

LEAF COLOUR CHART-GUIDED PRESCRIPTION MAPPING FOR UNMANNED VEHICLE-ASSISTED NITROGEN DISPENSATION IN RICE (*ORYZA SATIVA* L.)

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ABSTRACT

Nitrogen management through a leaf colour chart proved to be a cost-effective strategy for small-scale farmers. Identifying a research gap in the realm of variable rate technology, the integration of leaf colour chart readings into precision fertilizer application machinery became the focus. Consequently, a study was initiated to utilize the leaf colour chart data in creating digital prescription maps for unmanned aerial or ground vehicles. Two experimental rice fields were established and assessed for nitrogen deficiency using the leaf colour chart, paired with GPS coordinates. The collected data underwent processing in Google Earth Pro and ArcMap softwares for spatial interpolation of observed data to generate digital prescription maps through predicted data. The Karl Pearson correlation coefficient and Goodness of Prediction (G) of the predicted values with observed values were 0.93 and 0.85. The statistical analysis also confirms (p and f value) the non-existence of significant differences between observed and predicted data. The developed maps were extracted with set of geopositioning and corresponding prescription categories as input data to the precision machinery. This research highlights the potential application of leaf colour chart data and geographical information system tools in unmanned precision fertilizer application machinery.

Keywords: GIS; Leaf colour; Nitrogen management; Precision farming; Rice nutrition.

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INTRODUCTION

Globally, rice (*Oryza sativa* L.) plays a crucial role as a primary agricultural crop in eighty-nine countries, serving as the primary nutritional source for half of the world's population (Adhikari *et al.*, 2023). Nitrogen (N) stands out as the most essential nutrient for plants due to its pivotal role in various plant activities, often acting as a limiting factor in both plant growth and crop production (Dubey *et al.*, 2021). The nitrogen use efficiency (NUE) in rice is currently estimated at only 30 to 40%, with approximately one-third of the applied N being lost through various pathways (Abrol *et al.*, 2007). Nitrogen is lost by various modes such as 10-40% denitrification (Sahu and Samant, 2006), 15-45% nitrification-denitrification process in rice soils (Russo, 1996), as negligible to 50% ammonia vapours (Keller and Men-gel, 1986), 23.9% volatilization from rice fields (Yu *et al.*, 2013).

Numerous researchers aim to enhance NUE by minimizing losses and increasing N uptake in rice crops. To enhance NUE, a common effective approach involves optimizing N utilization through variable rate technology. This optimization relies on high spatial resolution sampling of crop parameters, achievable through either proximal or remote sensing technologies (Mouazen *et al.*, 2020). However, the measurement techniques employed must be rapid, cost-effective, and convenient (Kodaira and Shibusawa, 2013). Various decision support tools, such as Soil Plant Analysis Development (SPAD), (Ban *et al.*, 2022), GreenSeeker, Leaf Colour Chart (LCC), Chlorophyll meter, Yara-N sensor, Urea Super Granules (USG), and split application methods, have demonstrated their effectiveness in N management, contributing to the increased NUE in paddy fields (Lee, 2021). Various sophisticated data acquisition systems, including multispectral imaging and simultaneous or subsequent image processing, can autonomously provide digital geotagged data like NDVI, NDRE, and CCI, enabling

drones to distribute N. In contrast, the least expensive option, LCC, is a manual tool that farmers can easily utilize without extensive skill requirements (Leghari *et al.*, 2016). With seven colour shades of greenness, LCC was developed by Furuya (1987) followed by International Rice Research Institute with five or six shades and there are lot many developments done in LCC like Mirror made LCC in Pakistan (Leghari *et al.*, 2016), wheat and maize LCC in India (Singh *et al.*, 2014).

A study revealed that wheat crops managed with LCC-based N practices show a significantly higher profit of nearly Rs.7,000 ha⁻¹ (Mondal and Mitra, 2022). Similarly employing LCC for N management in paddy during active tillering and panicle initiation stages can lead to a more than 9.5% increase in paddy grain yield (Gudadhe and Shah, 2022). Additionally, it helps reduce NO₃⁻ leaching, NO₂⁻ emissions and enhances both gross and net monetary returns. Notably, omitting basal application resulted in a savings of 10 kg N ha⁻¹ through LCC-based N management practices (Lal *et al.*, 2021). The LCC developed by Punjab Agricultural University and the one by the International Rice Research Institute (IRRI), Philippines, can effectively estimate basmati rice grain yield in-season. Due to their economic feasibility, LCCs, in comparison to chlorophyll meters and canopy reflectance sensors, are viable options for small and marginal farmers in developing countries (Singh *et al.*, 2022).

