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Spatial Chlorophyll Estimation from Rice Field using Drone-derived Spectral Indices

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ABSTRACT

Background: Precision farming has significantly advanced the agricultural sector by enabling real-time canopy monitoring and crop condition evaluation, thus facilitating precise management strategies to enhance yields. This study investigated the use of drone-derived vegetation indices (VIs) for assessing spatial variability in crop conditions, offering a more cost effective and practical alternative to satellite data.

Methods: The field experiment was conducted during the *Kuruvai* season (July - November 2023) on a short-duration rice variety CO 55. Several vegetation indices *viz.,* BGI, CI, EVI, GNDVI, MCARI, MSAVI, NDRE and NDVI were calculated to predict chlorophyll content and correlated with the measured SPAD values.

Result: The results showed that indices like MCARI, GNDVI and NDVI had strong positive correlations with SPAD values, with MCARI exhibiting the highest correlation (R= 0.914) and an R^2 value of 0.836. The findings underscore the effectiveness of using drone-derived indices for precise chlorophyll estimation, which is crucial for variable rate fertilizer application in precision agriculture.

Key words: Chlorophyll, Precision farming, Rice, Vegetation indices.

INTRODUCTION

Precision farming has revolutionized the agricultural sector in recent years, real-time canopy monitoring and crop condition evaluation aid in developing precise management strategies that boost yields (Cuaran *et al.,* 2021). Unmanned aerial vehicles (UAVs), sometimes referred to as drones (dynamic remotely operated navigation equipment) fitted with multispectral and hyperspectral sensors have been used to derive these vegetation indices (Rani *et al.,* 2019). It can gather data about the spatial variability of crop conditions in the field with temporal dimensions and serve as a more affordable and useful substitute for satellite remote sensing in agriculture to track vegetation status (Tahir *et al.,* 2018). It gives more accurate and efficient assessment of spatial variability in crop conditions.

Vegetation Indices (VIs) are the ratio of difference between the reflectance of different spectral bands. The spectral bands consist of blue (440-510 nm), green (520-590 nm), red (630-685 nm), red edge (690-730 nm) and near-infrared (760-850 nm) (Marang *et al.,* 2021). Nigon *et al.,* (2015) stated that the physiological characteristics of a crop could be retrieved using the absorption and reflectance characteristics. VIs are useful tools for crop health monitoring, nutrient, water status, pest infestations and projecting crop yield and productivity (De Castro *et al.,* 2021).

Chlorophyll content in crops is a vital indicator of plant health, vigour and predicts the final crop yield (Na *et al.,* 2024). Chlorophyll levels indirectly reflect the crop nitrogen status, ultimately influencing crop productivity. Healthy green vegetation strongly absorbs the visible light especially in the red spectrum, due to chlorophyll content. The highest red absorption occurs between 660 and 680 nm, a range that tends to saturate at low chlorophyll levels and reflect in the near-infrared region, due to the internal structure of the leaves. Traditional methods of measuring chlorophyll content using SPAD (Soil Plant Analysis Development) meters are destructive, time-consuming, and spatially inaccurate. In this context, the drone-based derived indices provide detailed spatial chlorophyll content analysis. Vegetation indices such as NDVI (Normalized Difference Vegetation Index) (Rouse *et al.,* 1974, Minh *et al.,* 2022), GNDVI (Green Normalized Difference Vegetation Index) (Gitelson *et al.,* 1996), SAVI (Soil Adjusted Vegetation Index) (Huete, 1988), NDRE (Normalized Difference Red Edge Index), Transformed Soil

