



Hyperspectral and multispectral imagery for optimizing nitrogen management and harvest assessment in bread wheat

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Received: 12 February 2026 / Accepted: 4 May 2026 / Published online: 19 May 2026
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Abstract

Purpose Remote sensing is a valuable tool for creating site-specific maps to reduce the environmental impact of excessive nitrogen (N) fertilization and for predicting crop yield and quality in harvest planning and food security. The aim of this study was the application of remote sensing to improve N management and harvest assessment in bread wheat (*Triticum aestivum* L.).

Methods A wheat field experiment with four N levels and two water regimes was conducted in Central Spain over 2 years. Ground-truth measurements of biomass, plant N concentration, and nitrogen nutrition index (NNI) were collected at three growth stages, with grain yield and N concentration recorded at harvest. Close to the dates of the ground measurements, hyperspectral imagery was acquired covering the visible and near-infrared regions (400–850 nm) and part of the short-wave infrared (950–1750 nm) from an aircraft flying 300 m above the experiment. Sentinel-1 and Sentinel-2 imagery of the site was downloaded and processed. Vegetation indices extracted from the airborne imagery were tested to assess NNI and combined with satellite data by ensemble models (multiple linear regression, artificial neural network, random forest) to predict wheat traits at harvest.

Results The canopy chlorophyll content index (CCCI) was the best proxy for crop N status, assessing NNI with root mean square error of 0.21. The NNI maps from aerial imagery reflected the spatial distribution of wheat N requirements and enabled identification of N-responsive and nonresponsive sites for yield at stem elongation and for grain N concentration at flowering. Visible and near-infrared regions provided reliable yield estimates, and bands from the red-edge and the short-wave infrared regions improved prediction of N-related crop traits. Models using hyperspectral imagery and Sentinel-2 data performed comparably.

Conclusion The findings highlight the effectiveness of hyperspectral and multispectral imagery for crop monitoring, N-fertilizer management, and harvest planning.

Impact

The data provided in this manuscript enable the creation of in-season N fertilizer application maps and the assessment of wheat yield and grain quality at harvest using sensors on

aerial or satellite platforms. These maps reflect the spatial variability of the crop N status and are needed for site-specific N management at the field scale.

Highlights

- Canopy chlorophyll content index (CCCI) correlates with nitrogen nutrition index (NNI).
- Crop N status maps based on NNI can guide N fertilizer recommendations.
- Yield response to N fertilization was assessed more accurately than grain quality response.
- Airborne hyperspectral and multispectral satellite sensors estimate wheat traits similarly at flowering.
- Assessing wheat N-related traits improves when SWIR and narrow red-edge bands are included.

Keywords Nitrogen · Wheat · Fertilizer application maps · Yield assessment · Grain quality · Machine learning

Introduction

Nitrogen (N) is an essential nutrient that supports plant growth and productivity; therefore, it is frequently applied as a fertilizer for optimizing crop production or quality (McLellan et al., 2018). However, N use efficiency is relatively low and only about half of the N fertilizer applied is assimilated by crops (Lassaletta et al. 2014). The rest of the N is lost to the environment causing serious problems for water and air quality (Mosier et al., 2013). In addition, overfertilization to compensate for the large spatial variability of the soil available N is common practice in many fields (Fageria & Baligar, 2005). Adjusting fertilization to crop needs is a key strategy for increasing N efficiency and reducing water and air pollution (Gabriel et al., 2017).

Wheat occupies 15% of the world's total area of arable land dedicated to primary crops and accounts for 17% of global N fertilizer use (FAOstat, 2023). A common strategy to improve N efficiency in winter wheat is through split fertilization, with the last topdressing applied up to the end of stem elongation to ensure yield (Arregui et al., 2006). Additional topdressings can be applied during flowering and early grain filling to boost grain protein content (Ravier et al., 2017), a quality trait strongly associated with water and N availability (Zhao et al., 2005). Early in-season assessment of crop N status enables farmers to adjust N fertilizer application (Raun et al., 2005). An accurate estimate of crop traits in late growth stages can be useful for predicting yields and grain protein levels to ensure compliance with market demands.

Spectral remote sensors have proven to be a reliable tool for estimating crop N status and crop traits that determine production in many crops, including winter or spring wheat (Chen et al. 2010), maize (Quemada et al., 2014), rice (Huang et al., 2015), and many others. The nitrogen nutrition index (NNI) is the most widely recognized diagnostic tool for crop N status (Lemaire et al., 2008), and it is best monitored with remote sensing proxies, enabling fertilization to be adjusted to N crop needs (Chen 2015). The NNI is calculated as the ratio of the actual shoot N concentration to the minimum shoot N concentration required for maximum biomass accumulation. When $NNI < 1$, the crop is N-deficient, and

when $NNI > 1$, the crop is overfertilized. Various studies have successfully estimated NNI based on remote sensing for wheat (Chen 2015; Pancorbo et al., 2021), maize (Xia et al., 2016), and rice (Huang et al., 2015) among other crops. Some of these studies used sophisticated tools such as machine learning (Pan et al., 2025) or radiative transfer model inversion (Raya-Sereno et al. 2021a) to accurately estimate crop N status. Nevertheless, there is also a need for simple and reliable relationships that estimate NNI based on well-known vegetation indices (VIs) derived from remote sensing imagery (Lemaire et al., 2008). To this end, two main approaches have been followed. Chen et al. (2010) proposed estimating crop traits (biomass, shoot N concentration) by remote sensing, and then using them as inputs to calculate NNI. Many VIs have been used as proxies for biomass and shoot N concentration; in this study, we tested the most common ones (Table 1). Besides, regression models between specific VIs and NNI have been created to find a reliable semi-empirical approach. The VIs applied to wheat that showed higher potential are the crop canopy chlorophyll index (CCCI; Fitzgerald et al., 2010) and the red-edge inflection point (REIP; Mistele & Schmidhalter, 2008). Such relationships could be useful for reflecting the NNI in-field variability and obtaining maps for variable N fertilizer rate application.

In wheat, the most accurate assessment of yield and grain quality based on remote sensing imagery is obtained between flowering and early grain filling, when the maximum plant biomass has already accumulated but before crop senescence (Raya-Sereno et al. 2021b). In some cases, this assessment is useful for adjusting late foliar N fertilization to boost grain protein content, while generally enabling accurate predictions of harvest yield. Relevant crop traits to be predicted are grain yield (kg ha^{-1}), grain N concentration (%; GNC), and

Table 1 Vegetation indices used in this study with equations and references

Vegetation indices	Equation	Reference
<i>VNIR and red-edge-based indices</i>		
Normalized difference vegetation index	$NDVI = (R_{800} - R_{670}) / (R_{800} + R_{670})$	Rouse et al., 1974
Green normalized difference vegetation index	$GNDVI = (R_{800} - R_{570}) / (R_{800} + R_{570})$	Gitelson et al., 1996
Optimized soil-adjusted vegetation index	$OSAVI = (1 + 0.16) \times (R_{800} - R_{670}) / (R_{800} + R_{670} + 0.16)$	Meier et al., 1997
Transformed chlorophyll absorption in reflectance index	$TCARI = 3 [(R_{700} - R_{670}) - 0.2 \times (R_{700} - R_{550}) \times (R_{700} / R_{670})]$	Haboudane et al., 2002
Combined TCARI/OSAVI	$TCARI/OSAVI$	Haboudane et al., 2002
Normalized difference red edge	$NDRE = (R_{790} - R_{720}) / (R_{790} + R_{720})$	Barnes et al., 2000
Double peak canopy nitrogen index	$DCNI = (R_{720} - R_{700}) / (R_{700} - R_{670}) / (R_{720} - R_{670} + 0.03)$	Chen et al., 2010
Red-edge inflection point	$REIP = 700 + 40 \times [(R_{670} + R_{780}) / 2 - R_{700}] / (R_{740} - R_{700})$	Mistele and Schmidhalter (2008)
Canopy chlorophyll content index	$CCCI = (NDRE - NDRE_{min}) / (NDRE_{max} - NDRE_{min})$	Fitzgerald et al., 2006
<i>VNIR-SWIR-based indices</i>		
Normalize difference index (1240, 705)	$N_{1240, 705} = (R_{1240} - R_{705}) / (R_{1240} + R_{705})$	
Normalize difference index (1640, 705)	$N_{1640, 705} = (R_{1640} - R_{705}) / (R_{1640} + R_{705})$	

