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RESEARCH

Use of Drone Imagery to Predict Leaf Nitrogen Content of Sugarcane Cultivated Under Organic Fertilizer Application

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ABSTRACT

This study investigated the potential of unmanned aerial vehicle (UAV) based multispectral imagery (MI) to predict the leaf nitrogen (N) content of sugarcane (*Saccharum officinarum L.*). MI of canopy cover of two sugarcane varieties (Co 775 and SL 96 128) applied with different doses of N (0 – 550 kg/ha) were captured at 4½ months after planting. These images were used to calculate 10 different vegetation indices (VIs). Five machine learning (ML) models were tested for their potential to predict leaf N status using the most appropriate VIs. The correlation analysis showed that DVI (Difference Vegetation Index) was the most powerful VI for the prediction of leaf N ($r = 0.81$), followed by the RVI (Ratio Vegetation Index) and NDVI (Normalized Difference Vegetation Index) ($R^2 = 0.78$ and 0.77, respectively). A threshold correlation ($r > 0.6$) was applied to select predictive variables for ML models and performance was evaluated using a validation data set of leaf N content. Individual variety testing revealed that PLSR (Partial Least Squares Regression) and SVR (Support Vector Regression) models as the best prediction models with the highest Coefficient of determination ($R^2 > 0.72$) and the lowest Root Mean Square Error values (RMSE<0.11). When both variety data were pooled, RF (Random Forest) demonstrated the highest predictive performance on the validation dataset, with an R^2 value of 0.66 with a RMSE value of 0.12. Generally, the prediction accuracy of models was less when data from both varieties were pooled. This study postulated the potential for the fusion of UAV MI and ML approaches to predict leaf N states and the importance of developing varietal-specific prediction models for the sugarcane vegetation.

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INTRODUCTION

Plant nutrient analysis is essential for determining the correct fertilizer requirement of crops, including sugarcane, particularly requirements of nitrogen, phosphorous, and potassium, which are required in higher quantities. Many studies have shown spatial variability of the nutrient status in sugarcane (Dongare et al., 2022; Salgado et al., 2020; Silva et al., 2020). Several factors have been linked with this spatial variability including sugarcane variety (Sumesh et al., 2021), water regime (Li et al., 2022), soil characteristics (Ortuani et al., 2019), management practices, and agro-climate. Site-specific fertilizer recommendations attempt to address this variability and optimize nutrient use efficiency (Nawar et al., 2017) by adjusting the application rate, time, and type of fertilizers such as organic and chemical fertilizers. However, studies showed that the type of fertilizer has variable effects on nutrient availability in soil and nutrient absorption in sugarcane cultivation. Hence, the determination of plant nutrient availability is critical to maintain an adequate nutrient supply to achieve optimum yield in sugarcane cultivation when using organic fertilizers as an option in site-specific fertilizer recommendations. In this context, plant nutrient analysis plays an important role in sustainable nutrient management for organic sugarcane cultivation. Accurate sugarcane plant nutrient analysis requires to obtain leaf samples and subsequent preparation of nutrient maps depending on the area of cultivation. However, the applicability of this approach in large sugarcane cultivations is limited due to cost and time constraints (Sanches et al., 2021).

Precision agriculture technologies have shown promise in gathering big data in agricultural systems in a cost and time-efficient manner (Carrer et al., 2022). Latest developments in Unmanned Aerial Vehicles (UAVs) and multispectral camera systems have opened new opportunities to gather accurate bio-physical data much more efficiently. This technology has been successfully used for making sugarcane yield predictions (Chea et al., 2020), disease detection (Narmilan et al., 2022), and nutrient status (Shendryk et al., 2020) prediction. The ability to capture multispectral images in lower altitudes with higher resolutions makes UAVs an excellent tool for replacing costly and low-resolution satellite images (Barbosa et al., 2022).

Reflections of sugarcane plant canopy can be captured using UAV-based multispectral imaging and different vegetative indices (VIs) are generated by using different ratios of multispectral bands. Several studies concluded that these VIs have a higher correlation with the crop attributes of the sugarcane plant. Narmilan, et al., (2022) studied the relationship between sugarcane leaf chlorophyll content and different vegetative indices derived from UAV multispectral images. Rahman et al., (2020) performed time-series data analysis using two different satellite data integration for the prediction of sugarcane crop yield at block level. Lisboa et al., (2018) found that NDVI effectively predicts the sugarcane yield and leaf nutrient content under different straw removal rates.

