



Linking organic fertilizer properties to in-season N dynamics using multispectral UAV imagery

Matthias Diener^{1,3} · L. Agostini^{2,3} · F. Argento¹ · E. K. Bünemann² · A. Walter³ · J. Mayer¹ · F. Liebisch¹

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Abstract

Purpose Alignment of crop nitrogen (N) demand with N supply is crucial to improve N use efficiency of organic fertilizers whose N is largely bound organically. This study aimed to evaluate the potential of unmanned aerial vehicle (UAV)-based multispectral imagery to monitor in-season N uptake and to assess how different organic fertilizers affect N dynamics.

Methods A field trial in Wallbach, Switzerland, compared untreated cattle slurry, anaerobically digested slurry, solid digestate, a mineral N control, and a zero-N control over two winter cereal seasons. UAV-acquired multispectral data were combined with environmental data (weather, soil and fertilizer) to model dry matter, N concentration, N uptake and the nitrogen nutrition index using random forest regression.

Results The random forest models combining UAV-based multispectral imagery with environmental data showed good performance in predicting in-season N uptake of winter wheat ($R^2=0.85$, RMSE=13.9 kg N ha⁻¹) and of winter barley ($R^2=0.78$, RMSE=9.3 kg N ha⁻¹). Predicted N dynamics revealed transient N uptake maxima in organic treatments before fertilization, likely due to legacy fertilizer effects. Post-fertilization, N uptake increased most under mineral fertilization. N uptake dynamics were affected by fertilizer properties, with low C/N ratio and high NH₄-N proportion showing stronger effects.

Conclusion Highly temporal UAV-based multispectral imagery captures in-season N uptake dynamic and reveals differences in fertilizer N release caused by quality differences of organic fertilizers. These insights support optimized fertilizer application for better synchronization of N mineralization with crop demand.

Keywords Nitrogen use efficiency · Organic fertilizers · N dynamics · multispectral imagery · UAV

✉ Matthias Diener
matthias.diener@agroscope.admin.ch

¹ Agroscope, Reckenholzstrasse 191, Zürich 8046, Switzerland

² Research Institute of Organic Agriculture (FiBL), Ackerstrasse 113, Frick 5070, Switzerland

³ ETH Zürich, Universitätstrasse 2, Zürich 8092, Switzerland

Abbreviations

B	Blue band
C/N	Carbon-to-nitrogen ratio
DM	Dry matter
DOK	trial Bio-dynamisch – organisch – konventionell (German); long-term field trial comparing bio-dynamic, organic and conventional farming systems
DOY	Day of the year
G	Green band
GDD	Growing degree days
N	Nitrogen
N_c	Nitrogen concentration
N_{crit}	Critical N curve
N_{up}	Nitrogen uptake
NDRE	Normalized difference red-edge index
NDVI	Normalized difference vegetation index
NIR	Near-infrared band
NNI	Nitrogen nutrition index
N_{org}	Organic nitrogen
NON	Zero-N fertilization treatment
N_{tot}	Total nitrogen
NUE	Nitrogen use efficiency
MIN	Mineral fertilization treatment
PRIF	Principles of fertilization of agricultural crops in Switzerland
R	Red band
R^2	Coefficient of determination
RE	Red-edge band
RF	Random forest regression
RMSE	Root mean square error
SD	Solid digestate treatment
SLA	Anaerobically digested slurry treatment
SLU	Untreated cattle slurry treatment
UAV	Unmanned aerial vehicles

Introduction

The use of nitrogen (N) in agriculture is key to guaranteeing high yields and ensuing food security. However, active N forms are very susceptible to being lost to the environment via ammonia volatilization (Bouwman et al., 2002), nitrate leaching (Zhou & Butterbach-Bahl, 2014), and denitrification as N_2 or N_2O emissions (Feigenwinter et al., 2023).

The N input from organic fertilizers is of great importance in livestock-based and mixed farming systems. Applications of organic fertilizers, pig and cattle slurry being the most used, averaged $41 \text{ kg N ha}^{-1} \text{ yr}^{-1}$ across the entire EU in 2017 (Velthof et al., 2024). Due to the high livestock density in certain regions the amount of N applied by organic fertilizers can reach $200 \text{ kg N ha}^{-1} \text{ yr}^{-1}$ (Lessmann et al., 2025), in extreme cases even $400 \text{ kg N ha}^{-1} \text{ yr}^{-1}$ (Baumgartner et al., 2025).

Organic fertilizers recycled from agricultural and non-agricultural sources (e.g., food industry) show great potential to decrease mineral fertilizer input and N surplus and, consequently, increase N circularity (Harder & Liebisch, 2025; Velthof et al., 2024; Wei et al., 2020). However, the short-term N release of organic fertilizers varies greatly, ranging from 0% mineral fertilizer equivalents for some composts to almost 100% for pure urine (Gutser et al., 2005). Since, only the ammonium-N ($\text{NH}_4\text{-N}$) fraction of the organic fertilizers is plant-available and organic N (N_{org}) has to undergo mineralization, alignment of N supply and N demand of the crop is challenging. Poor synchronization of N supply from the fertilizer and N demand of the crop can deteriorate yield and N uptake and finally lead to N losses to the environment (Harder & Liebisch, 2025). The $\text{NH}_4\text{-N}$ proportion and the carbon-to-nitrogen (C/N) ratio of an organic fertilizer partially determine the short-term N release and contribute significantly to the N uptake of the crop in the year of application (Gutser et al., 2005; Qian & Schoenau, 2002). Anaerobic digestion is an option to increase $\text{NH}_4\text{-N}$ and lower C/N ratio due to the decomposition of organic matter and mineralization of bound organic N during digestion (Möller & Müller, 2012).

Soil fertility is a key component of effective nutrient management, particularly in organic farming, where restrictions on mineral fertilizer use increase the reliance on N mineralization (Smith et al., 2019). Nevertheless, these restrictions can limit nutrient availability and contribute to lower yields in organic farming than those achieved in conventional cropping systems (Mayer et al., 2015; Seufert et al., 2012). The main driver of the yield gap between conventional and organic farming systems is the lack of mineral fertilizers in organic farming (Knapp et al., 2023). In the DOK long-term experiment in Switzerland, the yield gap between conventional and organic farming reached 13–34% for non-legume crops, which is mainly explained by the different amounts of mineral (soluble) N applied (Knapp et al., 2023). Thus, enhancing yield and NUE in organic farming systems is particularly important for achieving environmentally sustainable agriculture with sufficient and stable yields (Tuomisto et al., 2012).

The nitrogen nutrition index (NNI) is a well-established indicator of crop N status derived from a crop-specific N dilution curve, which defines the critical N concentration (N_{crit} , %) required to achieve maximum dry matter (DM, t ha^{-1}) (Justes, 1994; Prost & Jeuffroy, 2007). Over the growing season, N_{crit} declines due to an increase in plant components with low N concentration (N_c , %) and a decrease in foliar N levels (Fernandez et al., 2022; Lemaire et al., 2008). The ratio of the actual crop N_c to N_{crit} at a given biomass is defined as the NNI. Values below 0.8 indicate N deficiency, values above 1.2 indicate N excess, and a value of 1 denotes optimal N status (Fabbri et al., 2025). Ravier et al. (2021) proposed a more flexible threshold of NNI to optimize fertilizer application, ranging from 0.6 to 0.9, depending on the crop's development stage. For winter wheat, the NNI concept is well established (Justes, 1994; Prost & Jeuffroy, 2007) and has recently been validated under Swiss pedoclimatic conditions (Fontana et al., 2021).

Remote sensing allows the optimization of NUE at the crop level through site-specific fertilizer application (Argento et al., 2022; Basso et al., 2016; Cammarano et al., 2021) and optimized fertilizer timing (Zhou et al., 2025). Monitoring the spatial and temporal patterns of crop N status is essential for understanding and improving the synchronization of N supply with crop N demand, thereby enhancing NUE and reducing the risk of N losses (Radočaj et al., 2022). Unmanned aerial vehicle (UAV) imagery enables high-resolution monitoring of crop biomass development, and N status throughout the growing season (Bendig et al.,

2015; Wang et al., 2019; Yang et al., 2020). Several studies have shown strong correlations between crop N uptake and spectral vegetation indices (Argento et al., 2021; Cammarano et al., 2021). In particular, indices including the red-edge band, such as the normalized difference red-edge (NDRE) index have been shown to be sensitive to N levels due to their change in reflectance characterized by high absorption in the red and high reflectance in the near-infrared region (Magney et al., 2017; Shu et al., 2021; Zhou et al., 2025). Therefore, the NDRE proved to be a good proxy for remotely estimating N uptake (Argento et al., 2022; Prey & Schmidhalter, 2019; Wang et al., 2019). The normalized difference vegetation index (NDVI) shows quicker saturation and is more suitable to estimate aboveground biomass (Cabrera-Bosquet et al., 2011; Rouse et al. Jr., 1974; Serrano et al., 2000). However, recent research has shown that machine learning approaches integrating spectral bands with supplementary information, such as weather and soil data, outperform classical vegetation indices (Chen et al., 2025; Pan et al., 2025; Wang et al., 2025). This is particularly true for the prediction of N_c (Chen et al., 2025; Zhou et al., 2025), which has been deemed insufficiently robust by spectroscopy and imaging approaches (Homolová et al., 2013; Perich et al., 2021). The possibility of measuring N_c at sufficient performance allows for a solely remotely sensed calculation of the NNI and subsequent N fertilization decisions (Perich et al., 2025; Tanaka & Gislum, 2025; Zha et al., 2020; C. Zhang et al. 2025a, b).

Multispectral imagery has proven to be robust for estimating in-season crop N nutrition under mineral fertilization (Perich et al., 2025; Zha et al., 2020; C. Zhang et al. 2025a, b). However, the application of remote sensing techniques is more challenging when organic fertilizers are used, due to their more complex N release dynamics (Roel-Rezk et al., 2025; Schuster et al., 2023). Therefore, the objectives of this study were to (a) employ multispectral imagery to monitor temporal variations in crop N uptake as affected by mineral and organic fertilizers with distinguished properties, (b) compare NDRE and NDVI with machine learning models integrating multispectral bands, weather, soil and fertilizer data to estimate dry matter, N concentration, N uptake and NNI and ultimately (c) relate the remotely assessed N dynamics to the properties of the applied organic fertilizers.

Materials and methods

Study site, management and weather

In Wallbach (47.56225° N, 7.88766° E) Switzerland, a field trial was conducted from 2018 to 2024. The field was characterized as a Haplic Luvisol (World Reference Base of Soil Resources (FAO, 2014)) from aeolian Loess deposits and was located at 330 m a.s.l. Mean annual precipitation was 1166 mm and mean annual temperature was 11.0 °C (2004–2023, Agrometeo, 47.56967° N, 7.89844° E). Further information on the study site is provided by Efosa et al. (2023).

The present experiment was conducted in 2023 cultivating winter wheat (*T. aestivum*, variety ‘Wiwa’) and in 2024 cultivating winter barley (*H. vulgare*, variety ‘Higgins’). After the harvest of winter wheat, the yellow mustard was sown as an intermediate cover crop. The whole mustard biomass was mulched before tillage and sowing of winter barley.

The field was managed following the standards of the Swiss Organic Farming Association (Bio Suisse, 2023) starting in 2017. Therefore, no chemical plant protection products or

growth regulators were applied. Weeding was performed mechanically with a tine harrow. Detailed information on the cultivation management is provided in Supplemental Information 2.

Temperature and precipitation anomalies from monthly means of the years 2004–2023 (indicated numerically on top) for the two growing seasons are shown in Fig. 1. The 2023 growing season was characterized by below-average precipitation and above-average temperatures. In April, a temporary decrease in temperature occurred and was accompanied by low precipitation. Toward the end of May and the beginning of June 2023, the experimental site experienced a severe drought, with high temperatures and below-average precipitation. By contrast, during the 2024 growing season, both precipitation and temperatures were above average for most of the season, with the exception of April. These conditions provided a favourable environment for disease and weed development.

