54. Airborne and satellite imagery for optimizing nitrogen management in bread wheat (*Triticum aestivum* L.)

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Abstract

This study evaluated remote sensing for early estimation of yield, grain protein concentration, and nitrogen (N) output in bread wheat (*Triticum aestivum* L.). Conducted over two years in Spain, it combined hyperspectral and thermal airborne imaging with Sentinel satellite data, applying models to assess estimation accuracy. Visible and near infrared (VNIR) and short-wave infrared bands (SWIR) provided reliable yield estimates, and red-edge indices improved N output and grain protein predictions. Models using Sentinel-2 VNIR and SWIR data performed comparably to VNIR hyperspectral models, with short-wave infrared bands enhancing N-related trait accuracy. The findings highlight the effectiveness of Sentinel-2 for crop monitoring, N-fertilization management and food security.

Keywords: fertilization, grain quality, machine learning, nitrogen, yield prediction

Introduction

Nitrogen (N) and water are the main limiting factors in agriculture and, therefore, they are frequently applied for optimizing crop production or quality (Gonzalez-Dugo *et al*., 2009). As a consequence, overfertilization is a common practice and only about half of the N fertilizer applied is assimilated by the crops. The rest of the N is lost to the environment causing serious problems for water and air quality (Mosier *et al*., 2013). Adjusting fertilization to crop requirements is a crucial strategy for increasing N use efficiency and reducing water and air pollution (Gabriel *et al*., 2017).
Spectral remote sensors have proven to be a reliable tool for estimating crop N status and crop traits that determine production; therefore, they can contribute to optimizing N fertilization (e.g., Quemada *et al*., 2014). However, the interaction between N and water status may produce confounding effects in the acquired spectral reflectance and thermal sensors may be needed to disentangle between crop N and water stress (Pancorbo *et al*. 2021). The simultaneous use of various remote sensing (RS) equipment provides multiple advantages, but it is necessary to identify the most suitable and affordable sensor as well as the most sensitive spectral region in order to optimize early crop trait prediction (Prey and Schmidhalter, 2019).
Hyperspectral sensors are more sensitive than broader-band multispectral and offer more spectral information that can be useful for crop monitoring (Li *et al*., 2021). However, hyperspectral

sensors are less affordable and have spatial coverage limitations. For these reasons, freely accessible multispectral satellite images for crop monitoring or yield forecasting receive increasing attention. The error committed in the assessment of many crop traits is still high using parametric statistical models, particularly for many traits related to crop N status and grain quality (Raya-Sereno *et al.*, 2021a). Non-parametric models, such as random forest (RF) or artificial neural network (ANN) are expected to improve crop traits prediction base on RS thanks to their ability to find patterns and extract information from big datasets (Van Klompenburg *et al.*, 2020).
The objectives of this study were (i) to evaluate the potential of airborne hyperspectral and multispectral satellite sensors to map grain yield, N output and grain protein concentration (GPC) in bread wheat (*Triticum aestivum* L.) and (ii) to assess the role of models to improve N fertilizer recommendation.

