Yield Stability in Continuous Corn Under Three Years of Nitrogen Management: Linking UAV-Derived Vegetation Indices to Temporal Variability

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Abstract.

Continuous corn production systems are highly sensitive to nitrogen (N) management, and year to year variability in weather conditions can strongly influence crop performance and yield stability. Understanding how different N fertilization strategies affect yield evaluation and fertilizer recommendations from remote sensing platforms, consistency across multiple growing seasons, is essential for the development of future decision support systems. Because vegetation indices (VIs) derived from unmanned aerial vehicles (UAVs) can capture at high-definition crop vigor, canopy structure, and physiological status throughout the season, they offer a practical approach for assessing spatial and temporal variability in crop response to N.

In this study, a three-year field experiment (2021–2023) was conducted under continuous corn using five N treatments (T1: 0N+0N, T2: 0N+85N, T3: 40N+0N, T4: 40N+130N, and T5: 170N+130N kg ha^{-1}; Initial + post-emergence) to evaluate the temporal stability of grain yield under contrasting fertilization regimes designed to favor yield variability (three blocks × five nitrogen treatments × two sowing dates). The relationships between yield stability quantified using the coefficient of variation (CV) of grain yield across years, and 16 multi-temporal VIs derived from UAV-based multispectral imagery was evaluated at 3 m resolution.

The CV across the five N treatments confirmed a consistent temporal stability pattern with high N inputs. Results demonstrated that with split nitrogen applications, the T4 and T5 treatments exhibited superior yield stability compared to single applications or control treatments, with CV values ~32% lower than T1 and T3. Treatments T4 and T5 also exhibited the lowest average CVs across nearly all VIs (T4 = 15.3% and T5 = 15.0%), compared to T2 (19.5%), T1 (22.5%), and T3 (27.8%) indicating that adequately fertilized corn produces more consistent spectral signatures year over year, even in this unusual system. As an example, NDVI CV dropped from 11.2% (T1) and 12.9% (T3) to just 5.3% and 5.0% for T4 and T5, respectively. A similar pattern held for NDRE (CV from 30–38% in T1/T3 down to ~13%), GNDVI (CV from 13.6–17.2% down to ~6%), and EVI (CV from ~20–24% down to ~11–13%).

Treatment T3 (40N+0N, starter only, no post-emergence) was consistently the most temporally unstable across almost every index, often exceeding even the unfertilized control (T1). This *suggests that a modest starter dose without follow-up N leaves the crop especially vulnerable to seasonal variability. T2 (0N+85N, post-emergence only) occupied an intermediate position, performing notably better than T1 and T3 but still less stable than T4 and T5. Among the VIs, NDVI, GNDVI, MCARI, OSAVI, and NDYI were the most temporally stable (lowest absolute CVs), while Ratio-based indices like NGRDI and VARI showed moderate but elevated variability (21–30%), limiting their reliability for dynamic yield stability assessment. By linking specific split-application N strategies to temporally stable UAV-derived VI signatures, this work provides insights into how remote sensing metrics can support the identification of N strategies that promote stable yields in corn systems, and opens some avenues into the creation of better artificial intelligence assisted decision support systems.*

Keywords.
Unmanned Aerial Vehicle, Yield stability, Continuous corn, Vegetation indices, Agriculture 5.0

Introduction

Corn (*Zea mays* L.) production faces increasing challenges from climate variability, requiring management strategies that enhance both productivity and stability. Continuous corn rotation is one of the most nitrogen demanding cropping systems. Compared with normal crop rotation, continuous corn consistently produces lower yields and leads to greater interannual yield variability. This is in part related to reduced soil nitrogen (N) mineralization, increased allelopathy between corn residue and growing plants, and higher sensitivity to yearly climatic variability (Seifert et al., 2017). In a 16-year experiment in Iowa, Puntel et al. (2016) reported a coefficient of variation (CV) of grain yield of 17.8% in continuous corn rotation vs 12.9% in corn-soybean (*Glycine max* L.) rotations. They also observed that increasing N fertilization decreased this yield CV in continuous corn from 24.8% (0 N rate) to 15.4% (268 kg N ha^{-1}). A similar pattern was observed in Canada by Grover et al. (2009) where continuous corn rotation led to the highest yield CV (28%) among four rotations. Seifert et al. (2017) also showed that the strongest effect, decreased yield and highest CV, from continuous corn rotation appeared by year 3.