However, with the development of new remote sensing technologies, processing methods, and higher computing power, the estimation of crop nutrient status can be improved. Machine Learning (ML) algorithms have recently been applied to various agricultural remote-sensing techniques to monitor and predict sugarcane crop parameters (Benos et al., 2021). ML modeling creates an empirical relationship between independent and dependent variables without relying on specific crop attributes (Benos et al., 2021). Random Forest (RF), Partial Least Square Regression (PLSR), Multiple Linear Regression (MLR), Extreme Gradient Boosting (XGB), Support Vector Regression (SVR) and other machine learning algorithms are used for processing of UAV-based multispectral images (Benos et al., 2021; Ray, 2019). Xu et al., (2020) used different machine learning models to estimate sugarcane yield using UAV-LIDAR data and Canata et al., (2021) concluded that the RF regression method enabled the development of yield models for sugarcane cultivations than MLR at higher accuracy.

However, a limited number of studies have been conducted to predict sugarcane leaf nitrogen using machine learning modeling especially with the application of organic fertilizers. Hence, the main objective of the study was to assess the potential of the UAV-based multispectral imaging and ML algorithms to predict the status of sugarcane leaf nitrogen at the vegetative stage of the crop when organic fertilizers are used to provide the N requirement of the plants.

MATERIALS AND METHODS

Experimental field trial

The research study was carried out at the research farm of the Sugarcane Research Institute, Uda Walawe located in the low country dry zone of Sri Lanka. The experimental site (0.5 ha, central coordinates of 6°24' N Latitude and 80°49' E Longitude) was selected considering the land slope, flight suitability, and previous cropping history, which had more than two years of fallow period (Figure 1).

A research field trial was conducted during the growing season of 2020/2021 to assess the impact of various organic fertilizer rates on the growth and development of two major sugarcane varieties: SL 96 128 and Co 775. These varieties are widely cultivated in Sri Lanka and Co 775 is considered as one of the standard varieties for the breeding program of Sugarcane Research Institute (Sumedha et al., 2021).

The trial consisted of 64 research plots, each containing 5 rows of sugarcane plants (row spacing = 1.21 m) with a length of 7 meters, and four replicated plots for each of the seven treatments designed to provide varying amounts of nitrogen to the sugarcane plants. Commercially available organic fertilizers (product of Gal-Oya plantation [pvt] Limited) with around1% available nitrogen content made from sugarcane industry by-products (filter mud and Vinasse) was used as the nitrogen source for this study. Total organic fertilizer requirement for each plot was determined based on the supply of available nitrogen amount by the organic fertilizers. Table 1 shows the specific amounts of nitrogen provided under each treatment.

UAV survey

Sugarcane leaf sampling and UAV flight mission was carried out at 4½ months after planting representing the latter stages of the vegetative stage.Multispectral images were captured in the selected research field trial using a DJI P4 multispectral UAV. The DJI P4 UAV has a takeoff weight of 1487 g and an average flight time of 27 minutes. The DJI P4 multispectral imaging system is equipped with six cameras, including one RGB camera that produces images in JPEG file format and five other cameras that capture different multispectral images in TIFF file format. The multispectral cameras capture images in five imaging bands (Table 2).

Figure 1 Experiment site

Table 1. Treatments of the field trial

Treatments	Nitrogen rate
T1	550 kg/ha
T2	140 kg/ha
T3	40 kg/ha
T4	20 kg/ha
T5	10 kg/ha
T6	5 kg/ha
T7	0 kg/ha

Table 2. Spectral band information for the DJI P4 Multispectral UAV

Image band	Central wavelength (nm)	Wavelength width (nm)
Blue	450	32
Green	560	32
Red	650	32
Red-edge	730	32
Near-infrared	840	32