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Adjusted Vegetation Index (TSAVI) (Baret and Guyot, 1991), Modified Soil Adjusted Vegetation Index (MSAVI) (Qi *et al.,* 1994), Difference Vegetation Index (DVI), Green Normalized Difference Vegetation Index (GNDVI), Chlorophyll Index Green (CIG), Chlorophyll Vegetation Index (CVI), Enhanced Vegetation Index (EVI) (Janarth *et al.,* 2024), Leaf Chlorophyll Index (CI) and Triangular greenness index (TGI) predicted the crop chlorophyll content efficiently. The use of these indices aims to detect subtle changes in nitrogen content and deficiencies, which is crucial for precision agriculture. It enhances the estimation of crop biomass and nitrogen content estimation, providing a more efficient and comprehensive approach. Yang *et al.* (2017) stated that hyperspectral imaging became a common method of retrieving crop water content, leaf nitrogen concentration, chlorophyll content, LAI and other physical and chemical parameters. In precision agriculture, the spatial chlorophyll map helps in decision-making with variable rates of fertilizer applications. This research aimed to estimate the chlorophyll content of rice crops at a spatial level using drone-derived indices and to validate the vegetation indices with *in situ* data.

MATERIALS AND METHODS

Study location

The field experiment was conducted in the *Kuruvai* (July-November, 2023) at Agricultural Research Station, Bhavanisagar, Tamil Nadu. Short duration rice variety CO 55 (110-115 days) was grown during the season. The experimental site is located at 11.29′N latitude and 77.08′ E longitude, with an altitude of 256 and belongs to the Western agro-climatic zone of Tamil Nadu (Fig 1). Image acquisition DJI Phantom 4 drone was used to acquire multispectral images during the maximum tillering stage. Drone specifications are given in Table 1. It captures images in the spectral bands *viz.,* Blue: 450 nm, Green: 560 nm, Red: 650 nm, Red Edge: 730 nm, Near-Infrared: 840 nm. A flight mission was carried out during active tillering stage on September 2023 under a clear sky between 11 AM to 12 noon.

Ground data collection

The ground data on SPAD chlorophyll was collected for 15 points during the maximum tillering stage of the crop as when drone images were captured to validate the vegetation index. The atLEAF CHL PLUS handheld chlorophyll (SPAD) meter was used to measure the light transmittance ratio at 640 nm and 940 nm wavelengths.

Processing of drone image and generation of vegetation indices

The multispectral images were processed using Pix4D mapper software. The data processing includes geo-referencing, point cloud densification, generation of Digital Surface Model (DSM), ortho-mosaic and generation of indices. The vegetation indices were calculated from processed

