108. Optimizing nitrogen management in wheat production based on management zones and remote sensing data

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Abstract

Optimizing nitrogen (N) management in wheat production requires balancing yield and environmental sustainability. This study evaluated four N management strategies: uniform N management, precision N management (PNM) based on management zones (MZ-PNM), remote sensing (RS-PNM), and their combination (RSMZ-PNM). The results showed that the RS-PNM strategy was the most effective strategy for fields with small-scale variability (spatial range=25 m), resulting in a 17.3–20% increase in yield and a 17.6–20.1% improvement in partial factor productivity compared to uniform N management. These findings provide valuable guidance for selecting the optimal N management strategy based on field-specific spatial variability.

Keywords: management zones, N strategy, remote sensing, winter wheat

Introduction

Effective nitrogen (N) management is essential for meeting wheat growth demands while minimizing the environmental impacts of over-application. Excessive N application often leads to substantial losses through leaching, runoff, denitrification and ammonia volatilization, contributing to environmental degradation (Cordero *et al.*, 2019). Precision N management (PNM) offers a viable solution by synchronizing crop N demand with soil N supply across spatial and temporal scales (Li *et al.*, 2024).

Various strategies have been developed for delineating site-specific management zones (MZs) to address the spatial variability in N application. MZs, defined as sub-field areas with relatively uniform characteristics, are established based on factors such as soil properties (Fleming *et al.*, 2004), multi-year yield maps (Miao *et al.*, 2018), remotely sensed spectral data (Cicore *et al.*, 2016), or combinations of multiple data sources (Jin *et al.*, 2017). Soil-based MZ delineation often incorporates traits indicative of high productivity, such as depressed terrain and darker soils (Khosla *et al.*, 2002). However, relying solely on soil information fails to account for seasonal and short-term variability in crop N status, which is strongly influenced by fluctuating weather conditions (Maestrini and Basso, 2018). Vegetation indices derived from spectral reflectance data complement soil-based approaches by capturing real-time crop conditions. Normalized difference vegetation index (NDVI) calculated from near-infrared and red reflectance is strongly correlated with key agronomic traits such as leaf area index, biomass, and leaf N content (Shaver *et al.*, 2010).

Although both soil- and plant-based approaches have proven effective, their integration offers significant potential to improve N management. Soil-based data enhance the accuracy of crop-based methods, providing complementary insights to optimize N use efficiency, increase economic returns, and improve environmental sustainability (Jin *et al.*, 2017). However, systematic evaluations of integrated approaches remain limited. Furthermore, merging soil and remote sensing data addresses the complexities of variable-rate N applications by leveraging the strengths of each method.

This study aimed to introduce an innovative approach by integrating high-resolution remote sensing with soil-based MZs (RSMZ-PNM) to optimize N application and systematically evaluate its effectiveness compared to uniform N management (UNM), MZ-PNM, and RS-PNM strategy. Furthermore, the most effective N management approach for field-specific conditions would be identified using semi-variogram analysis.

Materials and methods

Study site and data collection

The experiment was conducted from 2023 to 2024 in Dancheng County, Henan Province, P.R. China. This region has a typical temperate monsoon climate, with an average annual temperature of 15°C and an average annual precipitation of 700–800 mm. The experimental field, previously used for grape cultivation, was managed under standardized agricultural practices.

Soil brightness index (BI) and NDVI values were derived from PlanetScope satellite imagery with a spatial resolution of 3m. The BI is influenced by soil moisture, the presence of salts, and organic matter content on the soil surface (Escadafal, 1989). Soil brightness obtained from bare soil imagery can be used for MZ delineation (Cammarano *et al.*, 2020) as an indirect method to capture soil spatial variations. NDVI provides insights into crop growth. Reflectance data were collected across the blue (455–515 nm), green (500–590 nm), red (590–670 nm), and near-infrared (780–860 nm) spectral bands, with a scaling factor of 10 000 applied to ensure accurate reflectance (Planet Labs, 2019). At harvest, six random sampling points (1 m^2 size) were selected from each treatment to measure grain yield. Geographic coordinates were recorded for spatial analysis.