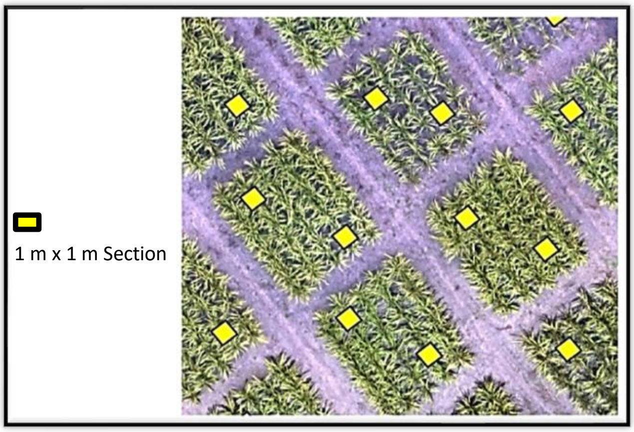

Figure 2 Demarcated 1 m^2 region of interest for leaf sample collection

Table 3 UAV flight mission parameters

Parameter	Value
Height	35 m
Ground sampling distance (GSD)	1.42 cm/px
Speed	6 ms^{-1}
Overlap	Front – 80 %, Side – 70 %
Time	9.30 am to 11.30

To enhance the accuracy of the flight mission, a D-RTK 2 (Real-time kinematics) mobile station was connected to the UAV. This technology allows for the UAV to be positioned with high precision without the need for an internet connection. Captured images were stored in the UAV hardware and downloaded for post-processing (Glavačević et al., 2023; Rabah et al., 2018). During the UAV flight mission for multispectral image capture, a clear day with a bright sky was selected between 9:30 a.m. and 11:30 a.m. The UAV was flown at a constant height of 35 m, and the flight height was maintained using the Barometer sensor in the UAV. Table 3 provides an overview of the parameters used in the UAV flight mission.

Leaf analysis of N content

Leaf samples were collected on the same day as the UAV flight mission. The research field trial was divided into 112 regions of interest (ROI) of 1 m^2 area, covering the middle three rows of each plot (Figure 2). Central GPS locations were obtained for each ROI using a Garmin Montana 700i™ GPS receiver. Four top visible dewlap (TVD) leaves were collected from each 1 m^2 section and combined to create a composite sample. Total of 112 leaf samples were tagged separately, placed in sealed polythene bags, and transported to the laboratory for further analysis.

The leaf samples were processed in the laboratory for analysis of total leaf nitrogen. The leaves were folded at their midpoint and a section of approximately 20 cm in length was cut from the folded end, taken from the middle portion of the leaf. The midrib was removed and the leaf sections were dried in an oven at 70 °C for 48 hours by following the method outlined by Calcino et al., (2000). The dried leaf samples were then ground using a leaf grinding machine and passed through a 1 mm mesh sieve. The ground leaf samples were stored in airtight containers for subsequent chemical analysis.

One hundred and twelve leaf samples were prepared for the analysis of total leaf nitrogen using the standard colorimetric method as described by Okalebo et al., (2002) and analyzed at the laboratory of the Crop Nutrition Division at the Sugarcane Research Institute in Sri Lanka.

Multispectral image analysis

Multispectral image map development was performed using Agisoft Metashape (Version 1.6.6; Agisoft LLC, Petersburg, Russia) mapping software. All bands were processed into individual maps using Agisoft Metashape (version: 1.8.5) and imported into ArcGIS software (version: 10.8). The reflectance values in the Red, Green, Blue, Red-Edge, and Near-Infrared band maps were utilized to create vegetation indices. Ten (10) distinct vegetation indices were produced using the raster calculator function in the ArcGIS software (version: 10.5), as presented in Table 4. The Soil-adjusted Vegetation Index (SAVI) was applied to remove soil and background shadow and isolate the sugarcane canopy for the prediction of sugarcane leaf nitrogen content, following the methodology proposed by Huete, (1988).

$$\text{Soil Adjusted Vegetation Index} = \frac{(NIR - R)}{(NIR + R + L)} \times (1 + L)$$

where, NIR, R and L are near-infrared, red band and 50% vegetation cover, respectively. GPS locations were imported into the ArcGIS and 1 m^2 ROIs shape files were created, using GPS location as the middle point of the 1 m^2 shape file. Each vegetation index map was extracted into 112 ROIs and average vegetation indices values of each ROI were taken into further analysis.