Precision agricultural machinery (Nath, 2024; Tey *et al.*, 2024) is a wide sector with numerous categories including precise fertilizer applying machinery. The major two categories of fertilizer application machinery are real-time and map-based. Real-time application machinery may not rely on GPS, as they make use of encoders and onboard sensors mounted on

the machinery. The map-based machinery utilizes GPS (Qi *et al.*, 2020; Rathinavel *et al.*, 2023a), GLONASS (GLObal NAVigation Satellite System), BeiDou, EGNOS, SBAS, and similar radio navigation tools for navigation and spatial information. The input data is essentially to be georeferenced, for precise placement of fertilizer. The machinery might be tractor-based (Mirzakhani-fachi *et al.*, 2021), UAV-mounted (Song *et al.*, 2021; Su *et al.*, 2022) or autonomous, also the state of fertilizer might be solid (Zhang *et al.*, 2020) or liquid (Zhou *et al.*, 2023). Shortly, autonomous and robotic machinery was about to boom, the data supplied for those unmanned precision machineries are supposed to be digitized and detailed, to achieve the maximum possible precision.

The existing practice of using LCC is still in manual mode, in which farmer observes a portion of land through several observations and arrives at a single dose of N application based on the average of observed values. As discussed earlier, we need digital spatial data of LCC value throughout the field, for applying LCC in precision machinery. Hence, against the backdrop of enhancing NUE through a straightforward approach, this study aimed to digitize LCC data with geotags and develop digital N management maps. The objective was to facilitate the prescription of precision fertilizer application machinery for rice crops.

MATERIALS AND METHODS

The outline of the study representing workflow is presented in Fig.1. To carry out the study a field experiment was done followed by data acquisition, software processing, and analysis, explained as follows.

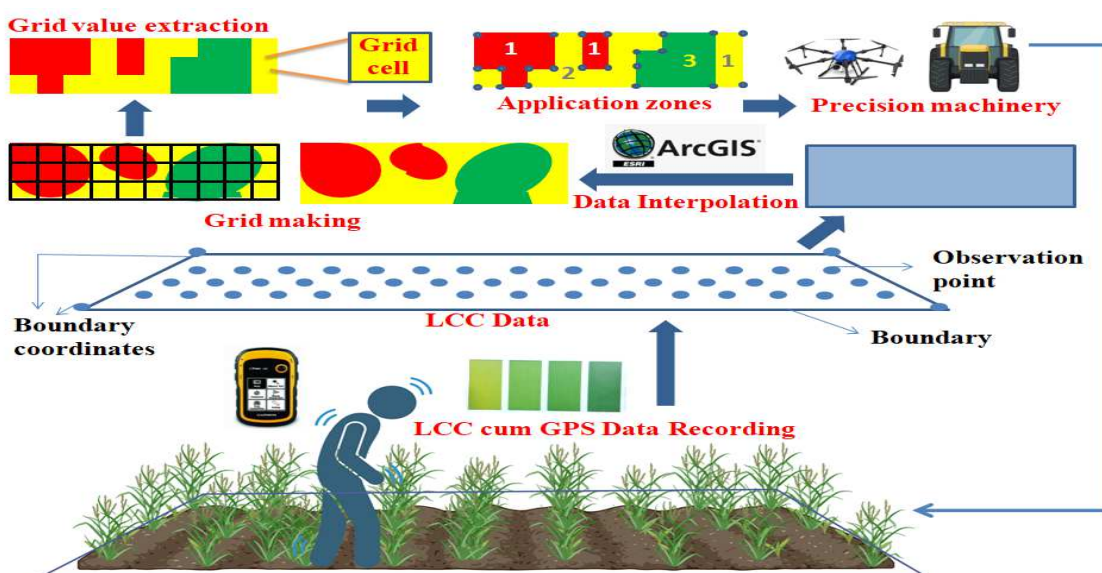


Fig. 1. Workflow of the study

Study area: To conduct the designated research, two experimental rice fields were set up at Tamil Nadu Agricultural University in Kumulur, Trichy during the year 2023. The average rainfall of the Kumulur campus was 862 mm (Rathinavel *et al.*, 2020), and located 72 m above mean sea level. Temperature ranges between 25 to 32° C and mean was 28.8° C.

Experiment details: The experimented field is shown in Fig. 2. The chosen rice variety, TRY 3, was cultivated through the transplanting method (Mechanical transplanting with 8-row, riding type Yanmar YP8DN transplanter). A spacing of 30x20 cm was maintained

through a mechanical transplanter. Being medium duration crop variety, the fertilizer application plan involved four splits of N, encompassing the recommended doses of, phosphorus, and potassium in a single basal dose. Hand weeding was done twice and no significant weed effect or pest infestations were found. Irrigation was followed for the required times regularly ensuring adequate moisture. The population was consistently maintained, and other variables were kept constant throughout the study. For the TRY 3 variety, the critical LCC value was 4, as per the recommendation from TNAU.