total grain N exported from the field (kg N ha^{-1} ; N_{area}). Reflectance across spectral regions can be used to estimate these crop traits. Chlorophyll activity absorbs light in the visible region (450–680 nm) and can be used as a proxy for crop productivity and N status (Sims & Gamon, 2002). The red-edge region (680–780 nm) is highly related to chlorophyll content and shows a strong relationship with crop N content (Inoue et al., 2016). Reflectance in the near-infrared (NIR, 780–1100 nm) and short-wave (SWIR, 1100–2500 nm) regions is affected by internal leaf structure and composition (Serrano et al., 2002) and has been used to estimate N (Camino et al., 2018) and water content (Quemada et al., 2018). If high spectral resolution images are available, solar-induced fluorescence (SIF) can be calculated as a proxy for photosynthetic activity and has shown strong relationships with crop and water N content (Camino et al., 2018). The relevance of the interaction between N and water in crop productivity suggests that combining the information from reflectance and thermal sensors may improve predictions of crop traits, as it was shown to disentangle crop N stress and water stress (Tilling et al., 2007; Pancorbo et al., 2021). While the simultaneous use of various remote sensing equipment offers multiple advantages, it is necessary to identify the most sensitive spectral region to optimize early predictions of crop traits alongside the most suitable and affordable sensor (Prey & Schmidhalter, 2019).

Errors in assessing numerous crop traits remain high with parametric statistical models (Colaço & Bramley, 2018), particularly for many traits related to crop N status and grain quality (Raya-Sereno et al. 2021b). Non-parametric models, such as artificial neural network (ANN) or random forest (RF), improve crop trait prediction based on remote sensing owing to their ability to detect patterns and extract information from big datasets (Van Klompenburg et al., 2020).

In this study we focused on the application of multispectral and hyperspectral remote sensing to improve N management and harvest assessment in bread wheat (*Triticum aestivum* L.). The specific objectives were as follows: (i) to identify VIs that can accurately assess in-season NNI providing maps that reflect the spatial variability of crop N status; (ii) to examine the potential of airborne hyperspectral and multispectral satellite sensors for estimating crop traits associated with productivity such as yield, GNC, and N_{area} ; and (iii) to evaluate the role of non-parametric models in assessing these crop traits.

Materials and methods

Experimental site and ground level data collection

The study was carried out at La Chimenea field station (Aranjuez, Madrid, Spain) in an 8-ha plot occupying half of a larger field covered by a circular pivot (220 m radius; Fig. 1). The field is located at 550 m.a.s.l. with a BSk, cold semi-arid climate according to the Köppen classification. The soil is mapped as *Haplic calcisol* with the topsoil characterized by $\text{pH} \approx 8.1$, organic matter content between 1.4 and 1.6%, $\text{C/N} = 10.1$, silty clay loam texture, and high fertility levels of phosphorus and potassium.

In November 2017, half of the experimental field was sown with winter wheat (*Triticum aestivum* L.) at a seeding rate of 220 kg ha^{-1} , and the other half was sown in 2018 using the same seeding rate (Fig. 1). A factorial experiment with four replications was established by randomly distributing 32 plots ($25 \text{ m} \times 25 \text{ m}$ in 2018; $22 \text{ m} \times 22 \text{ m}$ in 2019) into four

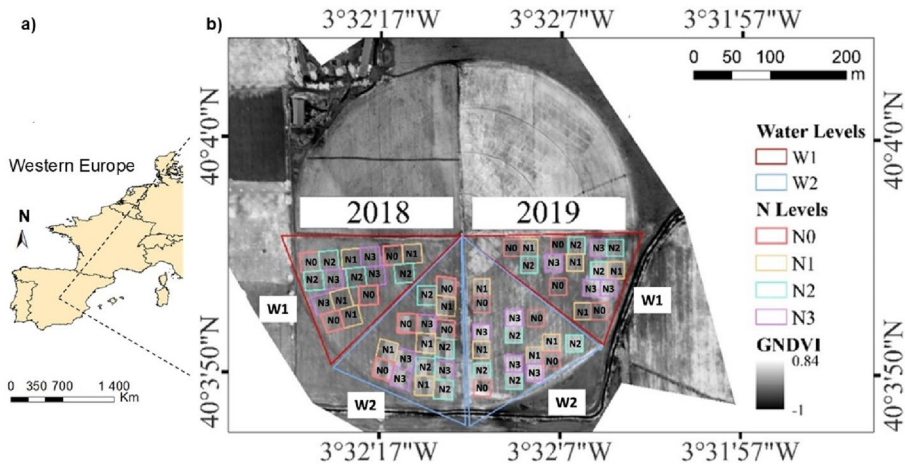


Fig. 1 Location of the experiment (a) and green normalized difference vegetation index (GNDVI) at flowering calculated from hyperspectral imagery (b) with the 32 plots for each year separated by water (W1, W2) and N levels (N0, N1, N2, N3)

N levels (0, 50, 100, and 150 kg N ha⁻¹; N0, N1, N2, and N3, respectively) and two water regimes (rainfed (W1) and irrigated at flowering (W2)). To guarantee accurate georeferentiation, plots were marked with real-time kinematic (RTK) through the National Geodetic Network of Reference Stations GNSS, with a Topcon HiPer Pro receiver (Topcon Singapore Holdings Pte. Ltd, Singapore) using permanent stations at Sonseca (Toledo) and Aranjuez (Madrid). No organic amendments were applied for 4 years before the experiment. Low levels of soil inorganic N content in the upper 0.9 m (36 kg N ha⁻¹ in 2018 and 57 kg N ha⁻¹ in 2019) before the first fertilizer application were ensured by cropping maize in the field in previous years. The fertilization with nitrate ammonium sulfate was split into two topdressings: 66% applied at tillering and 33% at final stem elongation. The four N levels corresponded to N0 (control), N1 (N stress), N2 (recommended N rate calculated with FertiliCalc (Villalobos et al., 2020), and N3 (overfertilized).

The crop evapotranspiration (ETc) was calculated by the FAO (Food and Agriculture Organization) method, calculating the reference evapotranspiration (ETo) with the Penman-Monteith model, and using the crop coefficient provided by Allen et al. (1998). The ETc from sowing to flag leaf stage (Zadoks growth stage Z39 (Zadoks et al., 1974) was 321 mm in 2018 and 261 in 2019, whereas the rainfall was 276 mm in 2018 and 126 in 2019. Due to water scarcity in winter 2019, all plots were irrigated twice with 25 mm at 13/03/2019 and 15/04/2019. From early boot stage (Z41) to the end of flowering (Z69) the ETc was 154 mm in 2018 and 187 in 2019, whereas the rainfall was 41 mm in 2018 and 2 in 2019. The two water regimes were established at the beginning of flowering (Zadoks growth stage Z63 (Zadoks et al., 1974) by irrigating (25 mm in May 2018, and 39 mm in 2019) half of the plots (Fig. 1).

Wheat response to N and water treatments was determined by (i) analyzing two samples of aerial biomass (0.5 m × 0.5 m) per plot that were hand-harvested at mid-stem elongation (22/03/2018 (Z32); 11/03/2019 (Z34), final stem elongation (17/04/2018 (Z37); 12/04/2019 (Z39), and flowering (11/05/2018 (Z65); 13/05/2019 (Z65), and by (ii) recording grain yield

with an experimental combine that harvested the central fringe (1.4 m × 20 m) of each plot in July (20/07/2018; 3/07/2019). Additionally, a grain sample from the combine was saved from each plot for later analysis. The aerial biomass and grain samples were dried at 65 °C for 48 h and weighed to determine the above-ground biomass (kg dry matter ha⁻¹) and yield (kg dry grain ha⁻¹). Subsamples of each biomass and grain sample were analyzed in the laboratory to determine the N concentration (%N) using the Dumas combustion method (LECO FP-428 analyzer, St. Joseph, MI, USA). For each plot, the N_{area} (kg N ha⁻¹) was calculated by multiplying yield by GNC. More details on the field experiment and the crop sampling can be found in Pancorbo et al. (2021) and Pancorbo et al. (2023).