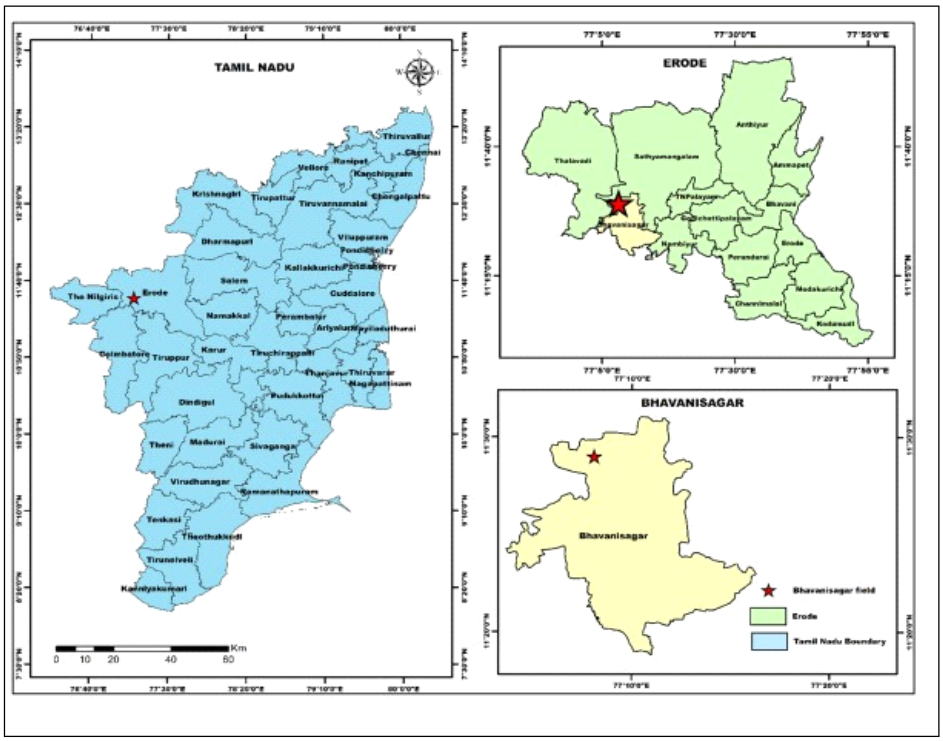
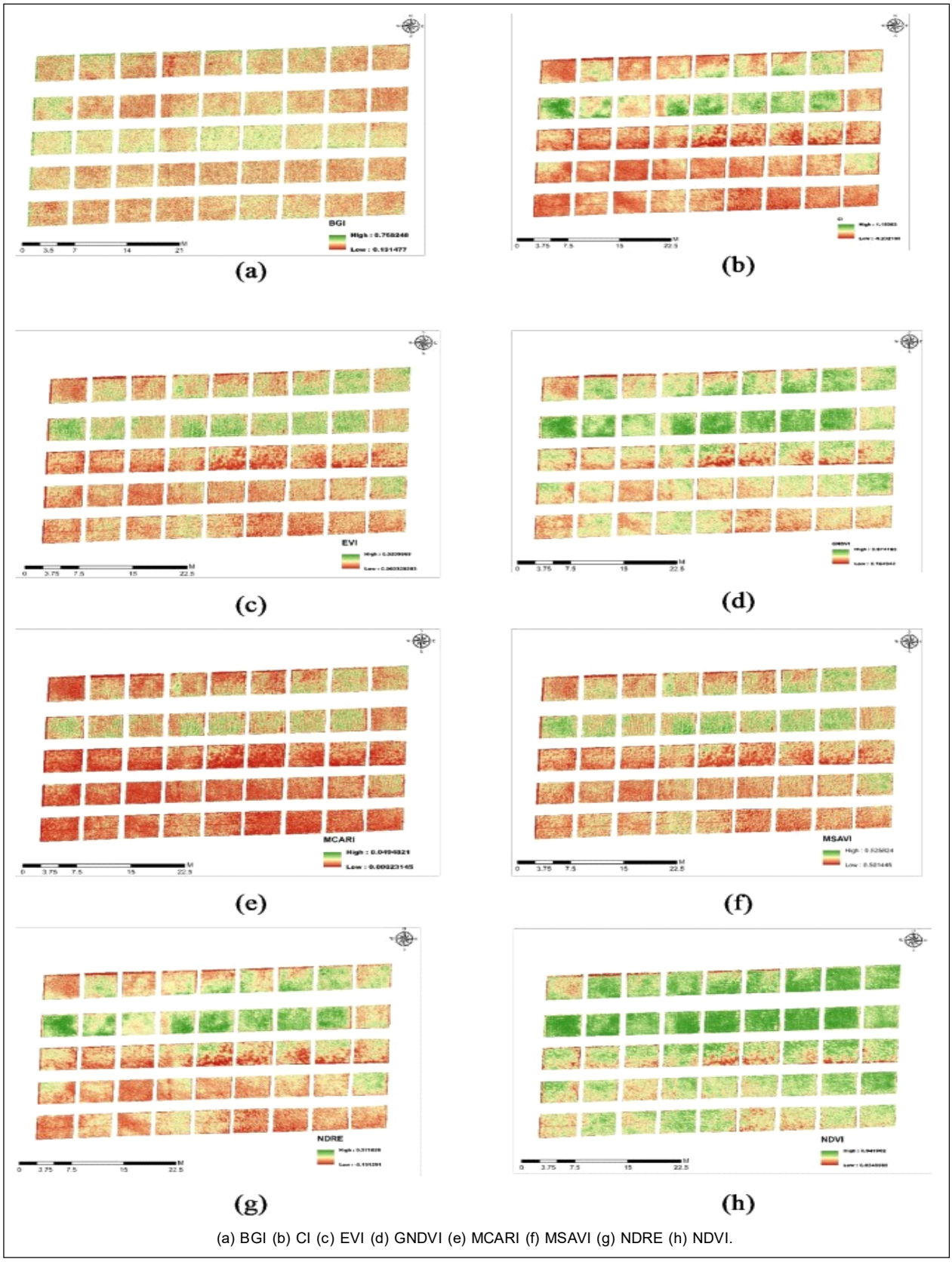


Fig 1: Location of the study area.