While N supply is a primary modulator of temporal yield stability in corn rotations, optimal N input can dramatically fluctuate between years at the same site due to weather-driven N mineralization, denitrification and leaching (Cambouris et al., 2016). Indeed, Basso et al. (2019) classified ~8 million ha of corn into stable high-yield, stable low-yield and unstable categories, demonstrating that nitrogen use efficiency (NUE) ranged from 48% in stable low-yield areas to 88% in stable high-yield areas. This suggests that fertilizer application should not be uniform across years but should be modulated according to the temporal stability of each zone. Therefore, assessment of yearly yield stability and identification of those stable zones (low CV), whose productivity is consistent between contrasting growing seasons, is important since it can help prioritize management decisions.

Unmanned aerial vehicles (UAVs) are now being used for the creation of management maps based on vegetation indices (VI), correlating with plant vigor, growth parameters and allowing yield prediction (Vidican et al., 2023, Vigneault et al., 2026). For corn, VIs based on the red, red-edge and near-infrared (NIR) bands are the most commonly used. This includes the Normalized Difference Vegetation Index (NDVI), Green NDVI (GNDVI), Normalized Difference Red-Edge Index (NDRE), Soil-Adjusted Vegetation Index (SAVI), Enhanced Vegetation Index (EVI) and the Modified Chlorophyll Absorption Reflectance Index (MCARI) (Table 1). While multiple VIs are correlated with corn yield (Vidican et al., 2023) and using multiple VIs lead to better predictive analytics (Vigneault et al., 2026), some are more responsive to in-season N fertilization. Indeed, NDRE outperformed NDVI and GNDVI in detecting in-season corn N response, while all three were preferable to morphological trait measurements for grain prediction (Jang et al., 2024). NDRE was also preferred to NDVI for the creation of a decision support system to maintain corn yield while reducing N fertilization rates by 31 kg N ha^{-1}, for its sensitivity to increasing chlorophyll levels (Thompson and Puntel, 2020). Colaço and Bramley (2018) also noted that temporal (year-to-year) variability in VI–yield relationships is a major source of uncertainty for sensor-based decision tools.

To our knowledge, few studies have investigated the correlation of VI derived from UAVs data with the CV of multi-year cropping systems. This three-year experiments (2021-2023) was designed with five contrasting N fertilization treatments (T1 0 kg N ha^{-1} to T5 300 kg N ha^{-1}N) with two sowing in continuous corn to maximize yield variability and address this gap in yield stability assessment using VI. This work provides a foundation for new artificial intelligence models embedded on UAVs, able to perform automatic fertilization during the growing season.

Material and Methods

Study areas and data acquisition

Field trials were conducted from 2021 to 2023 at the Agriculture and Agri-Food Canada L'Acadie experimental farm in Quebec, Canada (73° 20′ 47″ W; 45° 17′ 39″ N), using the royalty-free maize cultivar "Horizon HZ 3015" (Fig. 1). To generate spatial variability across the site, the experiment was structured around three contrasting factors that produced distinct growth regimes: soil profile, sowing date, and five nitrogen fertilization treatments.

With triplicate block replicate, each block contained ten plots arranged in 24 maize rows spaced 75 cm apart, giving plot dimensions of 18 m × 50 m. These ten plots were split into two sets of five, with each set assigned to a distinct sowing window. The early sowing date (S1) took place during the second week of May, whereas the late sowing date (S2) followed roughly 35 days later.