The crop N status for each plot and growth stage was estimated by calculating the NNI using the critical dilution curve for winter wheat proposed by Justes et al. (1994):

$$\%N_{critical} = 5.35 * Biomass^{-0.442} \quad (1)$$

and the critical dilution curve proposed by Pancorbo et al. (2021) under water stress conditions:

$$\%N_{critical} = 4.42 * Biomass^{-0.832} \quad (2)$$

where $\%N_{critical}$ is the minimum %N in aerial shoots that produces the maximum growth for a given *Biomass* value.

The NNI was calculated as the ratio of %N measured in the samples and the $\%N_{critical}$ for the actual value of biomass following:

$$NNI = \%N / \%N_{critical} \quad (3)$$

Therefore, NNI values close to 1 show that available N matches the crop demand; values above 1 correspond to overfertilization; and values below 1 indicate N deficiencies. At flowering, the spikes were excluded, and the NNI was calculated with the shoots and leaves to consider the N dilution effect.

Airborne campaigns

Hyperspectral and thermal airborne images were captured 300 m above the experimental site at mid-stem elongation (11/03/2019; not image at this growth stage was captured in 2018), final stem elongation (19/04/2018; 12/04/2019), and flowering (15/05/2018; 16/05/2019). In both years, the spectral sensors were installed in a Cessna aircraft flying at 75 km h⁻¹ over the experimental field, following the solar plane at 11 GMT, and covering the visible-NIR (400–850 nm) and the NIR-SWIR (850–1750 nm) regions. Airborne campaigns were operated by the Laboratory for Research Methods in Quantitative Remote Sensing of the Consejo Superior de Investigaciones Científicas (QuantaLab, IAS-CSIC, Spain). Images were acquired under cloud-free sky conditions and as close as possible to biomass collection.

One of the hyperspectral sensors (Hyperspec VNIR model, Headwall Photonics, Fitchburg, MA, USA) captured reflectance in the visible (VIS) and NIR regions (400 and 850 nm) with a spectral resolution of 6.5 nm full-width at half maximum (FWHM) and 50° field of view (FOV) that yielded 0.2-m spatial resolution. The other sensor (NIR-100 model, Head-

wall Photonics, Fitchburg, MA, USA) captured reflectance in the SWIR (950–1750 nm) with an FWHM of 6.05 nm, an FOV of 38.6° and 0.6-m spatial resolution. The hyperspectral sensors were radiometrically calibrated with an integrating sphere (CSTM-USS-2000 C LabSphere, North Sutton, NH, USA) using four levels of illumination and six integration times. Atmospheric correction was made by measuring incoming irradiance concurrently with the flights and by SMARTS model simulations using aerosol optical depth and weather data (Gueymard, 2001). Smoothing of the spectral data was performed following the Savitzky–Golay method with a filter length of 9 interpolated to 1 nm.

The thermal sensor (SC655 model, FLIR Systems, Wilsonville, OR, USA) recorded surface temperature at a spatial resolution of 0.25 m, 16-bit radiometric resolution, focal length of 13.1 mm, and $45 \times 33.7^\circ$ FOV per flight. Thermal imagery was calibrated using ground temperature data collected with a handheld infrared thermometer (LaserSight, Optris, Germany).

From each plot, data were extracted from the orthorectified images using the RTK GNSS coordinates and leaving a 2 m buffer on all sides of the plots. Average spectra and temperature values were obtained from each plot. In addition, to construct a solid planar plot of NDVI and NDRE representing multiple combinations, the airborne images were resampled to 2 m for the entire wheat-cropped field each year.

Satellite imagery

Sentinel imagery (Sentinel-1 and Sentinel-2) corresponding to overpasses closest to biomass collection, ensuring cloud-free sky conditions, was downloaded from the European Space Agency DataHUB server (ESA, 2022a). Radiometric correction was applied to the Sentinel-1 ground range detected (GRD)-products to obtain the co- and cross-polarized backscatter (σ_{VV} 0 and σ_{VH} 0 (db) using the Sentinel Application Platform (SNAP) (Mandal et al., 2020). The modification of the quad-pol radar vegetation index (RVI) (Kim & Van Zyl, 2009) for dual-pol SAR data was calculated as $4\sigma_{VH}/(\sigma_{VV} + \sigma_{VH})$ (Trudel et al., 2012) and values were extracted for each plot.

The Sentinel-2 multispectral instrument provides 13 spectral bands from visible to SWIR regions at different spatial and spectral resolutions. The products downloaded were atmospherically corrected Sentinel-2 Level 2 A products. Values of the 10 m bands were extracted from the pure pixels (>95% of the Sentinel-2 pixel falls within the plot boundaries) of each plot. The average number of pure 10-m bands pixels per plot was 2.9 in 2018, and 4 in 2019 (in the second-year plots were RTK-marked to ensure that they contained 4 pixels). As no pure pixels were available for the 20 m bands for most plots, the average spectrum of the airborne imagery from each plot was convolved using the spectral response function (ESA, 2022b). The resulting bands were used to calculate the Sentinel-2 spectral indices applied in this study.

Vegetation indices for estimating NNI, biomass, and shoot %N

Common vegetation indices (VIs) were selected to achieve the first objective of this study (Table 1). The reliability of the VIs in assessing crop variables was evaluated based on the correlation coefficient (R^2), the root mean square error ($RMSE$), and the relative root mean square error ($rRMSE$) of the linear relationship using combined data from all growth stages.

The crop N status diagnosis maps for the study area were created based on the estimated NNI from the CCCI calculated with the airborne sensor's bands at final stem elongation for both experimental years. The reliability of NNI in distinguishing N-responsive from non-responsive plots was tested with the nitrogen sufficient index (*NSI*). The response curve of yield, GNC, and N_{area} to N application was generated, with optimal N defined as the minimum N rate yielding the maximum value for each crop trait. For each plot, relative values of yield, GNC, and N_{area} were calculated by dividing the crop trait of the plot by the average value of the plots treated with the optimal N rate. To determine the accuracy of each VI at distinguishing N-responsive from nonresponsive plots, the *NSI* was calculated as follows (Quemada et al., 2014):

$$NSI = \text{VI value for tested plot} / \text{Average VI value for WFRP}$$

where WFRP refers to well-fertilized reference plots (i.e., plots with the optimal N rate). Plots with $NSI > 1$ imply the VI would not recommend additional N, whereas a relative response below 1 indicates the plot was responsive; the opposite holds for $NSI < 1$. Plots with $NSI > 1$ and relative yield, relative RGNC, or relative $N_{\text{area}} < 1$ indicated fertilizer underestimation; plots with $NSI < 1$ and relative yield, relative RGNC, or relative $N_{\text{area}} > 1$ indicated overestimation. Both underestimated and overestimated plots were considered errors, and the accuracy of VIs was reported as the percentage of errors out of the total number of plots.

Selection of indices as proxies for yield, GNC, and N_{area}

The mean airborne spectrum of each plot was used to identify the best normalized difference spectral index (NDSI) for assessing yield, GNC, and N_{area} . Contour maps of R^2 values from the linear regression between crop traits (biomass, plant N%) and each NDSI [$NDSI(\lambda_1, \lambda_2) = (\lambda_1 - \lambda_2) / (\lambda_1 + \lambda_2)$] were constructed, with (λ_1, λ_2) being all possible combinations of the hyperspectral bands from 400 to 1750 nm. The NDSI with the highest R^2 value for each crop trait was selected and used as benchmark to test the potential improvement of combining several indices with the ensemble models. The tested combinations were:

- Best NDSI based on a visible and NIR band to estimate biomass (termed “Structural”) and best NDSI based on red-edge and NIR band to estimate plant N% (termed “Chlorophyll”). These NDSIs can be obtained from many hyperspectral or multispectral equivalent cameras.
- Structural NDSI and Chlorophyll NDSI combined with the best NDSI based on SWIR bands to estimate yield, GNC, or N_{area} . To obtain these additional NDSIs, a sensor that covers the SWIR region is needed.
- Solar-induced chlorophyll fluorescence (SIF) was added to the previous three NDSIs. SIF emission was calculated via the Fraunhofer line-depth (FLD) principle using solar irradiance and canopy-emitted radiance as explained in Zarco-Tejada et al. (2013). To calculate SIF, high-quality hyperspectral sensors are required as well as a sensor for measuring total incoming radiance.
- The water deficit index (WDI) was added to the previous three NDSIs and SIF as an indicator of crop water status. The WDI was calculated as described by Moran et al.

