Aerial Insights: Advancing Nitrogen Estimation in Field Crops using Multispectral Imaging

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Abstract

Estimating the nitrogen (N) content of crops is crucial for determining key indicators such as nitrogen use efficiency (NUE). Traditionally, most methods for assessing N content have been destructive, time-consuming, and labor-intensive. In this study, we present a non-destructive approach using unmanned aerial vehicle (UAV) multispectral imagery to estimate crop nitrogen content at various growth stages. Multispectral drone data were collected over canola and wheat fields at three growth stages across two experimental sites in Alberta, Canada, over two growing seasons (2023–2024). Simultaneously, leaf tissue samples were gathered from different nitrogen treatment levels, each replicated four times. Multiple machine learning (ML) models were developed and tested to predict plant nitrogen uptake. Our findings indicate that multispectral imagery can estimate N content in canola with a root mean square error (RMSE) ranging from 0.38 to 0.71 and a coefficient of determination (R^2) between 0.77 and 0.92. For wheat, the RMSE values ranged from 0.33 to 0.68, with R^2 values between 0.5 and 0.89. The models showed good transferability across both study sites and two years, suggesting the feasibility of scaling N-content estimation to broader areas. Overall, our results highlight the strong potential of UAV-based multispectral imaging as a reliable, non-invasive tool for estimating nitrogen-related parameters, including plant N-uptake and NUE.

1. Introduction

In precision agriculture, nitrogen (N) fertilizer is vital for improving crop yields and enhancing nutritional quality (Raghuram et al., 2022). However, the overuse and inefficient application of N fertilizers contribute significantly to greenhouse gas (GHG) emissions and pose considerable environmental risks (Herman et al., 1995). Therefore, accurately monitoring crop nitrogen status across various growth stages is critical for maintaining an optimal soil-plant nitrogen balance (Yousfi et al., 2019) and for assessing nitrogen-use efficiency (NUE).

Traditional methods for determining plant nitrogen content rely on destructive sampling techniques, which are often subjective, labor-intensive, time-consuming, and costly. In contrast, high-throughput multispectral imaging (MSI) has emerged as a promising non-destructive alternative for measuring plant nitrogen uptake, offering scalability for large-scale agricultural monitoring (Perich et al., 2021).

While remote sensing has been used for crop traits estimation for over a decade (Perich et al., 2021; Thieme et al., 2024), most of the earlier work focused on satellite-based observations (Thieme et al., 2024). Even with the increasing adoption of unmanned aerial vehicles (UAVs), their use has primarily been limited to mapping applications (Thieme et al., 2024; Valarezo-Plaza et al., 2024). Consequently, estimating crop N-content has remained a complex and often impractical task with traditional airborne remote sensing systems (Loozen et al., 2018). However, recent advancements in compact, lightweight multispectral sensors specifically designed for UAV platforms have enabled a range of new capabilities that were previously inaccessible (Phang et al., 2023). Among these, estimating nitrogen content has become especially valuable due to its implications for both agricultural productivity and environmental sustainability.

A number of recent studies have explored the feasibility of estimating N-content using multispectral and hyperspectral imagery (Chegoonian et al., 2024; Peddle et al., 2024). For example, one study successfully employed data fusion techniques and machine learning algorithms to estimate nitrogen levels in winter wheat (Ding et al., 2022). By combining multispectral, RGB, and thermal infrared imagery, the study demonstrated that machine learning models can effectively predict nitrogen content. Similarly, UAV-based hyperspectral imaging has been used to estimate nitrogen in paddy rice, with vegetation indices and ML approaches accurately capturing both leaf and whole-plant nitrogen levels at various growth stages (Wang et al., 2021).