Fig. 2. Experimental rice field



Fig. 3. LCC and data recording

LCC and data collection: LCC (Fig. 3) threshold from 2 to 5 was applied in conjunction with a hand-held Garmin unit (Model: Garmin GPS etrex 10) for the collection of GPS data (latitude and longitude) in the two experimented fields at regularly spaced (3m x 3m) observation points. At each observation point 10 plants were selected and 6 leaves for each plant were selected

randomly. Fully opened, young leaves (fully expanded middle part) from non-diseased plants were specifically chosen for recording observations, during the morning hours from 8:00 AM to 10:00 AM under bright sunshine, with a single person shielding the leaves and chart with body. The critical stages of active tillering and panicle initiation, identified as the most crucial periods (Gudadhe

and Shah, 2022), were observed in two experimented rice fields. The boundaries of field I and II derived from Google Earth Pro Environment was illustrated in Fig.4. The boundary files were extracted as KML (Keyhole

Markup Language) layer files and saved for further processing. Subsequently, the data, including GPS coordinates and average LCC values (threshold 2 to 5), were plotted using Microsoft Excel.

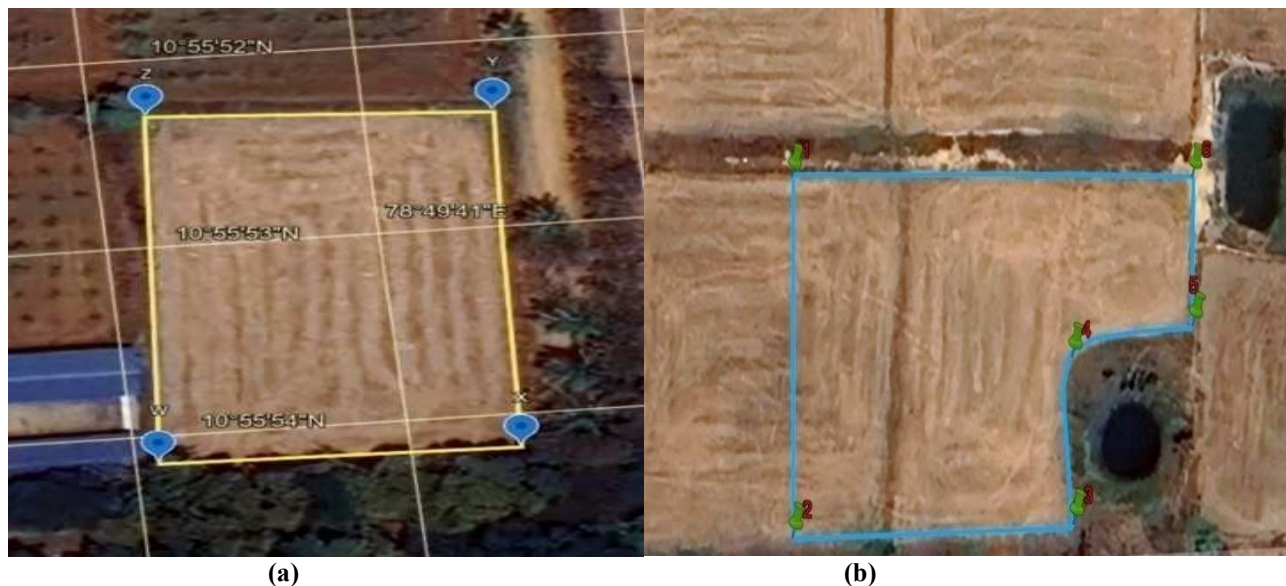


Fig. 4. Boundaries of field I (a) and field II (b) in Google Earth Pro Environment

Software and input data processing: Similar to the approach taken in soil sampling and mapping, interpolation techniques were adopted as suggested in previous studies (Khan *et al.*, 2021; Kumar *et al.*, 2021). Several researchers have utilized this methodology for investigating spatial variability (Reza *et al.*, 2019; Jin *et al.*, 2021; Malik *et al.*, 2022; Abdu *et al.*, 2023).