(1994) and requires additional thermal data to be computed.

To evaluate the capacity of satellites, Sentinel information was used to obtain satellite-based indices equivalent to the hyperspectral airborne ones. Structural, chlorophyll, and SWIR indices were calculated using the closest Sentinel-2 convolved bands. Band B11 was used as the SWIR band in all SWIR-based indices. The RVI calculated with Sentinel-1 was included to quantify the potential improvement of combining Sentinel-1 and Sentinel-2 for crop trait estimation. As SIF and WDI cannot be calculated from Sentinel imagery, they were excluded from the satellite analysis. The best structural, chlorophyll, and SWIR indices identified with the airborne sensors were calculated using the closest Sentinel-2 convolved bands. A summary of model input variables is presented in Table 3, and details on the index selection can be found in Pancorbo et al. (2023).

Ensemble models

Multiple linear regression (MLR), ANN, and RF models were applied to combine selected indices for estimating yield, GNC, and N_{area} . A 10-fold cross-validation approach was used, dividing data for training (30%) and testing (70%) to ensure the robustness of each model. The ANN used a back-propagation algorithm to optimize weights among neurons (Rumelhart et al., 1986), and it was executed using the “*neuralnet*” package implemented in R software (version 4.5.5; R Core Team, 2021). In this study, the ANN was run by setting the number of hidden layers to 2 and the number of neurons in the hidden layer equal to the number of input variables.

The random forest regression was performed using the “*randomForest*” R package (Liaw & Wiener, 2002). The optimal number of regression trees (*ntree*) was calculated from the training dataset by varying *ntree* from 50 to 1000 with 50 intervals while fixing *mtry* (number of variables at each node) as default (500). The capacity of all ensemble models to estimate yield, GNC, and N_{area} was assessed based on R^2 and *RMSE*.

Results

The response of yield, GNC, and N_{area} to fertilizer application varied with climate conditions and water regimes. In both years, yield response to N fertilization followed a quadratic plateau model, reaching plateau at N3 in 2018 (7369 kg ha^{-1}) and at N2 in 2019 (4430 kg ha^{-1}). Both GNC and N_{area} increased with N application, with water level differences appearing only in the highest treatment plots (N3) in 2018. The NNI was strongly related to wheat N status in both years. These results suggest year-specific interactions between crop traits and environmental conditions, highlighting the need for sensors that capture these interactions. More information on the field variables can be found elsewhere (Pancorbo et al., 2021, 2023); the datasets with crop and remote sensing data created during this study are available in public repositories (Quemada et al., 2023, 2025).

Vegetation indices for assessment of NNI and spatial variability of crop N status

The index that showed the stronger relationship with biomass was CCCI, followed by TCARI (Table 2). Plant N concentration did not show a good correlation with any of the VIs based on the VNIR and red-edge regions, but it showed a significant relationship with the index that incorporated a SWIR band (NDSI (1640, 705)). The NNI was best estimated by CCCI from the VNIR and red-edge regions and by NDSI (1640, 705) incorporating a SWIR band.

The equations of the upper ($\text{NDRE}_{\max}$) and lower ($\text{NDRE}_{\min}$) lines to envelope the airborne hyperspectral data had slopes of 0.68 and 0.16, respectively (Fig. 2). The total number of pixels extracted from each quarter of the wheat field was 20,512 in 2018 (two flight campaigns) and 28,995 in 2019 (three flight campaigns). The average of the 32 plots (8090 pixels/plot) obtained each year fell within the area delimited by the two diagonals, enabling calculation of the CCCI for each plot.

The relationship between CCCI and NNI followed a linear model, with the equation and statistics provided in Fig. 3. This relationship corresponds to the NNI calculated using the equation for water stress conditions (Pancorbo et al., 2021). The equation obtained for the most common wheat-NNI dilution curve (Justes et al., 1994) was $\text{NNI} = 0.263 + 0.72 \text{ CCCI}$ and showed similar statistics. Most of the errors of the linear model were associated with high CCCI values ($\text{CCCI} > 0.7$). The linear relationship obtained using the CCCI calculated from the Sentinel-2 imagery followed the equation $\text{NNI} = 1.64 \text{ CCCI} - 0.01$ ($\text{RMSE} = 0.29$; $R^2 = 0.36$).

The NNI map obtained by applying the CCCI equation to the airborne imagery reflected the crop N status variability at the end of stem elongation in the study field (Fig. 4). NNI varied from 0.1 in the non-fertilized areas (N0 plots and borders) to 1.2 in the overfertilized plots (N3). At this growth stage, in most plots the N-fertilizer recommendation to increase yield obtained from the ground-sampled NNI coincided with recommendations from the airborne-estimated NNI (Figs. 4 and 5).

Table 2 Coefficient of determination (R^2), root mean square error (RMSE), and relative root mean square error ($r\text{RMSE}$) of the linear relationship between nitrogen nutrition index (NNI), biomass (kg dm/ha), and shoot nitrogen concentration (% N in the aerial shoots of the crop) with spectral vegetation indices from airborne imagery

Vegetation indices	NNI			Biomass			Shoot N concentration		
	R^2	RMSE	$r\text{RMSE}$	R^2	RMSE	$r\text{RMSE}$	R^2	RMSE	$r\text{RMSE}$
NDVI	0.30	0.24	33.9	0.10	2980	37.4	0.19	0.55	28.7
GNDVI	0.41	0.23	32.5	0.12	2650	33.3	0.22	0.54	28.2
OSAVI	0.35	1.22	174	0.10	2644	33.2	0.28	0.53	27.7
TCARI	0.05	1.22	174	0.44	2041	25.6	0.10	0.64	33.4
TCARI/OSAVI	0.39	0.33	47.1	0.32	2246	28.2	0.10	0.61	31.8
NDRE	0.40	0.22	32.1	0.32	2251	28.3	0.13	0.59	30.8
DCNI	0.23	0.32	47.0	0.27	2317	29.1	0.10	0.64	33.4
REIP	0.39	0.22	31.8	0.16	2550	32.0	0.10	0.64	33.4
CCCI	0.42	0.21	30.1	0.56	1798	22.6	0.11	0.63	32.9
NDSI(1240,705)	0.43	0.19	19.7	0.16	2629	24.5	0.26	0.37	27.1
NDSI(1640,705)	0.55	0.15	17.6	0.10	2829	26.3	0.41	0.17	12.5

Bold values indicate the strongest relationships.

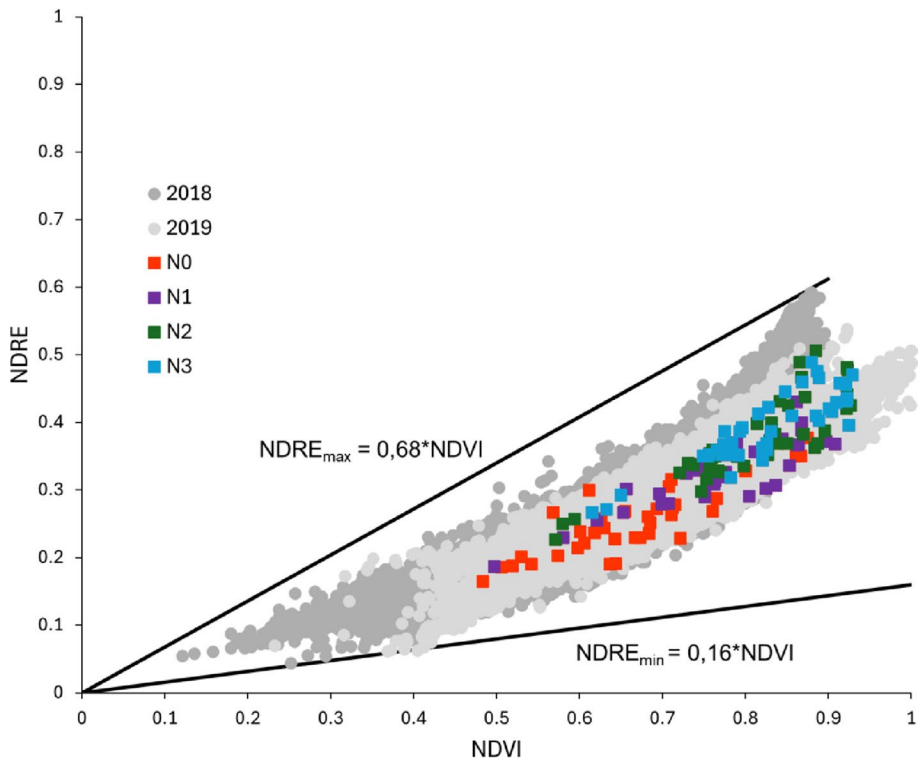


Fig. 2 Planar representation of the NDVI and NDRE values extracted from airborne hyperspectral imagery in all remote sensing campaigns. The gray symbols represent all 2 m wheat pixels in the experimental field (49,507). Colored symbols are the mean value for each plot assigned to the various N levels. Solid lines envelop all pixels from each sensor, enabling calculation of the canopy chlorophyll content index (CCCI) of a given NDVI as: $CCCI = (NDRE - NDRE_{min}) / (NDRE_{max} - NDRE_{min})$