Experimental design and treatments

The field trial followed a split-plot block design including five treatments with four replicates Fig. 2. The experiment is designed as an N-fertilization experiment with different organic fertilizer types: untreated cattle slurry (SLU), digested cattle slurry (SLA), solid digestate (SD), a zero-N control (NON) and full mineral fertilization control (MIN). All treatments, except NON, received the same amount of total N (N_{tot}), but differed in their amount of plant available $\text{NH}_4\text{-N}$, dry matter (DM) content, pH and C/N ratio (Table 1). Fer-

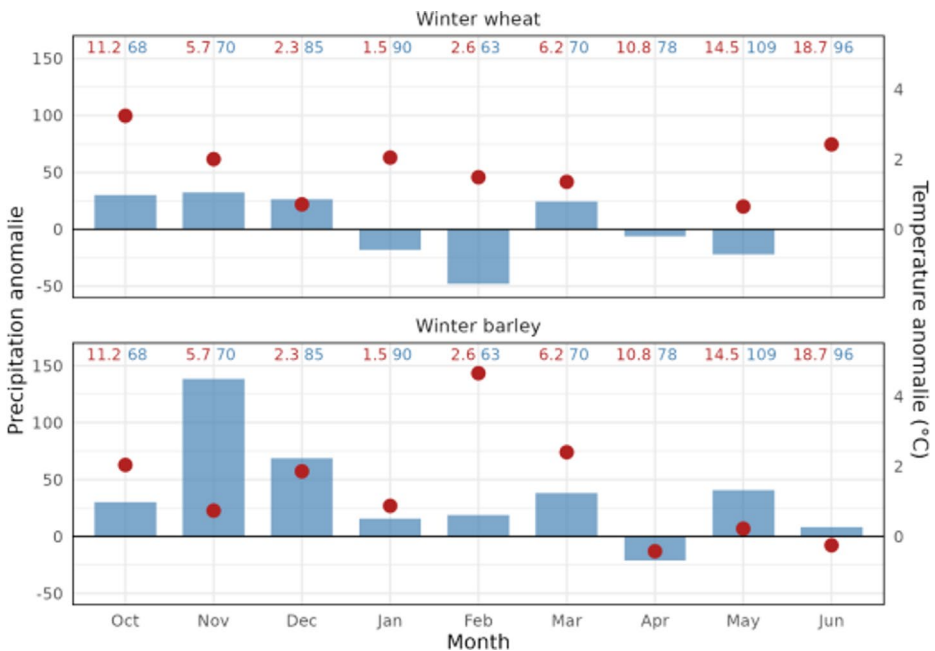


Fig. 1 Monthly precipitation (blue) and temperature (red) anomalies from the monthly means of the 20-year period 2004–2023 for the winter wheat season in 2023 (upper panel) and the winter barley season in 2024 (lower panel). Numbers at the top of the panel indicate the means of the 20-year period in the respective colour. Values above zero indicate higher monthly values than the mean, whereas values below zero indicate lower values than the mean.

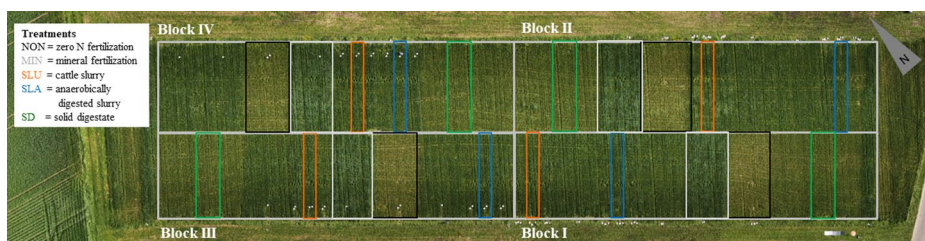


Fig. 2 Aerial drone image of the field trial in Wallbach (Switzerland) with the different fertilizer treatments: zero-N fertilization control (NON in black), mineral fertilization control (MIN in grey), untreated slurry (SLU in orange), anaerobically digested slurry (SLA in blue) and solid digestate from a commercial biogas plant (SD in green). The field trial followed a split-block design with four replicates.

Table 1 Total N applied ($N_{\text{tot applied}}$), total N (N_{tot}), $\text{NH}_4\text{-N}$, $\text{NH}_4\text{-N}$ proportion, dry matter, C/N ratio and pH of the applied fertilizers: mineral fertilization control (MIN), untreated slurry (SLU), anaerobically digested slurry (SLA) and solid digestate from a commercial biogas plant (SD) in 2023 (winter wheat) and 2024 (winter barley). The numbers for N_{tot} and $\text{NH}_4\text{-N}$ are displayed in g N kg^{-1} fresh weight.

Year and crop	Fertilizer properties	Unit	MIN	SLU	SLA	SD
2023 winter wheat	$N_{\text{tot applied}}$	kg N ha^{-1}	140.0	140.1	142.6	147.7
	N_{tot}	g N (kg FW)^{-1}	210	1.66	4.22	5.91
	$\text{NH}_4\text{-N}$	g N (kg FW)^{-1}	210	0.79	2.07	1.49
	$\text{NH}_4\text{-N proportion}$	%	100	48.6	50.2	20.9
	Dry matter	g g^{-1}	NA	4.3	6.9	25.2
	C/N ratio	unitless	0	10.9	6.2	20.9
	pH	unitless	NA	7.3	7.7	8.1
2024 winter barley	$N_{\text{tot applied}}$	kg N ha^{-1}	120.0	124.2	128.2	119.7
	N_{tot}	g N (kg FW)^{-1}	210	1.42	2.35	5.83
	$\text{NH}_4\text{-N}$	g N (kg FW)^{-1}	210	0.65	1.62	1.46
	$\text{NH}_4\text{-N proportion}$	%	100	45.8	68.9	25.0
	Dry matter	g g^{-1}	NA	5.1	3.8	32.6
	C/N ratio	unitless	0	12.1	5.7	26.0
	pH	unitless	NA	7.4	7.9	7.5

tilizer amounts were calculated based on N_{tot} following the recommendations of the Swiss Fertilization guidelines (Sinaj & Richner, 2017), being $140 \text{ kg } N_{\text{tot}} \text{ ha}^{-1}$ applied to winter wheat and $120 \text{ kg } N_{\text{tot}} \text{ ha}^{-1}$ to winter barley.

NON did not receive any N fertilizer throughout the experiment beginning in 2018, whereas MIN was fertilized with $(\text{NH}_4)_2\text{SO}_4$, except for 2021 and 2023, when $\text{Ca}(\text{NO}_3)_2$ was used to prevent soil acidification. Although the study was performed under organic farming regulations, MIN was integrated as a reference of yield and N uptake according to recommended fertilizer amounts. Both, NON and MIN received the recommended amounts of phosphorous (P) and potassium (K) to maintain N the only lacking nutrient.

In 2023, SLU originated from the nearby farm (Wallbach, Switzerland). In 2024, the farm installed a slurry separator, removing the straw from the slurry. To ensure comparability of the fertilizers, the origin of SLU was changed to a farm in Sulz (Switzerland). In 2023, SLA originated from an agricultural biogas plant running in Densbüren (Switzerland), which ferments farm cattle slurry with external co-substrates, such as horse manure and food-processing residues. Usually, digestates tend to have a higher amount of $\text{NH}_4\text{-N}$ com-

pared to untreated slurry (Möller & Müller, 2012). However, due to the C-rich co-substrates used, the $\text{NH}_4\text{-N}$ proportion of SLU and SLA did not differ in 2023. In 2024, the SLA was therefore sourced from a biogas plant in Dällikon (Switzerland), which used vegetable leftovers as co-substrates, to guarantee a high proportion of $\text{NH}_4\text{-N}$. In both years, anaerobic digestion was followed by a solid-liquid separation, of which SLA is the liquid fraction. In both years, SD was obtained from a commercial biogas plant (Pratteln, Switzerland), which uses plant material from urban green areas and organic wastes from households, supermarkets, food processing industries and gastronomy as feedstock. After solid-liquid separation, the solid fraction was stored at 10 °C to prevent decomposition before the field application. Table 1 shows characteristics of the applied fertilizers, indicating that the proportion of $\text{NH}_4\text{-N}$ in SLA was indeed greater in 2024 than in 2023, while contents of dry matter and N_{tot} were lower.

SLU, SLA and MIN were applied in two equal splits during the growing season, with the liquid fertilizers manually distributed using watering cans imitating a trailing hose. SD was applied in autumn before sowing and incorporated with a rotary harrow.

Environmental data acquisition

Weather data were retrieved from a local weather station (Agrometeo, Switzerland) at a distance of 1200 m from the experimental field. A moving average temperature was calculated by taking the average of the daily mean temperatures of the previous five days. Precipitation was summed up for the previous five days. Growing degree days (GDD) were calculated by summing up the average daily temperatures that lay above the baseline temperature (T_{base}). T_{base} was set to 0 °C for both winter wheat and winter barley (Grieder et al., 2015; Liu et al., 2025). Soil temperature and water content at a depth of 0.10 m were logged with a 15 min resolution and averaged daily (TEROS 11, Meter Group, USA).

Plant sampling and performance measurement

In 2023 (14 Apr, 04 May, 12 June) and 2024 (26 Mar, 18 Apr, 14 May), plant samples (3×0.5 m) were harvested from different rows in each plot as ground truth data on the same days that UAV flights were conducted. At the final harvest, five 0.5 m rows were cut for both winter wheat and winter barley to determine straw yield and calculate straw N uptake. Grain yield was harvested from a strip ($1.5 \text{ m} \times 7 \text{ m}$) using a small combine harvester (Wintersteiger, Austria). For all samples at harvest and during the growing season, fresh weight was assessed before the samples were dried at 60 °C for 48 h. Samples were then ground on a cutting mill (SM 300, Retsch, Germany) and analyzed for N concentration (N_c , in %) by dry combustion on a C/N Elemental Analyzer (Max Cube, Elementar, Germany).

N uptake and nutrition status

Total N uptake in the aboveground biomass was calculated using the following formula:

Where N_{up} is the N uptake in kg ha^{-1} , DM is the dry matter of the aboveground biomass (straw and grains) in t ha^{-1} and N_c is the N concentration in % DM.

$$N_{\text{up}} = DM \times N_c \times 10 \quad (1)$$

The nitrogen nutrition index (NNI) was chosen to investigate the N status of the crop based on the critical N dilution curve. The equation for the critical N curve applies only to closed canopies (Justes, 1994). A transition point (in plant DM) is defined, under which the plants are considered to be isolated and the N_{crit} value is constant. According to Justes et al. (1994), the constant N_{crit} was set to 4.4% and the transition point was set at 1.65 t ha^{-1} . For DM samples above the transition point, NNI for winter wheat was calculated as follows:

$$NNI = N_c / (5.35 \times DM^{-0.442}) \quad (2)$$

To calculate the NNI for winter barley, the critical N dilution curve developed by Zhao (2014) was used. The transition point for winter barley was set to 1.79 t ha^{-1} dry matter, and the constant N_{crit} was set to 3.77%. This resulted in the following NNI formula:

$$NNI = N_c / (4.76 \times DM^{-0.390}) \quad (3)$$

Acquisition of images

Weekly to biweekly drone flights using a DJI Phantom 4 Multispectral (Shenzhen, China) were conducted throughout 2023 and 2024, capturing image data across both full vegetation periods. Flights were conducted at a height of 50 m, perpendicular to the treatment plots with an 80% front and 75% lateral overlap. The drone integrated a real-time kinematic module for precise GPS positioning. The correct location was verified using four ground control points at the edges of the field. The ground truth pixel resolution was 2.7 cm per pixel. Spectral information was recorded in five bands of the light spectrum, namely blue (B) centred at $450 \text{ nm} \pm 16 \text{ nm}$, green (G) at $560 \pm 16 \text{ nm}$, red (R) at $650 \pm 16 \text{ nm}$, red-edge (RE) at $730 \pm 16 \text{ nm}$ and near-infrared (NIR) at $840 \pm 26 \text{ nm}$. The images were ortho-mosaiced with Pix4Dmapper software (Lausanne, Switzerland) and georeferenced in QGIS (Version 3.36.0-Maidenhead (QGIS Development Team, 2026)). Median reflectance values for each multispectral band were extracted for each plot. Calibration of the images was conducted by fitting a linear model between the measured reflectance values from customized reflectance panels using a spectrometer and the corresponding field values assessed with the drone ($R^2 > 0.95$). Two out of five brightest panels were overexposed and excluded from the calibration. Spectral information was extracted in R (version 4.4.1) using the *raster* package. Segmentation between soil and vegetation was based on normalized difference vegetation index (NDVI, see Table 2), where $\text{NDVI} > 0.35$ was chosen as vegetated pixels for winter wheat, and $\text{NDVI} > 0.25$ for winter barley. Finally, vegetation indices were calculated (see Table 2).