Statistical analysis and machine learning modeling

To investigate the relationship between UAV-derived vegetation indices and sugarcane total leaf nitrogen content, statistical analysis was performed using machine learning modeling in Python (version 3.8.10). Tested machine learning approaches included MLR, PLSR, RF, SVR, and XGB. To identify the most significant vegetation indices, Pearson's correlation coefficient (r) was applied. Five machine learning algorithms were employed after feature selection. The suitability of each algorithm was evaluated by calculating the root mean square error (RMSE) and coefficient of determination (R^2) for datasets that were randomly divided into 80% training sets (n=90) and 20% validation sets (n=22).

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

where, $\hat{y}_1$ and y_1 are the predicted and observed N content of ith sample and n is the total number of samples. Thus, lower values of RMSE show more accurate predictions of a model. On the other hand, higher R2 values show more accurate predictions.

Table 4 Different vegetation indices used in this study

No	Vegetation Index	Formula	Purpose
01	Normalized Difference Vegetation Index (NDVI)	$NDVI = \frac{NIR - R}{NIR + R}$	Estimation of vegetation biomass (Singh et al., 2006)
02	Green Normalized Difference Vegetation Index (GNDVI)	$GNDVI = \frac{NIR - G}{NIR + G}$	Estimation of vegetation fraction (Rahman et al., 2020)
03	Leaf Chlorophyll Index (LCI)	$LCI = \frac{NIR - Red\ Edge}{NIR + Red}$	Estimation of chlorophyll content (Narmilan et al., 2022)
04	Difference Vegetation Index (DVI)	$DVI = NIR - R$	Comparison of different reflectance indices for vegetation analysis (Scher et al., 2020)
05	Ratio Vegetation Index (RVI)	$RVI = \frac{NIR}{R}$	Sugar yield parameter detection (Chea et al., 2020)
06	Green Difference Vegetation Index (GDVI)	$GDVI = NIR - G$	Estimate productivity and assess phylogenetic heritability (Kumar et al., 2018)
07	Normalized Difference Red Edge Index (NDRE)	$NDRE = \frac{NIR - Red\ Edge}{NIR + Red\ Edge}$	Detect differences in vegetation and chlorophyll content (Boiarskii, 2019)
08	Green Chlorophyll Index (GCI)	$GCI = \frac{NIR}{R} - 1$	Estimation of leaf area index and green leaf biomass (Haboudane, 2004)
09	Normalized Green Red Difference Index (NGRDI)	$NGRDI = \frac{G - R}{G + R}$	Monitoring of crop biomass (Gitelson et al., 2003)
10	Enhanced Normalized Difference Vegetation Index (ENDVI)	$ENDVI = \frac{(NIR + G) - (2 \times B)}{(NIR + G) + (2 \times B)}$	Mapping of sugarcane to assess phylogenetic heritability (Scher et al., 2020)

The experimental process is shown in Figure 3.

