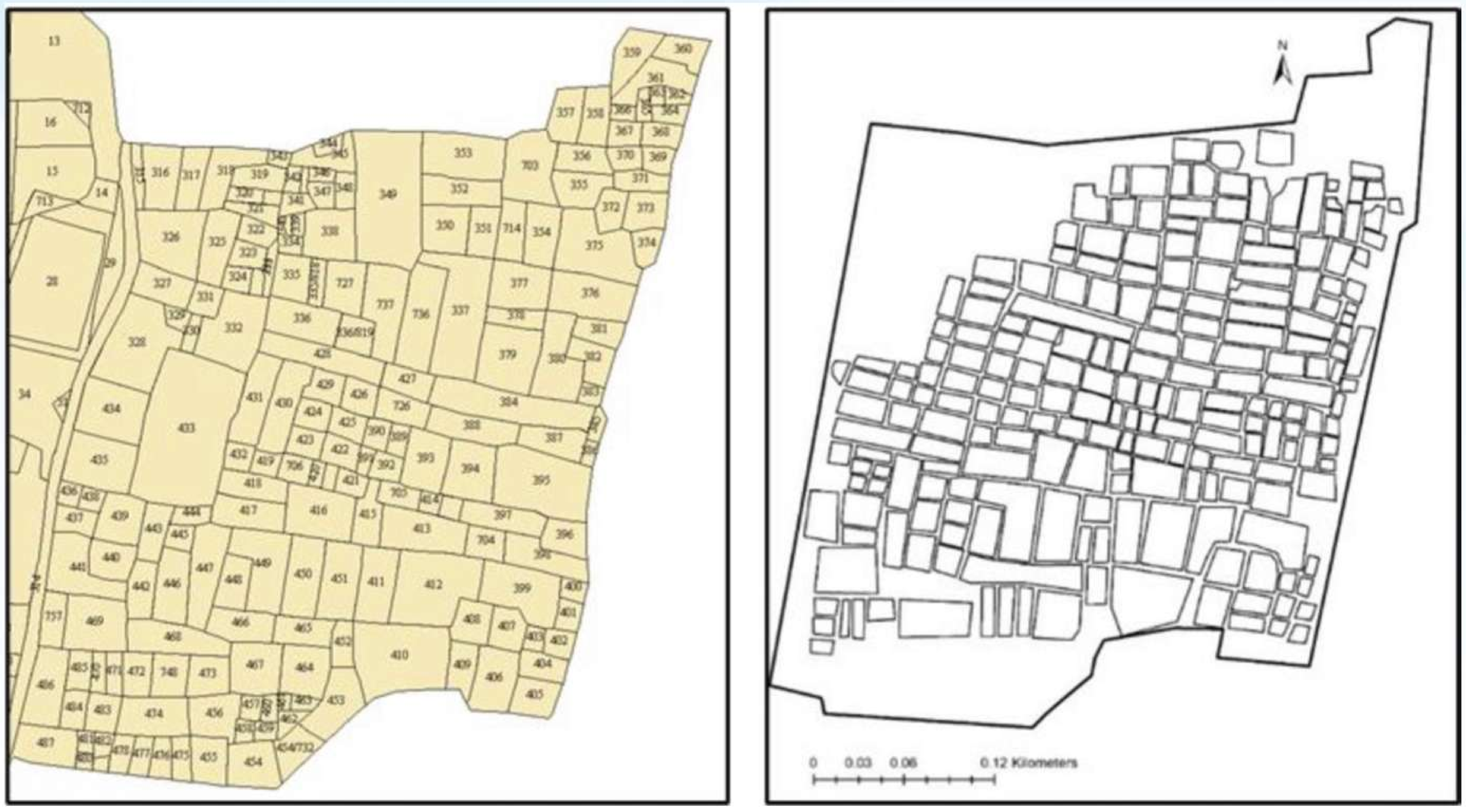

Fig. 21 The figure represents Cadastral map of the village and Digitization of farmers plot from cadastral map available online (https://bhulekh.ori.nic.in/RoRView.aspx).