Table 2 Calculated vegetation indices from multispectral images acquired with a DJI Phantom 4 Multispectral.

Vegetation Index	Acronym	Formula	Reference
Normalized difference vegetation index	NDVI	$\frac{NIR - R}{NIR + R}$	(Rouse Jr. et al., 1974)
Normalized difference red-edge	NDRE	$\frac{NIR - RE}{NIR + RE}$	(Barnes et al., 2000)

Correlation analysis and statistics

All statistical analyses were conducted using R (version 4.4.1 (R Core Team, 2025)). After tests for normal distribution and homogeneity, analysis of variance was performed, followed by Tukey HSD post-hoc tests ($\alpha < 0.05$). Correlation analysis between sensed vegetation indices and in-season plant parameters (DM, N_c , N_{up} , NNI) was performed using a linear mixed model from the R-package *lme4* (Bates et al., 2015), with sampling date as a random effect, accounting for the dependence of sampling dates. Model fit was assessed using marginal and conditional R^2 , explaining variance by fixed effects alone and fixed and random effects respectively. Due to the saturation of vegetation indices, a negative log transformation was applied. Correlations were performed on both years individually, since the crops differed between years. The last ground truth sampling date in both years was excluded from the correlation analysis, because crops already started to senesce, exhibiting a different spectral signal.

Random forest regression for predicting plant parameters

A 10-fold cross-validation random forest model was implemented using the *caret* package in R to predict in-season dry matter ($t\ ha^{-1}$), N_c (%), N_{up} ($kg\ N\ ha^{-1}$) and NNI. Predictor variables included the multispectral drone-derived bands (R, G, B, RE, NIR), weather data (GDD, 5-days mean air temperature, 5-day precipitation sum), soil data (soil temperature and soil water content), and fertilizer characteristics (NH_4 -N proportion and C/N ratio). Separate random forest models (Table 3) were developed for different predictor subsets representing the type of data (multispectral, weather, soil and fertilizer). For model evaluation, data corresponding to drone flight dates corresponding with destructive ground truth plant sampling was split into 80% training and 20% testing dataset. The number trees and the regression split rule were set by default to 500 and *variance*, respectively.

After model training, the best performing model was selected based on the lowest root-mean-square error (RMSE). The selected model was then used to predict dry matter, N_c , N_{up} and NNI on an independent data set comprising all drone flight dates without corresponding

Table 3 Separate random forest regression models to predict dry matter ($t\ ha^{-1}$), N concentration (N_c , %), N uptake (N_{up} , $kg\ N\ ha^{-1}$) and nitrogen nutrition index (NNI) for different subsets representing the type of data (multispectral, weather, soil and fertilizer). Predictor variables included the multispectral drone-derived bands (R, G, B, RE, NIR), weather data (GDD, 5-days mean air temperature, 5-day precipitation sum), soil data (soil temperature and soil water content), and fertilizer characteristics (NH_4 -N proportion and C/N ratio). A model including NDRE, weather and fertilizer data was additionally developed.

RF model	multispectral	weather	fertilizer	soil
multispectral + weather + fertilizer + soil	R, G, B, RE, NIR	GDD, temperature, precipitation	NH_4 -N proportion, C/N ratio	temperature, water content
multispectral + weather + fertilizer	R, G, B, RE, NIR	GDD, temperature, precipitation	NH_4 -N proportion, C/N ratio	
multispectral + weather	R, G, B, RE, NIR	GDD, temperature, precipitation		
NDRE + weather + fertilizer	NDRE	GDD, temperature, precipitation	NH_4 -N proportion, C/N ratio	

ground-truth sampling. In addition, N_{up} (kg N ha^{-1}) was also derived indirectly using the Eq. 1, and NNI was calculated using Eq. 2 for winter wheat and Eq. 3 for winter barley.

Linking fertilizer characteristics to predicted N uptake

The effect of fertilizers was assessed over the period from the start to the end of the growing season, which was defined as the time point of maximum N uptake. For each plot a linear model of N uptake versus the days of the year was fitted. Slopes of the individual linear regression were extracted and related to $\text{NH}_4\text{-N}$ proportion using a linear function and to C/N ratio using a quadratic function to examine the N release dynamics of the different fertilizers.

Results

Yield and N uptake

In 2023, the highest aboveground biomass yield (Fig. 3a) of winter wheat was observed under MIN with $14.90 \pm 0.65 \text{ t ha}^{-1}$ (mean $\pm$ standard deviation), consisting of $4.05 \pm 0.44 \text{ t ha}^{-1}$ grains and $10.85 \pm 0.86 \text{ t ha}^{-1}$ straw. The harvested total grain yields of the liquid fertilizer treatments (SLU and SLA) and MIN did not differ significantly (Tukey, $p < 0.05$). By contrast, NON showed significantly lower total, straw and grain yields (Tukey, $p < 0.05$). The straw and grain yield of SD was between MIN and NON and differed significantly from both (Tukey, $p > 0.05$). Generally, the grain yields of all fertilized treatments were low and

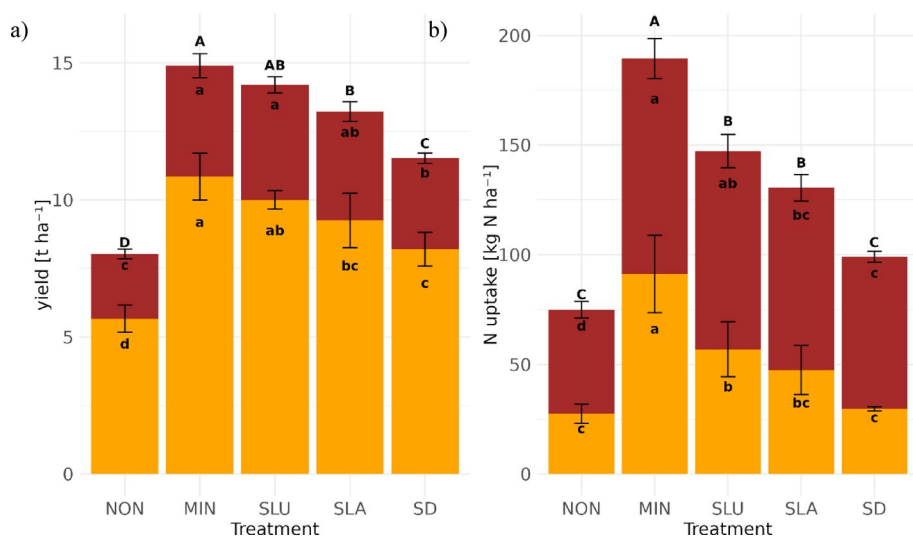


Fig. 3 Dry matter yield (t ha^{-1}) (a) and N uptake (kg N ha^{-1}) (b) of winter wheat in 2023 from different fertilizer treatments: zero-N fertilization control (NON), mineral fertilization control (MIN), untreated slurry (SLU), anaerobically digested slurry (SLA) and solid digestate from a commercial biogas plant (SD). Red colours show grain and orange straw fractions. Error bars indicate standard deviation, lowercase letters indicate significant differences of the fractions, and uppercase letters indicate significant differences in total aboveground biomass (Tukey, $p < 0.05$).

the straw yield relatively high, compared to a standard reference yield of Switzerland (grain, 15% DM at harvest = 5.1 t ha^{-1} ; straw, 10% DM at harvest = 6.3 t ha^{-1} ; total = 11.4 t ha^{-1} , (Sinaj & Richner, 2017).

The highest total N_{up} by winter wheat in 2023 (Fig. 3b) occurred in MIN with $189.5 \pm 15.8 \text{ kg N ha}^{-1}$ (grain: $98.3 \pm 9.2 \text{ kg N ha}^{-1}$, straw: $91.3 \pm 17.6 \text{ kg N ha}^{-1}$) and was significantly higher than for the organic fertilizers (Tukey, $p < 0.05$). The SLU and SLA did not show significant differences in N_{up} , but the values were significantly higher than those for NON and SD (Tukey, $p < 0.05$). Although the total N recovery observed in SD was similar to that of NON, N_{up} by the grain was significantly higher. N_{up} of the whole crop in MIN was higher than the Swiss standard reference N_{up} for winter wheat (grain = 121 kg N ha^{-1} , straw = 22 kg N ha^{-1} , total = 143 kg N ha^{-1}), but lower in grain.

Winter barley had a weak agronomic performance in 2024 Fig. 4. MIN had a winter barley grain yield of $1.10 \pm 0.14 \text{ t ha}^{-1}$, which is only 20% of the Swiss reference yield (Sinaj & Richner, 2017). Total aboveground biomass under MIN yielded only $4.15 \pm 0.23 \text{ t ha}^{-1}$. Due to the generally low grain yield, the differences between the treatments were also less pronounced. Under NON only a grain yield of $0.83 \pm 0.19 \text{ t ha}^{-1}$ was observed. SLA exhibited yields similar to those of MIN.

The highest total N_{up} of winter barley was observed under MIN ($72.5 \pm 6.2 \text{ kg N ha}^{-1}$) and was together with SLA significantly higher than SD and NON, whereas SLU was only higher than NON. The N_{up} by the straw was above the standard reference for straw N_{up} , but below that for the grain N_{up} (N_{up} : grain = 89 kg N ha^{-1} , straw 26 kg N ha^{-1} , total = 115 kg N ha^{-1}).

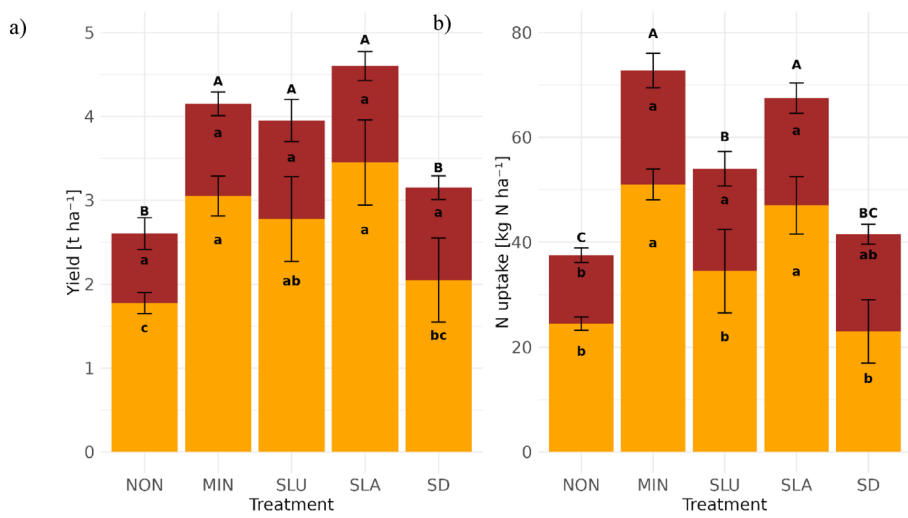


Fig. 4 Dry matter yield (t ha^{-1}) (a) and N uptake (kg N ha^{-1}) (b) of winter barley in 2024 from different fertilizer treatments: zero-N fertilization control (NON), mineral fertilization control (MIN), untreated slurry (SLU), anaerobically digested slurry (SLA) and solid digestate from a commercial biogas plant (SD). Red colours show grain and orange straw fractions. Error bars indicate standard deviation, lowercase letters indicate significant differences of the fractions, and uppercase letters indicate significant differences in total aboveground biomass (Tukey, $p < 0.05$).