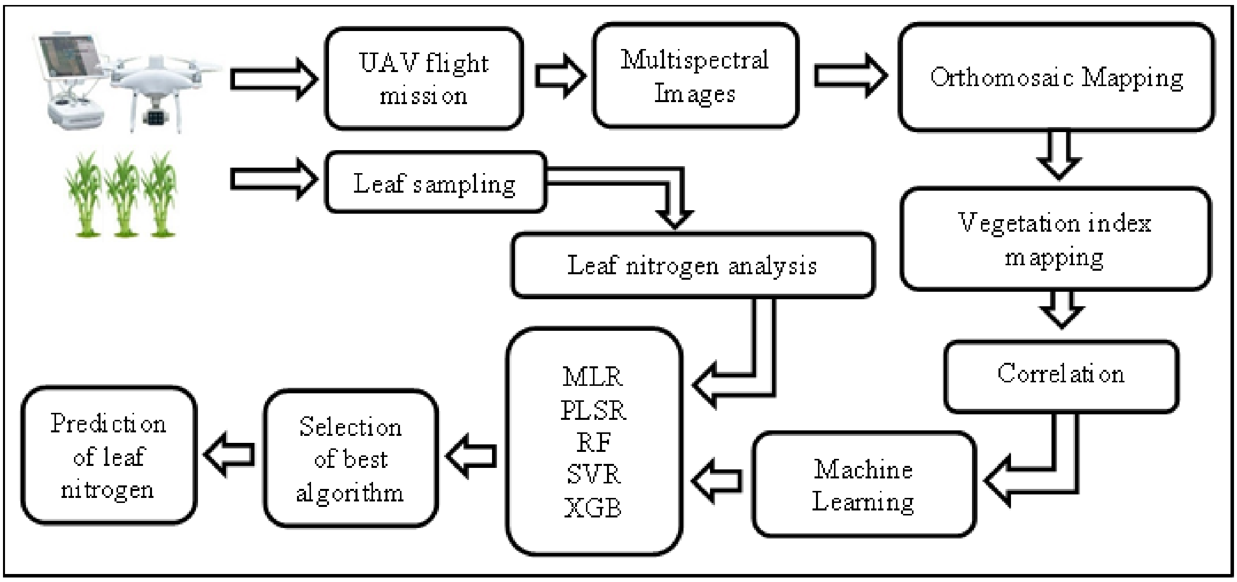

Figure 3 Summary of the methodology used in the prediction of leaf nitrogen content of sugarcane

RESULTS AND DISCUSSION

Correlation between vegetation indices and leaf nitrogen content

Table 5 shows the descriptive statistics for different VIs used in this study. LCI and NGRDI showed the highest variability (CV>75 %) and NDRE showed the lowest variability (CV<10 %). However, many VIs showed higher CV values (>30%) since the treatments used in this study supplied a range of nitrogen nutrient between 0 kg/ha to 550 kg/ha. Treatment variations were properly reflected in the VI results.

Several studies concluded that VI-derived CV has a strong correlation with sugarcane plant variations and the relationships were used in decision-making in sugarcane cultivation. Chanda et al., (2018) reported that CVs from the red-edge band had consistently negative linear relationships ($p < 0.001$), the strongest being at the early tillering stage (R^2= 0.61–0.73) which coincides with our findings. Raun et al., (2005) incorporated CV values derived from optical sensor readings (VIs) to adjust nitrogen recommendations for sugarcane cultivation. Arnall et al., (2006) analyzed midseason NDVI changes and harvested winter wheat yield in response to applied N, using NDVI-derived CV. Results indicated an improved linear relationship, with R^2 values increasing from 0.17 to 0.37.

According to the literature around 1.8 mg/kg to 2.5 mg/kg leaf nitrogen contents are categorized as optimum for sugarcane cultivation (Barros et al., 2022). The values represented in table 06 suggest T1 and T2 plots received optimum nitrogen supply, whereas T3 to T7 showed nitrogen stress. Descriptive statistics of leaf nitrogen content showed a good variability among different treatment suggesting its suitability for proper model development using machine learning models (Narmilan et al., 2022; You et al., 2023).

The Pearson`s Correlation Coefficients (r) showing the relationship between different vegetation indices and sugarcane leaf nitrogen content are shown in Figure 4

Table 5. Descriptive statistics of different vegetation indices

VIs	Minimum	Maximum	Range	Mean	CV (%)
NDVI	0.14	0.67	0.53	0.42	31
GNDVI	0.05	0.54	0.49	0.31	29
LCI	-0.27	0.33	0.60	0.10	100
DVI	29.15	145.10	115.95	89.03	31
RVI	1.33	5.10	3.78	2.69	33
GDVI	10.26	122.33	112.07	71.16	33
NDRE	-0.18	0.27	0.45	0.80	9
GCI	0.10	2.31	2.21	0.97	46
NGRDI	-0.10	0.34	0.43	0.13	77
ENDVI	0.02	497.45	0.34	0.37	19

Table 6. Descriptive statistics of leaf nitrogen content in different treatments and varieties

SL 96 128				Co 775			
Treatment	Mean	SD	SE	Treatment	Mean	SD	SE
T1	1.61	0.17	0.06	T1	1.79	0.29	0.09
T2	1.58	0.14	0.05	T2	1.73	0.34	0.12
T3	1.52	0.16	0.05	T3	1.58	0.28	0.10
T4	1.51	0.21	0.07	T4	1.56	0.15	0.05
T5	1.39	0.19	0.06	T5	1.54	0.26	0.10
T6	1.36	0.10	0.04	T6	1.52	0.23	0.08
T7	1.27	0.09	0.03	T7	1.44	0.29	0.10