7.4 Validation of topdressing N recommendation model in farmers' field

The validation experiment was conducted in farmers' fields in Dakhinasailo village, Cuttack district, to validate the N recommendations under farmers' field conditions. Two treatments: Recommended Dose of Fertilizer (RDF) and Drone based N recommendation were applied at PI stage of rice. The rice varieties were Pooja and Swarna. Each treatment was applied and some larger plots were divided into three sub-plots to accommodate all treatments (Fig. 22). The experiment was conducted in clusters, with all three treatments implemented within the same cluster to avoid the impact of external variables. In RDF the NPK were applied as 80:40:40, the Phosphatic (40 kg P_2O_5 ha^{-1}) and potassic (40 kg K_2O ha^{-1}) fertilizers was applied basal whereas first topdressing of N (20 kg N ha^{-1}) was applied at active tillering stage of rice whereas second topdressing of N (20 kg N ha^{-1}) was applied at panicle initiation stage of crop. Nitrogen use efficiency was assessed using Agronomic Use Efficiency (AUE) and Partial Factor Productivity of Nitrogen (PFPN).

Fig. 22 Nitrogen management on the basis of recommended dose of fertilizer (RDF) at farmer's field

- AUE = (Yield in treated plot - Yield in control plot) / Nitrogen applied.
- PFPN = Crop yield / Nitrogen applied.

The values of the NDVI index were in the range of 0.39 to 0.88, showing variability due to N levels and rice varieties. The INSEY values (0.006 – 0.014) correlated well with grain yield with R^2 values of 0.71. Drone-based N recommendations ranged from 3 to 40 kg ha^{-1} (Fig. 23). Drone-based N recommendations achieved higher yields with AUE values of 19.18 kg kg^{-1} and PFPN of 73.70 kg kg^{-1} compared to RDF, demonstrating the effectiveness of precision N management over traditional N management methods (Fig. 24) (Tripathi et al., 2025c, Communicated).

