Deriving structural and biochemical crop traits from one UAV sensor: Investigating a multiband VNIR/SWIR imaging system for crop trait monitoring

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Abstract

Frame-based VNIR/SWIR multispectral sensors on UAVs offer promising capabilities for precision agriculture by enabling the easy simultaneous acquisition of spectral and structural crop information. This study provides an independent validation of a two-band VNIR/SWIR sensor system for monitoring winter wheat traits and compares the results with previous findings. The UAV flights were conducted on a single date (May 11, 2022), capturing image datasets at wavelengths of 910, 980, 1100, 1200, 1510, and 1650 nm. Structure from Motion (SfM) processing enabled crop height extraction from the same multispectral datasets. Ground-truth data included fresh and dry biomass, moisture, nitrogen concentration, and nitrogen uptake from 36 samples across six varieties and three fertilization levels. Bivariate regression analyses revealed moderate performance for spectral vegetation indices (NRI: R^2=0.52-0.61; GnyLi: R^2=0.50-0.62), which was lower than that previously reported. Crop height showed a superior predictive capability (R^2=0.63-0.75), demonstrating consistency across studies. Multivariate models combining vegetation indices with crop height significantly improved trait estimation (R^2=0.72-0.84, nRMSE=0.12-0.15), confirming that integrated spectral-structural approaches provide robust performance even when individual predictors show limitations. While this single-date analysis limits conclusions about temporal stability throughout the growing season, it provides valuable validation of the capabilities of the sensor system. The ability to derive both structural and biochemical data from single-sensor imagery is the key advantage of this camera system. Future research should expand to multi-temporal analyses across complete growing seasons and implement the recently developed 6-channel VNIR/SWIR system to address the current limitations. This study reinforces the fact that combining SWIR spectral features with structural parameters is essential for reliable estimation of crop traits.

1. Introduction

Spatial heterogeneity plays a central role in the approaches of precision agriculture (Mulla, 2013). For many applications, satellite-based remote sensing does not provide the desired spatial and temporal resolutions for within-field variability. The highest spatiotemporal resolution from remote sensing approaches is provided by different types of sensors carried by Unmanned Aerial Vehicles (UAVs) (Bareth, 2021). Optical multispectral or hyperspectral sensors are generally used to derive biochemical crop traits (e.g., chlorophyll) or structural properties (e.g., LAI) (Roberts et al., 2019). For the latter, Structure from Motion and Multiview Stereopsis (SfM/MVS) (Bendig et al., 2015), and laser scanning (Hütt et al., 2023) have been applied to UAV-based data acquisition.

Recent advances in UAV-based shortwave infrared (SWIR) sensing have shown promising results for crop monitoring. Bendig et al. (2015) demonstrated that combining SWIR vegetation indices (VIs) with crop height (CH) has high potential for robust crop trait estimation. Following this approach, Jenal et al. (2019) developed a frame-based multiband SWIR imaging system capable of deriving both spectral and structural information from the same sensor platform, similar to the approach presented by Oliveira et al. (2019). Initial validation showed promising results (Jenal et al., 2021); however, independent verification across different growing seasons and conditions is essential to establish the reliability of this technology.

The importance of integrating spectral and structural data is further supported by Näsi et al. (2018) and Viljanen et al. (2018), who independently validated this approach using different sensor configurations. Näsi et al. (2018) conducted a comprehensive evaluation of UAV-based hyperspectral and RGB imaging for barley and grass biomass estimation, demonstrating that the integration of spectral and 3D features consistently improved estimation accuracy. Similarly, Viljanen et al. (2018) achieved Pearson correlation coefficients (PCCs) of up to 0.98 for grass biomass using machine learning to combine photogrammetric CH with multispectral VIs, confirming that this integrated approach maintained robust performance even when individual predictors showed limitations.

Although single-date analyses using traditional optical visible and near-infrared (VNIR) sensors often show moderate to weak performance for crop trait estimation, the integration of SWIR spectral features with structural parameters offers a potential solution. However, the consistency of this approach across different years and environmental conditions requires further investigation to support its operational deployment in precision agriculture.

Therefore, this study aimed to (i) provide independent validation of the frame-based VNIR/SWIR sensor system for winter wheat monitoring, (ii) evaluate the individual and combined performance of SWIR vegetation indices and crop height for trait estimation, and (iii) compare the results with previous findings to assess temporal consistency. We hypothesized that the integration of SWIR VIs with CH will significantly improve crop trait estimation compared to bivariate approaches, validating the methodology proposed by Bendig et al. (2015) and demonstrated by Jenal et al. (2025).