(a) BGI (b) CI (c) EVI (d) GNDVI (e) MCARI (f) MSAVI (g) NDRE (h) NDVI.

Fig 2: Vegetation index map generated.

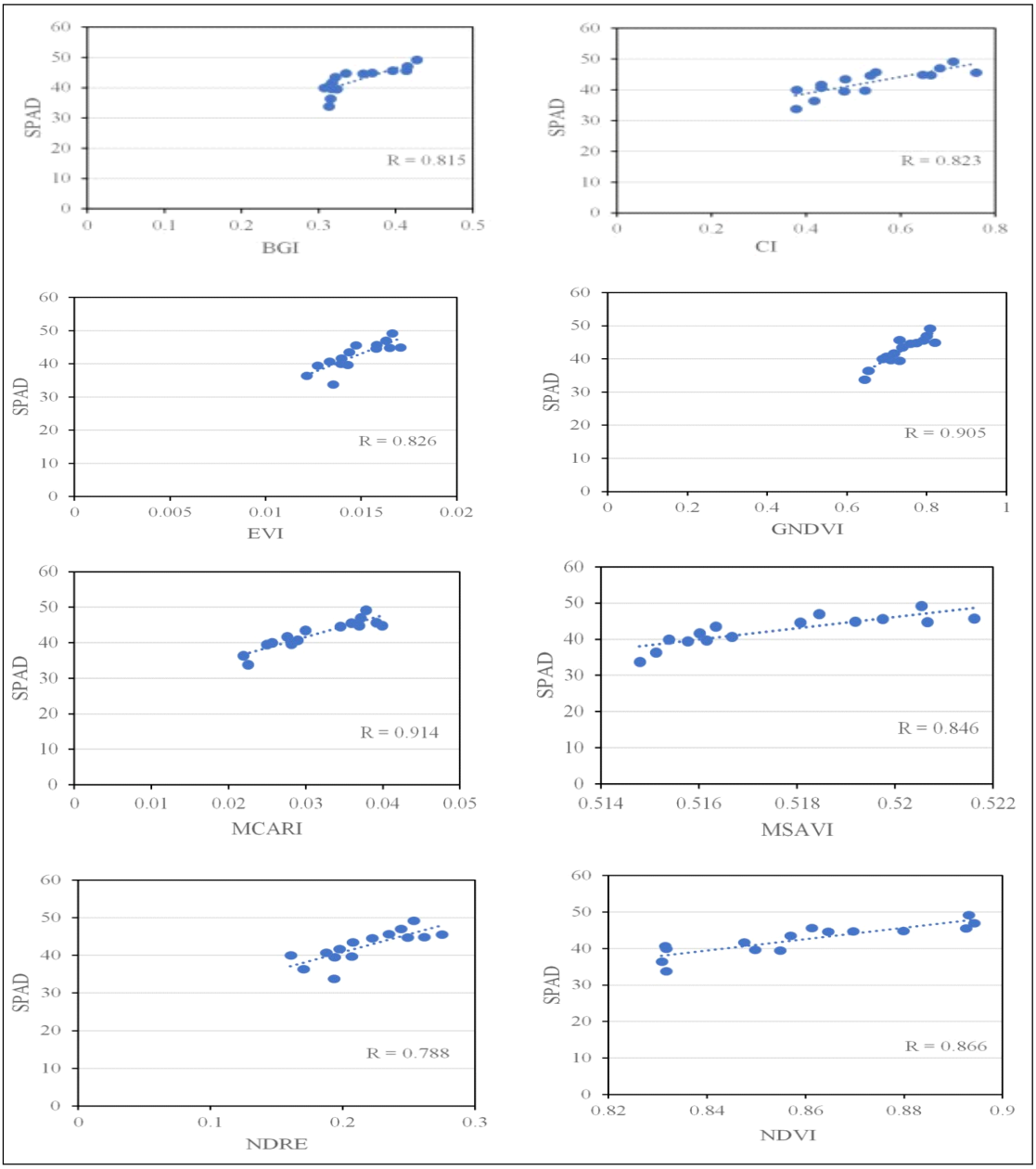


Fig 3: Relationship between BGI, CI, EVI, GNDVI, MCARI, MSAVI, NDVI, NDRE with SPAD chlorophyll readings.