In this study, we present findings on nitrogen content estimation in canola and wheat crops subjected to different nitrogen treatments. Using two years of multispectral imagery collected via UAV, we evaluated the performance of six machine learning models: Partial Least Squares Regression (PLSR), Support Vector Regression (SVR), Extreme Gradient Boosting (XGBoost), multi-layer perceptron artificial neural networks (ANN), Random Forest (RF), and Gradient Boosting Regression (GBR). Model predictions were validated using ground-truth data obtained from leaf tissue sampling conducted throughout the growing season in two sites in Alberta, Canada. The following sections provide a comprehensive overview of the methodology, followed by detailed results and discussion.

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2. Materials and Methods

2.1 Study Sites

The study was carried out on two sites: an Agriculture and Agri-Food Canada (AAFC) trial at Lethbridge County (Fairfield farm - 49°42'12.7"N, 112°41'51.4"W) in Southern Alberta and a John-Deere (JD) trial at Wheatland County (Strathmore - 51°3'30.17"N, 113°10'26.34"W) in central Alberta. For simplicity, the former trial will be referred to as "AAFC" and the latter as "JD" in the following text. While the former site was seeded by spring wheat and canola for 2023 and 2024, the latter was only planned in 2024.

These two sites were selected based on uniform soil fertility, texture, and moisture characteristics. AAFC-Fairfield is an irrigated site, and it has an average temperature of 14°c and accumulated precipitation of ~200 mm during the growing season, while these values are 13°c and ~250 mm for the JD-Strathmore trial, which is a rain-fed site. The landscape of the AAFC field is gently rolling with a very low slope of around 2%, where the dominant soil is an Orthic Dark Brown Chernozem. In contrast, the JD trial exhibits a hummocky or ridged, medium-relief terrain with a steeper, limiting slope of approximately 9%. Here, the soils include both Orthic Dark Brown Chernozem and Calcareous Dark Brown Chernozem on moderately coarse-textured sediments. Together, these diverse soil and weather characteristics guarantee that the results of this study could represent irrigated and non-irrigated agricultural fields in Alberta.

2.2 Experimental Design

The experimental design of the trials followed a randomized complete block design (RCBD), with Lethbridge having 10 treatments and 4 replicates (40 plots total) and Strathmore having 10 treatments and 2 replicates (20 plots total), including untreated control plots. The field trials ensured uniform soil fertility, texture, and moisture conditions, with nitrogen applied at variable rates based on location-specific equipment and capabilities.

At AAFC, plots measured 2.5m × 6m with 2.5m pathways and 4m alleyways, while JD plots were 76.2m × 12.2m with 12.2m pathways. The seeding rate was 120 seeds/m² for canola and 300 seeds/m² for wheat. Nitrogen treatments included an untreated control, 100% nitrogen at seeding, and various split applications between seeding time and in-crop, i.e., 90%-10%, 80%-20%, 70%-30%, 60%-40%, 50%-50%, 70%-0%, 50%-20%, 50%-0%. The only difference between this design for 2024 and the design for 2023 was the addition of three extra treatments, bringing the total to ten treatments per crop compared to seven treatments in 2023. We used 46-0-0 fertilizer, with UAN applied at late tillering for wheat and at the 4-6 leaf stage in canola prior to bolting. These treatments helped assess the effects of different nitrogen application strategies on crop yield and quality. Figure 1 shows the location of two sites within Alberta and Canada as well as the location of canola and wheat trials in the AAFC and JD sites.

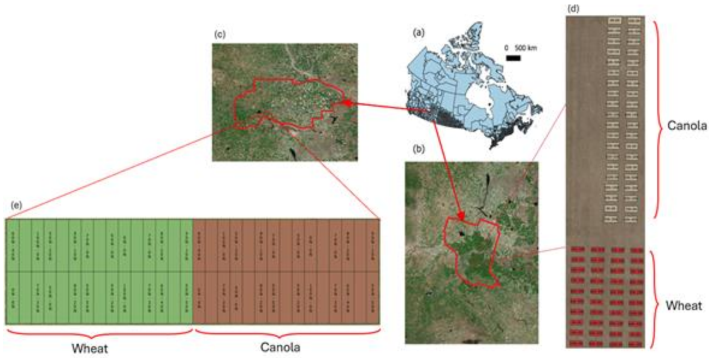

Figure 1. The geographical location of field trials (a) in Canada, (b) in Lethbridge County agricultural division, (c) in Wheatland County, and (d) showing canola and wheat plots at Fairfield and Strathmore trials with their associated UAN application at and after seeding.