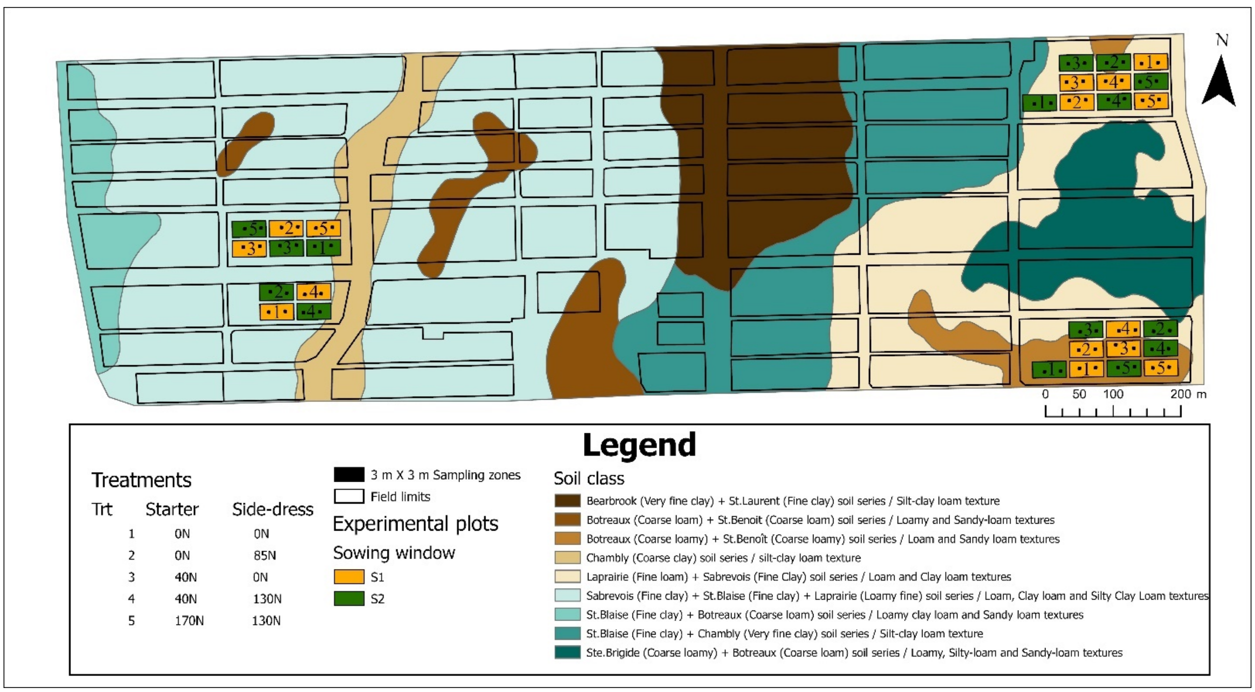

Fig. 1 Overview of the study area with highlighting for the different soil classes. Black squares indicate the biomass sampling zones (3 × 3 m), numbers indicate the different fertilizer treatments, and the UAV grid covered the entire plots.

Nitrogen fertilizer was applied at-seeding (starter) with the seeder and set to 0 N, 40 N and 170 N kg ha^{-1}. A second nitrogen application (side-dress) was broadcast 35 to 42 days after seeding, with timing adjusted according to soil, weather conditions and crop phenology. Post-emergence nitrogen rates were set at 0 N, 85 N, and 130 N kg ha^{-1} (Fig. 1).

Due to complications with late sowing in 2022, the 2022–S2 cycle was excluded from the study, reducing the number of growing cycles from six to five. Consequently, 150 samples were analyzed for the biomass, instead of the initially planned 180 (Samples = 30 sampling zones × 2 sowings × 3 years). Corn cobs were hand-harvested within each sampling zone once grain moisture reached 25–28%. Cobs were shelled with an electric sheller, and the fresh grain weighed. Fresh grain yield (kg ha^{-1}) were adjusted to and reported at a standard moisture content of 14.5% for all years. Final yield (Mg ha^{-1}) was obtained by dividing the adjusted grain weight from each 3 m × 3 m zone (9 m²) by the zone area and scaling to a per-hectare basis.

UAV data acquisition

UAV flights were carried out on a weekly basis throughout the corn growing season. Each mission took place between 10:00 AM and 2:00 PM, weather permitting, yielding roughly 20 flights annually. Image acquisition was performed using a fixed-wing eBee X UAV (EagleNXT Inc., Wichita, KS, USA) equipped with a Micasense RedEdge MX multispectral sensor. This sensor captures imagery across five narrow spectral bands: blue (center 475 nm, bandwidth 32 nm), green (560 nm center, 27 nm bandwidth), red (668 nm center, 14 nm bandwidth), red-edge (717 nm center, 12 nm bandwidth), and near-infrared (842 nm center, 57 nm bandwidth). Flights were conducted at an altitude of 75 m above ground level, producing a ground sampling distance (GSD) of about 5 cm. A minimum forward and side overlap of 75 % was maintained during image capture to optimize orthomosaic reconstruction quality, which was carried out using the Pix4Dmapper software (Pix4D S.A., Switzerland, version 4.9.0). Then, Vis (Table 1) were calculated for each 9m^2 region (grid) using ArcGis Pro (ESRI, USA, version 3.6.1) by averaging the spectral signal over the specific sampling point area. In total, 196 485 data points were processed (~100 points/field) with the 16 VIs.