2. Study Area and Methods

2.1 Study Area

This study was conducted at Campus Klein-Altendorf, the largest external laboratory of the University of Bonn's Faculty of Agriculture, during the 2021/2022 growing season. The winter wheat field trial employed a split-plot design consisting of five replicates arranged in rows, with each replicate containing three nitrogen fertilization treatments (0, 120, and 240 kg/ha). Six

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winter wheat varieties were randomly distributed within each nitrogen treatment across 7.0 × 1.5 m plots, maintaining 11.3 cm spacing between seed rows. This design resulted in 18 plots per replicate, with a total of 90 experimental plots across the field (Figure 1).

Winter wheat cultivars were sown in November 2021. Two replicates (rows 2 and 4) were designated for destructive sampling throughout the growing season. Sampling commenced in early April 2022, with subsequent collections occurring at two-week intervals, coinciding with fertilization treatment applications. Seven sampling dates were established, with 36 samples collected on each occasion.

Each sampling event was accompanied by a UAV-based VINIR/SWIR data collection campaign. During the May 11, 2022, UAV campaign, 1 × 0.3 m sampling areas were harvested (indicated by dark red squares in Figure 1) for comprehensive laboratory analysis, including fresh biomass (FBM), dry biomass (DBM), moisture content, and nitrogen concentration (N_{conc}). Nitrogen uptake (N uptake) was calculated from DBM and N_{conc} measurements (Lemaire and Gastal, 1997). Twelve ground control points (GCPs) were strategically positioned across the field to ensure precise geolocation accuracy for all the image datasets.