$$BI=\sqrt{(red^2+green^2)/2} \quad (1) \tag{1}$$

Management zones and experimental design

The fuzzy c-means (FCM) clustering algorithm was used to delineate MZs (Fridgen *et al.*, 2004), incorporating BI and NDVI data. The FCM parameters included a fuzzification exponent of 1.3, a maximum of 300 iterations, and a convergence threshold of 0.0001. The number of MZs matched the number of experimental treatments. FCM clustering analysis was conducted using the fuzz module in the skfuzzy package in Python. Three N rates (N220, N250, and N280 kg N/ha) were applied based on expert recommendations. Plot sizes varied based on the operational width of the fertilizer spreader and field length: 27×250 m^2 for N220 treatment, 233×250 m^2 for N250 and 50×250 m^2 for N280. Four N strategies were evaluated:

1. UNM: Uniform N application, ignoring MZ and NDVI variations.
2. RS-PNM: NDVI-based variable rates, with higher N in low-NDVI areas and lower N in high-NDVI areas (Guerrero *et al.*, 2021).
3. MZ-PNM: MZ-based N rates, applying higher N to high-productivity zones.
4. RSMZ-PNM strategy: Combines soil and crop data to optimize N rates.

Comprehensive irrigation, pest control, and weed management were performed throughout the growing season.

Strategy evaluation

Partial factor productivity (PFP), a key indicator of N use efficiency, was calculated as the ratio of grain yield to total N input, accounting for the total available N from both soil and fertilizer inputs. Grain yield for UNM was modeled as a quadratic function of N rates (Ren *et al.*, 2022), while yields for PNM strategies were derived from site-specific observations that met predefined criteria. Economic benefits were assessed by subtracting fertilizer costs from yield income, using market prices for fertilizer (US$0.79/kg) and grain (US$0.34/kg). All values were normalized for comparison by subtracting the mean and dividing by the standard deviation, ensuring a standard scale with a mean of 0 and a standard deviation of 1.

To assess the spatial suitability of PNM strategies, semi-variograms were used to analyze spatial structure. These semi-variograms represent semi-variance as a function of the distance between yield observations. A Gaussian model was fitted to empirical semi-variogram, with key parameters such as range, sill, and nugget used to describe spatial variability. All analyses and computations were performed using Python.

Results

The delineated MZs based on soil BI and NDVI values were shown in Figure 1. The number of zones was equal to the number of N levels. The results revealed significant spatial variability in soil properties and crop growth within the field, demonstrating its suitability for variable-rate fertilization management.

Grain yield and PFP response to N applications

Grain yield consistently increased with N fertilizer application (Figure 2a). Among the N management strategies, PNM approaches outperformed the UNM strategy, with yield increases of 17.3% at N220, 10.8% at N250 and 29.4% at N280. The RS-PNM strategy performed the best. In contrast, the PFP value decreased as N rates increased (Figure 2b). The PFP values for the UNM strategy were consistently lower than those for any PNM strategy. Notably, the RS-PNM strategy achieved the highest PFP values (36.1 kg/kg at N220 and 35.6 kg/kg at N250), surpassing, reflecting better nitrogen use efficiency compared to MZ-PNM (30.1 kg/kg at N250 and 29.7 kg/kg at N280) and RSMZ-PNM (31.9 kg/kg at N250) strategies. Moreover, the RS-PNM strategy improved PFP by 17.6–20.1% compared to UNM.

Evaluation of N management strategies

A radar chart illustrates the contributions of each N management strategy to grain yield, economic benefits, and PFP (Figure 3). The PNM strategies provided clear advantages in terms of yield, economic returns, and PFP over the UNM strategy. Among the PNM strategies, RS-PNM demonstrated the best performance, delivering higher economic returns and improved N use efficiency.

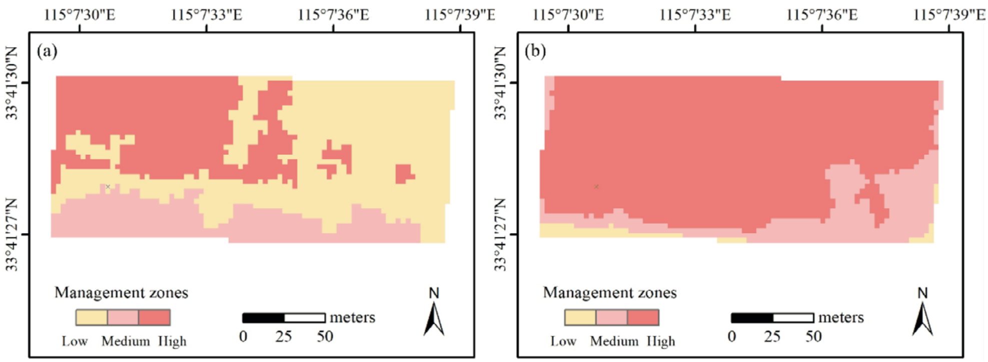

Figure 1. Delineated management zones based on soil brightness index (a) and NDVI (b).