Table 1. Vegetation indices evaluated

Vegetation indices (VI)	Full Name	Formula
NDVI	Normalized Difference Vegetation Index	*(NIR − Red) / (NIR + Red)*
NDRE	Normalized Difference Red Edge Index	*(NIR − RedEdge) / (NIR + RedEdge)*
GNDVI	Green Normalized Difference Vegetation Index	*(NIR − Green) / (NIR + Green)*
EVI	Enhanced Vegetation Index	*2.5 × (NIR − Red) / (NIR + 6 × Red − 7.5 × Blue + 1)*
SAVI	Soil-Adjusted Vegetation Index	*1.5 × [(NIR − Red) / (NIR + Red + 0.5)]*
CIG	Chlorophyll Index – Green	*(NIR / Green) − 1*
CIRE	Chlorophyll Index – Red Edge	*(NIR / RedEdge) − 1*
MCARI	Modified Chlorophyll Absorption Ratio Index	*[(RedEdge − Red) − 0.2 × (RedEdge − Green)] × (RedEdge / Red)*
TVI	Triangular Vegetation Index	0.5 × [120 × (NIR - Green) - 200 × (Red - Green)]
OSAVI	Optimized Soil-Adjusted Vegetation Index	*1.16 × (NIR - Red) / (NIR + Red + 0.16)*
NDYI	Normalized Difference Yellowness Index	*(Green − Blue) / (Green + Blue)*
NGRDI	Normalized Green-Red Difference Index	*(Green − Red) / (Green + Red)*
EVI2	Enhanced Vegetation Index 2	*2.5 × (NIR − Red) / (NIR + 2.4 × Red + 1)*
TGI	Triangular Greenness Index	*-0.5 × [(λred - λblue) × (Red - Green) - (λred - λgreen) × (Red - Blue)]* *λgreen = 560 nm, λred = 668 nm, λblue = 475 nm*
VARI	Visible Atmospherically Resistant Index	*(Green - Red) / (Green + Red - Blue)*
MSAVI	Modified Soil-Adjusted Vegetation Index	*0.5 × [2 × NIR + 1 - √((2 × NIR + 1)² - 8 × (NIR - Red))]*

Refers to Vigneault et al. (2026) and Vidican et al. (2023) for specific VI information.

Weather data

Meteorological data (Table 2) was acquired from an on-site weather station (Environment and Climate Change Canada). Corn Heat Units (CHU) was calculated from daily temperature using Eq. 1, as follows:

$$(1.8 \times (MinT - 4.4) + 3.33 \times (MaxT - 10) - 0.084 \times (MaxT - 10)^2) \div 2.0 \quad (1)$$

Where *MinT* and *MaxT* are respectively the minimum and maximum daily temperature in °Celsius.

Statistical analysis

Analysis of variance was conducted using R (version 4.5.1). Treatment effects on yield (Mg ha^{-1})

and CV were evaluated using one-way ANOVA, with the F-statistic and *p*-value used to assess overall significance. When significant treatment effects were detected, pairwise differences between treatments were examined using Tukey's HSD post-hoc test.

Results and discussion

Continuous corn yield

On average, temperature was typical across this three-year study. The first year (2021) was drier than average (Table 2). No significant effect on yield was found between the bloc (replicate), sampling zone withing the bloc, sowing, interaction between the treatment bloc × treatment ($p>0.05$). However, a significant effect was found for the treatment ($p<0.0001$, $F=69.9$) and unsurprisingly, for the sampling year ($p<0.0001$, $F=7.5$), with the experiment designed to show the cumulative effect of low fertilization application.

Table 2. Average weather conditions during the 3 years study

Period[1]	Avg. Temp.	Cum. Prec.	Cum. CHU
Year/Season/Sowing	**°C**	**mm**	**°C-day**
2021	8.1 (1.2)	782 (-197)	4041 (486)
season	16.2 (1.3)	519 (-113)	3926 (372)
S1	17.6 (1.4)	459 (-114)	3605 (314)
S2	17.2 (1.1)	354 (-58)	2697 (249)
2022	7.3 (0.3)	1124 (145)	3801 (245)
season	15.2 (0.3)	768 (136)	3653 (99)
S1	17.2 (0.2)	620 (117)	3394 (-18)
2023	8.3 (1.3)	1201 (221)	3896 (340)
season	15.7 (0.8)	795 (163)	3883 (329)
S1	17.1 (0.7)	686 (157)	3588 (227)
S2	17.5 (0.8)	660 (237)	3049 (267)
Mean	7,9	1036	3913
Season	15,7	694	3821
Sowing	17,3	556	3267
STDEV	0,53	223	121
Season	0,50	152	147
Sowing	0,22	143	389
CV	7%	22%	3%
Season	3%	22%	4%
Sowing	1%	26%	12%

[1]Average Temperature, cumulative precipitation and cumulative Corn Heat Units (CHU) with deviation from average conditions across the study period (2021-2023) in parenthesis for each year, along with mean, standard deviation (STDEV) and coefficient of variation (CV) for each system. Data for the entire year (2021, 2022 and 2023), the growing season (Season: April 1st to October 31st), and from each sowing to harvest (referred as S1 and S2) are presented.