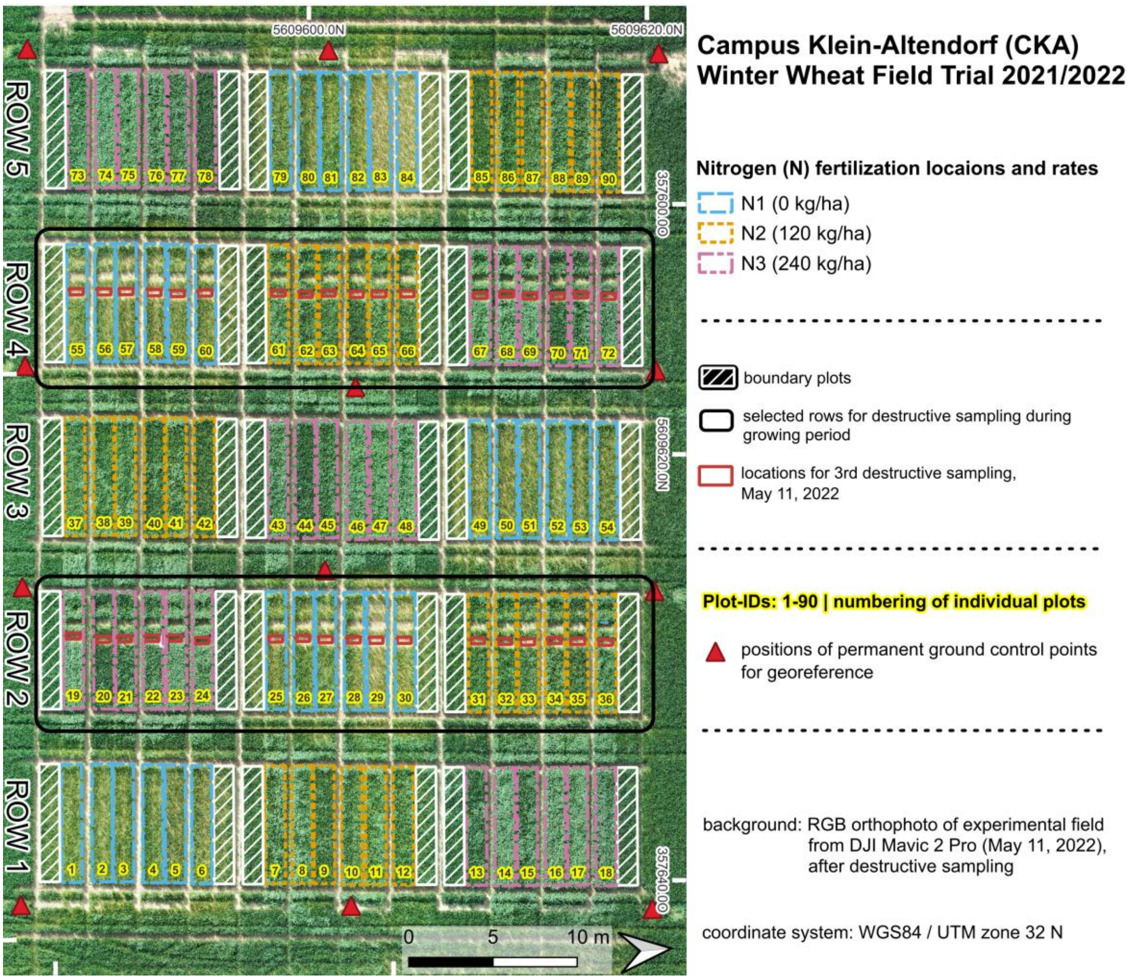

Figure 1: Layout of winter wheat experiment 2022 at Campus Klein-Altendorf (CKA). A Digital Orthophoto (DOP) of May 11, 2022, plot outlines and areas of destructive samplings in row 2 and 4 (black outlines) are shown.

2.2 UAV-based Image Acquisition

Data acquisition was conducted using a newly developed multispectral imaging system optimized for UAV applications, focusing on the shortwave infrared (SWIR) region (Figure 2; modified from Jenal et al., 2019). To the best of our knowledge, this is the first multispectral multi-camera imaging system designed specifically for UAV-based applications. The unique two-band VNIR/SWIR multicamera system comprises three integrated modules: an UAV equipped with a gimbal stabilization system, a sensor-managing unit (SMU), and a spectral camera unit (SCU).

The SCU forms the core of the instrument and incorporates two VNIR-enhanced SWIR cameras based on indium gallium arsenide (InGaAs) technology. These cameras feature interchangeable narrow bandpass filters mounted via a specialized filter flange system, enabling adaptation to specific wavelength combinations between 600 and 1700 nm. This configuration allows the collection of two image datasets per flight at selected wavelengths, with additional wavelengths requiring multiple flights and corresponding filter changes. The SMU provides centralized control of the SCU while managing the readout and storage of the raw image data.

On May 11, 2022, around solar noon, the UAV-based system acquired image data across six spectral bands (910, 980, 1100, 1200, 1510, and 1650 nm) during three consecutive four-minute flights conducted at approximately 30 m above ground level. High-resolution image datasets were recorded at a ground sampling distance (GSD) of 4 cm/px. Data collection was performed under clear-sky conditions.

2.3 Data Processing and Analysis

After flat field correction, each spectral channel image dataset was calibrated from digital numbers to reflectance values using an empirical line method with six grayscale panels strategically positioned next to the experimental field. The image datasets were processed using the Agisoft Metashape software (version 1.8.2) to generate georeferenced digital orthophotos (DOPs) and digital elevation models (DEMs).
Two vegetation indices were derived from the DOPs at 910, 980, 1100, and 1200 nm for subsequent analysis. The four-band GnyLi (Eq. 1; Gnyp et al., 2014), and two-band Normalized Ratio Index (NRI) (Eq. 2; Koppe et al., 2010). Canopy height (CH) was determined by subtracting the mean DEM heights on May 11, 2022, from the baseline model obtained at the start of the growth period. Spectral and structural information was extracted from the destructively sampled areas using zonal statistics. The derived data were analyzed using regression-based models with sampled ground-truth data, with data from the six varieties pooled within each of the three fertilization treatments to establish robust general relationships.

$$\mathrm{GnyLi} = \frac{(\mathrm{R}_{910} \cdot \mathrm{R}_{1100}) - (\mathrm{R}_{980} \cdot \mathrm{R}_{1200})}{(\mathrm{R}_{910} \cdot \mathrm{R}_{1100}) + (\mathrm{R}_{980} \cdot \mathrm{R}_{1200})} \tag{1}$$

$$\mathrm{NRI} = \frac{R_{910} - R_{1200}}{R_{910} + R_{1200}} \tag{2}$$

Figure 2: Concept of the modular VNIR/SWIR system design (modified from Jenal et al. 2019)

3. Results

The predictive performance of spectral vegetation indices (NRI and GnyLi) and crop surface height (CH) for estimating crop traits was evaluated using both bivariate and multivariate linear regression models for the dataset of May 11, 2022. Pooled data from six crop varieties (n = 36) were analyzed for five key traits: fresh biomass matter (FBM), dry biomass matter (DBM), moisture content, nitrogen concentration (N_{conc}), and nitrogen uptake (N uptake). The model performance was assessed using the coefficient of determination (R^2), root mean square error (RMSE), normalized RMSE (nRMSE), and statistical significance tests. The results are presented in the following two sections. First, the individual predictive capabilities of each variable were examined through bivariate models, followed by an evaluation of combined predictor models to test the hypothesis that multivariate approaches improve trait estimation accuracy.

