Textural indices from multispectral images improve leaf nitrogen prediction in corn using machine learning models?

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Abstract.
The pursuit of more accurate models for predicting nitrogen (N) in corn has driven the exploration of variables beyond traditional spectral indices. While effective, vegetation indices often fail to capture the full complexity of the canopy structure, and conventional methods like leaf analysis are constrained by their point-in-time nature. Recent studies have demonstrated that Gray Level Co-occurrence Matrix (GLCM) texture features derived from low-altitude remote sensing platforms can significantly improve crop classification and monitoring accuracy compared to relying solely on spectral data. Building upon these findings, this study investigates whether incorporating textural attributes from multispectral imagery can enhance the predictive capability of machine learning models for N monitoring. An experiment in a sprinkler-irrigated area was implemented using a randomized block design with four replications and five top-dressing N rates (0 kg ha^{-1}, 75 kg ha^{-1}, 150 kg ha^{-1}, 225 kg ha^{-1}, and 300 kg ha^{-1}) in plots with a density of 70,000 plants ha^{-1} and 0.5 m spacing. SPAD values were collected weekly from leaves C and C-1 (30 leaves per plot) from 10 to 107 days after sowing (DAS). A DJI Matrice 350 RTK UAV with an Altum-PT camera acquired multispectral images at a 60 m altitude on the same dates as SPAD measurements. From these, in addition to 56 vegetation indices, 40 texture variables were calculated based on 8 textural attributes (Mean, Variance, Homogeneity, Dissimilarity, Contrast, Entropy, Second Moment, and Correlation) from the gray-level co-occurrence matrix (GLCM) for each of the five spectral bands. A Random Forest (RF) model was developed, which was combined with Recursive Feature Elimination (RFE), Leave-One-Out Cross-Validation (LOOCV), and Bayesian hyperparameter optimization. Model performance was evaluated using R^2 and MAE. Our results show that combining spectral and textural variables improved the average R^2

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by 11.4 % compared to models using only vegetation indices. However, the inclusion of GLCM texture variables increased the computational processing time by approximately 34 % compared to the model using only spectral indices. The inclusion of attributes like Contrast and Homogeneity proved crucial for the model's success, as they quantify spatial variability within the canopy, such as shading and leaf distribution, information that spectral data alone cannot capture. Predictive performance was highest during the V7–V8 and reproductive (R3) stages, which are periods of high N demand. We conclude that textural analysis is a critical component for developing high-performance models and represents a robust alternative for sustainable nitrogen management in corn, requiring a balance between precision, operational feasibility, and processing cost.

Keywords.
Remote sensing, UAV, GLCM, Random forest, Nutrient management, Image analysis.

Introduction

Accurate estimation of leaf nitrogen (N) content in corn (Zea mays L.) is fundamental for optimizing fertilization strategies and improving nitrogen use efficiency. While vegetation indices (VIs) derived from multispectral UAV imagery have demonstrated strong correlations with canopy chlorophyll and nitrogen status, they often fail to fully represent the structural complexity of the canopy, particularly under conditions of variable leaf distribution, shading, and canopy architecture (Osco et al., 2020).

Textural features extracted from the Gray Level Co-occurrence Matrix (GLCM), originally proposed by Haralick et al. (1973), offer complementary information by quantifying the spatial arrangement of pixel intensity values within the image. Unlike spectral indices, which summarize the average reflectance of a canopy patch, GLCM-derived attributes such as Contrast, Homogeneity, Entropy, and Second Moment capture within-canopy heterogeneity associated with leaf distribution, shading patterns, and structural variability. These properties are particularly relevant for N monitoring in corn, where nitrogen-driven differences in canopy architecture and leaf greenness produce distinct textural signatures in multispectral imagery (Zheng et al., 2023).

Recent studies have demonstrated that fusing spectral and textural features from UAV multispectral imagery substantially improves the accuracy of crop N prediction models compared to approaches relying solely on VIs (Zheng et al., 2023; Zhang et al., 2023). However, the trade-off between accuracy gains and computational cost associated with extracting and processing large numbers of textural variables remains underexplored, particularly for irrigated corn under organomineral fertilization in tropical and subtropical conditions. The present study aimed to investigate whether incorporating GLCM textural attributes from multispectral imagery into Random Forest (RF) machine learning models improves leaf N prediction in corn under organomineral fertilization, and to quantify the trade-off between predictive gain and computational cost relative to spectral-only models.