2.3 Data Acquisition

Figure 2 presents a workflow chart of the methodology used in this study. Data collection included soil samples for pre-seeding and post-harvest nitrogen levels, as well as weather data from on-site stations monitoring rainfall, temperature, and soil moisture.

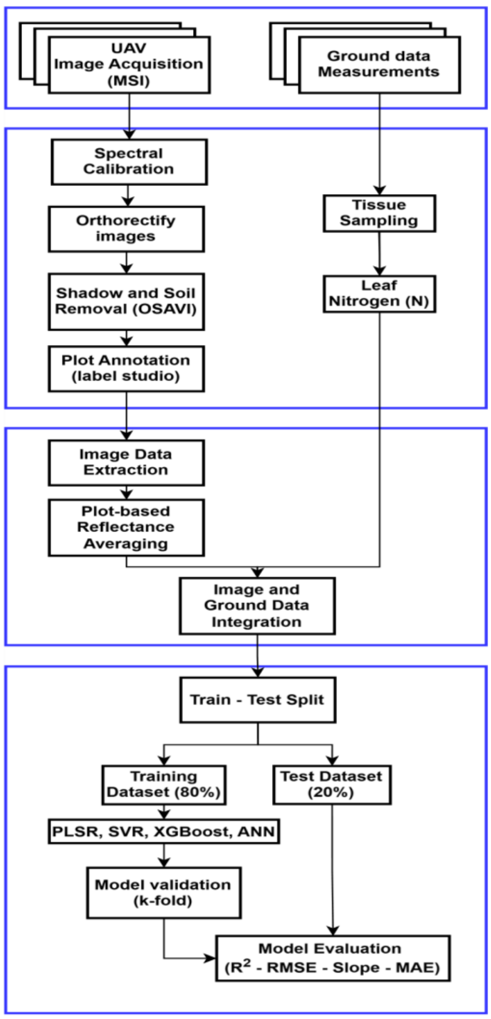

Figure 2. A flowchart of the methodology of the study.

For MSI imaging, a RedEdge multispectral camera (MicaSense, Inc., Seattle, WA, USA) mounted on a DJI-M300 RTK drone (SZ DJI Technology Co., Ltd., Shenzhen, China) gathered imagery during in-crop nitrogen application (Baseline - BL), two intermediate dates (~30DAT and ~60DAT), and during crop maturity before harvesting (only for the AAFC trial). UAV flight altitude was set to 25m above ground level (AGL), with the imaging speed of 2.5 m/s. The flight parameters were established with the overlap of 80%-85% in forward and lateral directions that resulted in a ground sampling distance (GSD) of 1.63 cm/pix. A D-RTK2 GNSS base station was deployed during the image acquisition to improve the positional accuracy. Imagery was captured on sunny days around solar noon and calibrated using the known values of a white reflectance panel along with the downwelling irradiance sensor (DLS-2) to compensate for the variable incident light conditions (Panigrahi et al., 2025). Figure 3 shows some steps of UAV data collection conducted in this project.