Table 1: Bivariate regression results for UAV-derived VIs (GnyLi and NRI) and CH against destructively measured crop traits for May 11, 2022.

Crop Trait	NRI			GnyLi			CH		
	R^2	RMSE	nRMSE	R^2	RMSE	nRMSE	R^2	RMSE	nRMSE
FBM (t/ha)	0.54	7.18	0.21	0.55	7.10	0.21	0.73	5.43	0.16
DBM (t/ha)	0.55	0.91	0.19	0.58	0.89	0.18	0.70	0.75	0.15
Moisture (t/ha)	0.52	6.40	0.22	0.53	6.34	0.22	0.73	4.84	0.17
N_{conc} (%)	0.55	0.32	0.19	0.55	0.32	0.19	0.63	0.29	0.17
N uptake (kg/ha)	0.61	31.5	0.18	0.62	31.3	0.18	0.75	25.5	0.15

3.1 Bivariate Analysis

All three predictors (NRI, GnyLi, and CH) showed highly significant relationships ($p < 0.001$) with all crop traits across the six pooled varieties (Table 1, Figure 3). Among the spectral vegetation indices, GnyLi marginally outperformed NRI for most traits, with R^2 values ranging from 0.53-0.62 compared to 0.52-0.61 for NRI. However, crop surface height (CH) demonstrated consistently superior predictive capability, achieving R^2 values between 0.63-0.75 across all traits.

The strongest relationships were observed for N uptake (Figure 3, bottom row), where CH explained 75% of the variance (R^2 = 0.75, nRMSE = 14.8%), followed by VIs (NRI: R^2 = 0.61, nRMSE = 18.3%; GnyLi: R^2 = 0.62, nRMSE = 18.1%). For biomass-related traits (FBM and DBM), CH also showed superior performance, with R^2 values of 0.73 and 0.70, respectively, representing improvements of approximately 18-20 percentage points over the spectral indices. The scatter plots revealed tighter clustering around the regression lines for CH compared to both vegetation indices, particularly for moisture and biomass traits (Figure 3). The normalized RMSE values indicate good model precision, ranging from 14.8-21.8% across all models, with CH consistently achieving the lowest values.