At mid-stem elongation (Z32), the error rate in distinguishing between N-responsive and non-responsive plots was above 38% for both yield and grain protein content (Fig. 5). At final stem elongation (Z37 to Z39), the error rate was 18% for yield and 26% for GNC. The lowest error was at flowering (Z65), i.e., 18% error in identification of N-responsive sites for wheat and 22% for GNC.

Potential of airborne sensors for assessing productivity-associated crop traits

Selection of indices

NDSIs from hyperspectral sensors outperformed GNC and N_{area} for yield prediction at flowering (Fig. 6), achieving an $R^2 > 0.75$ for various NDSIs that used combinations of NIR or SWIR bands with a visible band. The strongest correlation ($R^2 = 0.83$) was obtained for NDSI (773 nm, 753 nm). The structural VI selected for the ensemble models was NDSI (800 nm, 550 nm), equivalent to GNDVI, due to the high correlation with yield. The VI selected as a proxy for chlorophyll content was NDSI (799 nm, 755 nm), and the SWIR-based index

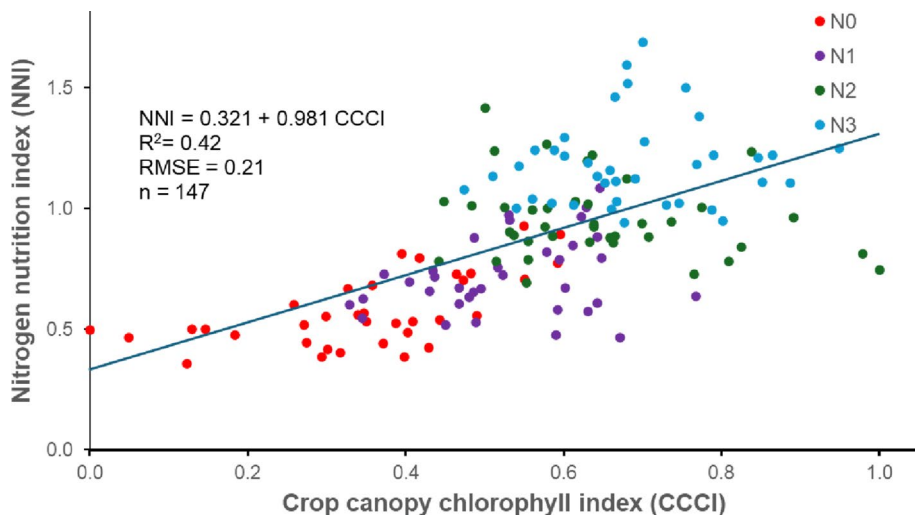


Fig. 3 Relationship between wheat nitrogen nutrition index (NNI) calculated from ground-collected samples and crop canopy chlorophyll content index (CCCI) calculated from airborne imagery in two experimental years at three different growth stages (mid-stem elongation, final stem elongation, and flowering). Symbols represent paired values from the nitrogen treatments. The solid line is the linear regression with the corresponding equation, coefficient of determination (R^2), root mean square error (RMSE), and number of paired values used to fit the model

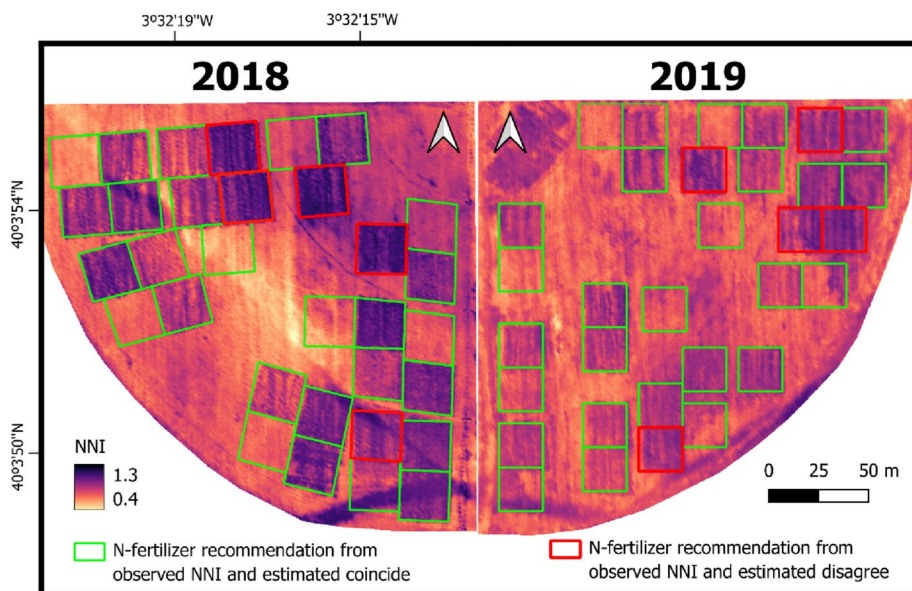


Fig. 4 Nitrogen nutrition index (NNI) maps from a hyperspectral sensor on-board an aircraft at final wheat stem elongation in both experimental years. Plots marked in green are those in which the N-fertilizer recommendation to increase yield from the ground-sampled NNI and the airborne-estimated NNI coincide, whereas plots marked in red indicate cases where there was disagreement

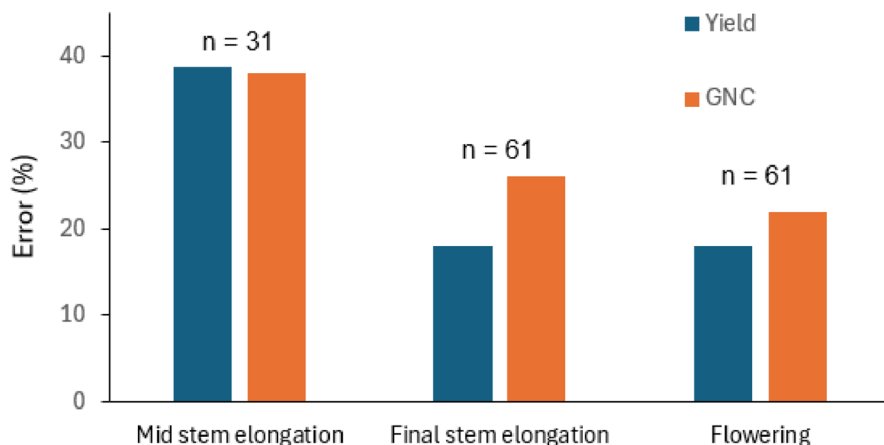


Fig. 5 Error of NNI estimated from airborne imagery in assessing wheat yield and grain nitrogen concentration (GNC) at three different growth stages over the two experimental years. *n* indicates the number of values used to calculate the error