In-season N uptake and growth dynamics

Table 4 shows the results of the three plant sub-samplings during both seasons. MIN performed best for N_c , N_{up} and NNI throughout the season. During the first two sampling dates in 2023, SLU exhibited the highest biomass ($t\ ha^{-1}$), whereas SLA's biomass was highest across all sampling dates in 2024. At the first sampling date, SLU in 2023 and SLU and SLA in 2024 showed no significant differences in N_{up} from MIN. However, at the second sampling in both years, differences were observed between the plots fertilized with liquid organic fertilizers (SLU, SLA) and MIN was observed. The NNI showed the same significant differentiation ($NON < SLU$, $SLA < MIN$) throughout both seasons, with values

Table 4 Aboveground biomass dry matter (DM, $t\ ha^{-1}$), N_c (%), N uptake (N_{up} , $kg\ N\ ha^{-1}$) and nitrogen nutrition index (NNI) sampled during the two growing seasons from different fertilizer treatments: zero-N fertilization control (NON), mineral fertilization control (MIN), untreated slurry (SLU), anaerobically digested slurry (SLA) and solid digestate from a commercial biogas plant (SD). Values show mean values with standard deviation, bold values indicate the highest mean values and letters indicate significantly different groups ($p < 0.05$).

		2023			2024		
Treatment		14 Apr	04 May	12 June	26 Mar	18 Apr	14 May
DM ($t\ ha^{-1}$)	NON	1.53±0.17 b	2.60±0.41 b	8.07±1.49 b	0.38±0.09 a	0.90±0.15 b	2.17±0.20 a
	MIN	2.25±0.53 ab	4.24±0.21 a	15.62±1.54 a	0.46±0.14 a	1.44±0.33 ab	2.63±0.35 a
	SLU	2.36±0.51 a	4.41±0.57 a	14.48±2.13 a	0.61±0.22 a	1.48±0.40 ab	2.87±0.54 a
	SLA	2.00±0.39 ab	4.01±0.59 a	13.76±2.18 a	0.65±0.18 a	1.62±0.49 a	2.91±0.55 a
N_c (%)	NON	2.19±0.18 c	1.53±0.11 c	0.71±0.06 c	2.77±0.39 c	2.30±0.35 b	1.63±0.38 c
	MIN	3.49±0.15 a	2.77±0.27 a	0.95±0.12 a	4.35±0.13 a	4.27±0.30 a	2.69±0.31 a
	SLU	2.71±0.28 b	1.82±0.19 bc	0.81±0.08 b	3.10±0.33 b	2.58±0.37 b	1.91±0.20 bc
	SLA	2.74±0.22 b	2.00±0.19 b	0.80±0.08 b	3.50±0.34 b	2.74±0.38 b	2.06±0.18 b
N_{up} ($kg\ N\ ha^{-1}$)	NON	33.19±2.00 c	39.31±4.62 c	56.97±8.93 c	11.09±1.34 b	21.92±1.95 c	38.69±8.32 b
	MIN	77.11±14.71 a	117.35±9.68 a	148.77±26.70 a	21.67±6.38 a	64.80±12.95 a	76.55±11.92 a
	SLU	63.40±14.61 ab	79.26±10.11 b	118.64±23.46 ab	20.60±6.39 ab	39.77±8.07 b	59.42±12.06 a
	SLA	54.81±10–29 b	79.43±11.75 b	109.34±20.07 b	24.42±4.85 a	46.22±11.33 b	65.20±10.44 a
NNI	NON	0.49±0.03 c	0.43±0.02 c	0.33±0.03 c	0.39±0.02 c	0.46±0.03 c	0.46±0.08 c
	MIN	0.91±0.06 a	0.98±0.09 a	0.60±0.09 a	0.67±0.07 a	1.03±0.06 a	0.82±0.09 a
	SLU	0.73±0.10 b	0.65±0.06b	0.49±0.07 b	0.53±0.07 b	0.62±0.06 b	0.60±0.07 b
	SLA	0.69±0.07 b	0.68±0.07 b	0.47±0.06 b	0.61±0.04 b	0.68±0.07 b	0.66±0.05 b

for MIN close to 1. Similar treatment effects were observed for N_c , while the very low N_c ($<1\%$) at the sampling date 12 June 2023 indicated advanced senescence.

NNI measured during the season including the critical N curve can be found in Supplemental Information 4.

Relationship of vegetation indices and in-season measured plant parameters

In winter wheat (2023), both tested vegetation indices were significantly positively associated with aboveground dry matter ($t\ ha^{-1}$), N_{up} ($kg\ N\ ha^{-1}$) and NNI when analysed with linear mixed-effects models accounting for sampling date as a random effect Table 5. The best model performance with N uptake in 2023 was shown by NDRE (marginal $R^2=0.73$, RMSE = $12.5\ kg\ N\ ha^{-1}$). NDVI provided the highest predictive performance for dry matter with a marginal R^2 value of 0.81 and RMSE of $0.43\ t\ ha^{-1}$. N_c (%) showed low marginal R^2 for both vegetation indices (e.g., NDRE: Marginal $R^2=0.13$), but high conditional R^2 (e.g., NDRE: conditional $R^2=0.92$).

In 2024, the model fit for NDVI and NDRE decreased due to generally low reflectance signals throughout the season. Marginal R^2 values for DM and N_c were very low for NDVI and NDRE, indicating that NDVI and NDRE (fixed effects) alone explained little of the variation. The best model performance for N_{up} in winter barley was observed with NDRE (Marginal $R^2=0.26$, RMSE = $14.8\ kg\ N\ ha^{-1}$). NNI showed the strongest association with NDRE, yielding the highest marginal R^2 . The high conditional R^2 values for all plant parameters, except for NNI, highlight that variability between sampling dates contributed substantially to the total variation of the measured plant traits.

Prediction of plant parameters by random forest regression models

The best performing random forest (RF) model of the 2023 data was the model including the multispectral bands, weather, soil and fertilizer data (Table 6), with high accuracy to predict N_{up} ($R^2=0.85$, RMSE = $13.9\ kg\ N\ ha^{-1}$). Simpler models that included only the single bands, GDD and fertilizer characteristics also showed robust model outputs, especially for predicting NNI and N_{con} .

The performance of the models of the 2024 data for all target variables was slightly worse compared to 2023. RMSE was lower in 2024 for dry matter and N uptake. However,

Table 5 Marginal coefficients of determination (R^2) and root mean square error (RMSE) of linear mixed models of plant parameters~vegetation indices with sampling date as random effect for winter wheat in 2023 (left panel), and winter barley in 2024 (right panel)

Variable	Vegetation Index	2023			2024		
		Marg. R^2	Cond. R^2	RMSE	Marg. R^2	Cond. R^2	RMSE
DM ($t\ ha^{-1}$)	NDVI	0.81	0.85	0.43	0.06	0.91	0.96
	NDRE	0.50	0.82	0.59	0.04	0.89	0.86
N_{con} (%)	NDVI	0.11	0.91	0.77	0.03	0.63	0.75
	NDRE	0.13	0.92	0.74	0.04	0.70	0.79
N_{up} ($kg\ N\ ha^{-1}$)	NDVI	0.62	0.87	17.1	0.14	0.85	18.4
	NDRE	0.73	0.89	12.5	0.26	0.82	14.8
NNI	NDVI	0.33	0.90	0.20	0.32	0.42	0.11
	NDRE	0.38	0.92	0.17	0.41	0.50	0.11

Table 6 Marginal coefficients of determination (R^2) and root mean square error (RMSE) of random forest models using 10-fold cross validation with in-field sampled ground truth data on the variables dry matter (t ha^{-1}), N concentration (N_c , %), N uptake (N_{up} , kg N ha^{-1}) and nitrogen nutrition index (NNI). Metrics show the average of the 10 cross validated models. Different models were constructed according to the type of data.

Variable	model	2023		2024	
		R^2	RMSE	R^2	RMSE
DM (t ha^{-1})	MS bands + weather + fertilizer + soil	0.97	0.98	0.87	0.44
	MS bands + weather + fertilizer	0.97	1.11	0.86	0.48
	MS bands + weather	0.96	1.13	0.85	0.48
	NDRE + weather + fertilizer	0.95	1.25	0.87	0.47
N_{con} (%)	MS bands + weather + fertilizer + soil	0.94	0.22	0.92	0.25
	MS bands + weather + fertilizer	0.94	0.22	0.91	0.25
	MS bands + weather	0.92	0.25	0.85	0.36
	NDRE + weather + fertilizer	0.95	0.20	0.88	0.28
N_{up} (kg N ha^{-1})	MS bands + weather + fertilizer + soil	0.85	13.9	0.71	10.4
	MS bands + weather + fertilizer	0.84	15.8	0.71	10.3
	MS bands + weather	0.84	16.3	0.68	10.7
	NDRE + weather + fertilizer	0.83	14.9	0.78	9.3
NNI	MS bands + weather + fertilizer + soil	0.82	0.07	0.66	0.08
	MS bands + weather + fertilizer	0.71	0.07	0.67	0.08
	MS bands + weather	0.76	0.08	0.59	0.09
	NDRE + weather + fertilizer	0.86	0.07	0.68	0.08

Table 7 Comparison of direct and indirect predictions of the best performing models in 2023 and 2024 in estimating nitrogen nutrition index (NNI) and N uptake (N_{up} , kg N ha^{-1}). Direct predictions are random forest (RF) predictions. Indirect predictions are calculated with Eq. 1 to get N_{up} and with Eq. 2 or Eq. 3 for NNI of winter wheat and winter barley, respectively.

Variable	method	2023		2024	
		R2	RMSE	R2	RMSE
N_{up} (kg N ha^{-1})	Direct RF predictions	0.85	13.9	0.78	9.3
	Indirect predictions	0.90	12.4	0.81	10.7
NNI	Direct RF predictions	0.86	0.07	0.68	0.08
	Indirect predictions	0.82	0.08	0.72	0.08

the relative RMSE was higher in 2024 due to the low dry matter yield and N uptake by the crop. The model including all variables was also best suited to model dry matter; however, a simpler model that only included NDRE, GDD and slurry characteristics showed the best performance in modelling NNI and N_{up} ($R^2=0.78$, $\text{RMSE}=9.3 \text{ kg N ha}^{-1}$).

Table 7 presents the model performance for direct and indirect predictions of N_{up} and NNI. In 2023, N_{up} predicted indirectly (as $\text{DM} \times N_c$) outperformed direct prediction using the trained RF model for N_{up} . In contrast, in 2024 the indirect prediction did not perform

better. No difference in model performance was observed between the direct and indirect methods for predicting NNI.

Seasonal dynamics of predicted N uptake

The predicted N_{up} showed a distinct pattern for the different fertilizers during the season (Fig. 5). Before fertilization in 2023, the plots fertilized with SLU showed the highest early N_{up} , followed by those fertilized with SD, indicating mineralization of organic N in the early spring. However, differences in N_{up} were negligible prior to the first fertilization, and no significant differences were observed (ANOVA, $p > 0.05$). At the beginning of the season,

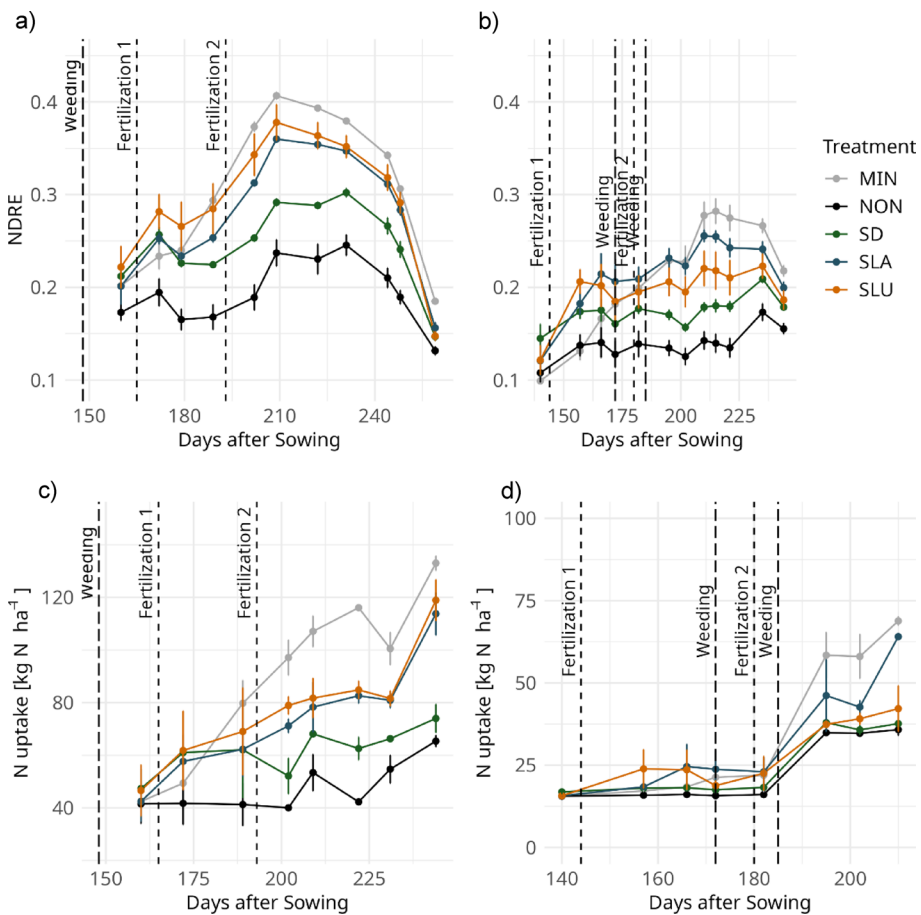


Fig. 5 Normalized difference red-edge (NDRE) values for winter wheat in 2023 (a) and winter barley in 2024 (b), and predicted N uptake (kg N ha⁻¹) for winter wheat in 2023 (c) and winter barley in 2024 (d) from different fertilizer treatments: zero-N fertilization control (NON), mineral fertilization control (MIN), untreated slurry (SLU), anaerobically digested slurry (SLA) and solid digestate from a commercial biogas plant (SD). Predictions are based on the best-performing random forest models, including multispectral imagery, environmental variables (GDD, precipitation and soil temperature) and fertilizer characteristics (C/N ratio and NH_4 -N concentration). Data of N_{up} is shown for the time until maximal predicted N uptake.

the fertilizer treatments ran almost in parallel, but two weeks after the first fertilization, the MIN plots showed the strongest fertilizer effect with the highest increase in N_{up} . The NON plots exhibited minimal N_{up} , with N_{up} reaching its maximum during the later stages when soil N mineralization was presumed to be highest.