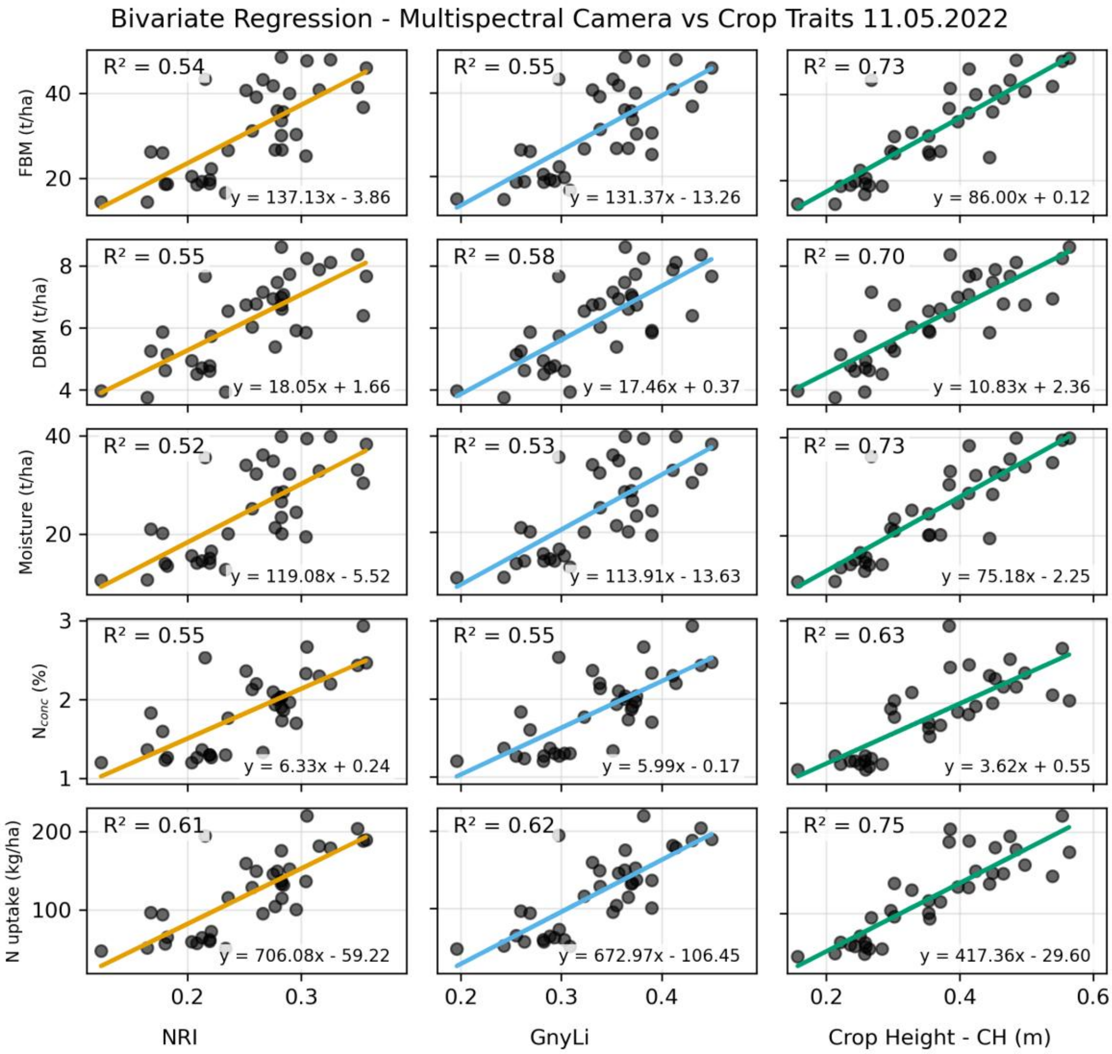

Figure 3: Bivariate linear regression models between spectral VIs (NRI, GnyLi), crop surface height (CH), and five crop traits for May 11, 2022.

3.2 Multivariate Analysis

Combining spectral vegetation indices with crop surface height significantly improved model performance for all traits (Table 2). The NRI plus CH models achieved R^2 values ranging from 0.72-0.84, while GnyLi plus CH combinations showed similar performance (R^2 = 0.72-0.84). Both multivariate approaches resulted in substantial improvements over their respective bivariate VI models, with R^2 increases of 17-24 percentage points for biomass traits and 21-23 percentage points for N uptake.

The three-dimensional response surfaces illustrate the complementary nature of combining spectral and structural information (Figure 4 and Figure 5). For both, DBM and N uptake, the regression planes showed how the traits increased with both predictor variables, with steeper gradients along the CH axis indicating a stronger influence. The highest predictive accuracy was achieved for N uptake, in which both multivariate models explained 84% of the variance (R^2 = 0.84, nRMSE = 12%). The surface plots demonstrate minimal interaction effects between the predictors, as evidenced by the relatively planar response surfaces rather than the curved or warped surfaces.

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All regression coefficients remained highly significant ($p < 0.01$) in the multivariate models, indicating that both predictors independently contributed to the explained variance. The F-statistics (42.38-84.41) confirmed the overall significance of all the multivariate models ($p < 0.001$). Notably, the improvement from bivariate CH to multivariate models was modest (6-9 percentage points), suggesting that CH already captured much of the trait variation independently. The similar performance of NRI & CH versus GnyLi & CH combinations indicates that either vegetation index can be effectively paired with crop height for improved trait estimation.

Table 2: Multivariate regression results combining VIs and crop height (GnyLi & CH, NRI & CH) against destructively measured and derived crop traits

Crop Trait	NRI & CH			GnyLi & CH		
	R^2	RMSE	nRMSE	R2	RMSE	nRMSE
FBM (t/ha)	0.79	4.83	0.14	0.79	4.79	0.14
DBM (t/ha)	0.77	0.65	0.13	0.78	0.64	0.13
Moisture (t/ha)	0.78	4.36	0.15	0.78	4.34	0.15
N_{conc} (%)	0.72	0.25	0.15	0.72	0.25	0.15
N uptake (kg/ha)	0.84	20.56	0.12	0.84	20.47	0.12