The interpolation works based on the principle that unsampled location values were estimated (equation 1) from the neighbouring sampled location. Based on the distance of sampled location, the weights (equation 2) are considered. The Inverse Distance Weighting (IDW) weights are typically proportional to the inverse of the squared distance between the predicted value and the observed value, and they total to 1.

$$Z_{a_0} = \sum_{i=1}^n w_i Z_{a_i} \tag{1}$$

Z_{a_0} -Estimated value of unsampled locations
 Z_{a_i} -Observed *known* at surrounding locations
 w_i - Weight assigned

$$w_i = \frac{\frac{1}{D_i^2}}{\sum_{i=1}^n \frac{1}{D_i^2}} \tag{2}$$

D_i -Distance between sampled and unsampled locations

The above process was done from a Geographical Information System (GIS) based software. The data recorded in an MS Excel sheet was imported into appositional point data file into ArcMap (version 10.7.1) with X (latitude), Y(longitude), and Z (LCC data). The boundary KML file developed from Google

Earth Pro was imported and laid with the point data. The IDW spatial analyst tool was employed to interpolate the data within the defined field boundary. The interpolation process results in a generation of maps. Resulting maps were overlaid with a grid of cells using fishnet and sample tools. The average value for each grid was calculated and then classified to provide recommendations for fertilizer dosage. To assess the accuracy of the developed maps, test values recorded away from the observation points were used.

Data Analysis: Descriptive statistics were analysed for the observed LCC data for both fields and stages. The predicted data extracted from the prescription maps developed was correlated with test data recorded using the Karl Pearson correlation coefficient. Mean Absolute Error (Equation 3), Mean Square Error (Equation 4), Root Mean Square Error (Equation 5) and Coefficient of Determination (Equation 6) ranging from 0 to 1 was determined from the predicted and test data using the following formulae (Yao *et al.*, 2013).

$$MAE = \frac{1}{n} \sum_{i=1}^n |x - y| \tag{3}$$

$$MSE = \frac{1}{n} \sum_{i=1}^n (x - y)^2 \tag{4}$$

$$RMSE = \sqrt{MSE} \tag{5}$$

$$G = 1 - \frac{\sum_{i=1}^n (x-y)^2}{\frac{1}{n} \sum_{i=1}^n (x-A)^2} \tag{6}$$

MAE – Mean Absolute Error
 MSE – Mean Square Error

RMSE – Root Mean Square Error
 G – Goodness of Prediction
 n – Number of samples
 x – Observed value
 y – Predicted value
 A – Mean of Observed values

Using R software, ANOVA was carried out for each set of experiment data. p-value and F-value were discussed.

RESULTS

Digital N management maps and recommendations were generated based on the recorded LCC values observed in two rice fields. The statistical analysis of the observed LCC data was presented in Table 1. The LCC data from the field I indicate a platykurtic

distribution with fewer extreme values in both stages. Conversely, field II exhibits leptokurtic and platykurtic kurtosis in stages 1 and 2, respectively, suggesting slight extremes in stage 1. Skewness analysis reveals a rightward skew in both stages of field I and stage 1 of field II, while field II stage 2 exhibits a leftward skew. Overall, the standard deviation and variance indicate a relatively small variance, as the values are not significantly distant from each other.

The Fig. 5 depicts a strong positive correlation between all 4 (both fields and both stages) datasets of observed test value and predicted value (derived from interpolated maps). Table 2, Fig. 6 and Fig. 7 represents the relationship between observed and predicted data with other statistical data. There is no significant difference exists between observed and predicted values in all 4 sets of data.

Table 1. Basic statistics of observed LCC values at different stages of rice growth.

Parameters	Field I		Field II	
	Active Tillering Stage	Panicle Initiation Stage	Active Tillering Stage	Panicle Initiation Stage
Mean	3.00	3.20	2.90	3.30
Median	3.00	3.00	3.00	3.50
Mode	3.50	3.00	3.00	3.50
Range	2.50-3.50	2.50-4.00	2.50-3.50	2.50-4.00
Standard Deviation	0.37	0.42	0.26	0.41
Variance	0.14	0.18	0.06	0.17
Skewness	0.13	0.64	0.32	-0.67
Kurtosis	-1.40	-0.38	0.17	-0.11