Across three years of continuous corn (Figure 2), mean annual yields were 4.6 ± 1.3 (T1), 8.9 ± 2.0 (T2), 5.0 ± 1.7 (T3), 10.1 ± 1.2 (T4), and to 11.9 ± 1.5 Mg ha^{-1} (T5), consistent with the range of corn yield responses to N rate reported across the US Midwest and eastern Canadian sites (Tremblay et al., 2012; Cambouris et al., 2016; Puntel et al., 2016). Similar to the work of Seifert et al. (2017), we found that the third year showed greater variation in yield CV, with 2021 vs 2023 ($p<0.05$, $F=39.7$) and 2022 vs 2023 ($p<0.05$, $F=41.5$), a pattern also documented in long-term continuous corn systems where rotation effects and cumulative stress amplify interannual variability (Grover et al., 2009). Interestingly, T3 had similar yield and CV as T1 after three years ($p>0.05$), even though T3 received 40 kg N ha^{-1} each year. This suggests that low N rates under continuous corn are insufficient to overcome the yield penalty associated with monoculture and cumulative N demand (Seifert et al., 2017). Furthermore, this also indicates that sub-optimal N rates fail to remove this yield gap regardless of repeated application (Puntel et al., 2016).

With average interannual yield coefficients of variation of 9.4% (T1), 15.2% (T2), 22.6% (T3), 5.4% (T4) and 5.2% (T5), even if yield CV was higher after three years of continuous corn, average yield CV was still lower for high N treatments in agreement with Basso et al. (2019), who showed that under-fertilized and spatially unstable zones contribute disproportionately to yield variability and N loss across the US Midwest.

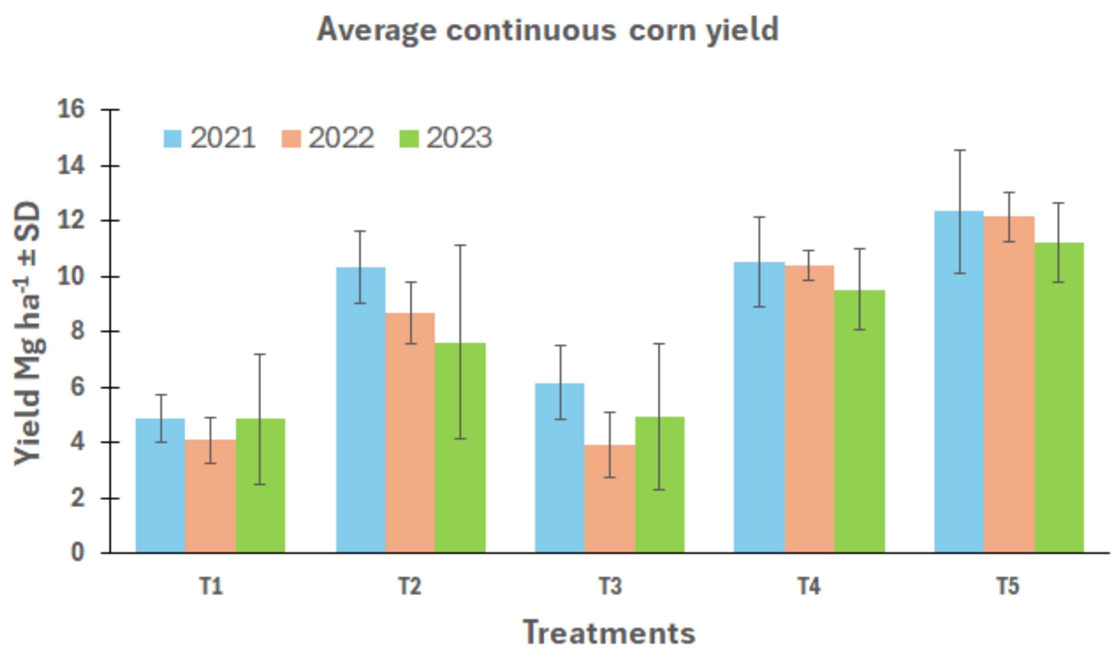

Fig. 2 Average Yield Response to Nitrogen Treatments Over Three Years. Error bar shows ± standard deviation**.**

Vegetation indices

VIs were calculated for all the experimental plots in a 3 × 3 m grid, up to the manual harvest. Figure 3 present the evolution of all the calculated VI over each growing season (only the first sowing is plotted). It can be observed that while all VIs show the same trends, they also show differences in the separation of their curves for different treatments.