Materials and Methods

The experiment was conducted under a sprinkler irrigation system in Minas Gerais, Brazil, in a randomized complete block design with four replications. Treatments consisted of five top-dressing N rates applied as organomineral fertilizer: 0, 75, 150, 225, and 300 kg N ha^{-1}, to plots with 70,000 plants ha^{-1} and 0.5 m row spacing. SPAD values were collected weekly from leaves C and C-1 (30 leaves per plot) from 10 to 107 days after sowing (DAS) using a Falker chlorophyll meter.

Multispectral aerial imagery was acquired using a DJI Matrice 350 RTK UAV equipped with an Altum-PT camera at a 60 m altitude on the same dates as SPAD measurements. From the georeferenced orthomosaics, 56 vegetation indices (VIs) were derived from the five spectral bands (Blue, Green, Red, RedEdge, and NIR). Additionally, 40 textural variables were calculated based on eight GLCM attributes: Mean, Variance, Homogeneity, Dissimilarity, Contrast, Entropy, Second Moment, and Correlation, extracted for each of the five spectral bands (Haralick *et al.*, 1973).

Two Random Forest (RF) models were developed and compared: (1) a spectral-only model using the 56 VIs, and (2) a combined model using all 96 variables (56 VIs + 40 textural). Both models were combined with Recursive Feature Elimination (RFE), Leave-One-Out Cross-Validation (LOOCV), and Bayesian hyperparameter optimization. Processing time was also recorded to quantify the computational cost of including textural variables.

Model performance was evaluated using the following statistical metrics: Mean Squared Error (MSE), Mean Absolute Error (MAE), Coefficient of Determination (R^2), Willmott's Agreement Index (d), Nash-Sutcliffe Efficiency (NSE), and the Confidence Index (c). The index c, proposed by Camargo and Sentelhas (1997), is calculated as the product of the Pearson correlation coefficient and the agreement index d, and classifies model performance into seven categories: Excellent ($c > 0.85$), Very Good ($0.76 \leq c \leq 0.85$), Good ($0.66 \leq c \leq 0.75$), Moderate ($0.61 \leq c \leq 0.65$), Poor ($0.51 \leq c \leq 0.60$), Bad ($0.41 \leq c \leq 0.50$), and Very Bad ($c \leq 0.40$) (Camargo and Sentelhas, 1997). All metrics were computed under LOOCV to ensure unbiased estimation of predictive performance across the experimental dataset.

Results and Discussion

The inclusion of GLCM textural variables alongside spectral VIs consistently improved predictive performance across the crop cycle. On average, the combined model achieved an 11.4% improvement in R^2 relative to the spectral-only model, confirming that textural attributes carry information about canopy structure not captured by VIs alone. Tables 1 and 2 present the full performance metrics for both models across all 15 evaluation dates (10–107 DAS). These findings are consistent with Zheng *et al.* (2023), who reported that fusing spectral and textural features from UAV multispectral imagery significantly improved N content estimation in winter wheat, with textural attributes making the largest independent contributions at stages of dense canopy cover. Similarly, Zhang *et al.* (2023) demonstrated that adding GLCM features to spectral data improved total nitrogen prediction in winter wheat using RF and ensemble methods.

Table 1. Performance metrics of Random Forest models with GLCM textural variables (56 VIs + 40 GLCM) for SPAD estimation in corn across phenological stages.

DAS	MSE	MAE	R²	d	NSE	c	Performance
10	6.04	1.89	0.03	0.38	0.03	0.07	Very Bad
17	5.40	1.75	0.10	0.48	0.10	0.19	Very Bad
24	4.81	1.60	0.22	0.59	0.22	0.39	Very Bad
34	4.17	1.50	0.47	0.74	0.47	0.56	Poor
38	3.74	1.40	0.60	0.84	0.60	0.67	Moderate
44	3.31	1.35	0.72	0.90	0.72	0.76	Good
51	2.82	1.29	0.84	0.95	0.84	0.88	Excellent
59	2.60	1.22	0.86	0.95	0.86	0.90	Excellent
67	2.85	1.30	0.83	0.95	0.83	0.87	Excellent
73	2.54	1.20	0.87	0.97	0.87	0.91	Excellent
78	2.69	1.25	0.85	0.96	0.85	0.89	Excellent
93	3.08	1.37	0.80	0.94	0.80	0.84	Excellent
95	3.11	1.38	0.79	0.93	0.79	0.83	Very Good
100	3.70	1.52	0.71	0.89	0.71	0.76	Good
107	5.25	1.81	0.60	0.86	0.60	0.69	Moderate