Table 1: Specifications of DJI Phantom 4 drone.

Platform	Quadcopter
Max speed	6 m/s
Focal length	5.74 mm
Size of the sensor	4.87 × 3.96 mm
Built-in battery	6000 mAh LiPo 2S
Spectral bands	Blue, green, red, red edge, near-infrared

images using the Raster calculator tool in ArcGIS 10.8 software. Indices like BGI, CI, CVI, GNDVI, MCARI, MSAVI, NDRE and NDVI were used in predicting SPAD chlorophyll values. Based on ground truth coordinates, the spectral information from different vegetation indices were extracted (Table 2).

Statistical analysis

Pearson correlation analysis (R) was carried out to find the best vegetation index by correlating with ground truth data and the coefficient of determination for predicting the model accuracy. The regression (R^2) values were calculated for vegetation indices (independent variable) and ground truth data (dependent variable) to assess the best line of fit. The Root Mean Squared Error (RMSE) was used to

measure the average difference between te predicted value and observed value.

$$R = \frac{n\Sigma xy-(\Sigma x)(\Sigma y)}{\sqrt{n\Sigma(x^2)-(\Sigma x^2)}\ \sqrt{n\Sigma(y^2)-(\Sigma y)^2}}$$

$$R^2 = \frac{\sum_{i=1}^{n}(y_i - x_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{n}}$$

RESULTS AND DISCUSSION

The multispectral images acquired during maximum tillering stage of rice for calculating chlorophyll, have strong positive correlation with ground data. Indices like BGI, CI, CVI, GNDVI, MCARI, MSAVI, NDRE and NDVI were used to calculate chlorophyll (Fig 2). The vegetation indices and SPAD values for the 15 points are given in Table 3. These indices were used to detect the greenness and chlorophyll contents of crops. Indices values extracted were positively correlated with chlorophyll content positive and linear correlation between different VIs and ground-truth chlorophyll data. The correlation between different indices and ground chlorophyll data was given in Fig 3. The field SPAD values measured from the field ranged from 33.80 to 49.20 with mean value of 42.47. The range of values for different VIs was as follows: BGI from 0.3071 to 0.4269, CI from 0.3782 to 0.7588, EVI from 0.0121 to 0.0171, GNDVI from 0.6441 to 0.8196, MCARI from 0.0219 to 0.0399, MSAVI from 0.5148 to 0.5216, NDRE from 0.1605 to 0.2751, NDVI from 0.8315 to 0.8942. The lowest values indicate the non-photosynthetic materials and bare soil background.

Table 2: Vegetation indices and their formula.

Index	Equation
Blue-green pigment index (BGI)	B/G
Chlorophyll index (CI)	$\frac{NIR}{RE} - 1$
Enhanced vegetation index (EVI)	$\frac{2.5\,(NIR-R)}{NIR + 6\,R - 7.5\,B + 1}$
Green normalized difference vegetation index (GNDVI)	$\frac{NIR-G}{NIR+G}$
Modified chlorophyll and reflectance index (MCARI)	$\frac{RE}{R} \times\{(RE-R) - 0.2(RE-G)\}$
Modified soil adjusted vegetation index (MSAVI)	$\{2 \times NIR + 1 - \sqrt{2 \times NIR + 1)^2 - 8 \times (NIR-RED)}\}/2$
Normalized difference vegetation index (NDVI)	$\frac{NIR-R}{NIR+R}$
Normalized difference red edge index (NDRE)	$\frac{NIR-RE}{NIR+RE}$