Generally, the predicted N_{up} in 2024 was lower because of weather conditions, but the patterns were similar to 2023. SD and SLU had the highest N_{up} directly after winter. After the first fertilization, SLU performed well and had the highest N_{up} . The steepest slope of the N_{up} curve over the entire growth period was observed again under MIN, however, it started differentiating from other treatments only after the second fertilization. The dynamics of N_{up} of SD and NON were almost parallel throughout the season but shifted by $\sim 7 \text{ kg N ha}^{-1}$. This difference can be attributed to the application of the organic N of the fertilizer.

N dynamics affected by slurry characteristics of the fertilizers

In both years, N uptake over time was clearly correlated with slurry characteristics (Fig. 6). In particular, the $\text{NH}_4\text{-N}$ proportion in the fertilizer showed a strong positive effect on the slopes of the predicted N_{up} curves. The C/N ratio showed a negative correlation with N_{up} per day, indicating a weak effect of fertilizers with a wide C/N ratio. In 2023, the C/N ratio differed between untreated slurry (SLU) and anaerobically digested slurry (SLA), but the $\text{NH}_4\text{-N}$ proportion was equal (Table 1), which did not result in a higher N_{up} per day. In 2024, the difference in $\text{NH}_4\text{-N}$ proportion between SLA and SLU was larger compared to 2023, which led to a steeper slope, indicating that the variation in $\text{NH}_4\text{-N}$ proportion can be directly attributed to the N_{up} per day. The relationship between the variables and daily N_{up} ($\text{kg N ha}^{-1} \text{ d}^{-1}$) were significant ($p < 0.05$).

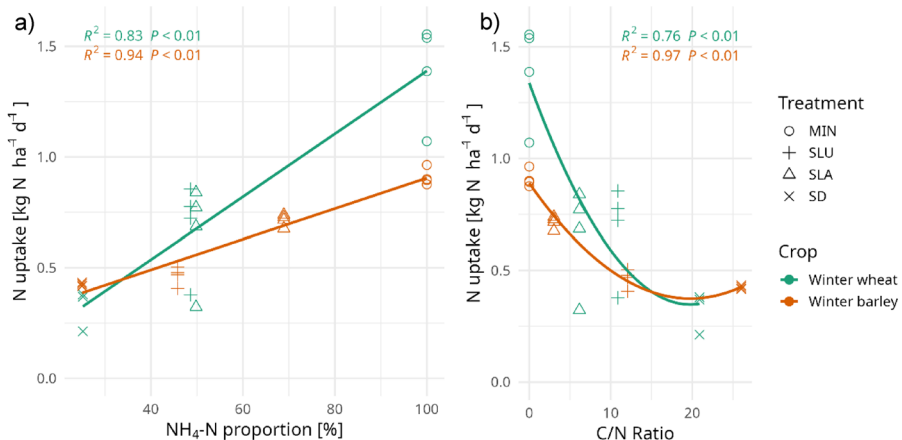


Fig. 6 Relationship between the predicted daily N uptake ($\text{kg N ha}^{-1} \text{ d}^{-1}$) and (a) $\text{NH}_4\text{-N}$ proportion (%) and (b) C/N ratio, differentiated by different fertilizer treatments: mineral fertilization control (MIN), untreated slurry (SLU), anaerobically digested slurry (SLA) and solid digestate from a commercial biogas plant (SD). Colors indicate the different crops and shape indicates the different treatments. The lines and the equation in **a**) indicate the linear function of each crop and in **b**) the quadratic function.

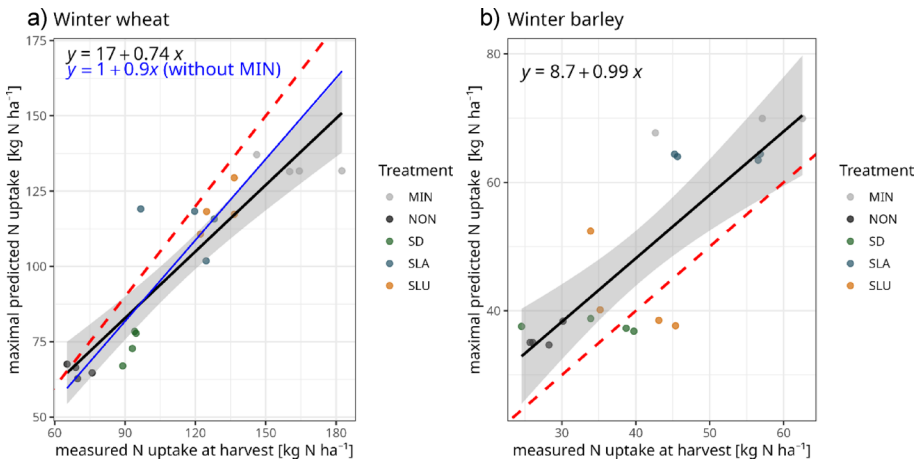


Fig. 7 Comparison of maximal predicted N uptake and N uptake at harvest for winter wheat (a) and winter barley (b) from different fertilizer treatments: zero-N fertilization control (NON), mineral fertilization control (MIN), untreated slurry (SLU), anaerobically digested slurry (SLA) and solid digestate from a commercial biogas plant (SD). The black line represents the linear regression, while in 2023 the regression excluding MIN is shown in blue. Red dashed lines indicate the 1:1 relationship.

Predicted N uptake at harvest

To assess the accuracy of the RF model at harvest, the predicted N_{up} and N_{up} at harvest were compared individually for both seasons. The maximal predicted N_{up} of each plot, was determined as the predicted total aboveground biomass N_{up} and related to total N_{up} at harvest.

For winter barley in 2024, the model accurately predicted total N_{up} at harvest, as reflected by a correlation with an intercept of 9 kg N ha⁻¹ and a slope of 0.99 (Fig. 7). By contrast, in 2023, predictions for the MIN treatment (representing the highest N up) reached a plateau, resulting in an underestimation of total N_{up} at harvest. When MIN was excluded, due to the saturation the relationship improved, achieving a slope of 0.9 and intercept of 1 kg N ha⁻¹, indicating very accurate predictions across the remaining treatments.

Discussion

Yield and N uptake of crops

In both 2023 and 2024, extreme weather strongly affected crop performance, resulting in grain yields below the Swiss organic yield averages in those years (Biderbost, 2024). In 2023, a severe thunderstorm in June was followed by heat and subsequent drought, while the 2024 season was wet, preventing mechanical weeding and resulting in high weed and disease pressure. In particular the winter barley yields were low, possibly due to compaction caused by the research team associated with sampling activities under too wet conditions.

Minerally fertilized cereals in this trial had lower grain yields than Swiss standard reference (Sinaj & Richner, 2017) in both years. MIN did not receive any plant protection product, which can explain the lower grain yields, since apart from applied plant-available

N, plant protection is crucial to guarantee yield stability (Knapp et al., 2023). The below-reference yields of the mineral fertilization and the small difference in yields to the fertilization with liquid organic fertilizers might additionally be explained by the used wheat variety 'Wiwa', which was bred for organic farming, therefore benefitting from a system with organic fertilization and without plant protection (Bio Aktuell, 2026).

In 2023, total N uptake across treatments was high, but grain N uptake was low, with above-average N retained in the straw (Hildermann et al., 2009). Similarly, in 2024, straw N exceeded grain N despite low yields, indicating that N allocation to the grain was constrained in both years. Factors limiting N allocation to the grain were possibly heat (Farooq et al., 2011) and drought stress (Kost et al., 2024; Wittwer et al., 2023) in 2023 and disease pressure (Barbottin et al., 2005) in 2024, due to the beforementioned weather extremes.

The use of anaerobically digested slurries did not show a consistent effect on dry matter yield or N uptake compared to untreated cattle slurry. There are similar reports of variable yield responses to digestate application compared to untreated slurry, ranging from increased to unchanged or even reduced yields, depending on environmental conditions (Frick et al., 2024; Möller & Müller, 2012). Ammonia (NH_3) emissions can contribute to substantial N losses and reduce NUE (Bouwman et al., 2002; Pan et al., 2016). During the early stages of the experiment in 2018, losses accounted for 31% of the applied $\text{NH}_4\text{-N}$ for SLU and 42% for SLA, which was attributed to the higher pH and dry matter content of the digestate (Efosa et al., 2025). It is therefore likely that N losses due to NH_3 emissions also occurred in 2023 and 2024, particularly for SLA, owing to its higher $\text{NH}_4\text{-N}$ proportion and pH, which is consistent with the generally higher risk of NH_3 emissions associated with digestates (Pedersen & Hafner, 2023).

Solid digestate resulted in higher grain N uptake compared to the zero-N control. Since 2018, approximately 75% of the total N applied to SD has been in organic form. The repeated fertilizer application likely led to the accumulation of organic C and N in the soil (Gutser et al., 2005). Subsequent N mineralization from slow-release fertilizers during critical the growth stages of the crop is crucial for improving N efficiency (Reimer et al., 2023), which is supported by this study showing higher N retrieval of SD compared to NON.

NNI reveals suboptimal N nutrition

Only MIN showed an optimal nutritional N status with an NNI above 0.8 (Fabbri et al., 2025) during the season, whereas the organically fertilized crops showed a lack of N. The lack of N in treatments with organic fertilizers was especially pronounced late in the season, indicating a poor N supply which resulted in low grain N content. N deficiencies during the grain filling stage and reduced grain N content in the present study are in line with other studies comparing mineral and organic fertilization (Knapp et al., 2023; Mayer et al., 2015; Seufert et al., 2012). The organically fertilized treatments in the present study lie above the minimal NNI threshold, but are below the threshold to achieve robust yields, using the dynamic NNI concept of Ravier et al. (2021). During early growth in 2024, SLA was the only organic treatment with NNI values above 1, indicating a temporary N surplus, likely due to its higher $\text{NH}_4\text{-N}$ proportion that year (Table 1).

Justes (1994) defined the critical N curve under the condition that the canopy is closed entirely. In our experiment, the row distance was 0.25 m in both years. Such wide row spacing might lead to a less dense canopy, resulting in a different critical N curve and therefore

a different NNI. Wide row spacing is frequently adopted in farming systems relying on mechanical weed control to ensure the feasibility of tine harrowing. Tanaka and Gislum (2025) emphasized the necessity of calibrating the critical N curve for local environments, management and cultivars to reveal robust NNI predictions, highlighting the necessity to calibrate the NNI concept for organic farming systems. High temporal and spatial resolution monitoring of NNI supports site-specific N fertilization, reducing excess N fertilization while maintaining yield and quality (Fabbri et al., 2025). NNI-supported fertilization offers a promising opportunity for optimized fertilization in organic farming, to enhance the synchrony between fertilizer N release and crop N uptake.