*All the values are in mg/kg

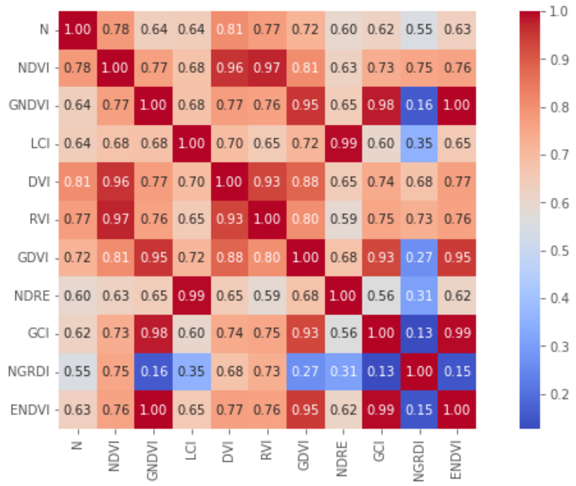

Figure 4 Correlation matrix for different vegetation indices and sugarcane leaf nitrogen contents

The DVI had the highest correlation (r= 0.81) with the leaf nitrogen level. The RVI and NDVI also had comparable high correlations (r = 0.78 and 0.77, respectively). This was further explained by maps of these VI's.

Vegetation reflect more spectrum of light near the NIR and Red region (Reisi Gahrouei et al., 2020; Yu et al., 2021) compared to other spectrum regions. Corti, (2016) observed that both normal and nitrogen-stressed crop canopies had greater reflectance (0.6) of electromagnetic radiation spectrum between 750 to 1000 nm region (NIR). Also, Scotford & Miller, (2005) indicate that the "Red-Edge" (at nearly 700 nm) is the narrow portion of the spectrum between R and NIR regions where vegetation uniquely causes reflectance to spike because R light is mostly absorbed by chlorophyll and NIR radiation is reflected.

The amount of reflections of these spectra is influenced by the chlorophyll content, leaf structure, presence of water, and chemical composition of the leaf canopy Hence vegetative indices derived from NIR and Red spectrum bands are suitable for the detection of the healthiness of the vegetation (Figure 5).

Prediction of sugarcane leaf nitrogen

Machine learning prediction algorithms were applied separately (separate analysis) to each sugarcane variety and to both varieties together (pooled analysis). Table 7 shows the model strength and prediction accuracies of different machine learning models applied for two varieties and Table 8 shows both varieties together.

Values of R^2 and RMSE of training data sets for both varieties of SL 96 128 and Co 775 revealed the most accurate predictions by RF and XGB models. However, high accuracies revealed for training data sets are not adequate to choose the best ML-based models due to their inherent nature of optimizing predictions (over fitting) to suit the training data set. Thus, many researchers have suggested using independent set data to choose the best prediction models. Interestingly, the validation of models using an independent validation data set revealed that the PLSR and SVR models as the best models resulted in the highest R^2 (>0.72) and the lowest RMSE values (<0.11). Studies conducted to predict sugarcane leaf nitrogen content using statistical and machine learning models had similar results. Barros et al., (2022) concluded that hyperspectral data to predict leaf nitrogen content in sugarcane with wavelengths were best correlated with leaf nitrogen selected using partial least square regression. Zheng et al., (2018) used PLSR mode and got better estimations of efficiency of the foliar N content prediction with lower RMSE and higher R^2 values. However, it should be noted that all prediction models resulted in accurate predictions of leaf N concentrations.