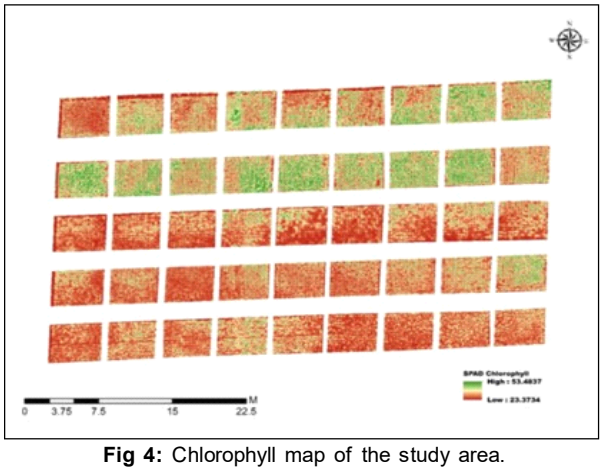


Fig 4: Chlorophyll map of the study area.

The regression equation and RMSE values of different vegetation indices are given in Table 4. Among all the indices, MCARI has the highest positive correlation (0.914) with SPAD values measured from the field. MCARI has R^2 and RMSE value of 0.836 and 1.74, respectively. GNDVI has higher positive correlation (R = 0.905), R^2 value of 0.820 and RMSE of 1.82. NDVI had a positive correlation coefficient R = 0.866 and recorded R^2 value of 0.75 and RMSE of 2.15. Higher R^2 value indicates higher chlorophyll content (healthy vegetation), while lower values indicate low chlorophyll content (stressed vegetation). The lower positive correlation coefficient (R = 0.788) was recorded with NDRE, having R^2 value of 0.622 and RMSE of 2.64.

The high R^2 value (0.836) for MCARI suggests that this index is particularly effective in capturing variations in chlorophyll content, thus serving as a robust indicator of crop health. Similarly, GNDVI and NDVI exhibited strong positive correlations with SPAD values, further emphasizing their utility in quantifying chlorophyll content and assessing the overall health status of rice crops. Vegetation indices sensitive to chlorophyll particularly indices using green and red wavelengths performed better in the prediction of chlorophyll. Baloloy *et al.* (2018) study shown that GNDVI predicted chlorophyll content well as compared to other indices. These chlorophyll-sensitive indices serve as indirect proxies to crop biochemistry (Gitelson *et al.,* 2006; Shanmugapriya *et al.,* 2022), when compared to red and blue wavelengths, red edge wavelengths have more into the leaf cell structure. Hence, to estimate chlorophyll concentration the spectral indices containing these bands in the later regions would be more accurate (Yao *et al.,* 2014). As a result, MCARI and crop chlorophyll content have a stronger correlation than the other indices. Shanmugapriya *et al.* (2022) also suggested that MCARI was the best index to predict chlorophyll content as it has both red and red edge bands and is more specific for detecting vegetation status. This is consistent with Raper and Varco (2015) finding that VIs specific to chlorophyll is a better fit for predicting chlorophyll content. VIs have the potential to predict N deficiency using readings from the SPAD (Pagola *et al.,* 2009) as these indices employ the same wavebands (650 and 940 nm) used in SPAD meter. Yuhao *et al.* (2020) correlated

Table 3: Ground truth SPAD value and vegetation indices value for geo-tagged points.