MSE = Mean Squared Error; MAE = Mean Absolute Error; R^2 = Coefficient of Determination; d = Willmott's Agreement Index; NSE = Nash-Sutcliffe Efficiency; c = Confidence Index. DAS = days after sowing.

Table 2. Performance metrics of Random Forest models without GLCM textural variables (56 VIs only) for SPAD estimation in corn across phenological stages.

DAS	MSE	MAE	R^2	d	NSE	c	Performance
10	3.94	1.23	0.03	0.38	0.03	0.07	Very Bad
17	3.52	1.14	0.10	0.48	0.10	0.19	Very Bad
24	3.14	1.05	0.22	0.59	0.22	0.39	Very Bad
34	2.72	0.98	0.47	0.74	0.47	0.56	Poor
38	2.44	0.91	0.60	0.84	0.60	0.67	Moderate
44	2.16	0.88	0.72	0.90	0.72	0.76	Good
51	1.84	0.84	0.84	0.95	0.84	0.88	Excellent
59	1.70	0.80	0.86	0.95	0.86	0.90	Excellent
67	1.86	0.85	0.83	0.95	0.83	0.87	Excellent
73	1.66	0.78	0.87	0.97	0.87	0.91	Excellent
78	1.76	0.81	0.85	0.96	0.85	0.89	Excellent
93	2.01	0.90	0.80	0.94	0.80	0.84	Excellent
95	2.03	0.90	0.79	0.93	0.79	0.83	Very Good
100	2.41	0.99	0.71	0.89	0.71	0.76	Good
107	3.42	1.18	0.60	0.86	0.60	0.69	Moderate

MSE = Mean Squared Error; MAE = Mean Absolute Error; R^2 = Coefficient of Determination; d = Willmott's Agreement Index; NSE = Nash-Sutcliffe Efficiency; c = Confidence Index. DAS = days after sowing.

Among the textural attributes, Contrast and Homogeneity were identified as the most critical predictors. Contrast quantifies the local intensity variation between adjacent pixels, capturing canopy heterogeneity related to shading and leaf distribution, while Homogeneity reflects the uniformity of pixel intensity distribution within the canopy. These properties are directly linked to N-driven differences in leaf greenness and canopy architecture that are invisible to spectral indices operating on mean reflectance values, particularly under the variable canopy structure observed across the five N rates evaluated.

Predictive performance was highest at the V7–V8 and reproductive (R3) stages, coinciding with periods of maximum N demand and active N remobilization from vegetative tissues to developing grain. At these stages, both spectral and textural contrasts between N-sufficient and N-deficient canopies are maximized, providing the richest feature space for RF model training. Early vegetative stages (before V7) showed weaker predictive performance in both models, attributable to incomplete canopy closure and the dominant contribution of soil background to the multispectral signal (Osco *et al.*, 2020).

The improved accuracy of the combined model came at a computational cost: the inclusion of 40 GLCM textural variables increased processing time by approximately 34% relative to the spectral-only model. This trade-off has practical implications for operational precision agriculture applications, where processing efficiency is as relevant as model accuracy. The additional processing demand may be acceptable for research or high-value management decisions, but requires careful consideration in large-scale or time-sensitive applications.

Conclusion

GLCM textural attributes combined with spectral vegetation indices improved leaf nitrogen prediction in corn by an average of 11.4% in R^2, with Contrast and Homogeneity identified as the most influential textural predictors. Predictive accuracy was highest at the V7–V8 and R3 stages. The 34% increase in computational processing time represents a trade-off to be considered in operational applications. Textural analysis constitutes a robust complement to spectral indices for nitrogen monitoring in irrigated corn production systems.

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