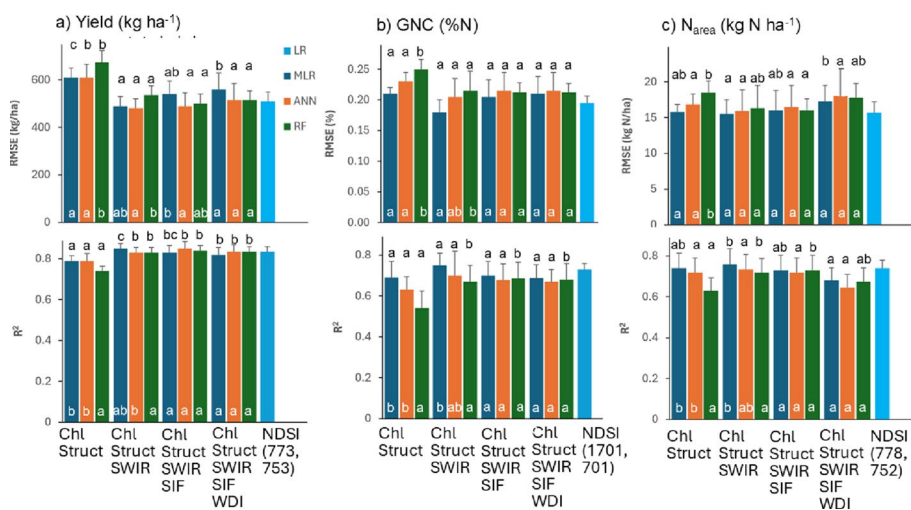


Fig. 6 Root mean square error (*RMSE*) and coefficient of determination (*R*²) using airborne sensors at flowering to estimate wheat (**a**) yield, (**b**) grain nitrogen content (GNC), and (**c**) total grain N exported from the field (*N_{area}*) with linear regression (LR), multiple linear regression (MLR), artificial neural network (ANN), and random forest (RF). Variables used in the models are on the X axis and are spectral vegetation indices based on visible-near infrared regions related to chlorophyll content (Chl) and plant structure (Struct) or based on a band from the short-wave infrared region (SWIR), solar-induced fluorescence (SIF), and water deficit index (WDI). Black letters indicate differences ($p \geq 0.05$) between the same ensemble models using a different set of variables. White letters inside bars indicate significant differences between ensemble models with the same set of variables

was NDSI (1106 nm, 1066 nm). Both indices showed a strong linear correlation with yield ($R^2=0.83$) but were not linearly correlated with each other (Pearson coefficient ≤ 0.75).

The best GNC estimation ($R^2=0.73$) with an NDSI based on the hyperspectral sensors was the combination of a SWIR (1701 nm) and a red-edge (701 nm) band. For the ensemble models, the proxies selected were NDSI (795 nm, 750 nm) as a chlorophyll index and NDSI (1650 nm, 545 nm) as a SWIR index, since both showed the strongest correlation with GNC in their group ($R^2>0.64$) and low collinearity (Pearson coefficient <0.75). All structural NDSIs exhibited a weak correlation with GNC ($R^2<0.1$), but GNDVI was selected because the green and NIR band combination showed a marginally stronger relationship and weak collinearity with the other GNC estimators.

The best NDSI estimator ($R^2=0.74$) of N_{area} combined the hyperspectral bands 778 nm and 752 nm; therefore, it was used in the linear regression model. This NDSI indicator was also chosen as the chlorophyll index in the ensemble models because it did not show collinearity with the SWIR-based NDSI (1650 nm, 520 nm) that best correlated with N_{area} ($R^2=0.62$). The GNDVI was selected as the structural index due to its high correlation with N_{area} ($R^2=0.65$).

Application of ensemble models

When using information from the hyperspectral sensors at flowering, at least one ensemble model improved the prediction of yield, GNC, and N_{area} compared to the linear regression (Fig. 6). The most accurate estimation ($RMSE=493 \text{ kg ha}^{-1}$; $R^2=0.86$) was obtained with ANN combining the structural, chlorophyll, and SWIR indices (Fig. 6a). The linear regression model that used only NDSI (773 nm, 753 nm) to estimate yield achieved $RMSE=521 \text{ kg ha}^{-1}$ and $R^2=0.84$.

The most accurate GNC estimation ($RMSE=1.19\%$; $R^2=0.73$) was obtained with MLR combining the structural, chlorophyll, and SWIR indices (Fig. 6b), and it was the only model that outperformed linear regression ($RMSE=1.25\%$; $R^2=0.72$). Using only structural and chlorophyll indices gave $R^2<0.68$, but introducing the SWIR-based NDSI substantially improved the correlation with GNC.

The best estimation of N_{area} ($RMSE=15.5 \text{ kg N ha}^{-1}$; $R^2=0.74$) was obtained with MLR combining the structural, chlorophyll, and SWIR indices (Fig. 6c). Using only structural and chlorophyll indices gave $R^2<0.75$ but introducing the SWIR-based NDSI improved the correlation. The linear regression model that used only NDSI (778 nm, 752 nm) to estimate N_{area} achieved $RMSE=15.7 \text{ kg ha}^{-1}$ and $R^2=0.73$.

When either SIF or WDI was added, no improvement was observed in the performance of the ensemble models in assessing any of the crop traits related to productivity.

Potential of Sentinel sensors for assessing productivity-associated crop traits

The Sentinel-2-based NDSIs used in the ensemble models for yield, GNC, and N_{area} prediction are shown in Table 3. The main differences appeared in the SWIR-based indices, all involving the B11 band (central band 1610 nm) from Sentinel-2 combined with a different band depending on the crop trait to be assessed.

The accuracy was similar when yield was estimated from hyperspectral airborne or Sentinel-2 imagery (Figs. 6a and 7a). The most accurate estimation ($RMSE=507 \text{ kg ha}^{-1}$;

Table 3 Structural, chlorophyll, and SWIR vegetation indices used as input variables in the ensemble models based on the hyperspectral or Sentinel-2 sensors to estimate yield, grain nitrogen concentration (GNC), and total grain N exported from the field (N_{area}). Normalized difference spectral indices are calculated as $NDSI (\lambda_1, \lambda_2) = (\lambda_1 - \lambda_2) / (\lambda_1 + \lambda_2)$, where λ is the wavelength used with the hyperspectral imagery or the Sentinel-2 band

Vegetation indices	Yield	
	Hyperspectral	Sentinel-2
Structural	NDSI (800,550)	NDSI (B8,B3)
Chlorophyll	NDSI (795,755)	NDSI (B8,B6)
SWIR	NDSI (1106,1066)	NDSI (B11,B8)
<i>Grain nitrogen concentration (GNC)</i>		
Structural	NDSI (800,550)	NDSI (B8,B3)
Chlorophyll	NDSI (795,750)	NDSI (B8,B6)
SWIR	NDSI (1650,545)	NDSI (B11,B3)
<i>Total grain N exported from the field (N_{area})</i>		
Structural	NDSI (800,550)	NDSI (B8,B3)
Chlorophyll	NDSI (778,752)	NDSI (B7,B6)
SWIR	NDSI (1650,520)	NDSI (B11,B2)

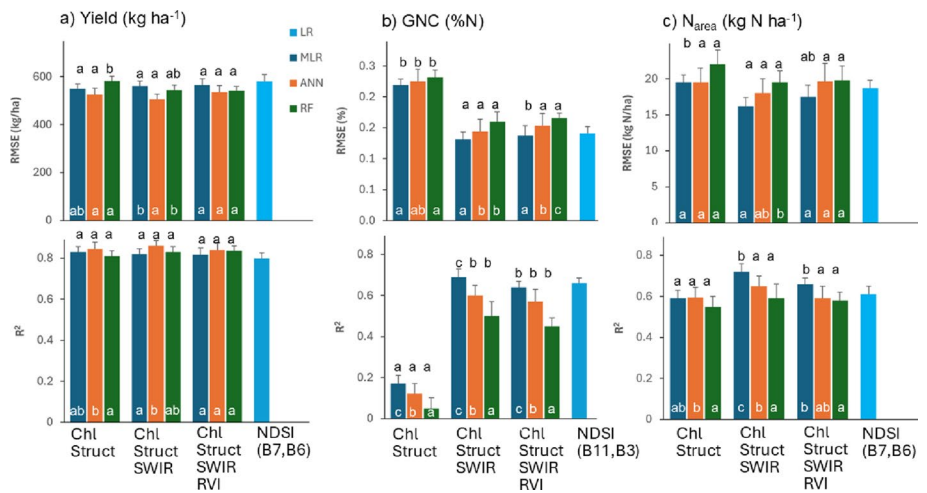


Fig. 7 Root mean square error ($RMSE$) and coefficient of determination (R^2) using Sentinel imagery acquired at flowering to estimate wheat (a) yield, (b) grain nitrogen content (GNC), and (c) total grain N exported from the field (N_{area}) with linear regression (LR), multiple linear regression (MLR), artificial neural network (ANN), and random forest (RF). Variables used in the models are on the X axis and are spectral vegetation indices based on visible-near infrared regions related to chlorophyll content (Chl) and plant structure (Struct) or based on a band from the short-wave infrared region (SWIR), and radar vegetation index (RVI). Black letters indicate differences ($p \geq 0.05$) between the same ensemble models using a different set of variables. White letters inside bars indicate significant differences between ensemble models with the same set of variables

$R^2=0.85$) was obtained with ANN combining the structural, chlorophyll, and SWIR indices (Fig. 7a). The linear regression model that used only one Sentinel-2 NDSI (bands 7 and 6) to estimate yield achieved $RMSE=582 \text{ kg ha}^{-1}$ and $R^2=0.80$, emphasizing the positive impact of combining various indices in the ensemble models.