Vegetation indices show high prediction power for N status in 2023, but weak in 2024

In 2023, both calculated vegetation indices were significantly related to aboveground dry matter production (t ha^{-1}), N uptake (kg N ha^{-1}) and NNI, when accounting for sampling date as random effect in a linear mixed effects model. Random effects explained a substantial proportion of the variance, indicating a strong influence of sampling time on vegetation indices.

The highest marginal R^2 for N uptake was observed by NDRE, which supports findings that N uptake can be assessed accurately with NDRE (Argento et al., 2021; Shu et al., 2021; Vuille-dit-Bille et al., 2025). Studies on winter wheat have shown similar relationship of N uptake and NDRE (Argento et al., 2022; Magney et al., 2017; Prey & Schmidhalter, 2019), and strong correlations of aboveground biomass production with NDVI (Cabrera-Bosquet et al., 2011; Serrano et al., 2000). Red-edge has shown high sensitivity to N levels due to its clear change in leaf reflectance characterized by high absorption in the red and high reflectance in the near-infrared region (Reisi Gahrouei et al. 2020; Zhang et al. 2025a, b). Despite the complex N release dynamics of organic fertilizers (Gutser et al., 2005), NDRE was well suited as a single vegetation index to sense N status of organically fertilized crops, which is in line with Roel-Rezk et al. (2025). Although the present study was conducted at one site in two growing seasons, the finding, that NDRE is suitable to sense N status is well supported by various studies showing high correlation in a wide range of pedoclimatic conditions (Argento et al., 2021; Prey & Schmidhalter, 2019; Roel-Rezk et al., 2025).

Marginal R^2 between vegetation indices and all plant parameters were weak for winter barley in 2024. Various studies have shown strong correlations between N uptake and winter barley (Bendig et al., 2015; Šušliková et al., 2023), which indicates that weaker correlations in this study are most likely affected by environmental conditions at the experimental site. The absolute NDVI and NDRE values measured in this study were lower than those reported in Harfenmeister et al. (2021), respectively Argento et al. (2021), potentially explaining the weaker relationships obtained. For all plant parameters and vegetation indices, conditional R^2 values were high, further indicating that a large proportion of the variance was explained by the random effect of the sampling date. In both years, the relationship between N concentration and vegetation indices showed very low coefficients of determination, which is in line with other studies showing weak predictive power to estimate N concentration with vegetation indices (Chen et al., 2025; Homolová et al., 2013).

Random forest regressions improve N status predictions

In 2023, coefficients of determination were high (R^2 : 0.71–0.97) and RMSE were low for all 10-fold cross validated RF models, indicating generally high model performance. In 2024, the model performance was generally lower, but still satisfactory for most models (R^2 : 0.59–0.92), possibly due to the extreme weather conditions. Compared to the single vegetation indices (NDVI and NDRE), the RF models significantly improved predictions in 2024, when a lot of variation was observed between sampling dates. The prediction of N uptake in 2024 was significantly improved by the RF model (RMSE of 9.3 kg N ha⁻¹) compared to NDRE only (RMSE of 14.8 kg N ha⁻¹).

In both years, the RF regression improved especially the prediction for N concentration, since the correlation with any single VI was not significant. This aligns well with recent results showing that RF models increase the predictive power of estimating crop N concentration (Chen et al., 2025; Tanaka & Gislum, 2025). The model outputs (R^2 and RMSE) in the present study are robust and in the range of other studies (Yu et al. 2021; Zhang et al. 2025a, b) that predicted N uptake with RF models including multispectral imagery and additional data sources.

In 2024, the RF model that included NDRE, weather data and fertilizer characteristics outperformed the more complex model that combined all single bands, weather, soil and fertilizer data. Since crop growth was seemingly constrained by weather conditions, it was effective to select NDRE which clearly correlated with N uptake in the field. Under extreme weather conditions, it seems advisable to preselect N-sensitive vegetation indices to prevent the model from including features that add noise (Wei et al., 2025). Moreover, given the small size of our dataset for RF predictions, minimizing input variables and reducing the complexity of the decision tree helps to avoid overfitting.

The models of the present study were robust when including GDD, which is in line with other studies that showed improved N monitoring when including the effective accumulated temperature and overcoming the problem of different sensing dates (Shu et al., 2021).

The random forest predictions for N uptake accurately captured the relative differences between treatments at harvest. In 2023, however, N uptake in MIN was underestimated, whereas the other treatments were predicted with high accuracy. The underestimation of MIN was likely due to insufficient data with high N uptake in the training dataset. Overall, the model effectively captured the general dynamics of N uptake but tended to underestimate extreme values at high N supply levels. Improving prediction accuracy would require data inclusion beyond the current range of interest. Additionally, the inaccuracy at harvest may be partly due to the drone flight schedule: flights were conducted every 10 days, so the absolute growth peak could have occurred between measurement dates and was therefore not captured. Since the variables affecting growth dynamics are different from those that affect senescence (Tschurr et al., 2024), the RF models were not able to model N uptake, when the growth peak had passed and crops were already in senescence.

The study was conducted at a single site over two growing seasons, which may limit the transferability to other pedoclimatic predictions and model performance might not fully represent different environmental conditions. The two monitored seasons were distinct in weather (2024: very wet) and crop performance (2024: very low yield), but the model performances were for both seasons satisfactory. Especially, in 2024, when crops grew badly within the season, the inclusion of temporal data (GDD) improved model performance,

indicating robustness against adverse temperature/weather effects. The multispectral bands as the basis of the model have shown to be very robust (Shu et al., 2021; Tanaka & Gislum, 2025), nevertheless, it should to be validated under various conditions, that supportive data, such as weather and fertilizer improve the predictions of N status for cereal crops.

Seasonal N dynamics of crops are linked to fertilizer characteristics

Crop N dynamics affected by fertilizers showed a distinct seasonal pattern. In the early 2023 season, SLU showed the highest N uptake before the first fertilization, revealing early N mineralization of the organic N from previous slurry applications. In line with other studies, regular slurry application led to long-term accumulation of organic N and thus had a residual effect in the subsequent years (Epper et al., 2025; Frick et al., 2022; Sørensen, 2004). However, in the present study, the absolute differences in N uptake after winter were small. The high N uptake from SLU persisted for up to three weeks after fertilization, revealing the duration, MIN required to compensate for the N deficit. The fact that the organically fertilized plots performed well in the early season is in contrast to studies showing organically managed systems with a strong N limitation in the early growth stages during tillering (Mayer et al., 2015). Both crops in the present experiment received the first fertilizer application late (winter wheat BBCH 31, winter barley BBCH 30) for weather and logistic reasons, compared to Swiss standards recommending BBCH 21 (Burton et al., 2024; Häner & Brabant, 2016). Due to the late fertilization timing the organic treatments outperformed mineral fertilization, because they profited from mineralization of the organic N of previous fertilizer applications. After fertilization, MIN showed the highest increase in N uptake per day in both years. This aligns well with the fact that mineral fertilizer is quickly taken up by the crop (Powelson et al., 1992).

The pattern of the N uptake of SD was almost parallel to that of NON, especially in 2024. In NON, all N was derived from soil, and the difference to SD can clearly be attributed to the mineralization of organic fertilizer N. The predicted N uptake of SD exhibited a similar, but elevated release pattern throughout the growing season when compared to NON, indicating that environmental factors (e.g., soil temperature) were the primary drivers of N release. The higher N uptake of the solid digestate highlights its ability to increase soil fertility via the mineralization of amended organic N (Egene et al., 2021). Soil N mineralization increases exponentially with temperature, leading to the highest mineralization rates late in the season (Miller & Geisseler, 2018). In the present experiment, most N was taken up late in the season for the NON and SD treatments following soil N mineralization.

In 2023, a drop in predicted N uptake was observed 222 days after sowing for SD and NON, and 231 days after sowing for MIN, SLU, SLA, which coincides with the heading of winter wheat. Under low N fertilization, crops tend to mature earlier. Since the plant-available N from fertilizer in SD and NON was little or none, respectively, the development in these treatments was quicker, leading to the early depression in the predicted N uptake. The reflectance changes after head emergence due to structural differences in the ears and leaves (Carlier et al., 2022). Therefore, the model had difficulties predicting the plant N status parameters robustly from heading onwards.

The N uptake dynamics were directly linked to the $\text{NH}_4\text{-N}$ proportion and C/N ratio of the applied fertilizers. Fertilizers with high plant available N and a wide C/N ratio had

a stronger in-season fertilization effect, supporting that these properties are specifically important for short-term N uptake (Gutser et al., 2005).

Conclusion

The growth and N dynamics of organically fertilized crops were predicted accurately with RF models based on multispectral imagery and supporting data on weather, soil and fertilizer. Highly temporal multispectral information proved to reveal subtle differences in in-season N uptake dynamics affected by quality differences of organic fertilizers. Before the first fertilization, the remotely sensed N uptake indicated a strong legacy effect from the previous application of organic fertilizers. Mineral fertilizer induced the strongest crop response after N application. Solid digestate followed a similar N dynamic to unfertilized treatments but at a higher level, suggesting mineralization of N_{org} of previous fertilizer applications. The N uptake dynamics could be directly linked to fertilizer characteristics, showing a larger fertilizer effect when fertilizer had high NH_4 -N proportion and a low C/N ratio. The findings of this study demonstrate the potential of using remote sensing coupled with supportive data to understand the in-season N uptake dynamics from different fertilizer types. Further research should focus on the transferability of in-season N uptake dynamics across different pedoclimatic conditions to improve the consistent management of organic fertilizers.

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Declarations

Competing interests The authors declare no competing interests.

Use of generative AI and AI-assisted technologies Large language models (Chat GPT, model 5.1) were used to support troubleshooting in R coding. All codes were checked for their task and simplicity. All text was generated by the main author. AI-assisted copy editing was used to rephrase and optimize use of language in the introduction and discussion section.