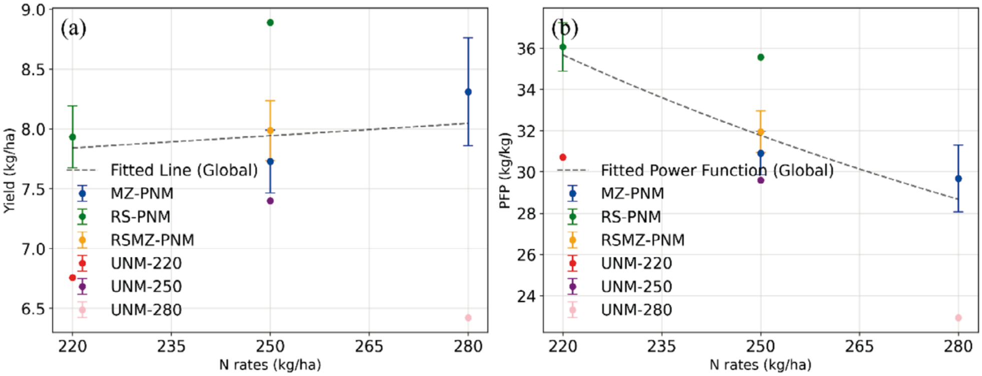

Figure 2. Relationship between the N rates and grain yield (a) and between the N rates and PFP (b) for uniform N management (UNM), PNM based on RS (RS-PNM), PNM based on MZ (MZ-PNM), PNM based on MZ and RS (RSMZ-PNM).

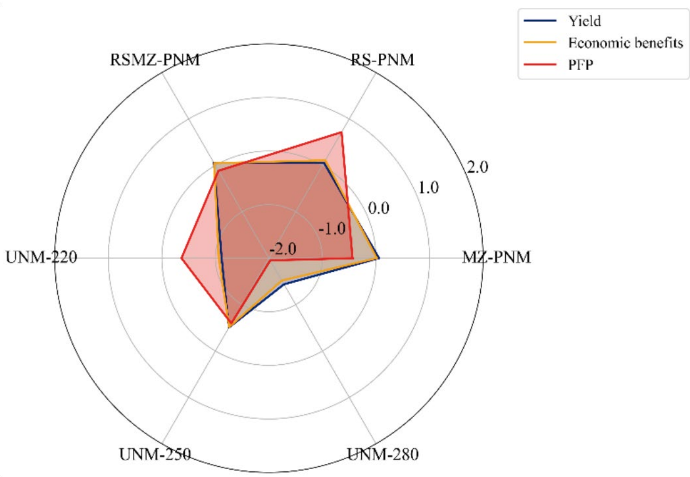

Figure 3. The contribution of yield, economic benefits, and PFP across N strategies.

Spatial variability

A theoretical semi-variogram model (Matheron, 1963) was used to analyze the spatial patterns of grain yield, linking spatial structure to the PNM strategies (Figure 4). The empirical semi-variogram was best fitted by a Gaussian model, with the spatial autocorrelation range determined to be 25 m. This finding indicates the scale of spatial dependency within the field, highlighting the need for management strategies that account for such spatial variability.

Discussion

The results of this study demonstrate that crop yield increases with higher N fertilizer application rates, though the relationship is nonlinear. These findings align with previous research by Barbieri *et al.* (2008) and Ma and Biswas (2016), which indicate that while higher N levels boost yield, they also result in diminishing marginal returns as the application rate increases. Moreover, PFP