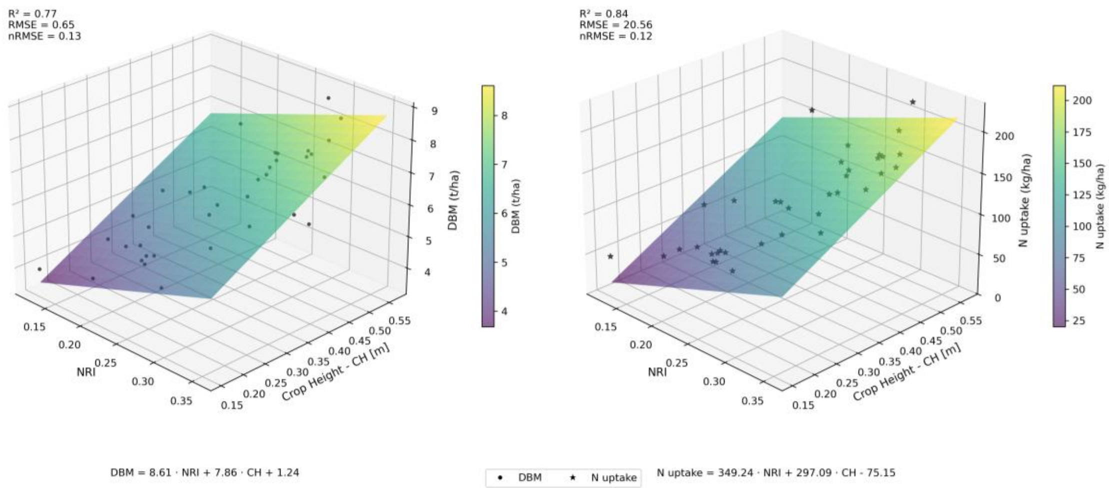

Figure 4: Three-dimensional response surfaces for multivariate regression models combining NRI and crop height (CH) as predictors for dry biomass matter (DBM, left) and N uptake (right). Color gradients indicate the predicted trait values.

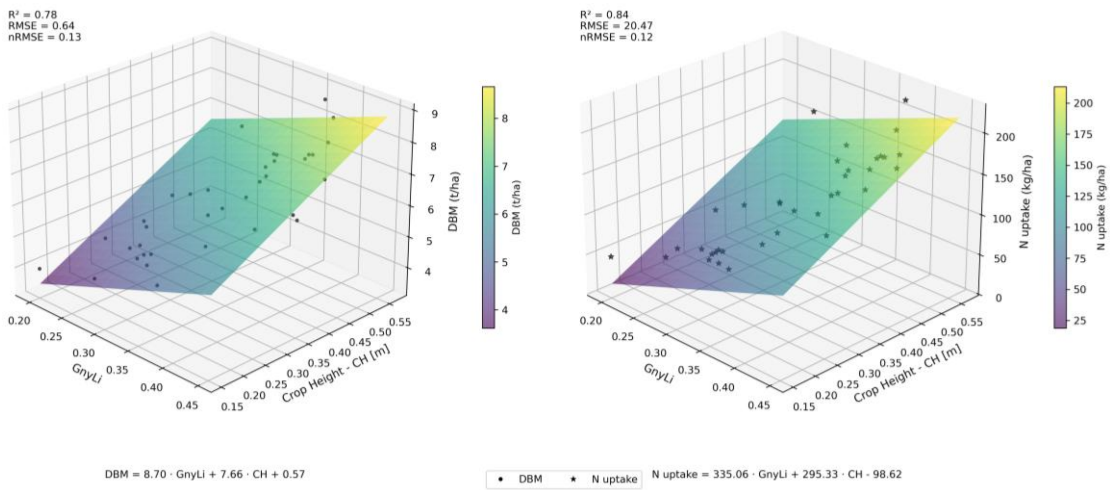

Figure 5: Three-dimensional response surfaces for bivariate regression models combining GnyLi and crop height (CH) as predictors for dry biomass matter (DBM, left) and nitrogen uptake (right). Color gradients indicate the predicted trait values.

4. Discussion

The present study evaluated the performance of a VNIR/SWIR multispectral UAV sensor system for monitoring winter wheat traits based on the methodology established by Jenal et al. (2025). Using the same sensor system and spectral bands (910, 980, 1100, and 1200 nm), our analysis provides an independent validation of this technology, while revealing both consistencies and notable differences in performance.