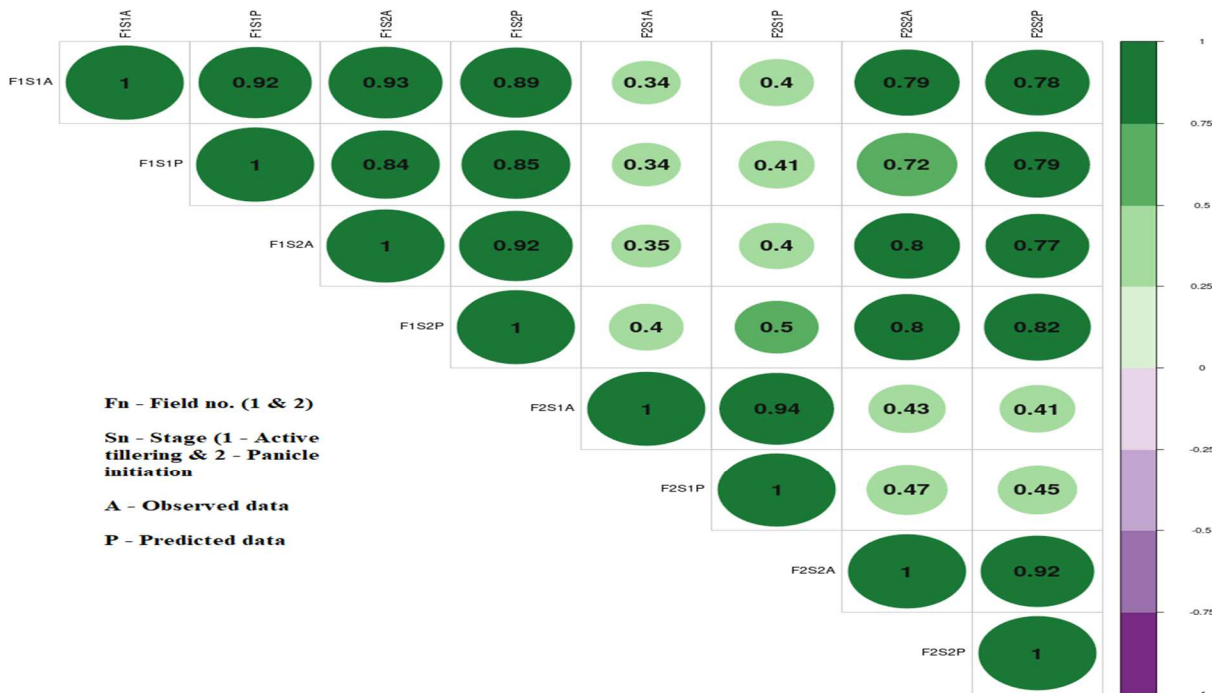


Fig. 5. Correlation between Observed and Predicted data sets

A digital map based on LCC for N management was created, as illustrated in Fig. 8. Previous studies by Wollenhaupt *et al.* (1994), Chan *et al.* (2004), Hedley *et al.* (2012), and Mezera *et al.* (2018) have classified zones differently based on specific field requirements. The map was divided into three zones according to the observed LCC values: Zone I (2.5 to 3.0), Zone II (3.0 to 3.5), and Zone III (3.5 to 4). In the active tillering stage of Field I, classes I, II, and III covered approximately 24%, 42%, and 38%, respectively. In the panicle initiation stage, these percentages changed to 38%, 33.5%, and 28.5%. The recommendations generated (Table 3) were validated through multiple replications within each class, comparing them with the statistics of LCC data. This

validation affirms that Field I does not exhibit extreme values.

In the case of field II, three categories of zones were identified, denoted as I (2.5 to 3.0), II (3.0 to 3.5), and III (3.5 to 4). During the active tillering stage, these classes covered approximately 20%, 80%, and 0% of the area, respectively. In the panicle initiation stage, the distribution shifted, with classes I, II, and III covering around 15%, 65%, and 20% of the area in field II. The resulting digital map (Fig. 9.) exhibited a subtle roughness consistent with the statistics from the observed data. The recommendation class of fertilizer dose was tabulated in Table 4.

Table 2. Evaluation of interpolated LCC map.

Parameter	Field I		Field II		Mean
	Active Tillering Stage	Panicle Initiation Stage	Active Tillering Stage	Panicle Initiation Stage	
Mean Absolute Error	0.11	0.068	0.065	0.082	0.081
Mean Square Error	0.024	0.017	0.01	0.026	0.01925
Root Mean Square Error	0.15	0.13	0.10	0.16	0.135
Goodness of Prediction	0.85	0.86	0.95	0.76	0.855
p-value	0.81	0.75	0.95	0.94	
F-value	4.09	4.11	4.09	4.09	