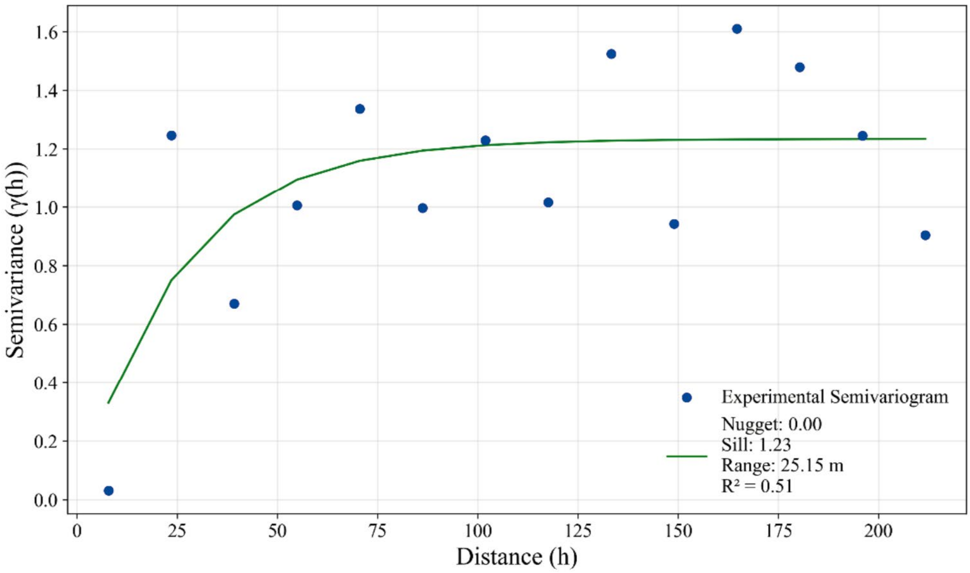

Figure 4. Semi-variograms of grain yield data.

decreased as N rates increased, consistent with the findings of Delgado *et al.* (2005), who highlighted that excessive N fertilization exacerbates N losses to the environment and reduces N use efficiency. PNM strategies not only enhance the sustainability of agricultural systems but also provide economic benefits that surpass the cost of N fertilizer, yielding significant positive impacts. By employing precision fertilization, farmers can optimize crop yields and improve N use efficiency, thereby increasing economic benefits and achieving multi-objective optimization of yield, PFP, and profitability.

In field management, the effectiveness of PNM strategies depends on accurately assessing the spatial variability of crop yield. Analysis of semi-variogram models in this study identified a spatial dependency range of grain yield. For fields with spatial variability below 25 m, N management strategies utilizing remote sensing emerged as the most suitable strategy. These findings align with those of (Cordero *et al.*, 2019), emphasizing the advantages of RS-PNM strategies in scenarios with small-scale spatial variability. Moreover, in fields with small variability (CV=13%), RS-PNM strategies enhance PFP by dynamically adjusting N rates to meet crop-specific needs, thereby maximizing yield and economic benefits, which is consistent with Guerrero *et al.* (2021). In fields with greater spatial variability, particularly where variability exceeds 100 m (Schepers *et al.*, 2004), the MZ-PNM strategy proved more effective. The combined RSMZ-PNM strategy exhibited flexibility in addressing both soil- and crop-based variability, making it particularly valuable for fields with moderate to high spatial variability. However, its performance slightly lagged behind RS-PNM in small-variability scenarios, indicating the need for further refinement. An innovation of this study is the dynamic evaluation of N management strategies concerning spatial variability, which can determine the appropriate spatial scale for each strategy.

In this study, a N increment of 30 kg N/ha was applied, which is suitable for fields with small to moderate variability. However, in regions with significant N deficiencies, such as highly variable southern areas, a higher increment of 50 kg N/ha may be necessary to meet crop demands and maximize yields. Under such conditions, RS-PNM technology can dynamically adjust fertilization rates, enhancing production potential across diverse zones. This adaptability is crucial for improving the sustainability and productivity of agricultural systems.

Semi-variogram analysis revealed that intrinsic spatial yield variability remained after N applications, suggesting that certain underlying soil differences were not fully captured by MZs. A limitation of soil brightness as a proxy for soil moisture is its weak correlation because soil-plant interactions extend beyond the top few centimetres of soil (Cammarano *et al.*, 2020). Moreover, image acquisition timing can influence soil brightness values. Future studies should consider incorporating advanced soil sensing techniques (e.g., Veris 3000 or SoilOptix sensors), or high-density soil sampling to better characterize spatial heterogeneity. While this study provides valuable insights into optimizing N management, the study was conducted at a single location with specific environmental conditions. The findings may not be universally applicable across different geographic regions and cropping systems. Future research should evaluate these strategies across diverse environmental conditions involving wet and drought years.

Conclusions

The findings demonstrate that RS-PNM and RSMZ-PNM strategies are effective for optimizing N management in wheat fields. RS-PNM strategy showed the highest N use efficiency and yield improvements in fields with small spatial variability (<25 m). This study provides a practical framework for selecting the most suitable PNM strategy based on field-specific conditions. However, further validation is needed across diverse environmental and agronomic conditions to assess the scalability of these strategies with more site-year data and advanced soil sensing techniques or high-density soil sampling.

Acknowledgments

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