Materials and methods

The study was carried out at La Chimenea field station, near Aranjuez, Madrid, Spain in an 8-ha field. The soil was mapped as Haplic Calcisol (pH≈8.1, medium organic matter content, and a silty clay loam texture*)* and the climate classified as cold semi-arid (Bsk). Half of the field was sown with winter wheat (*Triticum aestivum* L.) in November 2017, and the other half in 2018 (Figure 1). A factorial experiment was established by randomly distributing 32 plots (25×25 m^2) into four N levels (0, 50, 100 and 150 kg N/ha; N0, N1, N2 and N3, respectively) and two water levels (rainfed (W1) and irrigated at flowering (W2)), with four replications. At harvest (July 2018 and 2019) grain yield was recorded with a combiner and grain N concentration determined in the laboratory for each plot. More details can be found in Pancorbo *et al.* (2023).
Hyperspectral and thermal airborne images were captured 300 m above the experimental site at flowering in 2018 and 2019. The spectral sensors covered the visible-NIR (400 to 850 nm; Hyperspec VNIR model, Headwall Photonics, Fitchburg, MA, USA) and the NIR-SWIR (850 to 1750 nm; NIR-100 model, Headwall Photonics, Fitchburg, MA, USA) regions. The radiometric calibration of the sensors was performed with an integrating sphere (CSTM-USS-2000C LabSphere). The sentinel imagery (Sentinel-1 and Sentinel-2) coincident with the overpass closest to flowering, ensuring cloud-free sky conditions, was downloaded from the European Space Agency DataHUB server.
Hyperspectral imagery was atmospherically corrected measuring incoming irradiance and orthorectified using the RTK GNSS coordinates. The mean airborne spectrum of each plot was extracted leaving a 2-m buffer in each side of the plot and used to to construct a contour map for each winter wheat trait. The contour maps represent the R^2 value from the linear regression between each trait and each normalized difference spectral index (NDSI) calculated with a combination of all possible hyperspectral bands (λ). The NDSI with the highest R^2 value was selected to assess yield and GPC. The best structural, chlorophyll, and SWIR indices identified with the airborne sensors were calculated using the closest Sentinel-2 convolved bands. Similarly, a water deficit index (WDI; Moran *et al.*, 1994) was calculated from the thermal airborne sensor for each plot and a radar vegetation index (RVI, Kim & Van Zyl, 2009) from Sentinel-1.

Multiple linear regression (MLR), artificial neural networks (ANN), and random forest (RF) models were applied to combine selected indices, enhancing trait estimation. A 10-fold cross-validation approach was used, dividing data for training and testing to ensure the robustness of each model. MLR provided baseline estimations, ANN used back-propagation to optimize weights among neurons, and RF assessed multiple decision trees for high accuracy, evaluating each variable's importance as the increase in node purity. These models were assessed based on R^2 and root mean square error (RMSE), helping to validate trait estimation accuracy. The feasibility of using freely available multispectral satellite data was tested by applying the same methodology but using equivalent Sentinel-1 and Sentinel-2 bands.

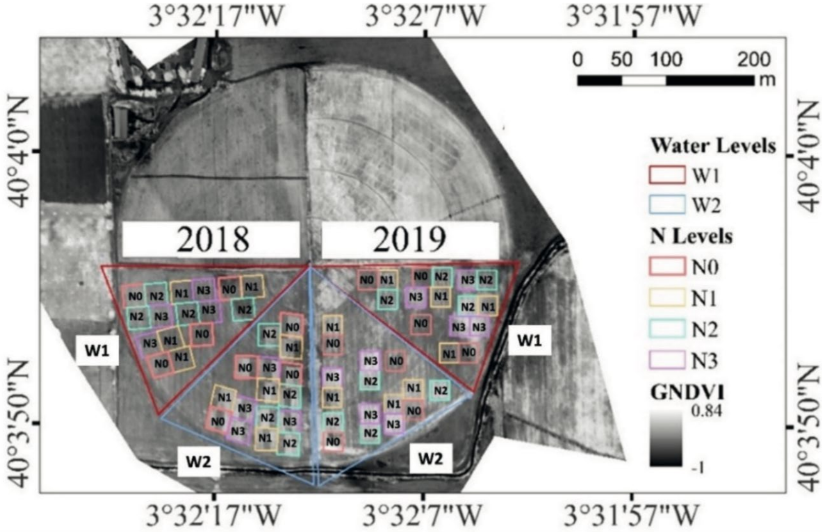

Figure 1. Airborne image of the field experiment showing the 32 plots of each year separated by N rates (N0, N1, N2, N3) and water levels (W1, W2).

Results and discussion

Different responses of yield, N output and GPC to fertilizer and water application were found for both years due to distinct climate conditions. Yield response to N fertilization followed a quadratic plateau model in both years and it was stronger in 2018 than in 2019. GPC was generally higher in 2019, and only in 2018 did it differ significantly between water levels in the highest N treatment plots (N3). For N output, 2018 showed higher values across most N levels. The effect of water levels on N output, as well as in GPC, was not apparent in 2019 and was only found in the N3 plots of 2018, with a higher value in W2. These results suggest year-specific interactions between crop traits and environmental conditions and remark on a role for sensors that capture these interactions. Therefore, a dataset with crop response and remote sensors readings was created to analyze the relationships among crop traits and spectral and thermal indices.