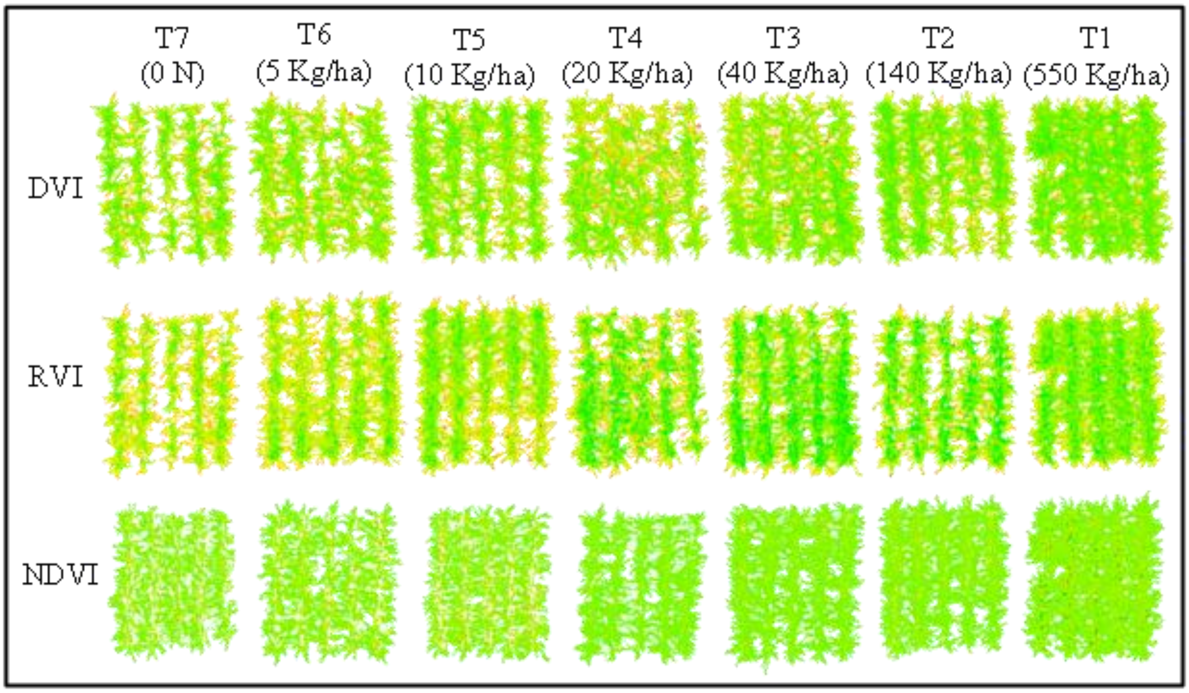

Figure 5 Maps of DVI, RVI, and NDVI pertaining to experimental plots supplied with different quantities of nitrogen

Table 7: Results of different ML models to predict leaf nitrogen in SL 96 128

ML model	SL 96 128				Co 775			
	R^2		RMSE		R^2		RMSE	
	Training	Validation	Training	Validation	Training	Validation	Training	Validation
MLR	0.74	0.61	0.10	0.13	0.75	0.68	0.10	0.13
PLSR	0.68	0.72	0.11	0.11	0.65	0.82	0.12	0.08
RF	0.94	0.66	0.05	0.12	0.94	0.65	0.05	0.11
SVR	0.70	0.70	0.11	0.11	0.65	0.85	0.12	0.08
XGB	0.99	0.36	0.01	0.16	0.99	-0.01	0.01	0.22

Table 8 Results of different ML models to predict leaf nitrogen in both sugarcanevarieties

ML model	R^2		RMSE	
	Training	Validation	Training	Validation
MLR	0.70	0.54	0.11	0.13
PLSR	0.68	0.54	0.12	0.13
RF	0.93	0.66	0.05	0.12
SVR	0.69	0.53	0.12	0.13
XGB	0.99	0.47	0.01	0.14

CONCLUSIONS

The objective of the study was to assess the potential of the UAV-based multispectral imaging and ML algorithms to predict the status of sugarcane leaf nitrogen at the vegetative stage of the crop when organic fertilizer is used to provide the N requirement of the plants. The findings showed the fusion of UAV-based multispectral imaging and ML algorithms leads to the prediction of leaf nitrogen status at a high accuracy even with the application of organic fertilizers. The PLSR, RF and SVM models gave higher predictive performances in both training and testing datasets. Overall, RF machine learning model performed well in both separate and pooled analysis and gave higher predictive accuracy. However, importantly the findings revealed that the predictive power of different machine learning approaches is dependent on the sugarcane variety. Therefore, the selection of an appropriate ML-based prediction model should take into account the distinct characteristics and requirements of the sugarcane variety being investigated. Further research is recommended to validate the performance of these models in other sugarcane varieties at different growth stages under different environmental conditions.

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