Fig. 23 Farmers individual plot wise topdressing N recommendation map

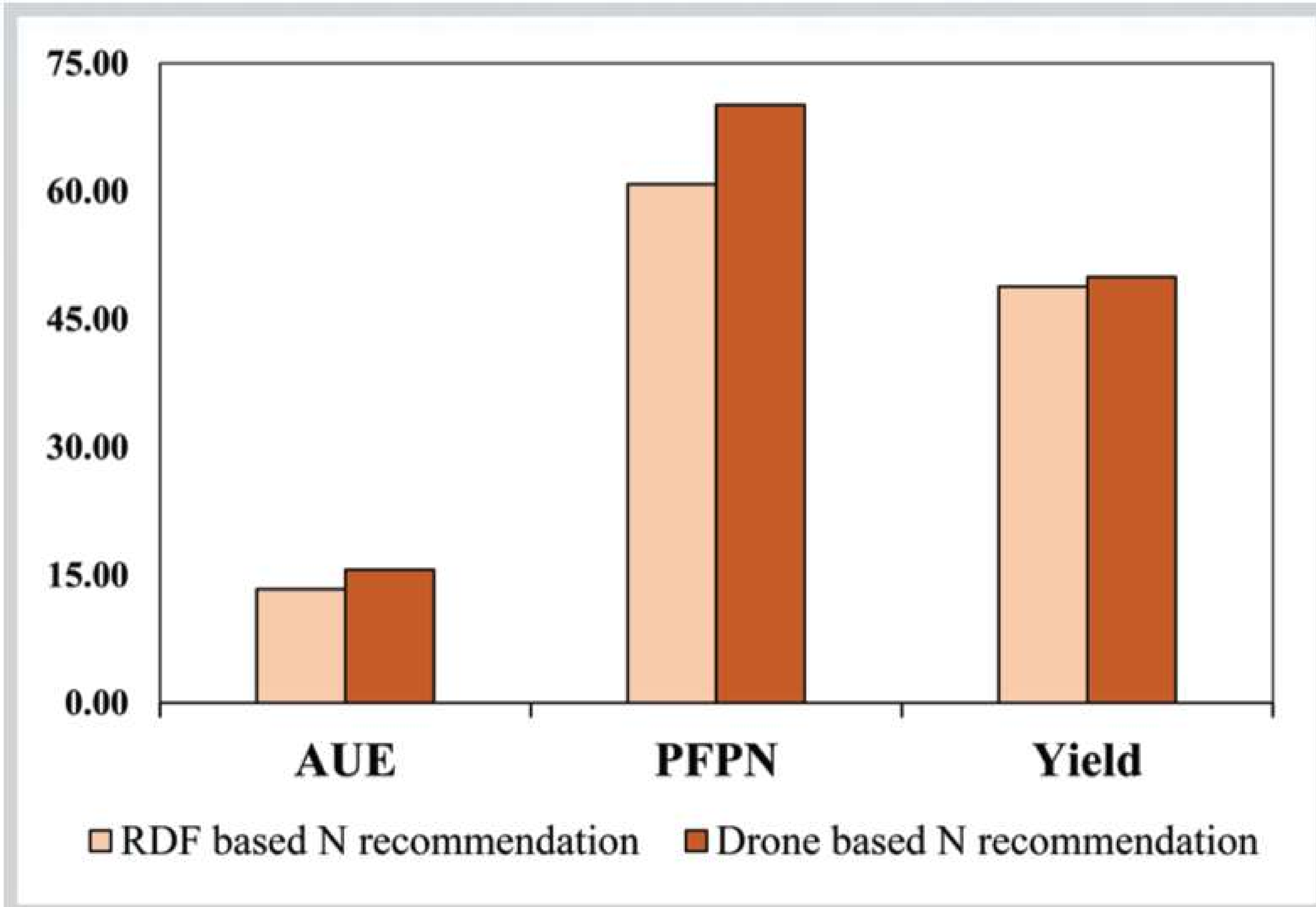

Fig. 24 Comparison of AUE, PFPN and Yield for RDF and drone based N recommendation at the validation site.

Note: AUE: Agronomic use efficiency (kg kg^{-1}) ; PFPN: Partial factor productivity of Nitrogen (kg kg^{-1}); Yield (Quintal hectare^{-1}); RDF: Recommended Dose of Fertilizer and Drone N: N recommendation generated using drone mounted sensors at validation site.

Salient findings:

- Drone-mounted multispectral sensors were used to estimate INSEY.
- A program was written in R software for optimizing INSEY based N topdressing in individual farmers plots
- The N recommendation in farmers field ranged from 3 to 40 kg N ha^{-1} in different plots.
- AUE and PFPN for the drone-based N recommendation were higher compared to RDF based N recommendation.

8. Rice yield prediction using drone mounted sensors

Site details

The experimental locations were within geographic coordinates ranging between 20°23′16″ to 20°27′03″ N latitude and 85°55′52″ to 86°07′47″ E longitude (Fig. 25). The experiments were conducted both at the research farm of ICAR–Central Rice Research Institute and on farmers' fields in Prahrajpur village, located in Cuttack district, Odisha, India. The experimental sites experiences a sub-humid tropical climate, receiving an average annual rainfall of about 1500 mm.

Experimental details of Model development

The experiments for developing the ML models was conducted at the ICAR–CRRI experimental farm, using two rice varieties Pooja and Swarna with a growth duration of 145 – 150 days. Eight nitrogen application rates (0, 20, 40, 60, 80, 100, 120 and 140 kg ha^{-1}) were used to create yield variability in rice (Fig.26). The experimental layout followed a Randomized Block Design (RBD) with four replications.

Experimental details of Model validation

The developed models were validated at Prahrajpur village using six nitrogen application rates (0, 40, 60, 80, 100 and 120 kg ha^{-1}). At all experimental sites, phosphatic and potassic fertilizers were applied as per the recommended doses of 40 kg P_2O_5 and 40 kg K_2O per hectare. The rice varieties used in the farmers' field experiments were Pooja and Gayatri.

Harvesting and recording yield

Rice plants from both the research farm and farmers' fields were harvested manually using hand-held sickles, cutting close to the soil surface. The harvested crop was then sun-dried to reduce the moisture content to 14%. After threshing, the rice grains were cleaned and weighed. The grain yield was calculated and expressed in tons per hectare (t ha^{-1}).

Fig. 25 Location of study sites in Cuttack district of Odisha in India

Fig. 26 Field experiment conducted with two rice varieties and eight different levels of nitrogen at ICAR-CRRI experimental farm, Cuttack

Multispectral image acquisition

The multispectral images (5 independent spectral bands) were captured on September 11th , 2023 at ICAR-CRRI and on September 28th , 2023 at farmers' field.