The most accurate GNC estimation with Sentinel-2 bands ($RMSE=1.4\%$; $R^2=0.69$) was obtained with MLR combining the structural, chlorophyll, and SWIR indices (Fig. 7b); this was the only model outperforming linear regression that used only one index based on Sen-

tinel-2 bands ($RMSE=1.5\%$; $R^2=0.72$). Using only structural and chlorophyll indices gave $R^2<0.20$, but adding the SWIR-based NDSI greatly improved the correlation with GNC.

The best estimation of N_{area} with Sentinel-2 bands ($RMSE=16.5 \text{ kg N ha}^{-1}$; $R^2=0.71$;) was obtained with MLR combining the structural, chlorophyll, and SWIR indices (Fig. 7c), as with the airborne imagery. The linear regression model that used only one Sentinel-2 NDSI (B7, B6) to estimate N_{area} achieved $RMSE=18.95 \text{ kg ha}^{-1}$ and $R^2=0.62$.

When RVI was added, no improvement was observed in the performance of the ensemble models in assessing any of the crop traits related to productivity.

Discussion

Vegetation indices for assessment of NNI and spatial variability of crop N status

This study confirmed the CCCI as a reliable indicator of the NNI; therefore, it can be used to obtain maps representing the spatial variability of crop N status. The error rate in differentiating N-responsive and nonresponsive plots was high ($>35\%$) at the beginning of stem elongation but it decreased to 18% for yield at final stem elongation and 22% for GNC at flowering. Therefore, NNI maps can be used to adjust topdressing N fertilization in order to increase yield (final stem elongation) or grain quality (after booting) in wheat.

The uncertainty in estimating shoot N concentration and biomass, variables required as inputs to calculate NNI, was high. The best relationships with wheat biomass were achieved by CCCI and TCARI, and the regression equations had R^2 values of 0.56 and 0.44 with corresponding $RMSE$ values of 1798 and 2041 kg dm/ha. The poor performance of NDVI, GNDVI and OSAVI in predicting biomass could be related to both saturation of both indices at high biomass content and narrow range of indices values (i.e. NDVI ranged from 0.5 to 0.92). Compared with other indices, OSAVI and GNDVI yielded relatively good relationships with wheat shoot N concentration. The R^2 values of the regression equations were 0.30 and 0.27, and the $rRMSE>30\%$. In general, indices based on bands from the VNIR region have a significant relationship with biomass, but including bands from the red-edge region improves the relationship with both biomass and shoot N concentration. These statistical indicators are low compared to others in the literature (Chen 2015) but similar to those reported by Mistele and Schmidhalter (2008) in Germany, Yu (2021) in China, Raya-Sereno et al. (2021b) in Mexico. It is unlikely to find a good remote VI proxy for shoot N concentration after booting because the input variable needed for NNI calculation is not the N concentration of the total plant but only of the shoots, and it is difficult for VI to separate reflectance signals from shoots vs. spikes. This uncertainty was transferred to the assessment of NNI calculated with Eqs. 1 and 2 using estimated crop traits as inputs (Table 2).

Consequently, we focused on the semi-empirical approach and compared the capacity of the indices to assess NNI directly. The best index based on VNIR was CCCI, which has been successfully applied to wheat in previous experiments (Rodríguez et al., 2006; Fitzgerald et al., 2010; Pancorbo et al., 2021). This index has several advantages. First, its conceptual basis is similar to NNI as it is a planar index in which the NDVI is a surrogate for biomass and NDRE a proxy for shoot N concentration (Fitzgerald et al., 2010). Second, it is very common that VIs saturate when the biomass is abundant (i.e., in the middle stages of the wheat cycle); this happens with indices based on the visible and NIR (i.e., NDVI) and is

slightly reduced when the VIs incorporate a red-edge (i.e., NDRE) band. The combination of both VIs in a planar representation helps minimize this drawback (Clarke et al., 2001). Finally, estimating NNI from CCCI can reflect the true crop N requirement, providing a clear rule for technicians, farmers, or decision tools. It resolves the dilemma of applying more N fertilizer to the least fertile zones (Robin Hood scheme) or to the zones with higher yield potential (Kings scheme), and it can be used in algorithms to translate the distance to Nc into actual fertilizer needs (Rodriguez et al., 2006).

From the data provided, NNI maps can be created to translate the crop N status information into a fertilizer application map (Fig. 4). These maps are needed in site-specific nutrient management at the field level to adjust N application to actual crop requirements (Argento et al., 2025). Additionally, in this study the error rate in distinguishing N-responsive from non-responsive sites was estimated from the NNI maps (Fig. 5). The lowest errors occurred at flowering for both crop traits; this can guide decisions on topdressing N fertilizer to enhance grain quality, as wheat GNC responds to N application from booting to early milk stage (Bogard et al., 2010). Nevertheless, N fertilizer to increase yield should be applied no later than stem elongation (Diacono et al., 2013); in this study, the error rate in identifying yield-responsive sites at the end of this stage was 18%. Using readings from early growth stages entails a high uncertainty in identifying responsive sites; although no fixed value for acceptable error exists, general consensus holds that an error $\approx 20\%$ is the maximum for farm N management decision-making (Raya-Sereno et al. 2021b).

The equations of $\text{NDRE}_{\max}$ and $\text{NDRE}_{\min}$ lines that enveloped the airborne data from both campaigns (Fig. 2) were slightly wider than those in Pancorbo et al. (2021), as they included all experimental field pixels. The lines are similar to but wider than those reported for VIs based on field-spectra radiometer measurements in winter wheat in Australia (Fitzgerald et al., 2010). Wider lines in planar domain indices imply lower sensitivity, but they are convenient for use in multiple experiments from the region or even from other regions. The equations that enveloped the Sentinel-2 data were slightly different, and we could not find satellite-based equations for comparison in the literature. Nevertheless, all the satellite-based data from the plots in this experiment could also be enveloped by the equations obtained from the airborne sensors. Determining the reliability of applying these equations to wheat across different sites and seasons remains a challenge that could be addressed by collaboration among research groups (Wang et al., 2025).

Another remarkable result from this study was the good relationship between SWIR-based indices for estimating NNI and plant N concentration. This agrees with the relevance of the specific absorption bands associated with the N–H bonds present in proteins, where most plant N is allocated (Berger et al., 2020), and is discussed in the next section. In this study, a planar index in which the SWIR-based NDSI was used as a surrogate for shoot N concentration instead of NDRE was tested, but it showed poor correlation with NNI (data not shown).

Other studies have revealed that NNI can be better estimated when CCCI is combined with a water stress indicator (Rodriguez et al., 2006; Pancorbo et al., 2021). The best proxies for assessing crop water status from remote sensing rely on canopy thermal information (Tilling et al., 2007) that is not always available with sufficient spatial resolution for crop management. Some researchers observed that a better estimation of NNI from remote sensors can be achieved by assessing growth stages separately (among others, Chen 2015). Nevertheless, Pancorbo et al. (2021) showed that the same equations can be used for vari-

ous growth stages, even if better NNI estimations were obtained after final stem elongation and flowering. Furthermore, emerging machine learning techniques (i.e., neural networks, random forest) could be used to combine the information from environmental conditions and other stress factors for better estimations of NNI, thereby improving decision-making in site-specific N fertilization (Pan et al., 2025).