The effect of the N levels on the reflectance spectra acquired by the airborne sensors was detected on the visible and NIR and particularly on the SWIR. Differences in the spectra between water levels were evident in the SWIR region and the thermal image.

Among the wheat traits, yield prediction presented the highest R^2 with reflectance information. The models showed that both hyperspectral (Figure 2) and Sentinel-2-based (Figure 3) data performed well (R^2≈0.84), suggesting that Sentinel-2 could effectively replace hyperspectral imagery for yield estimation in large-scale applications.

Hyperspectral sensors offered a slight advantage, but Sentinel-2 spatial coverage and free availability make it practical for operational use. SWIR indices, especially those linked to structural components such as lignin, played a crucial role, given that these components affect biomass production and yield. Additionally, when spectral information from the red-edge and NIR regions was used, yield estimates significantly improved, aligning with previous research on the importance of these regions in chlorophyll and biomass assessments (Camino *et al.*, 2018; Prey and Schmidhalter, 2019; Raya-Sereno *et al.*, 2024).

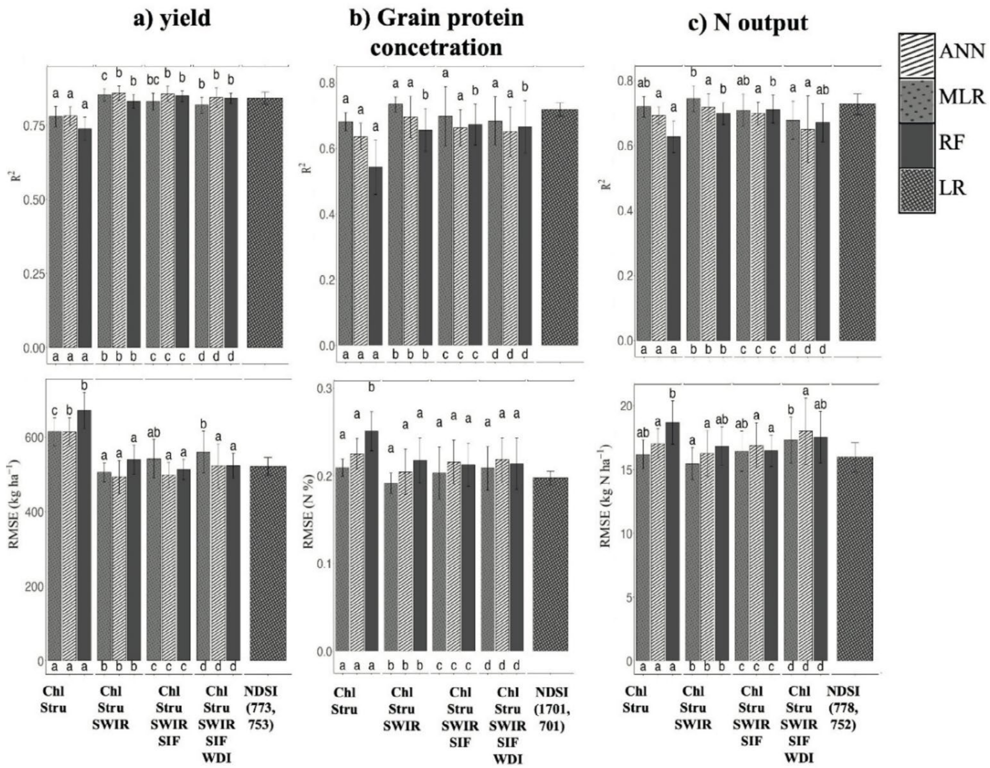

Figure 2. Coefficient of determination (R^2) and root mean square error (RMSE) obtained when using airborne sensors to estimate wheat traits: (a) yield (kg/ha), (b) grain protein concentration (%), and (c) N output (kg N/ha) with linear regression (LR), multiple linear regression (MLR), artificial neural network (ANN), and random forest (RF). Indices used are on the *x*-axis. Different letters underneath the bars indicate significant differences ($p \geq 0.05$) between models with the same set of indices. Letters on the top of the bars indicate differences between the same models using a different set of indices.