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4.1 Comparison with previous findings

Our bivariate regression results showed moderate to strong correlations between spectral indices and crop traits, although generally lower than those reported by Jenal et al. (2025) for a similar dataset on May 12, 2021. For instance, NRI achieved R^2 values of 0.52-0.61 across traits in our study, compared to 0.74-0.84 reported in 2021. Similarly, GnyLi performance was considerably lower, with R^2 values of 0.50-0.62 versus 0.59-0.85 in the previous study. This difference is particularly intriguing given that our data collection occurred under clear-sky conditions, whereas Jenal et al. (2025) reported challenging weather with variable cloud cover during the campaign on May 12, 2021.
The discrepancy in the bivariate model performance between studies suggests that factors beyond weather or illumination conditions may influence the effectiveness of the spectral index. Potential explanations include differences in crop development stages between the two sampling dates, variety-specific responses within the pooled datasets, or variations in soil background effects. Despite similar sampling dates in mid-May, the one-year gap between studies could result in different crop phenological stages owing to year-specific growing conditions and temperature patterns, potentially affecting the spectral response of vegetation indices, particularly in the SWIR region (Basinger et al., 2020; Longchamps and Philpot, 2023).
Comparing the improvements from bivariate to multivariate regression in both studies revealed an interesting pattern. In Jenal et al. (2025), the integration of vegetation indices with crop height improved the R^2 values by 6-11 percentage points for NRI and 23-31 percentage points for GnyLi. In contrast, our study showed substantially larger improvements for NRI (17-26 percentage points) but slightly smaller improvements for GnyLi (17-25 percentage points). This difference is particularly noteworthy because, despite starting from lower bivariate R^2 values in our study, the multivariate models achieved comparable performance to Jenal et al. (2025), with final R^2 values of 0.72-0.84. The larger relative improvement in our study, especially for NRI, demonstrates that the integration of structural information becomes even more valuable when spectral indices alone show weaker performance, effectively compensating for limitations in individual predictors, and confirming the robustness of the integrated approach across varying conditions.
The importance of integrating spectral and structural data has been supported by recent studies. Both Näsi et al. (2018) and Viljanen et al. (2018) independently demonstrated that combining 3D features with spectral data consistently outperformed single-modality approaches across different sensor configurations (hyperspectral FPI vs. RGB-NIR) and analytical methods (Random Forest vs. MLR), with performance improvements ranging from 10-20 percentage points in R^2. This aligns with our findings and reinforces the robustness of the integrated approach across studies and environmental conditions.

4.2 Structural information performance

Crop height demonstrated a consistently strong predictive capability in both studies. Our CH results (R^2 = 0.63-0.75) align well with the general findings of Jenal et al. (2021) and Jenal et al. (2025), who emphasized the importance of structural parameters for trait estimation. Similar findings are reported by Bareth et al. (2025, accepted). The robust performance of CH across both years and different weather conditions underscores its reliability as a predictive variable. This consistency suggests that structural information is less sensitive to atmospheric conditions and spectral variations than vegetation indices, making it a valuable complement to the spectral data.

4.3 Enhanced performance through data integration

Despite the lower bivariate performance of spectral indices compared to CH, our multivariate models combining VIs with CH achieved excellent results, with R^2 values ranging from 0.72-0.84 across all traits. These findings strongly support the integrated approach advocated by Bendig et al. (2015) and demonstrate that the complementary nature of spectral and structural information can compensate for the limitations of individual predictors. This improvement was particularly notable for biomass traits, where R^2 increased by up to 24 percentage points when combining predictors.
The success of multivariate models in our study, achieving similar or better performance than Jenal et al. (2021) despite weaker bivariate VI results, highlights the robustness of the integrated approach. This is consistent with the findings of Näsi et al. (2018) and Viljanen et al. (2018), who reported optimal performance when combining 3D and spectral features regardless of the sensor type or regression method used.
Our results confirm that frame-based VNIR/SWIR sensors can successfully derive both spectral and structural information from a single platform, thus validating the technological approach introduced by Jenal et al. (2019). The ability to extract crop height through SfM/MVS processing from multispectral SWIR imagery represents a significant advantage over pushbroom systems that are primarily designed for spectral data acquisition. The advantages of frame-based multispectral sensors for simultaneous spectral and structural data acquisition have been independently validated by Näsi et al. (2018) using FPI hyperspectral cameras, and Viljanen et al. (2018) using RGB-NIR sensors, both achieving optimal results through feature integration. This convergent evidence from multiple sensor configurations strengthens confidence in the operational deployment of integrated spectral-structural approaches for precision agriculture applications.
The varying performance of the spectral indices between years emphasizes the importance of multi-temporal validation studies. While our study provides valuable independent validation, the differences observed suggest that robust crop monitoring systems should not rely solely on spectral information but should integrate structural parameters to ensure consistent performance across varying conditions.