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References

- Argento, F., Anken, T., Abt, F., Vogelsanger, E., Walter, A., & Liebisch, F. (2021). Site-specific nitrogen management in winter wheat supported by low-altitude remote sensing and soil data. *Precision Agriculture*, 22(2), 364–386. <https://doi.org/10.1007/s11119-020-09733-3>
- Argento, F., Liebisch, F., Simmler, M., Ringger, C., Hatt, M., Walter, A., & Anken, T. (2022). Linking soil N dynamics and plant N uptake by means of sensor support. *European Journal of Agronomy*, 134, 126462. <https://doi.org/10.1016/j.eja.2022.126462>
- Barbottin, A., Lecomte, C., Bouchard, C., & Jeuffroy, M. H. (2005). Nitrogen remobilization during grain filling in wheat: genotypic and environmental Effects. *Crop Science*, 45(3), 1141–1150. <https://doi.org/10.2135/cropsci2003.0361>
- Barnes, E. M., Clarke, T. R., Richards, S. E., Colaizzi, P. D., Haberland, J., Kosterzewski, M., Waller, P., Choi, C., Riley, E., Thompson, T., Lascano, R. J., Li, H., & Moran, M. S. (2000). Coincident detection of crop water stress, nitrogen status and canopy density using ground-based multispectral data. *Proceedings of the 5th International Conference on Precision Agriculture*.
- Basso, B., Fiorentino, C., Cammarano, D., & Schulthess, U. (2016). Variable rate nitrogen fertilizer response in wheat using remote sensing. *Precision Agriculture*, 17(2), 168–182. <https://doi.org/10.1007/s11119-015-9414-9>
- Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, 67(1), 1–48. <https://doi.org/10.18637/jss.v067.i01>
- Baumgartner, S., Gilgen, A., Epper, C., Merbold, L., & Liebisch, F. (2025). Nährstoffbilanzvergleich: Betriebsbilanzierung von Stickstoff und Phosphor anhand zweier unterschiedlicher Methoden: Suisse-Bilanz und Bodenoberflächenbilanz. In *Agroscope Science* (Bd. 205). Agroscope. <https://doi.org/10.34776/AS205>
- Bendig, J., Yu, K., Aasen, H., Bolten, A., Bennertz, S., Broscheit, J., Gnyp, M. L., & Bareth, G. (2015). Combining UAV-based plant height from crop surface models, visible, and near infrared vegetation indices for biomass monitoring in barley. *International Journal of Applied Earth Observation and Geoinformation*, 39, 79–87. <https://doi.org/10.1016/j.jag.2015.02.012>
- Biderbost, S. (2024). *Weizensorten Streifenversuche 2023*. Forschungsinstitut für biologischen Landbau.
- Bio Suisse (2023). *Richtlinien für die Erzeugung, Verarbeitung und den Handel von Knospe-Produkten*.
- Bio Aktuell (2026). *Sortenliste Getreide 2026*. 1034.
- Bouwman, A. F., Boumans, L. J. M., & Batjes, N. H. (2002). Estimation of global NH₃ volatilization loss from synthetic fertilizers and animal manure applied to arable lands and grasslands. *Global Biogeochemical Cycles*, 16(2), 8–1. <https://doi.org/10.1029/2000GB001389>
- Burton, A., Häner, L. L., Schaad, N., Strebel, S., Vuille-dit-Bille, N., Bongiovani, P. D. F., Holzkämper, A., Pellet, D., & Herrera, J. M. (2024). Evaluating nitrogen fertilization strategies to optimize yield and grain nitrogen content in top winter wheat varieties across Switzerland. *Field Crops Research*, 307, 109251. <https://doi.org/10.1016/j.fcr.2024.109251>
- Cabrera-Bosquet, L., Molero, G., Stellacci, A., Bort, J., Nogués, S., & Araus, J. (2011). NDVI as a potential tool for predicting biomass, plant nitrogen content and growth in wheat genotypes subjected to different water and nitrogen conditions. *Cereal Research Communications*, 39(1), 147–159. <https://doi.org/10.1556/crc.39.2011.1.15>
- Cammarano, D., Basso, B., Holland, J., Gianinetti, A., Baronchelli, M., & Ronga, D. (2021). Modeling spatial and temporal optimal N fertilizer rates to reduce nitrate leaching while improving grain yield and quality in malting barley. *Computers and Electronics in Agriculture*, 182, 105997. <https://doi.org/10.1016/j.compag.2021.105997>
- Carlier, A., Dandrfosse, S., Dumont, B., & Mercatoris, B. (2022). Wheat ear segmentation based on a multi-sensor system and superpixel classification. *Plant Phenomics*, 2022, 9841985. <https://doi.org/10.34133/2022/9841985>

- Chen, X., Li, F., Chang, Q., Miao, Y., & Yu, K. (2025). Improving winter wheat plant nitrogen concentration prediction by combining proximal hyperspectral sensing and weather information with machine learning. *Computers and Electronics in Agriculture*, 232, 110072. <https://doi.org/10.1016/j.compag.2025.110072>
- Efosa, N., Krause, H. M., Hüppi, R., Krauss, M., Vaucher, N., Zourek, F., Mayer, J., Six, J., & Bünemann, E. K. (2023). Emissions of nitrous oxide and methane after field application of liquid organic fertilizers and biochar. *Agriculture Ecosystems & Environment*, 356, 108642. <https://doi.org/10.1016/j.agee.2023.108642>
- Efosa, N., Häni, C., Kupper, T., Krause, H. M., Six, J., & Bünemann, E. K. (2025). Ammonia emissions after trailing hose application of digestates and cattle slurry. *Nutrient Cycling in Agroecosystems*, 130(3), 419–426. <https://doi.org/10.1007/s10705-025-10407-7>
- Egene, C. E., Sigurnjak, I., Regelink, I. C., Schoumans, O. F., Adani, F., Michels, E., Sleutel, S., Tack, F. M. G., & Meers, E. (2021). Solid fraction of separated digestate as soil improver: Implications for soil fertility and carbon sequestration. *Journal of Soils and Sediments*, 21(2), 678–688. <https://doi.org/10.1007/s11368-020-02792-z>
- Epper, C. A., Zavattaro, L., Velthof, G. L., Thuriès, L., & Steinsberger, T. (2025). Optimizing nitrogen use efficiency in European livestock systems: From feed to plant growth. *Advances in Agronomy*, 277–362. <https://doi.org/10.1016/bs.agron.2025.01.003>
- Fabbri, C., Delgado, A., Guerrini, L., & Napoli, M. (2025). Precision nitrogen fertilization strategies for durum wheat: A sustainability evaluation of NNI and NDVI map-based approaches. *European Journal of Agronomy*, 164, 127502. <https://doi.org/10.1016/j.eja.2024.127502>
- FAO. (2014). *World Reference Base for Soil Resources WRB*. International Soil Classification System for Naming Soils and Creating Legends for Soil Maps.
- Farooq, M., Bramley, H., Palta, J. A., & Siddique, K. H. M. (2011). Heat stress in wheat during reproductive and grain-filling phases. *Critical Reviews in Plant Sciences*, 30(6), 491–507. <https://doi.org/10.1080/07352689.2011.615687>
- Feigenwinter, I., Hörtnagl, L., & Buchmann, N. (2023). N₂O and CH₄ fluxes from intensively managed grassland: The importance of biological and environmental drivers vs. Management. *Science of The Total Environment*, 903, 166389. <https://doi.org/10.1016/j.scitotenv.2023.166389>
- Fernandez, J. A., Van Versendaal, E., Lacasa, J., Makowski, D., Lemaire, G., & Ciampitti, I. A. (2022). Dataset characteristics for the determination of critical nitrogen dilution curves: From past to new guidelines. *European Journal of Agronomy*, 139, 126568. <https://doi.org/10.1016/j.eja.2022.126568>
- Fontana, M., Bélanger, G., Hirte, J., Ziadi, N., Elfouki, S., Bragazza, L., Liebisch, F., & Sinaj, S. (2021). Critical plant phosphorus for winter wheat assessed from long-term field experiments. *European Journal of Agronomy*, 126, 126263. <https://doi.org/10.1016/j.eja.2021.126263>
- Frick, H., Oberson, A., Frossard, E., & Bünemann, E. K. (2022). Leached nitrate under fertilised loamy soil originates mainly from mineralisation of soil organic N. *Agriculture Ecosystems & Environment*, 338, 108093. <https://doi.org/10.1016/j.agee.2022.108093>
- Frick, H., Efosa, N., Oberson, A., Krause, H. M., Nägele, H. J., Frossard, E., & Bünemann, E. K. (2024). Nitrogen dynamics after slurry application as affected by anaerobic digestion, biochar and a nitrification inhibitor. *Soil Use and Management*, 40(1), e12953. <https://doi.org/10.1111/sum.12953>
- Grieder, C., Hund, A., & Walter, A. (2015). Image based phenotyping during winter: A powerful tool to assess wheat genetic variation in growth response to temperature. *Functional Plant Biology*, 42(4), 387–396. <https://doi.org/10.1071/FP14226>
- Gutser, R., Ebertseder, T., Weber, A., Schraml, M., & Schmidhalter, U. (2005). Short-term and residual availability of nitrogen after long-term application of organic fertilizers on arable land. *Journal of Plant Nutrition and Soil Science*, 168(4), 439–446. <https://doi.org/10.1002/jpln.200520510>
- Häner, L. L., & Brabant, C. (2016). Die Kunst, den Stickstoffdünger für einen optimalen Ertrag und Proteingehalt von Weizen aufzuteilen. *Agrarforschung Schweiz*, 7(2), 80–87.
- Harder, R., & Liebisch, F. (2025). Exploring the strategic potential for Switzerland to reduce nitrogen and phosphorus surplus in agriculture. *Resources Conservation and Recycling*, 218, 108239. <https://doi.org/10.1016/j.resconrec.2025.108239>
- Harfenmeister, K., Itzerott, S., Weltzien, C., & Spengler, D. (2021). Detecting phenological development of winter wheat and winter barley using time series of Sentinel-1 and Sentinel-2. *Remote Sensing*, 13(24), 5036. <https://doi.org/10.3390/rs13245036>
- Hildermann, I., Thommen, A., Dubois, D., Boller, T., Wiemken, A., & Mäder, P. (2009). Yield and baking quality of winter wheat cultivars in different farming systems of the DOK long-term trial. *Journal of the Science of Food and Agriculture*, 89(14), 2477–2491. <https://doi.org/10.1002/jsfa.3750>
- Homolová, L., Malenovský, Z., Clevers, J. G. P. W., García-Santos, G., & Schaepman, M. E. (2013). Review of optical-based remote sensing for plant trait mapping. *Ecological Complexity*, 15, 1–16. <https://doi.org/10.1016/j.ecocom.2013.06.003>

- Justes, E. (1994). Determination of a critical nitrogen dilution curve for winter wheat crops. *Annals of Botany*, 74(4), 397–407. <https://doi.org/10.1006/anbo.1994.1133>
- Knapp, S., Gunst, L., Mäder, P., Ghiasi, S., & Mayer, J. (2023). Organic cropping systems maintain yields but have lower yield levels and yield stability than conventional systems – Results from the DOK trial in Switzerland. *Field Crops Research*, 302, 109072. <https://doi.org/10.1016/j.fcr.2023.109072>
- Kost, E., Kundel, D., Conz, R. F., Mäder, P., Krause, H. M., Six, J., Mayer, J., & Hartmann, M. (2024). Soil microbial resistance and resilience to drought under organic and conventional farming. *European Journal of Soil Biology*, 123, 103690. <https://doi.org/10.1016/j.ejsobi.2024.103690>
- Lemaire, G., Jeuffroy, M. H., & Gastal, F. (2008). Diagnosis tool for plant and crop N status in vegetative stage. *European Journal of Agronomy*, 28(4), 614–624. <https://doi.org/10.1016/j.eja.2008.01.005>
- Lessmann, M., Kros, H., Walvoort, D., Voogd, J. C., Renaud, L., & Cals, T. (2025). Uncertainties in nitrogen application from manure and synthetic fertilizers and ammonia emissions from agriculture in the Netherlands across different spatial scales. *Nutrient Cycling in Agroecosystems*, 131(1), 141–164. <https://doi.org/10.1007/s10705-025-10410-y>
- Liu, Z., Cammarano, D., Liu, X., Tian, Y., Zhu, Y., Cao, W., & Cao, Q. (2025). Winter wheat yield responses to growing degree days: Long-term trends and adaptability in major producing areas of China. *Ecological Indicators*, 170, 113058. <https://doi.org/10.1016/j.ecolind.2024.113058>
- Magney, T. S., Eitel, J. U. H., & Vierling, L. A. (2017). Mapping wheat nitrogen uptake from RapidEye vegetation indices. *Precision Agriculture*, 18(4), 429–451. <https://doi.org/10.1007/s11119-016-9463-8>
- Mayer, J., Gunst, L., Mäder, P., Samson, M. F., Carcea, M., Narducci, V., Thomsen, I. K., & Dubois, D. (2015). Productivity, quality and sustainability of winter wheat under long-term conventional and organic management in Switzerland. *European Journal of Agronomy*, 65, 27–39. <https://doi.org/10.1016/j.eja.2015.01.002>
- Miller, K. S., & Geisseler, D. (2018). Temperature sensitivity of nitrogen mineralization in agricultural soils. *Biology and Fertility of Soils*, 54(7), 853–860. <https://doi.org/10.1007/s00374-018-1309-2>
- Möller, K., & Müller, T. (2012). Effects of anaerobic digestion on digestate nutrient availability and crop growth: A review. *Engineering in Life Sciences*, 12(3), 242–257. <https://doi.org/10.1002/elsc.201100085>
- Pan, B., Lam, S. K., Mosier, A., Luo, Y., & Chen, D. (2016). Ammonia volatilization from synthetic fertilizers and its mitigation strategies: A global synthesis. *Agriculture Ecosystems & Environment*, 232, 283–289. <https://doi.org/10.1016/j.agee.2016.08.019>
- Pan, P. T., Bouzenbrak, Y., Quemada, M., & Tekinerdogan, B. (2025). Prediction of winter wheat nitrogen nutrition index using high-resolution satellite and machine learning. *Smart Agricultural Technology*, 12, 101119. <https://doi.org/10.1016/j.atech.2025.101119>
- Pedersen, J., & Hafner, S. D. (2023). Ammonia emissions after field application of anaerobically digested animal slurry: Literature review and perspectives. *Agriculture Ecosystems & Environment*, 357, 108697. <https://doi.org/10.1016/j.agee.2023.108697>
- Perich, G., Aasen, H., Verrelst, J., Argento, F., Walter, A., & Liebisch, F. (2021). Crop nitrogen retrieval methods for simulated Sentinel-2 data using in-field spectrometer data. *Remote Sensing*, 13(12), 2404. <https://doi.org/10.3390/rs13122404>
- Perich, G., Argento, F., Walter, A., & Liebisch, F. (2025). A calibration concept for satellite-based monitoring of the nitrogen nutrition index. In J. V. Stafford (Ed.), *Precision agriculture 25 (Set two volumes)* (pp. 760–767). Brill. Wageningen Academic. https://doi.org/10.1163/9789004725232_100
- Powlson, D. S., Hart, P. B. S., Poulton, P. R., Johnston, A. E., & Jenkinson, D. S. (1992). Influence of soil type, crop management and weather on the recovery of ^{15}N -labelled fertilizer applied to winter wheat in spring. *The Journal of Agricultural Science*, 118(1), 83–100. <https://doi.org/10.1017/S0021859600068040>
- Prey, L., & Schmidhalter, U. (2019). Temporal and spectral optimization of vegetation indices for estimating grain nitrogen uptake and late-seasonal nitrogen traits in wheat. *Sensors (Basel, Switzerland)*, 19(21), 4640. <https://doi.org/10.3390/s19214640>
- Prost, L., & Jeuffroy, M. H. (2007). Replacing the nitrogen nutrition index by the chlorophyll meter to assess wheat N status. *Agronomy for Sustainable Development*, 27(4), 321–330. <https://doi.org/10.1051/agro:2007032>
- QGIS Development Team. (2026). *QGIS Geographic Information System*. QGIS Association. <http://www.qgis.org>
- Qian, P., & Schoenau, J. J. (2002). Availability of nitrogen in solid manure amendments with different C:N ratios. *Canadian Journal of Soil Science*, 82(2), 219–225. <https://doi.org/10.4141/S01-018>
- R Core Team. (2025). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing. <https://www.R-project.org/>
- Radočaj, D., Jurišić, M., & Gašparović, M. (2022). The role of remote sensing data and methods in a modern approach to fertilization in precision agriculture. *Remote Sensing*, 14(3). <https://doi.org/10.3390/rs14030778>