Grain protein concentration predictions were less accurate overall, partly due to the complexity of protein-related spectral signatures and their interactions with crop physiology. The most accurate model for GPC combined chlorophyll, SWIR, and structural indices (R^2=0.73), with hyperspectral SWIR data improving accuracy by about 8.1% compared to Sentinel-2 data. SWIR bands (1600–1750 nm) showed high correlations with GPC due to their sensitivity to protein N–H bonds. This indicates the advantage of hyperspectral data for GPC estimation. Sentinel-2 can provide acceptable results, particularly if red-edge bands are included, but limitations were evident.

These findings align with prior research indicating that GPC estimation benefits from the narrow spectral bands provided by hyperspectral sensors (Prey and Schmidhalter, 2019; Camino *et al.*, 2018). The improvement in GPC prediction of using a SWIR narrow band is attributed to the N–H bond absorption feature in the SWIR region (Curran, 1989).

For N output, hyperspectral sensors demonstrated the highest accuracy (R^2=0.74). However, Sentinel-2 multispectral data offered only slightly lower accuracy (R^2=0.71) when SWIR bands were incorporated, indicating that Sentinel-2 data could still be valuable in large-scale N management applications. The study highlighted red-edge and NIR-based indices as critical for N output

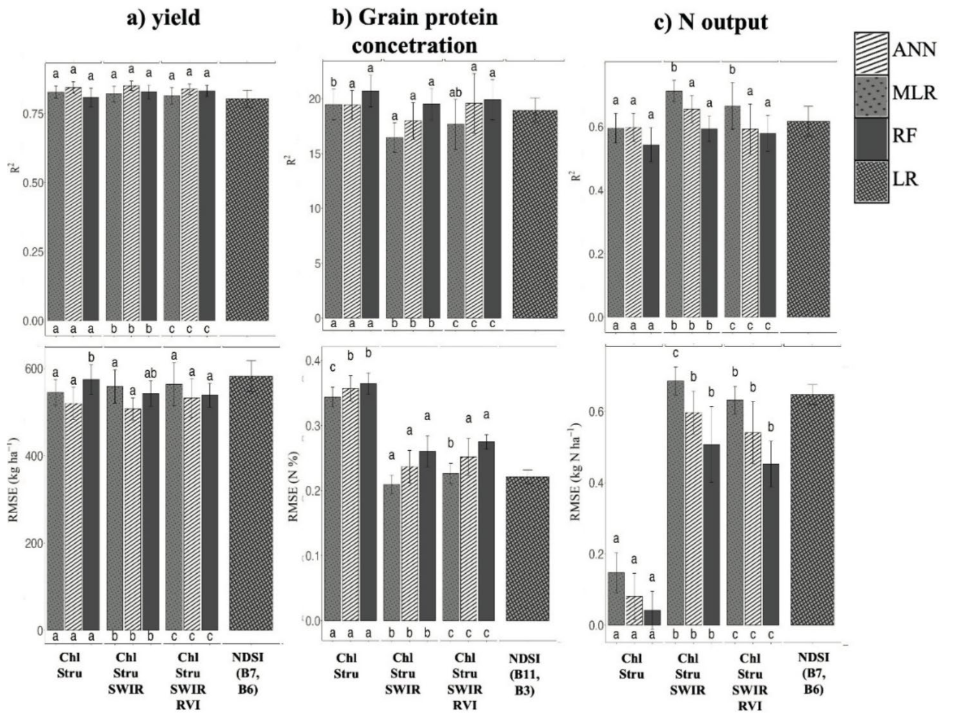

Figure 3. Coefficient of determination (R^2) and root mean square error (RMSE) obtained when using Sentinel imagery to estimate wheat traits: (a) yield (kg/ha), (b) grain protein concentration (%), and (c) N output (kg N/ha) with linear regression (LR), multiple linear regression (MLR), artificial neural network (ANN), and random forest (RF). Indices used are on the *x*-axis. Different letters underneath the bars indicate significant differences ($p \geq 0.05$) between models with the same set of indices. Letters on the top of the bars indicate differences between the same models using a different set of indices.

estimation due to their sensitivity to chlorophyll and N content in plants, making them valuable indicators of N efficiency (Raya-Sereno *et al.*, 2021b).