Next, we evaluated the % VI CV for the different treatments (Fig. 4). Supporting the hypothesis that different VIs will exhibit different responses, we observed that the CV among the different treatments was highly diverse. Comparing the average % VI CV across treatments, treatments T4 and T5 exhibited the lowest average CVs across nearly all VIs (T4 = 15.3% and T5 = 15.0%), compared to T2 (19.5%), T1 (22.5%), and T3 (27.8%). The simple ratio VI CIRE (Chlorophyll Index – Red Edge) and CIG (Chlorophyll Index – Green) showed the highest variability in their CV% across treatment groups (absolute ratio) yet showed almost no difference between treatments T4 and T5 (Fig. 4), limiting their usefulness. Other ratio-based indices like NGRDI and VARI showed the same trends as CIRE and CIG, but with higher differences between treatment T4 and T5 (~0.8% vs 0.4%), favoring them in differentiating variation at high N fertilization. Surprisingly, TGI and NDYI which use normal camera Red-Green-Blue signals and correlate for NDYI to the senescence and to the Chlorophyll content via visible-spectrum triangle for TGI, showed a dissimilar trend to other VI, with higher % VI CV variation for T2, then T1 or T3, limiting its use in this particular application.

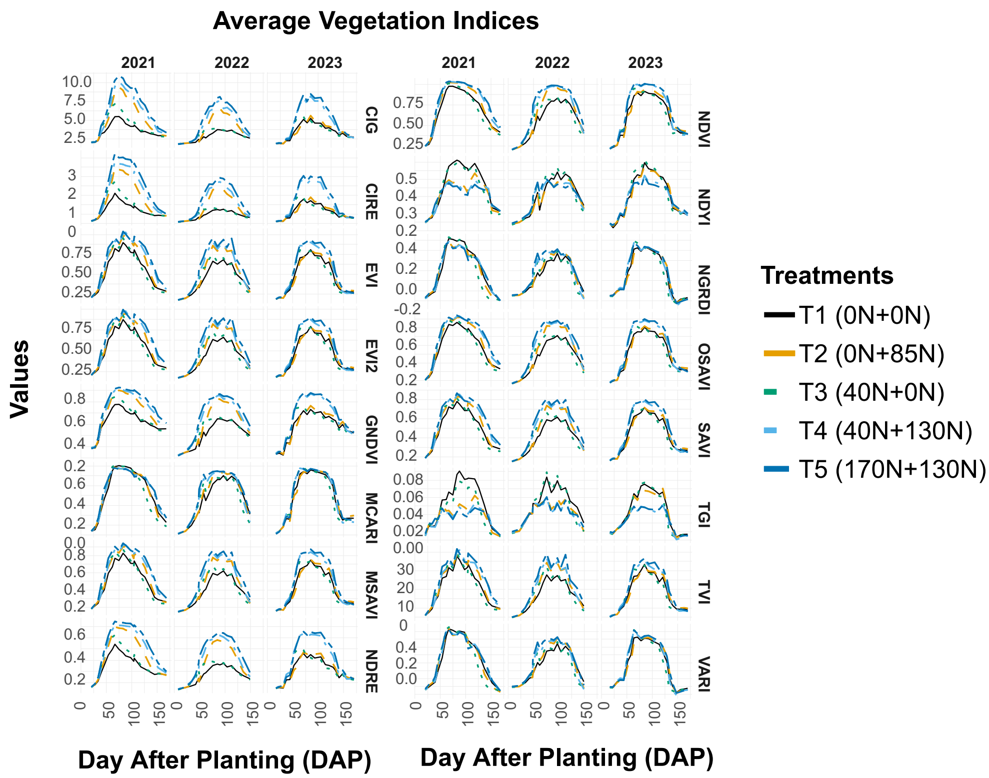

Fig. 3 Evolution of average Vegetation Indices (VIs) for the first sowing over the years.