8.1 Correlation analysis and Variable Selection:

The correlation analysis between rice yield (dependent variable) and 10 VIs (independent variable) was performed in R software (Fig. 27). The variable selection was performed using variance inflation factor (VIF) technique. The VIF technique selected 4 VIs (MGRVI, NDVI, NDRE, TCARI) with VIF < 10 for model building.

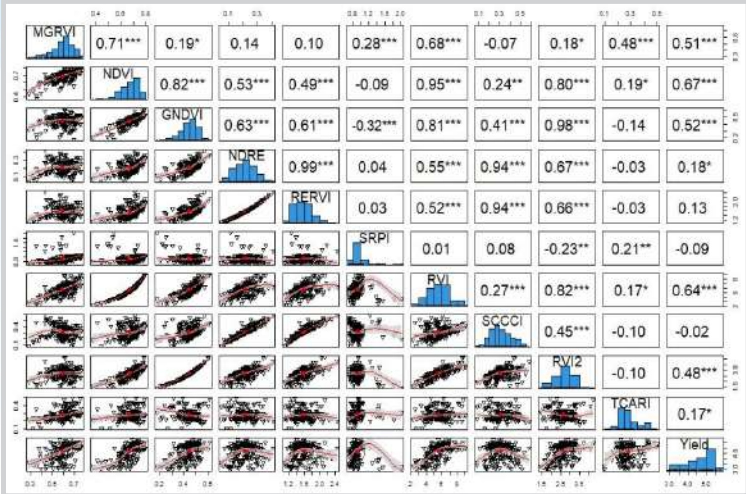

Fig. 27 Correlation matrix between vegetation indices and yield. The selected key variables for early rice.
Note: one (*), double asterisk (**), and three asterisks (***) indicate a correlation coefficient (r) with statistical significance levels of p-value ≤ 0.05, 0.01, and 0.001, respectively. MGRVI: Modified Green Red Vegetation Index; NDVI: Normalized Difference Vegetation Index; GNDVI: Green Normalized Difference Vegetation NDRE: Normalized Difference RedEdge Index; RERVI: Red Edge Ratio Vegetation Index; SRPI: Simple Ratio Pigment Index; RVI: Ratio Vegetation Index; SCCCI: Simplified Canopy Chlorophyll Content Index; RVI2: Ratio Vegetation Index 2; TCARI: Transformed Chlorophyll Absorption and Reflectance Index

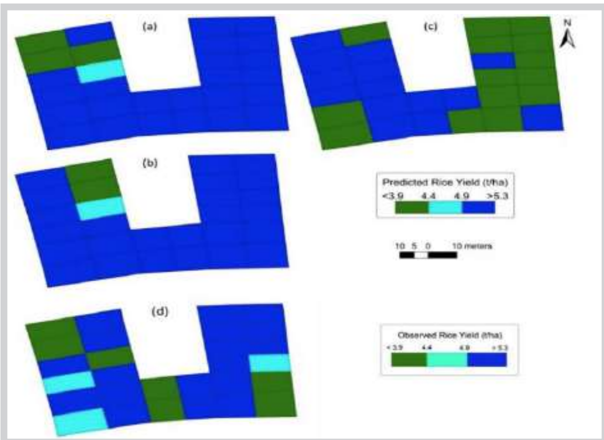

Fig. 28 Prediction maps for the testing plot using SVM (a), RF (b) and ANN (c) model and the observed rice yield for the test plots (d)

8.2 Development of machine Learning models

Three ML algorithms were developed in R software. The SVM model was tuned using radial basis kernel, grid search technique with a cost value of 2, gamma value of 0.125 and epsilon value of 0.1. The RF model was tuned with a ntree value of 30 and mtry value of 2. The ANN model was hypertuned with 1–9 neurons, decay value of 0 to 0.01and 5-fold cross-validation. The dataset was split in the ratio of: 80% training and 20% testing. Raster package used to generate yield prediction maps at validation sites using SVM, RF and ANN models.