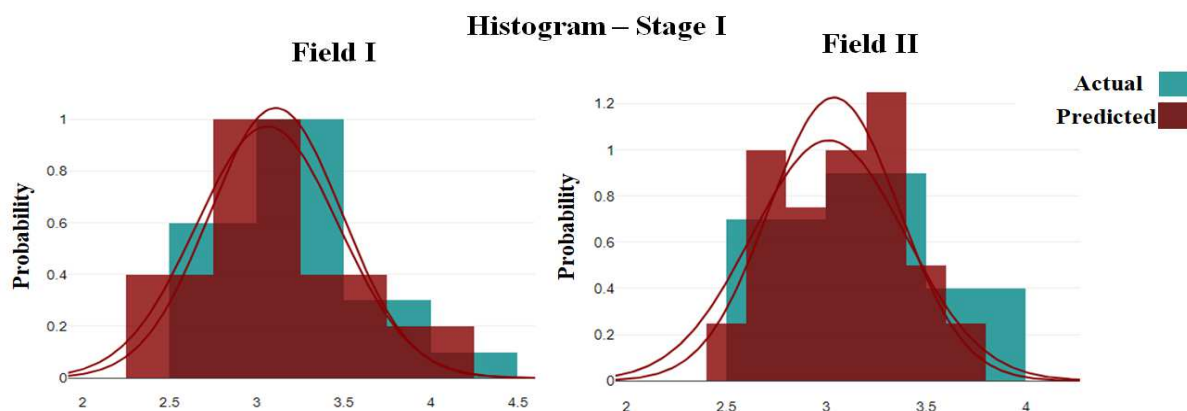


Fig. 6. Histogram for Active tillering stage

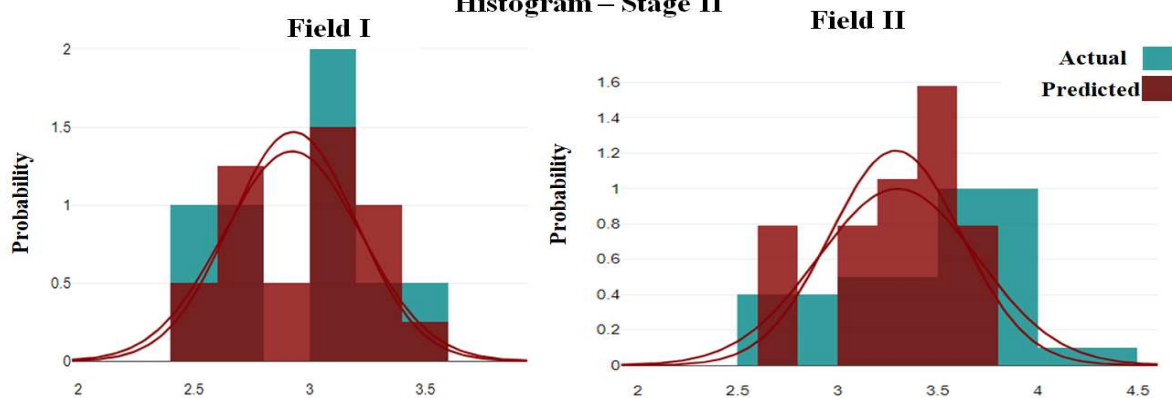


Fig. 7. Histogram for Panicle initiation stage

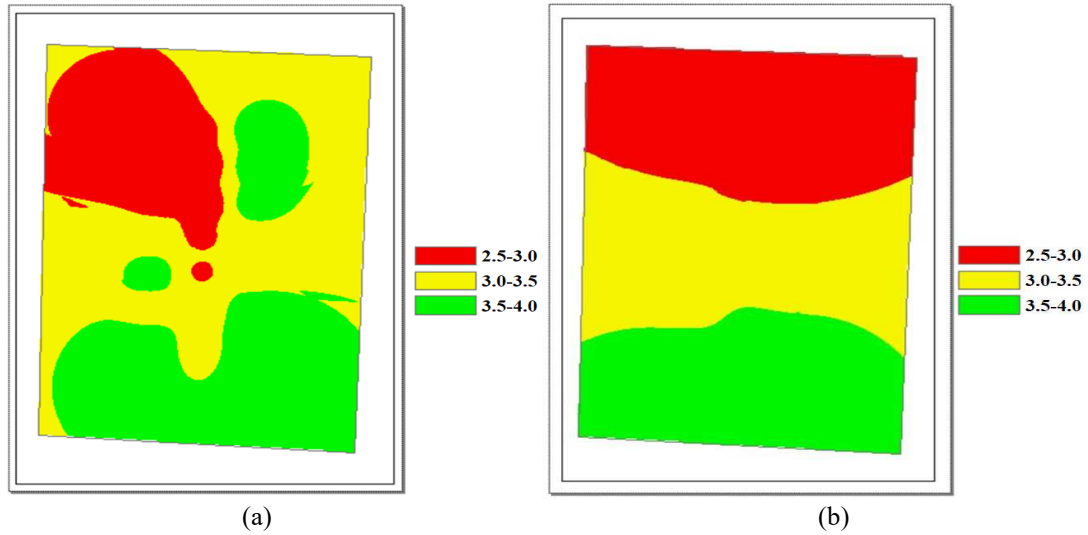


Fig. 8. LCC-based digital map on N management for the field I at (a) active tillering and (b) panicle initiation stages

Table 3. Recommended class of fertilizer dosage in field I.