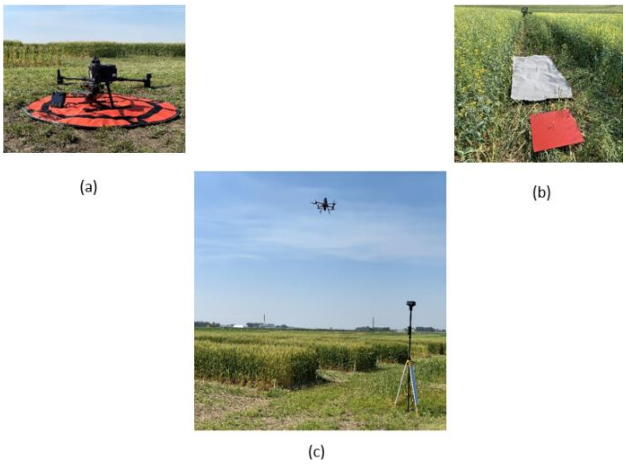

Figure 3. Photos of some steps of data collection conducted in this project. (a) UAV equipped with MSI sensor before flight, (b) calibration tarp used for radiometric calibration of taken images, (c) UAV over the crops with GPS instrument to orthorectify images.

Coinciding with UAV image capture, soil and leaf tissue samples were also collected for nutrient analysis at the Down to Earth Labs, Lethbridge, AB (www.downtoearthlabs.com). After crop harvest, grain yield, protein content, and nitrogen content were measured for wheat, while yield, protein, nitrogen, and oil content were measured for canola using a John Deere HarvestLab™ 3000 sensor. These ground-truth data were then matched with their corresponding image values and extracted by averaging reflectance values over corresponding plots. This results in 263 matchups (N) for each crop for which ground-truth N-content and multispectral reflectance values are known.

2.4 Image Processing and Analysis

Imagery data were processed using a commercial software package (Pix4D) and further analyzed using open-source Label Studio and Python packages to generate geo-referenced orthomosaic maps (Figure 4), extract plot-based reflectance values, and develop ML models, respectively.

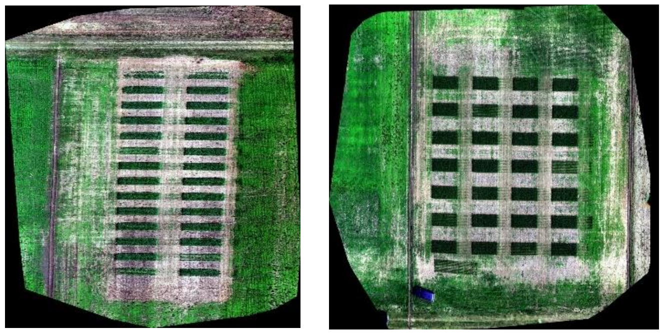

Figure 4. UAV captured MSI orthomosaic imagery generated for canola (left), and wheat (right) field trials in Lethbridge, AB. MSI images are visualized in true-color composition.

We then used PLSR, as a regression technique, since it is suitable for data with multicollinearity, making it useful for modeling spectral data (Geladi et al., 1986). SVR, based on Support Vector Machines, was also employed as it excels in handling non-linear relationships by mapping data to a higher-dimensional space (Drucker et al., 1997). XGBoost, GBR, and RF, as ensemble learning methods, which are popular for their speed and performance in structured data, especially with tabular data (Chen and Guestrin 2016), were also tested. Lastly, we investigated ANN as it leverages layers of interconnected nodes to capture complex patterns, making it adaptable across various datasets, particularly those with high-dimensional features (LeCun et al., 2015).

These ML models were trained by considering 80% of matchups and evaluated by the remaining in a five-fold cross-validation approach that set aside one fifth of the data in each round as unseen data. During the training phase, hyperparameters of the models were determined using a grid search algorithm that uses one fifth of training data for validation.

The performance of the models was evaluated based on their accuracy in estimating nitrogen uptake in terms of Coefficient of Determination (R^2), Slope, Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) estimates. The formulation of these evaluation metrics are provided in Equations 1-4, where: y_i is the observed value, $\hat{y}_i$ is the predicted value, $\bar{y}$ is the mean of observed values, n is the number of observations, and $\bar{\hat{y}}$ is the mean of predicted values.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad \text{Eq. 1}$$

$$\text{Slope} = \frac{\sum_{i=1}^{n}(y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad \text{Eq. 2}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad \text{Eq. 3}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad \text{Eq. 4}$$

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3. Results and Discussion

3.1 Canola

Table 1 shows the evaluation results for estimating nitrogen content in canola at AAFC and JD sites using different machine learning models for both MSI dataset in 2023 and 2024 years. The results suggests that MSI data can retrieve N-content in canola with reasonably high accuracy ($R^2 > 0.8$ and RMSE ≈ 0.5). Although all six tested models perform well, RF shows the best accuracy for MSI data.