8.3 Comparison of predicted and observed yield

The on-field rice yield at the test site ranged from 2.95 to 5.82 t ha^{-1}. The NDRE had the highest coefficient of variation (CV) of 34%, while NDVI had the lowest CV value of 11%. The NDVI value showed the strongest positive correlation with yield with R^2 value of 0.67, followed by RVI with R^2 value of 0.64. Among the VIs higher correlations was observed in RERVI and NDRE indices with R^2 value of 0.99 and NDVI and RVI index with R^2 value of 0.95. The VIF technique was used to select important VIs having greater significance in yield prediction and to minimize multicollinearity. The selected VIs is TCARI, NDRE, MGRVI and NDVI. The SVM model had the highest accuracy with the values of accuracy parameters (RMSE: 0.55, MAE: 0.39, MAPE: 9.33) compared to RF and ANN. The predicted yield for different models was for SVM (3.73–5.45 t ha^{-1}), RF (3.83 – 5.00 t ha^{-1}) and ANN (3.46–5.91 t ha^{-1}) (Fig. 28). The SVM model showed moderate to high accuracy with R^2 value of 0.88 when compared with observed yield (Fig. 29).

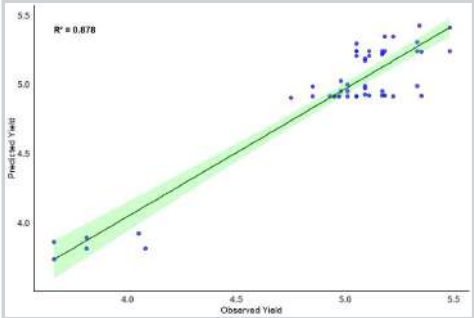

Fig. 29 Scatter plot comparing observed and predicted yield (t ha^{-1}) at farmers' field

Salient findings:

- The study demonstrated that drone-mounted multispectral sensors effectively predicted rice yield at the panicle initiation stage, aiding management decisions and policy formulation.
- The SVM model showed moderate to high accuracy (R^2 = 0.62) in predicting yield, demonstrating its potential for yield estimation.
- Among various derived vegetation indices, NDVI, NDRE, TCARI, and MGRVI indicated were strongest predictor for yield.
- The accuracy of these models can be further improved by multi-season and multi-location data for scalable and adaptable prediction models.
- Drone based yield monitoring offers high-resolution, non-destructive and cloud-independent management technology ideal for precision agriculture, making it a valuable tool for real-time crop assessment.

9. Conclusions

This study highlights the potential of drone-mounted multispectral sensors in precision agriculture, enabling accurate estimation of SOC, N levels and rice yield using machine learning models such as RF, SVM and ANN. Model performance varied, with R^2 values ranging from 0.55 to 0.67 for N and 0.60 to 0.65 for yield prediction, while the RMSE values for all the developed models varied from 0.03 to 0.07. NDRE index was the most significant index for N estimation and NDVI, NDRE, TCARI, and MGRVI indices were the most influential predictors for rice yield. The INSEY based plot specific N recommendation achieved higher yields with AUE values of 19.18 kg kg^{-1} and PFPN of 73.70 kg kg^{-1} compared to RDF and CLCC, demonstrating the effectiveness of precision N management over traditional N management methods. To upscale and enhance the reliability and accuracy of the developed ML models, incorporation of multi-location and multi-season data is recommended. This approach can significantly reduce the cost and time required involved in traditional methodologies used for soil and plant variable analysis associated, while minimizing the one-time cost involved in installing the setup. Additionally, government initiatives such as Drone Didi and Kisan drone are promoting the use of drone technology for agricultural management practices by providing financial support to farmers, making precision agriculture more accessible and efficient for small and marginal farmers.

10. Potential of drones and sensors and their future applications in agriculture

- Apart from the ML models used in this study, other ML models should be explored to get better prediction of soil and plant variables.
- The crop simulation models may be integrated with inputs generated from drone-mounted sensors for reasonable application.
- Weather and climatic parameters may be integrated for accuracy in site-specific nutrient management.
- Different kinds of sensors, i.e., multispectral, hyperspectral and thermal sensors, can be used for assessing crop, water and nutrient stresses along with other biotic stresses.
- Low-cost sensors like RGB should be utilized for wider adaptability across different stakeholders, including farmers.

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