Models (MLR, ANN, RF) selected structural, chlorophyll, and SWIR indices based on their correlation strength with each trait. GNDVI and NDSIs from NIR, red-edge, and SWIR bands were essential across models. The models improved trait estimation by combining these indices, particularly for yield, where ANN and SWIR-based indices achieved the highest R^2 (0.86) with hyperspectral data. For GPC and N output, MLR with SWIR and chlorophyll indices achieved the best accuracy. ANN consistently performed well across indices and sensor types, highlighting its potential in multispectral data applications. The three models performed similarly when using three or more indices, however, when using only two indices RF performed poorly.

The study underscores the significant role of RS in early wheat monitoring, providing an effective way to predict crop yield and grain quality before harvest. By enabling early predictions, these RS-based models can help farmers and policymakers optimize fertilizer applications, irrigation, and other resources, enhancing food security. The findings indicate that freely available Sentinel-2 data, particularly with SWIR bands, can reliably estimate wheat traits, making it accessible for large-scale agricultural management without the high cost of hyperspectral sensors. These methods could thus support precision agriculture by tailoring inputs to actual crop needs, thereby improving sustainability and reducing environmental impacts.

While RS offers valuable insights, certain limitations remain. GPC estimation was challenging due to the complex interplay of proteins with spectral indices, which current models could only partially capture (Raya-Sereno *et al.*, 2024; Rodrigues *et al.*, 2018). Narrow-bands acquisition in the VNIR-SWIR region showed large potential on improving management decisions on precision agriculture. The upcoming hyperspectral satellite missions with near-global coverage, such as Copernicus Hyperspectral Imaging Mission for the Environment (CHIME; Berger *et al.*, 2020) or Landsat Next (US Geological Survey, 2023), could greatly contribute to improve forecasting of GPC and N output. The study also noted that environmental factors, such as yearly variations, significantly influenced traits estimation accuracy, suggesting that integrating weather and soil data could further improve model reliability. Additionally, expanding research to other crops and climates would provide more generalized models, increasing the applicability of RS in global food security efforts.
In previous studies the water deficit index (WDI) was able to distinguish between water levels and showed promising results for wheat traits estimation (Pacorbo *et al.* 2021). However, in the current study, the WDI did not enhance any trait estimation despite being correlated with yield and N output. More research in the combination of reflectance and thermal sensors is required.
Due to the validation approach used (dividing data from the two years for training and testing) application to forecasting crop traits in different fields and years should be taken with care. Nevertheless, these data could be added to other data from different locations and years to build up a robust dataset that would allow generalization of the findings (e.g. Wang *et al.*, 2025).

Conclusions

In all cases, the best trait estimation was attained when combining spectral indices calculated by using bands from the visible, red-edge, NIR, and SWIR regions (i.e. VNIR + SWIR). Yield obtained the most accurate estimation and presented similar results when the spectral indices were retrieved from VNIR hyperspectral imagery or from VNIR+SWIR Sentinel-2 bands.
Assessing GPC was more challenging, and hyperspectral and satellite sensors obtained satisfactory results when the SWIR information was included. However, an improvement of 8.1% was obtained with the VNIR hyperspectral sensor. Nitrogen output estimation for both sensors was improved when using red-edge and SWIR-based indices. Despite a more accurate estimation being attained with the hyperspectral bands, the potential of using Sentinel-2 bands for wheat trait assessment at large scales is promising.
The performance of estimating wheat traits with a single NDSI improved when combining diverse indices within the models, underscoring that models and machine learning approaches will have a relevant role in fertilizer recommendation based on information from multiple sources. Nevertheless, the transfer to agricultural practices should be greatly simplified.
The data collected in this mission could be added to other data from different locations, crops and years to build up a robust dataset that would allow validation procedures capable of improving general forecasting of crop traits.

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