- Ravier, C., Sabatier, R., Beillouin, D., Meynard, J. M., Trépos, R., & Jeuffroy, M. H. (2021). Decision rules for managing N fertilization based on model simulations and viability assessment. *European Journal of Agronomy*, 125, 126247. <https://doi.org/10.1016/j.eja.2021.126247>
- Reimer, M., Kopp, C., Hartmann, T., Zimmermann, H., Ruser, R., Schulz, R., Müller, T., & Möller, K. (2023). Assessing long term effects of compost fertilization on soil fertility and nitrogen mineralization rate. *Journal of Plant Nutrition and Soil Science*, 186(2), 217–233. <https://doi.org/10.1002/jpln.202200270>
- Reisi Gahreuei, O., McNairn, H., Hosseini, M., & Homayouni, S. (2020). Estimation of crop biomass and leaf area index from multitemporal and multispectral imagery using machine learning approaches. *Canadian Journal of Remote Sensing*, 46(1), 84–99. <https://doi.org/10.1080/07038992.2020.1740584>
- Roel-Rezk, V., Lundy, M. E., & Pittelkow, C. M. (2025). Assessing crop nitrogen status under organic amendments to reduce nitrogen fertilizer inputs and improve sustainability. *Nutrient Cycling in Agroecosystems*, 131(2), 365–382. <https://doi.org/10.1007/s10705-025-10431-7>
- Rouse Jr., J. W., Haas, R., Schell, J., & Deering, D. (1974). Monitoring vegetation systems in the Great Plain with ERTS. *NASA Special Publication*, 351(309).
- Schuster, J., Hagn, L., Mittermayer, M., Maidl, F. X., & Hülsbergen, K. J. (2023). Using remote and proximal sensing in organic agriculture to assess yield and environmental performance. *Agronomy*, 13(7), 1868. <https://doi.org/10.3390/agronomy13071868>
- Serrano, L., Filella, I., & Peñuelas, J. (2000). Remote sensing of biomass and yield of winter wheat under different nitrogen supplies. *Crop Science*, 40(3), 723–731. <https://doi.org/10.2135/cropsci2000.403723x>
- Seufert, V., Ramankutty, N., & Foley, J. A. (2012). Comparing the yields of organic and conventional agriculture. *Nature*, 485(7397), 229–232. <https://doi.org/10.1038/nature11069>
- Shu, M., Gu, X., Zhou, L., Xu, B., & Yang, G. (2021). Establishing NDRE dynamic models of winter wheat under multi-nitrogen rates based on a field spectral sensor. *Applied Optics*, 60(4), 993. <https://doi.org/10.1364/AO.410470>
- Sinaj, S., & Richner, W. (2017). Principles of fertilization of agricultural crops in Switzerland (PRIF 2017). *Agrarforschung Schweiz*, 8(6), 1–46.
- Smith, O. M., Cohen, A. L., Rieser, C. J., Davis, A. G., Taylor, J. M., Adesanya, A. W., Jones, M. S., Meier, A. R., Reganold, J. P., Orpet, R. J., Northfield, T. D., & Crowder, D. W. (2019). Organic farming provides reliable environmental benefits but increases variability in crop yields: A global meta-analysis. *Frontiers in Sustainable Food Systems*, 3, 82. <https://doi.org/10.3389/fsufs.2019.00082>
- Sørensen, P. (2004). Immobilisation, remineralisation and residual effects in subsequent crops of dairy cattle slurry nitrogen compared to mineral fertiliser nitrogen. *Plant and Soil*, 267(1), 285–296. <https://doi.org/10.1007/s11104-005-0121-6>
- Šusliková, B., Lukas, V., Placatová, R., & Křen, J. (2023). Use of remote sensing data for crop monitoring in precision agriculture. *Agrofor International Journal*, 8(3). <https://doi.org/10.7251/AGRENG2303041S>
- Tanaka, T. S. T., & Gislum, R. (2025). Prediction of winter wheat nitrogen status using UAV imagery, weather data, and machine learning. *European Journal of Agronomy*, 164, 127534. <https://doi.org/10.1016/j.eja.2025.127534>
- Tschurr, F., Roth, L., Storni, N., Zumsteg, O., Walter, A., & Anderegg, J. (2024). Temporal resolution trumps spectral resolution in UAV-based monitoring of cereal senescence dynamics. *Plant Methods*, 20(1), 188. <https://doi.org/10.1186/s13007-024-01308-x>
- Tuomisto, H. L., Hodge, I. D., Riordan, P., & Macdonald, D. W. (2012). Does organic farming reduce environmental impacts? – A meta-analysis of European research. *Journal of Environmental Management*, 112, 309–320. <https://doi.org/10.1016/j.jenvman.2012.08.018>
- Velthof, G. L., Cals, T. C. A., Van, T., Hull, J. P., Lesschen, J. P., Lessmann, M., Porre, R. J., Ros, M. B. H., Rietra, R. P. J. J., Schoumans, O. F., Veenemans, L., & Westerk, D. (2024). Managing organic resources in agriculture: Future challenges from a scientific perspective. *Frontiers in Sustainable Food Systems*, 8. <https://doi.org/10.3389/fsufs.2024.1393190>
- Vuille-dit-Bille, N., Häner, L. L., Strebel, S., Burton, A., Schaad, N., Pellet, D., Wuyts, N., Treier, S., Bongiovanni, P. D. F., & Herrera, J. M. (2025). Evaluation of winter wheat varieties' responses to nitrogen supply supported by 10-band multispectral aerial imaging: Reproducibility over crop seasons and sites. *Smart Agricultural Technology*, 12, 101528. <https://doi.org/10.1016/j.atech.2025.101528>
- Wang, H., Mortensen, A. K., Mao, P., Boelt, B., & Gislum, R. (2019). Estimating the nitrogen nutrition index in grass seed crops using a UAV-mounted multispectral camera. *International Journal of Remote Sensing*, 40(7), 2467–2482. <https://doi.org/10.1080/01431161.2019.1569783>
- Wang, F., Zhang, J., Li, W., Liu, Y., Qin, W., Ma, L., Zhang, Y., Sun, Z., Wang, Z., Li, F., & Yu, K. (2025). Characterization of N variations in different organs of winter wheat and mapping NUE using low altitude UAV-based remote sensing. *Precision Agriculture*, 26(2), 40. <https://doi.org/10.1007/s11119-025-10234-4>

- Wei, Z., Ying, H., Guo, X., Zhuang, M., Cui, Z., & Zhang, F. (2020). Substitution of mineral fertilizer with organic fertilizer in maize systems: A meta-analysis of reduced nitrogen and carbon emissions. *Agronomy*, 10(8), 1149. <https://doi.org/10.3390/agronomy10081149>
- Wei, P., Ye, H., Nie, C., Zhang, Y., & Liu, R. (2025). Remote sensing estimation of nitrogen content in scenes of different crop types based on the random forest algorithm. *Computers and Electronics in Agriculture*, 231, 109987. <https://doi.org/10.1016/j.compag.2025.109987>
- Wittwer, R. A., Klaus, V. H., Oliveira, M., Sun, E., Liu, Q., Gilgen, Y., Buchmann, A. K., N., & Van Der Heijden, M. G. A. (2023). Limited capability of organic farming and conservation tillage to enhance agroecosystem resilience to severe drought. *Agricultural Systems*, 211, 103721. <https://doi.org/10.1016/j.agsy.2023.103721>
- Yang, M., Hassan, M. A., Xu, K., Zheng, C., Rasheed, A., Zhang, Y., Jin, X., Xia, X., Xiao, Y., & He, Z. (2020). Assessment of water and nitrogen use efficiencies through UAV-based multispectral phenotyping in winter wheat. *Frontiers in Plant Science*, 11. <https://doi.org/10.3389/fpls.2020.00927>
- Yu, J., Wang, J., Leblon, B., & Song, Y. (2021). Nitrogen Estimation for Wheat Using UAV-Based and Satellite Multispectral Imagery, Topographic Metrics, Leaf Area Index, Plant Height, Soil Moisture, and Machine Learning Methods. *Nitrogen*, 3(1), 1–25. <https://doi.org/10.3390/nitrogen3010001>
- Zha, H., Miao, Y., Wang, T., Li, Y., Zhang, J., Sun, W., Feng, Z., & Kusnierek, K. (2020). Improving unmanned aerial vehicle remote sensing-based rice nitrogen nutrition index prediction with machine learning. *Remote Sensing*, 12(2), 215. <https://doi.org/10.3390/rs12020215>
- Zhang, C., Lu, X., Zhang, H., Cui, H., Ma, H., Ji, J., & Ding, T. (2025a). Multispectral UAV imaging and machine learning for estimating wheat nitrogen nutrition index. *Frontiers in Plant Science*, 16, 1709459. <https://doi.org/10.3389/fpls.2025.1709459>
- Zhang, D., Qi, H., Guo, X., Sun, H., Min, J., Li, S., Hou, L., & Lv, L. (2025b). Integration of UAV multispectral remote sensing and random forest for full-growth stage monitoring of wheat dynamics. *Agriculture*, 15(3), 353. <https://doi.org/10.3390/agriculture15030353>
- Zhao, B. (2014). Determining of a critical dilution curve for plant nitrogen concentration in winter barley. *Field Crops Research*, 160, 64–72. <https://doi.org/10.1016/j.fcr.2014.02.016>
- Zhou, M., & Butterbach-Bahl, K. (2014). Assessment of nitrate leaching loss on a yield-scaled basis from maize and wheat cropping systems. *Plant and Soil*, 374(1), 977–991. <https://doi.org/10.1007/s11104-013-1876-9>
- Zhou, Y., Ma, Y., Ata-Ul-Karim, S. T., Wang, S., Ciampitti, I., Antoniuk, V., Wu, C., Andersen, M. N., & Cammarano, D. (2025). Integrating multi-angle and multi-scale remote sensing for precision nitrogen management in agriculture: A review. *Computers and Electronics in Agriculture*, 230, 109829. <https://doi.org/10.1016/j.compag.2024.109829>

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