Table 1. The results of nitrogen content estimation in **canola** at the AAFC and JD sites, utilizing various machine learning models. *N* shows the number of samples. Best performances are highlighted in bold text.

Model	Metric	MSI		
		AAFC		JD
		2023	2024	2024
PLSR	R^2	0.92	0.78	0.84
	RMSE	0.39%	0.63%	0.44%
SVR	R^2	0.92	0.84	0.84
	RMSE	0.38%	0.62%	0.45%
XGBOOST	R^2	0.77	0.81	0.82
	RMSE	0.59%	0.71%	0.47%
ANN	R^2	0.91	0.89	0.13
	RMSE	0.38%	0.5%	0.87%
RF	R^2	**0.93**	**0.9**	**0.87**
	RMSE	**0.38%**	**0.49%**	**0.4%**
GBR	R^2	0.8	0.83	0.84
	RMSE	0.71%	0.69%	0.46%
	N	84	119	60

To gain a more comprehensive understanding of model performance and limitations, we combined all available data—regardless of location (AAFC and JD sites) or year (2023 and 2024)—and used this aggregated dataset to train and test the machine learning models. This approach allowed us to evaluate model generalizability across varying conditions. The results of this assessment are presented in Figure 5.

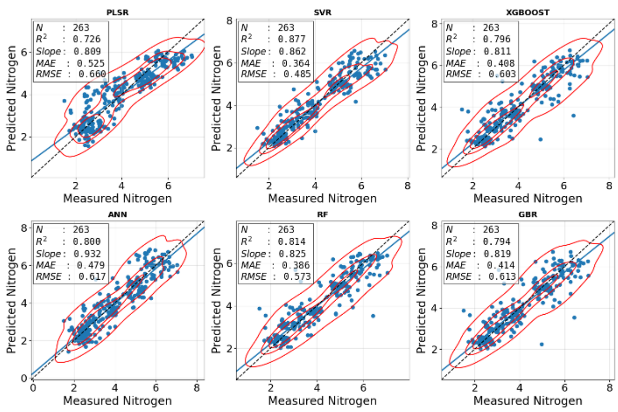

Figure 5. Evaluation results for nitrogen content estimation in **canola** using MSI data with different ML algorithms for all samples collected in two locations (AAFC, JD) and two years (2023 and 2024).

This assessment revealed the strong performance of the SVR model in estimating canola nitrogen uptake using MSI data, followed closely by the Random Forest (RF) model. The superior performance of SVR in this context may be attributed to its robustness in handling larger datasets and managing uncertainties more effectively than RF. With the exception of PLSR, all other tested models were able to predict nitrogen uptake from MSI data with $R^2 > 0.80$.

3.2 Wheat

Table 2 shows the evaluation results for estimating nitrogen content in canola at AAFC and JD sites using different machine learning models for MSI dataset in 2023 and 2024 years. The result shows that MSI data can retrieve N-content in wheat with reasonably high accuracy ($R^2 > 0.7$ and RMSE ≈ 0.6). Despite the good performance of all six tested models, SVR shows the best accuracy.

Table 2. Presents the assessment results of nitrogen content estimation in **wheat** at the AAFC and JD sites, utilizing various machine learning models with MSI dataset for the years 2023 and 2024. N shows the number of samples. Best performances are highlighted in bold text.