GPS Coordinates	78.82799°E		78.82811°E		78.82824°E	
10.93169°N	I	I	II	I	II	I
10.93161°N	I	I	I	I	II	I
10.93154°N	I	II	I	I	II	I
10.93146°N	II	II	II	II	II	II
10.93139°N	II	II	II	II	III	II
10.93132°N	III	III	II	III	III	III
10.93124°N	III	III	III	III	III	III

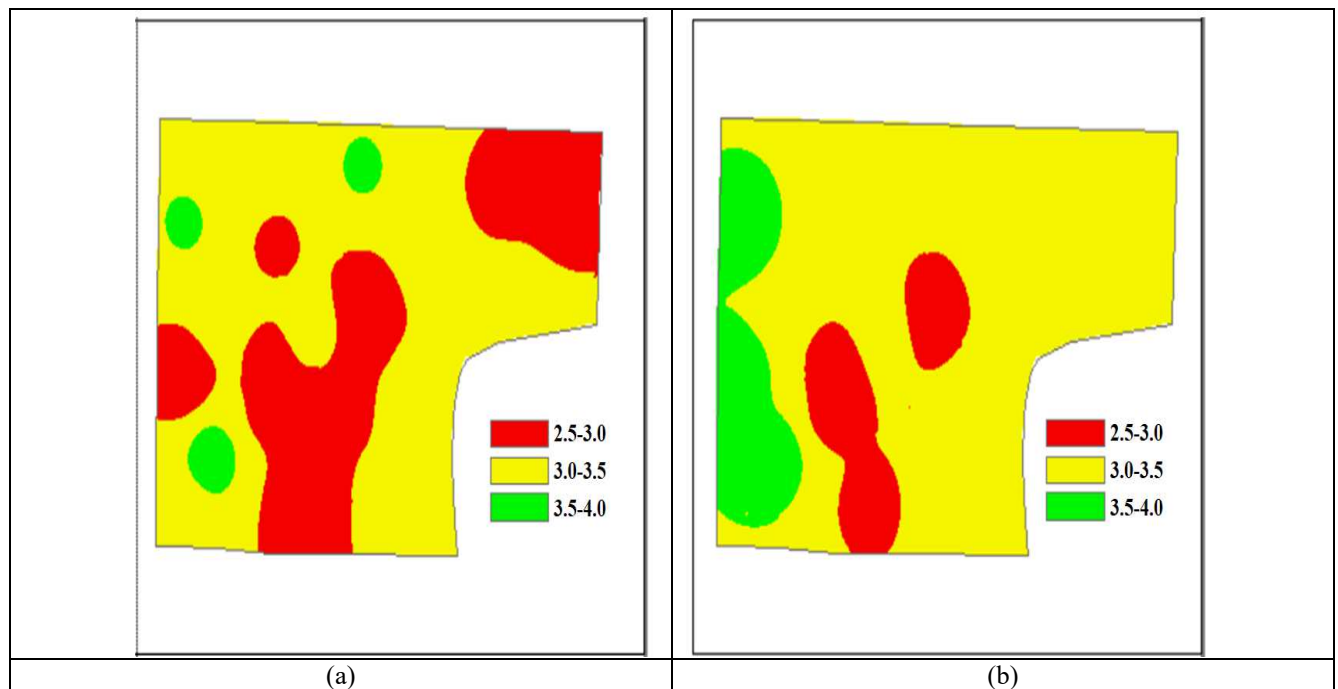


Fig. 9.LCC-based digital map on N management for field II ((a) active tillering and (b) panicle initiation stages)

Table 4. Recommended class of fertilizer dosage in field II.

GPS Coordinates	78.83066 ^o E	78.83078 ^o E	78.8309 ^o E	78.83102 ^o E	78.83114 ^o E
10.93222 ^o N	II	III	II	II	II
10.93214 ^o N	II	III	II	II	II
10.93205 ^o N	II	II	I	II	I
10.93197 ^o N	II	III	I	I	II
10.93189 ^o N	II	III	I	I	II

