Tracking Multi-Nutrient Dynamics in Spring Crops Using Field Hyperspectral Imaging and Chemometrics

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Abstract Crop nutrient ecology still lacks a clear, growth-stage-specific understanding of which nutrient elements are most limiting under field conditions and of how (co-)limitation patterns respond to management. This gap is particularly relevant in Nordic systems with short growing seasons, where precision nutrient management requires robust non-destructive field tools. In this study, proximal hyperspectral imaging (HSI) was combined with chemometric modelling to estimate canopy macronutrient status, with a focus on nitrogen (N) and potassium (K), in Swedish spring crops. A controlled-to-field calibration strategy is currently being tested using greenhouse and field datasets acquired with portable hyperspectral cameras. Preliminary greenhouse models predicted leaf N and K concentrations non-destructively, providing a benchmark for an imaging-to-modelling pipeline that is now being extended to more variable field spectra in order to track canopy nutrient status across the growing season.

Keywords Hyperspectral imaging; precision agriculture; plant nutrient status; partial least squares regression; nitrogen; potassium

Introduction

Within crop nutrient ecology, a clear and growth-stage-specific understanding is still lacking of which nutrient elements are most limiting under field conditions during different periods of the growing season, and of how (co-)limitation patterns are influenced by management. This question is particularly relevant in Nordic cropping systems, where short growing seasons mean that nutrient constraints can appear rapidly. At the same time, precision nutrient management continues to require robust, non-destructive tools that can be deployed under field conditions.

Hyperspectral imaging (HSI) is a powerful method for assessing plant nutrient dynamics because it captures high-dimensional spectral information linked to plant biochemical status and enables repeated, non-destructive measurements at the plot scale (Curran, 1989; Homolová et al., 2013, Grieco et al., 2022). However, most nutrient-focused HSI studies have been conducted in controlled environments, whereas field deployment remains less explored owing to the greater spectral variability introduced by illumination, canopy structure and background effects (Berger et al., 2020). The present study addresses this gap by working on an ongoing development and testing of a field-oriented HSI–chemometric workflow in Nordic spring crops. The specific objective is to test whether a controlled-to-field calibration strategy can robustly estimate canopy nutrient status over time, with a primary focus on N and K.

Materials and Methods

Field experiment. Field trials were conducted in Sweden over two growing seasons (2025 and 2026:in progress). Wheat, oat and faba bean were grown as pure stands under two contrasting nitrogen regimes: an unfertilised control (N0) and a fertilised treatment (N+) receiving 140 kg N ha^{-1} (Table 1).

Table 1 Crops and nitrogen fertilisation treatments in the two-season field experiment in Sweden; each crop was grown as a pure stand under an unfertilised control (N0) and a fertilised treatment (N+)

Crop	Species	Functional type	N0 (kg N ha^{-1})	N+ (kg N ha^{-1})
Wheat	*Triticum aestivum L.*	Cereal	0	140
Oat	*Avena sativa L.*	Cereal	0	140
Faba bean	*Vicia faba L.*	Legume	0	140

Image acquisition. Plot-scale reflectance was recorded at multiple growth stages with a portable hyperspectral camera (Specim IQ, 400–1000 nm; Specim, Spectral Imaging Ltd., Oulu, Finland). Plants were sampled concurrently for laboratory nutrient analysis to provide reference concentrations.

Controlled reference scanning. To support method development and comparability with earlier greenhouse work on wheat, harvested field samples were also scanned under controlled laboratory conditions using the

Specim IQ together with a Specim FX17e camera (900–1700 nm; Specim, Spectral Imaging Ltd., Oulu, Finland), providing a stable reference framework for calibration development and future transferability testing. The greenhouse calibration experiment used wheat grown under five nutrient treatments: an unamended control, +P+K, +N+P, +N+K and a commercial fertiliser (Wallco).

Chemometric modelling. Multivariate models relating spectral signatures to measured nutrient concentrations were developed in a Python workflow. Partial least squares regression (PLSR) was applied to first-derivative reflectance (Wold et al., 2001). The modelling strategy followed established chemometric practice, including targeted preprocessing to reduce scattering effects (Rinnan et al., 2009), spectral quality control with outlier screening, and structured external validation.

Preliminary Results

Preliminary greenhouse results showed that hyperspectral models could non-invasively predict multiple nutrient concentrations, with the strongest performance for N and K (Fig. 1). For green-leaf samples at the stem-elongation stage, PLSR on first-derivative Specim IQ reflectance explained most of the variation in N concentration ($R^2 = 0.875$; RMSE = 3.13 g kg^{-1}) and a substantial part of the variation in K concentration ($R^2 = 0.608$; RMSE = 2.22 g kg^{-1}). These controlled datasets provide a benchmark for the imaging-to-modelling pipeline and a basis for model updating as the analysis moves to more variable field spectra. Ongoing work focuses on field robustness and on whether the models can detect meaningful temporal patterns in canopy nutrient status throughout the growing season.

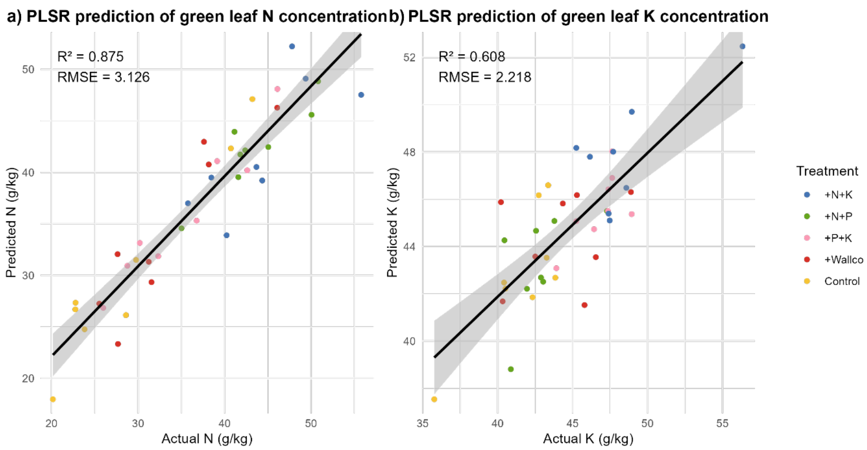

Fig. 1 Predicted versus measured green-leaf nitrogen (a) and potassium (b) concentrations from partial least squares regression (PLSR) models based on first-derivative hyperspectral reflectance acquired with the Specim IQ (400–1000 nm). Points represent individual wheat samples at the stem-elongation stage, coloured by treatment (Control, no added nutrients; +P+K; +N+P; +N+K; +Wallco, commercial fertiliser). The solid line shows the fitted linear relationship and the shaded band the 95% confidence interval

Fig. 2 Canopy image acquisition with portable camera Specim IQ and white reference on a pure wheat stand. Picture taken at Säby, Sweden, 2025, by Electra Lennartsson.

Conclusions

Combining proximal hyperspectral imaging with preliminary chemometric modelling indicates that N and K status may be estimated non-destructively, and the greenhouse calibrations could provide a transferable benchmark for field application. By tracking nutrient status at the plot scale over time, the approach may enable to contribute to a more explicit crop nutrient ecology and support precision nutrient management in short-season Nordic systems.

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