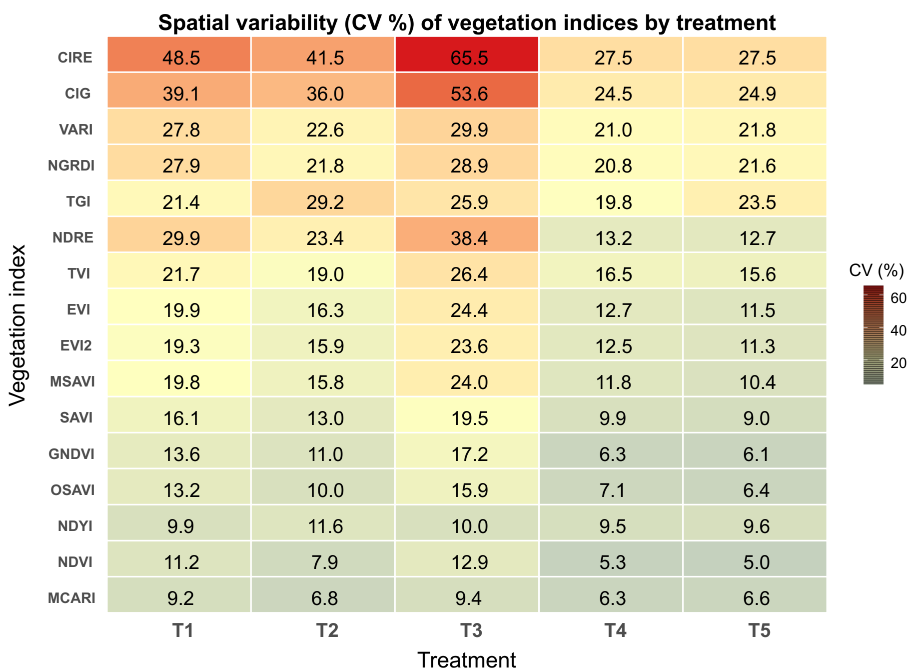

Fig. 4 Heatmap of vegetation index coefficient of variation (CV) across treatments for three years.

The NDVI and MCARI both presented low % VI CV (<15%, Fig. 4), which accounts for their temporal stability, as well as GNDVI and OSAVI with bellow 20% variation, even in the highly variable T3 treatment.

We next evaluated the overall correlation between the VI CV and the Yield CV, since we would normally select VIs well correlated with the variation in yield for fertilization (Fig. 5A), an approach commonly used to identify indices suitable for site-specific N management and yield prediction (Colaço and Bramley, 2018; Thompson and Puntel, 2020). As can be observed, most VIs had high correlation (>0.90) with the variation in yield CV, with the highest being GNDVI (r = 0.96), NDRE (r =0.96), NDVI (r = 0.95) and CIRE (r = 0.95), consistent with previous studies reporting that red-edge and green-based indices are among the most responsive to N status and yield variability in corn (Santana et al., 2021; Vigneault et al., 2026).