Lat	Lon	BGI	CI	EVI	GNDVI	MCARI	MSAVI	NDRE	NDVI	SPAD
11.48342	77.13471	0.3133	0.3782	0.0135	0.6441	0.0225	0.5148	0.1933	0.8317	33.80
11.48335	77.13466	0.3163	0.5244	0.0143	0.7096	0.0281	0.5162	0.2069	0.8497	39.70
11.48331	77.13477	0.3071	0.3795	0.0139	0.6889	0.0256	0.5154	0.1605	0.8317	40.00
11.48336	77.13483	0.3692	0.6463	0.0171	0.8196	0.0399	0.5192	0.2618	0.8798	44.90
11.48332	77.13487	0.3955	0.7588	0.0147	0.7921	0.0359	0.5197	0.2751	0.8925	45.60
11.48326	77.13465	0.4145	0.6826	0.0163	0.7998	0.0371	0.5185	0.2440	0.8942	47.00
11.48320	77.13471	0.3214	0.4817	0.0144	0.7378	0.0300	0.5163	0.2076	0.8569	43.50
11.48341	77.13491	0.3577	0.5355	0.0158	0.7590	0.0345	0.5181	0.2222	0.8645	44.60
11.48326	77.13483	0.3150	0.4164	0.0121	0.6536	0.0219	0.5151	0.1703	0.8308	36.40
11.48321	77.13486	0.3139	0.4315	0.0133	0.6989	0.0290	0.5167	0.1875	0.8315	40.70
11.48321	77.13501	0.3170	0.4310	0.0140	0.7180	0.0276	0.5160	0.1973	0.8475	41.70
11.48326	77.13507	0.3231	0.4802	0.0127	0.7315	0.0249	0.5158	0.1936	0.8548	39.50
11.48332	77.13502	0.4135	0.5467	0.0158	0.7316	0.0392	0.5216	0.2347	0.8612	45.70
11.48336	77.13497	0.3349	0.6625	0.0165	0.7738	0.0369	0.5207	0.2488	0.8697	44.80
11.48343	77.13508	0.4269	0.7107	0.0166	0.8075	0.0378	0.5205	0.2534	0.8931	49.20
Mean		0.3493	0.5377	0.0147	0.7377	0.0314	0.5176	0.2171	0.8593	42.47

Table 4: Regression equation of different vegetation indices.

Vegetation index	Regression equation	R^2	RMSE
BGI	y = 78.111x + 15.19	0.665	2.49
CI	y = 27.158x + 27.869	0.677	2.44
EVI	y = 2252.3x + 9.2881	0.683	2.42
GNDVI	y = 69.365x - 8.6978	0.820	1.82
MCARI	y = 608.76x + 23.361	0.836	1.74
MSAVI	y = 1555.9x - 762.9	0.716	2.29
NDRE	y = 94.766x + 21.898	0.622	2.64
NDVI	y = 156.57x - 92.074	0.750	2.15

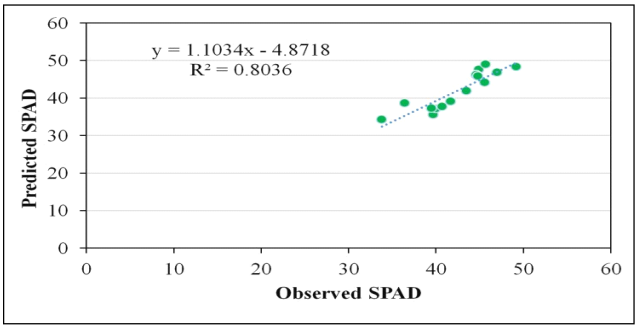


Fig 5: Accuracy assessment between observed and predicted SPAD values.

the SPAD values with NDVI, NDRE, SAVI and OSAVI indices and found high correlation in NDRE.

The chlorophyll map for the field was created using the regression equation of the highly correlated vegetation index (MCARI) given in Fig 4. The range of the SPAD valuewas ranges from 23.37 to 53.48. When the ground-truth SPAD data were used to assess the regression equation's accuracy, the R^2 value was 0.803 (Fig 5). A higher chlorophyll status indicates that the crop is in a healthy state, whereas a lower status indicates that it is under stress. The precise estimation of the chlorophyll content of crops can be useful in the application of N fertilizer dose.

CONCLUSION

The efficacy of using drone-derived vegetation indices for accurately estimating the chlorophyll content of rice crops provides valuable insights for precision agriculture. The field experiment highlighted the utility of various VIs, including NDVI, GNDVI and MCARI, in predicting chlorophyll content. Among these indices, MCARI exhibited the highest correlation with ground truth SPAD values (R = 0.914) and an R^2 value of 0.836, making it a particularly robust indicator of crop health. The high correlation between drone-derived indices and ground truth data underscores the potential of these indices to serve as reliable proxies for crop chlorophyll content and overall health. The spatial chlorophyll maps generated from these indices can significantly enhance decision-making in precision agriculture, particularly in the variable rate application of fertilizers. This approach not only optimizes nutrient management but also supports sustainable agricultural practices by ensuring efficient resource utilization.

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Conflict of interest

The authors declare no conflict of interest.

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