5. Conclusion

This study successfully validated a frame-based VNIR/SWIR UAV sensor system for estimating winter wheat traits by integrating spectral vegetation indices and structural parameters. Our independent evaluation confirms the technological approach introduced by Jenal et al. (2019), while revealing important considerations for operational deployment.
A clear advantage of a frame-based multispectral camera system is its ability to easily derive both spectral and structural information from the same image dataset. Through SfM/MVS processing, crop height can be extracted along with spectral vegetation indices from overlapping frame images, eliminating the need for separate sensors or multiple flights. This dual capability of a single sensor platform represents a significant advancement over pushbroom systems, which are primarily limited to spectral data acquisition. Our multivariate models combining vegetation indices (NRI and GnyLi) with crop height achieved high accuracy (R^2 = 0.72-0.84) across all traits, demonstrating that this integrated data acquisition approach can provide robust trait estimation even when individual spectral indices show variable performance.

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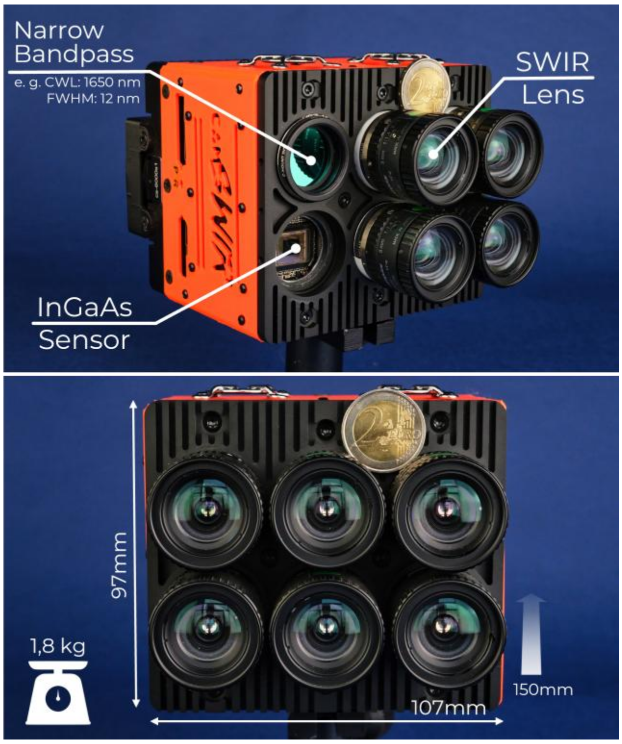

Figure 6: Advanced 6-channel VNIR/SWIR multicamera system for airborne (crewed and uncrewed) remote sensing applications (Jenal et al., 2024).

However, the differences in the bivariate spectral index performance between our study and those of Jenal et al. (2021) and Jenal et al. (2025) highlight critical areas for further investigation. The lower R^2 values observed for both the NRI and GnyLi, despite favorable weather conditions, suggest potential calibration uncertainties that require attention. Future implementations should prioritize rigorous calibration protocols and consider environmental factors beyond weather conditions that may influence the spectral responses.

The recent development of a 6-channel VNIR/SWIR multicamera system, as introduced by Jenal et al. (2024), offers promising solutions to the current limitations (Figure 6). This expanded system maintains the crucial advantage of deriving both spectral and structural information from frame-based imagery, while providing enhanced spectral capability. The increased number of parallel acquired bands should enable more robust vegetation indices by simultaneously capturing wavelengths critical for biochemical constituent detection, potentially reducing the sensitivity to calibration errors.

This study reinforces the idea that integrating spectral SWIR features with structural parameters, both derived from the same multispectral image datasets, is essential for achieving the consistency and accuracy required for practical precision agriculture applications. Future research should focus on multi-temporal and multi-site validation to establish robust operational protocols for this promising technology. The robustness of combining SWIR spectral features with structural parameters was independently confirmed by Näsi et al. (2018), who demonstrated similar improvements in the accuracy of crop trait estimation when integrating hyperspectral and 3D features across different sensor configurations and flying heights. This convergent evidence from multiple studies strengthens confidence in the operational deployment of integrated spectral-structural approaches for precision agriculture applications.

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