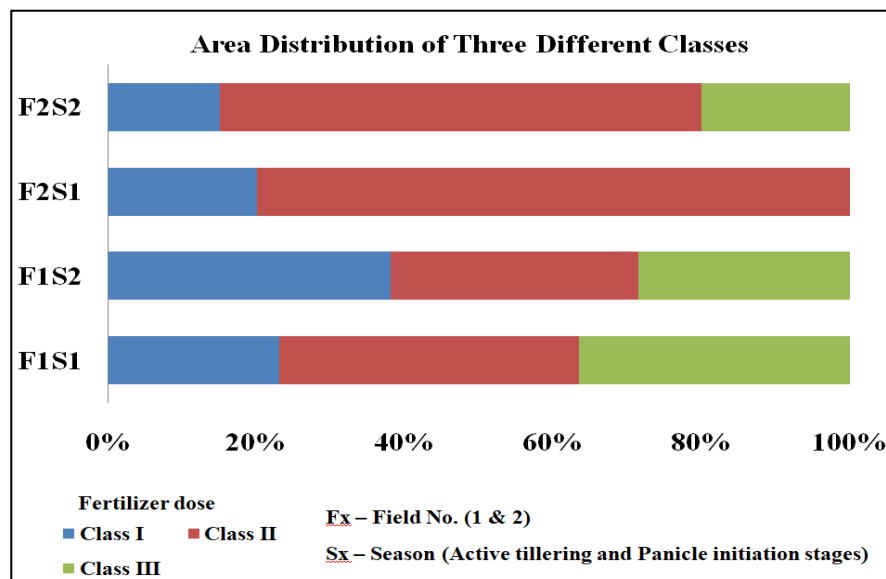


Fig. 10. Area distribution of three different classes on either fields or stages

DISCUSSION

Despite noting an increase from the active tillering to the panicle initiation stage, a majority of the field areas experienced N deficiency, categorized with varying intensity in both stages and plots. From Fig. 10 it is observed that majority of the area falls into class II, followed by class I, and last class III. From this area distribution of different classes, a 12.6% of N can be saved if the adjusted N application was set to 75-100% in comparison with blind application of 100% N to the entire field. This saves 32.5 kg of urea, which in turn saves cost, energy, labor, machinery wear, etc. Though the savings appears to be less in this experiment, situations with wider variations may have potential N savings.

The mean correlation coefficient was 0.93 and a goodness of fit value of 0.85. This implies a strong feasibility of the proposed technique for precision machinery applications. Similarly, Morgan *et al.* (2017) proved the use of the IDW technique in the agricultural sector and obtained a coefficient of correlation of more than 0.80.

Shukla *et al.* (2004) reported a correlation ranging from 0.84 to 0.91 between LCC and chlorophyll

content (SPAD observations) across all rice genotypes. This suggests that the developed map from LCC data could theoretically demonstrate a positive relationship of 78.5% to 85% with chlorophyll content. Different varieties of rice had significant effect on yield for LCC based N management (Bhat *et al.*, 2022). LCC use saved 10 to 40 kg N ha⁻¹ (Bhat, 2014). Hence the efficiency of the technique depends on the efficiency of LCC towards the variety also. Since, GPS is satellite-based navigation tool (Chaudhary *et al.*, 2024), the accuracy of positioning and navigation is crucial for a precision machinery (Nijak *et al.*, 2024). Hence the GPS is main affecting factor which is influencing the data acquisition and also the applying machine efficiency.

The positive relationship between the classification data and observed data statistics, as previously discussed, validates the accuracy of the developed map. With the recommended class and geotags, unmanned vehicles, whether aerial or ground-based, can efficiently dispense fertilizer using mechanisms such as a fluted roller or a variable flow liquid spray system. This approach is particularly viable for small farms where manual data acquisition is not cumbersome, showcasing the potential for precision farming in the predominant small-scale agriculture sector in India.

Table 5. Cost of various precision fertilizer management tools

S. No	Tool	Cost (Rs.)
1	GreenSeeker	1,50,000/-
2	Opti-Science Chlorophyll meter	1,00,000 – 1,50,000/-
3	SPAD Chlorophyll meter	1,00,000 – 1,50,000/-
4	Multispectral camera (Drone)	8,00,000 – 20,50,000/-
5	LCC	30/-
6	Spectrophotometer	50,000 – 5,00,000/-

The advantage of the proposed technique lies in the cheaper cost involvement in comparison with sophisticated technologies like SPAD meter, chlorophyll meter and multispectral imaging which are regarded as costlier (Table 5) in terms of data acquisition (Andrianto *et al.*, 2020; Kamarianakis and Panagiotakis, 2023). Further, the use of LCC by farmers was an existing practice and familiar to extend towards them. The technology holds good for an entrepreneur to undertake a precision agriculture custom hiring or project.

The limitation of the technology lies in the requirement of a skilled assistance for map generation and operating precision machinery based on the map. Accuracy and precision of results may not be on par with drone imaging and other sensor based techniques. Low-Cost Chlorophyll Content Meter developed by Kamarianakis and Panagiotakis (2023) had R^2 values of 0.95 to 0.99 found between their low cost chlorophyll content meter and SPAD 502 in different crops. GPS accuracy and boundary marking must be under utmost care for the successful results. Another fact is LCC is applicable only to the top-dressed N application and not suitable for basal N application (Rao and Das, 2023).

In future, with 5G enabled network facilities (Rathinavel *et al.*, 2023b), smart phone adoption by farmers, robust software application etc., will be easy to eliminate the limitations discussed above and can be a small scale technology for small, marginal farmers and custom hiring centres.

Conclusion: By addressing the research gap in variable rate technology, the study successfully generated digital N management maps for two experimental rice fields, achieving a significant correlation of more than 93% and 85% of goodness of fit models with ground truth test values. The utilization of LCC data and GIS tools presents a cost-effective and practical strategy for enhancing NUE in small-scale farming, showcasing the potential for widespread application in precision farming for the benefit of farmers in developing countries.

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