Potential of airborne hyperspectral and multispectral satellite sensors for estimating productivity-associated crop traits

This study shows that hyperspectral sensors offered a slight advantage over multispectral sensors for assessing crop traits associated with productivity. Nevertheless, Sentinel-2 data correctly assessed yield, suggesting it could effectively replace hyperspectral imagery in large-scale applications. The spatial and temporal coverage and free availability of Sentinel-2 make it practical for operational use in predicting wheat productivity. The Sentinel results agreed with the aircraft imagery, showing that N_{area} estimation was more accurate than GNC but less accurate than yield estimation.

It is known that adding spectral information from the red-edge to the visible and NIR regions significantly improves yield estimates (Inoue et al., 2016; Camino et al., 2018; Prey & Schmidhalter, 2019). In this study, NDSI based only on red-edge and NIR regions showed good performance in assessing wheat yield, which agrees with previous research (Adak et al., 2021; Wang et al., 2019) and can be explained by the strong relationship of the red-edge reflectance with chlorophyll content and biomass accumulation (Fitzgerald et al., 2006; Zillmann et al., 2015). Moreover, the NDSI (NIR, red-edge) was a strong indicator of GNC, also reported by Raya-Sereno et al. (2021b); Fu et al. (2022). Likewise, Li et al. (2013) and Prey and Schmidhalter (2019) highlighted the suitability of NDSI (NIR, red-edge) for assessing winter wheat N uptake and N_{area} . The red-edge requires narrow bands for accurate assessment, but fortunately many UAV/satellite multispectral sensors incorporate suitable bands in the red-edge region.

In this study, SWIR indices reduced uncertainty in yield assessment and played a crucial role in obtaining better GNC estimations. Some structural crop components associated with accumulated biomass have absorption features in the SWIR region (i.e., lignin at 1120 nm), which could explain the high correlation of the NDSI (1106 nm, 1066 nm) with yield. SWIR greatly improved the assessment of GNC, and to a lesser extent N_{area} , in both hyperspectral airborne and multispectral Sentinel-2 sensors. This improvement is explained by the absorption feature of N–H bonds and its strong relationship with protein content (Curran, 1989). Similarly, Zhao et al. (2005) and Pancorbo et al. (2023) reported the suitability of the SWIR region for GNC estimation in wheat, and Söderström et al. (2010) used the simple ratio of SWIR (1550–1750 nm range) and green reflectance for GNC estimation in barley. To maximize the N–H bond absorption feature, it is recommended to use narrow bands in the SWIR region (Berger et al. 2020; Raya-Sereno et al. 2021a). When SWIR bands were included in the current study, the airborne hyperspectral sensor decreased *RMSE* by 8.1%, like due to higher spatial resolution compared to Sentinel-2 20-m SWIR bands, from which pure pixels from individual plots could not be extracted. Hyperspectral SWIR sensors mounted on UAV and aircraft are available but not widespread due to the high cost; however, the new imaging spectrometers, such as the PRecursorre IperSpettrale della Missione Applicativa (PRISMA) or the Environmental Mapping and Analysis Program (EnMAP) that are precursors of the

Copernicus Hyperspectral Imaging Mission for the Environment (CHIME), already provide bands in the SWIR region. In addition, broader bands in this region are available in various satellites, and in the following years their spatial and spectral resolution will increase.

The role of non-parametric models for assessing productivity-associated crop traits

The performance of estimating wheat traits with a single NDSI was improved when combining different indices with the ensemble models. In this study, the three ensemble models performed similarly when using three or more indices to estimate any of the wheat traits. However, RF needs more than two indices to attain accuracy similar to the other models.

The structural index used in the ensemble models for estimating the three crop traits associated with productivity was the GNDVI (NIR, Green). It had strong collinearity with NDVI (NIR, Red) but tended to saturate later, as already shown by Gitelson et al. (1996). The chlorophyll index was based on the NIR and red-edge bands, with slight trait-specific differences. The SWIR-based index showed differences: the most appropriate for assessing yield was a combination with NIR, whereas for GNC and N_{area} a combination with a visible band worked best. In the best cases of this study, the *RMSE* of the satellite estimations was reduced to 507 kg ha⁻¹ for yield assessment, to 1.32% for GNC, and to 16.2 kg N ha⁻¹ for N_{area} . In the literature, Segarra et al. (2022) combined Sentinel-2 information from various dates with ensemble models to achieve an *RMSE* of 740 kg ha⁻¹. Hunt et al. (2019) obtained an *RMSE* of 610 kg ha⁻¹, reducing the *RMSE* by 7% when Sentinel-2 information was combined with climatological data. In our study, the average yield for all treatments was 5330 kg ha⁻¹; thus, the relative *RMSE* of yield estimation with Sentinel-2-based indices at flowering was 9.5%.

Among wheat traits, yield prediction presented the highest R^2 with reflectance information, whereas GNC prediction obtained the lowest value ($R^2=0.69$). Prediction of GNC remains challenging; as an example, Zhao et al. (2019) applied MLR using crop parameters together with Sentinel-2 information and obtained a maximum value of $R^2=0.47$ when estimating GNC. This limitation in GNC prediction at flowering may relate to multiple factors that affect N translocation to grain during the grain filling period, such as N availability, water access, and temperature (Martre et al., 2003). Therefore, ensemble models aiming to improve GNC prediction should incorporate additional information such as genotype and environmental conditions, particularly during the grain filling period (Rharrabti et al., 2001).

Conclusions

The vegetation index based on the VNIR regions that best estimated crop N status was the canopy chlorophyll content index (CCCI). The equations needed to calculate CCCI that enveloped the airborne data from this experiment were close to previously published data from different locations, suggesting that these curves can be widely used for wheat. Similar enveloping equations are presented in this work for Sentinel-2-based data.

Maps reflecting the spatial distribution of wheat NNI were produced from aerial imagery, and the ability of these maps to guide fertilizer recommendations was assessed through an error analysis based on the N sufficiency index. The error rate in assessing N-responsive

and non-responsive sites to increase yield at final stem elongation was 18% and to increase grain N concentration (GNC) at flowering, it was 22%. The relationship between CCCI and NNI provided in this work could be used to translate remote sensing information into a site-specific N fertilizer application map. This study confirms that the efficiency of N applied to wheat can be enhanced with split fertilization: 30 to 50% at tillering (uniform rate, as it is not possible to rely on crop N status) and a variable rate at the end of stem elongation (Z37) to adjust the rest of the N application to the crop N status assessed by remote sensing. An additional N application just after flowering to boost GNC could rely on remote sensing assessment as well.

Both airborne hyperspectral and multispectral satellite sensors showed high potential for wheat yield estimation, with yield being the crop trait that was better estimated. The *RMSE* of the hyperspectral assessment at flowering was 493 kg ha⁻¹ and increased to 521 kg ha⁻¹ when using Sentinel-2 imagery. As in the other crop traits, the best estimation was attained when combining spectral indices based on bands from the visible, red-edge, NIR, and SWIR regions. GNC showed the poorest assessment based on Sentinel-2 bands, but it was satisfactory when the SWIR bands were incorporated (*RMSE* = 1.32%). Similarly, the *N_{area}* estimation improved when red-edge and SWIR bands were considered. This study highlights that the assessment of wheat N-related traits can be greatly improved when the sensor provides information on the SWIR and the narrow red-edge bands.

The assessment of all crop traits at flowering improved when using non-parametric models combining various indices instead of a single-index model. The three ensemble models (multiple linear regression, artificial neural networks, and random forest) performed similarly, but random forest required a minimum of three indices to perform correctly. Model performance could be enhanced by including other environmental variables, particularly in the estimation of N-related crop traits.

Acknowledgements This study received funding from Agencia Estatal de Investigación of the Ministerio de Ciencia e Innovación of Spain (PID2021-124041OB-C21/C22) and from the European Union.

Author contributions M.Q. wrote the main manuscript. J.L.P. and N.A. prepared the figures. M.D., J.L.P., J.L.G. and M.Q. collected data in the field studies. A.H. lead the acquisition and process of airborne imagery. J.L.P. and N.A. downloaded and processed the satellite images. All authors reviewed the manuscript.

Funding Open Access funding provided thanks to the CRUE-CSIC agreement with Springer Nature.

Data availability Data available at <https://doi.org/10.17632/b7xg8d8m9k.1> and <https://doi.org/10.6084/m9.figshare.21865410>.

Declarations

Competing interests The authors declare no competing interests.

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