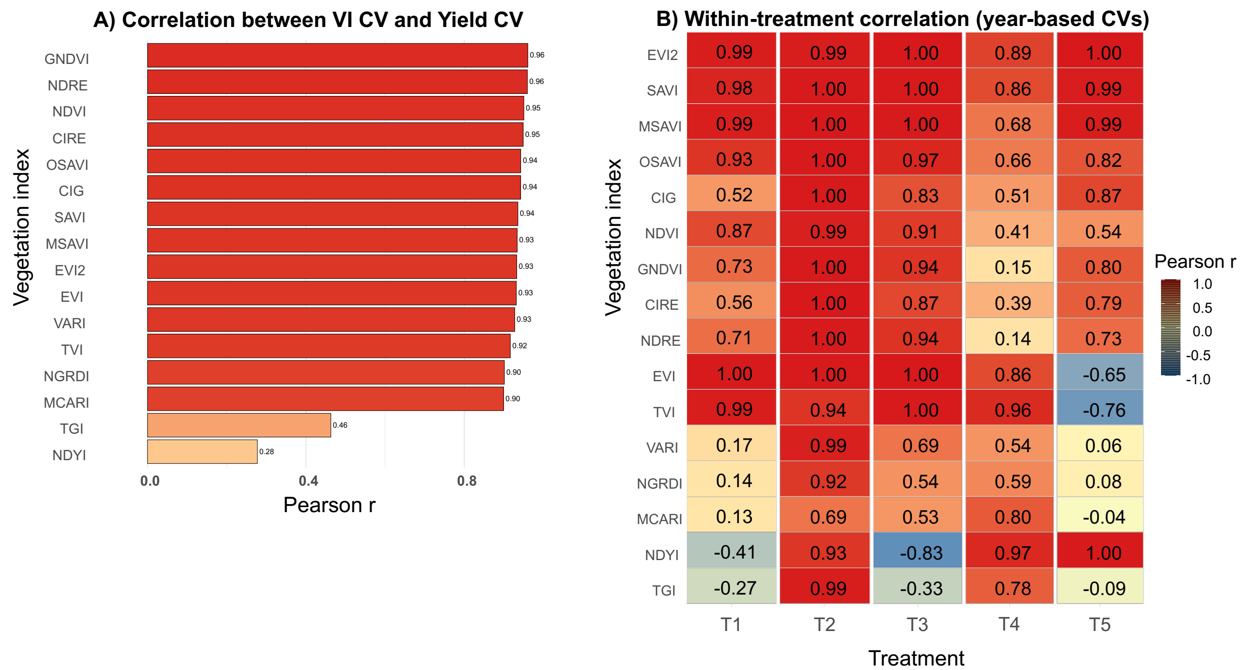

Fig. 5 Pearson's correlation (r) between Yield CV and VI CV for the overall experiment (A) or within treatments (B).

Finally, we evaluated the same correlation (VI CV vs yield CV) but within treatment (Fig. 5B). This final evaluation showed that while an overall correlation exists for some treatments, not all VIs are equally representative of all treatments, a limitation widely reported in crop performance remote sensing where index suitability varies with crop stage, canopy structure, and stress level (Vidican et al., 2023). For example, EVI showed high Pearson correlation for treatment T1 to T4, but poor correlation with T5, consistent with the known saturation of vegetation indices at high biomass and dense canopy conditions, typical of well-fertilized corn (Jang et al., 2024; Vigneault et al., 2026). Similarly, while NDVI correlated well with the yield CV% for T1 to T3 (r ~0.87–0.91), this correlation dropped to ~0.41–0.54 for T4 and T5 when evaluated using the yearly CV, a known observation for NDVI with decreased sensitivity under high N input and dense vegetation, limiting its usefulness for in-season N decision support (Colaço & Bramley, 2018; Thompson & Puntel, 2020). Only the EVI2, SAVI and MSAVI VIs maintained very high correlations (r ≥ 0.86) across T1 to T5, including the high-N treatments where canopy density was greatest, supporting prior findings that soil- and atmosphere-adjusted VI better track N-induced variability in corn than NDVI alone (Santana et al., 2021).

While NDVI, GNDVI, NDRE, and CIRE showed the highest correlation is the aggregate analysis, the reduced correlations at T4 (r = 0.14–0.41) and mixed performance at T5 (r = 0.54–0.80) reflect the difficulty of choosing the right VI. The well-documented saturation effect under high biomass and high LAI is typical of well-fertilized corn, where the VIs plateau and lose sensitivity to incremental variation (Colaço and Bramley, 2018; Thompson and Puntel, 2020; Jang et al., 2024).

While EVI2 and SAVI performance in aggregate correlation between % VI CV and yield CV (r = ~0.94) are not the best, they provided consistent yield CV tracking across all N levels and are therefore better candidates for UAV-based decision support systems. Those findings are compatible with those of Vigneault et al. (2026) which suggested the use of multiple-VIs in yield forecasting during the growing season. Those findings also reinforce the recommendation that VI selection should be validated under the specific range of N inputs and canopy densities expected in the target agricultural system, rather than transferred from aggregate benchmarking studies (Vidican et al., 2023).

Conclusion

This study was initiated to understand how different N fertilization strategies affect yield evaluation and fertilizer recommendation for remote sensing platforms such as UAVs, which could perform automatic N applications in the next Agriculture 5.0. The experimental design featured extreme N fertilization levels for corn (0 kg N ha^{-1}, low initial application only, side-dress only, and high rates 300 kg N ha^{-1}) in a continuous rotation to emphasize the year-to-year variation, allowing evaluation of different VIs for assessing the variation in crop response.

We found different correlation patterns between the VIs and the final yield across treatments. We also found that some VIs were more strongly correlated with the variability of yield (% CV). For our continuous corn experiment, EVI2 and SAVI were the most effective VIs, while other VI such as NDRE, NDVI, and GNDVI, despite presenting high correlation with yield CV, failed to capture each treatment variation.

While this study was limited to only small experimental fields, it demonstrated that multiple VIs would be required to help precision N fertilizer applications using autonomous drones.

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