Model	Metric	MSI		
		AAFC		JD
		2023	2024	2024
PLSR	R^2	0.82	0.67	0.75
	RMSE	0.39%	0.57%	0.4%
SVR	R^2	0.87	**0.69**	**0.8**
	RMSE	0.35%	**0.56%**	**0.36%**
XGBOOST	R^2	0.71	0.57	0.63
	RMSE	0.52%	0.68%	0.47%
ANN	R^2	**0.89**	0.65	0.75
	RMSE	**0.33%**	0.6%	0.4%
RF	R^2	0.6	0.59	0.7
	RMSE	0.65%	0.67%	0.43%
GBR	R^2	0.53	0.5	0.69
	RMSE	0.74%	0.75%	0.45%
	N	84	119	60

We also asses the models based on combining all available data, regardless of locations and years to evaluate model generalizability across varying conditions. The results of this assessment are presented in Figure 6.

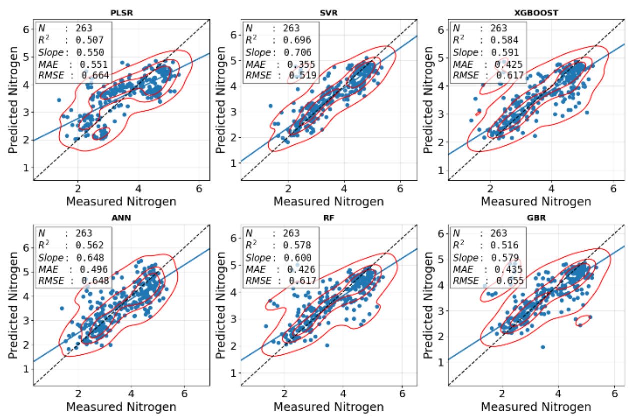

Figure 6. Evaluation results for nitrogen content estimation in **wheat** using MSI data with different ML algorithms for all samples collected in two locations (AAFC, JD) and two years (2023-2024).

The stronger performance of SVR ($R^2 \approx 0.7$ and RMSE ≈ 0.5%) compared to the other models for estimating the N-content of wheat using MSI data is drawn in Figure 6. SVR substantially outperformed the other models (10% higher accuracy). Again, the superior performance of SVR may be attributed to its robustness in handling larger datasets and managing uncertainties more effectively. All other models predict nitrogen uptake from MSI data with an $R^2 < 0.60$, with PLSR showing the lowest accuracy, a similar finding to what has been observed for canola. Overall, the estimation of N-content in wheat shows a substantial decrement in accuracy compared to predicting N-content in canola. The superior performance of the canola models suggests that differences in plant structure and spectral reflectance influence predictive accuracy. This is supported by findings in previous studies (Liu et al., 2023).

4. Conclusion

The results from this study demonstrated that N-uptake of canola and wheat crop could be estimated using multispectral drone sensors with high accuracy indicated by a high coefficient of determination ($R^2 > 0.7$) and low root mean square error (RMSE < 0.5) during the growing season. This promises that ML models, particularly SVR that overcome the other two models, could be applicable across different regions and crop types. However, the study faced limitations, particularly the small dataset size, which restricted the robustness of conclusions. Overfitting remains a concern with such a limited dataset, and future research should aim to incorporate more data from additional trials at diverse climatic regions to ensure broader generalizability.

The strong performance of the models may serve as a benchmark for future research. A key avenue for further investigation could involve exploring high-resolution hyperspectral imagery to estimate N uptake, allowing for a comparison of different datasets and methodologies to evaluate their relative advantages. This would provide deeper insights into the capabilities of optimal wavebands selection using advanced imaging technologies and refine current methods for assessing nitrogen dynamics in crops.

These findings represent an initial step in a larger effort to employ imaging technologies for more precise nitrogen management in agriculture. Accurate nitrogen uptake estimates can lead to improved nitrogen use efficiency assessments across different treatments and farming practices. In the long-term, this will likely have broader economic and environmental impacts by reducing nitrogen losses to the environment through leaching, emissions, or volatilization.

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