EFFECT OF TERRAIN AND SOIL PROPERTIES ON THE EFFECTIVENESS OF CROP-MODEL BASED VARIABLE RATE NITROGEN IN CORN

Paccioretti P.[1], Puntel A. L.[1], Thompson L.[1], Mieno T.[2], Balboa G.[1]

[1]Department of Agronomy and Horticulture, University of Nebraska – Lincoln, NE, United States
[2]Agricultural Economics, University of Nebraska – Lincoln, NE, United States

A paper from the Proceedings of the
16th International Conference on Precision Agriculture
21-24 July 2024
Manhattan, Kansas, United States

Abstract.

Growers may be reluctant to adopt variable rate nitrogen (VRN) management because of potential loss in profit and yield. This study assessed the influence of terrain attributes and soil characteristics on the effectiveness of crop-model-based variable rate nitrogen (N) for corn. To evaluate the effectiveness of the VRN methods, yield, total N rate, and N use efficiency (NUE) were compared with the grower's management. As a crop-model-based recommendation tool, Adapt-N was used. Production data from on-farm strip trials conducted at nine locations in Nebraska, USA, were augmented with various geospatial data layers, including elevation, derived terrain attributes, and vegetation indices. To compare treatment performance, these layers were used to delineate within-field homogeneous zones. Mixed effects models were used to determine the effect on the benefits of the crop-model-based VRN tool compared with the usual grower N rate. Comparisons between treatments were made at different scales, including an overall treatment effect across sites, and a within-field effect. A metanalysis was fitted using the nine between-fields mean treatment differences, obtained from the linear mixed model to calculate the overall treatment effect across sites. The within-field treatment response was fitted considering the interaction between treatments and homogeneous zones. The yield, N, and NUE performance between Grower's management and crop-model-based technology varied from field to field. The results suggest that within-field differences between grower's management and crop-model-based VRT depend on field characteristics. Yield differences between crop-model-based and Grower ranged from -0.30 t ha^{-1} to 0.17 t ha^{-1} for yield. N rates ranged between 15% less N than the Grower to 37% more N than the grower. The NUE ratio between the N recommendation tool and the Grower ranged between 28% less to 26% more NUE than the Grower. Overall differences for the three variables were not statistically significant. However, the adoption of VRN tool may be promising where variability in elevation and productivity zones are highly variable within the field. Characterizing the performance of these tools under different environments is key to better technology placement and promoting adoption in fields with similar characteristics to ensure positive outcomes.

Keywords.
Precision Agriculture, Site-specific management, variable rate, within-field variability, Adapt-N.

Introduction

Nitrogen (N) is one of the most essential plant nutrients and is critical for maximizing crop yield and profit (Gheith et al. 2022; Puntel et al. 2024). However, increased fertilizer consumption can produce higher N leaching, and reduce the nitrogen use efficiency (NUE). In addition to the direct economic costs of fertilizer and its application, there is also an additional cost to the environment (Dybowski et al. 2020). Excess N that is not used by the crop, is susceptible to being lost through denitrification, volatilization, leaching, and runoff, negatively affecting groundwater sources or streams (David et al. 2010; Van Es et al. 2020). This problem can be addressed by adjusting the N rate and better synchronizing the applied N rate with crop N demand. Nevertheless, the crop nutrient requirement depends on multiple interacting factors such as weather, soil characteristics, and environmental variables (Sela et al. 2018).

Most farmers make management decisions for the whole field. N management strategies typically involve a static rate, which does not account for variability within the field (Morris et al. 2018). Precision agriculture technologies allow farmers to manage within-field variability and make crop production more efficient. Site-specific management takes advantage of within-field variability to increase farm profitability and sustainability by reducing N rates and N leaching. Several N recommendation tools have been developed specifically for corn (*Zea Mayz* L.). The tools optimize the amount of N applied to the crop better synchronizing crop N requirements, rate, and time (Mandrini et al. 2021; Samborski et al. 2009; Sela et al. 2016; Van Es et al. 2020). However, growers may be reluctant to adopt variable rate nitrogen (VRN) management because of uncertain profits and the impact on crop yield.

N recommendation tools can be classified as static or adaptative. The former cannot predict site-specific N requirements. On the other hand, adaptative tools can be coupled with site-specific conditions to generate space and time-specific N recommendations (Sela et al. 2018). Adapt-N is a crop model-based tool that provides dynamic, adaptive side-dress N recommendations to optimize corn N management for specific growing environments. Growers can obtain near real-time recommendations with a 6-hour lag in season N recommendation rates in a web-based environment (Sela et al. 2016).

The objective of this study was to compare the yield, total N rate, and nitrogen use efficiency (NUE) of the Adapt-N tool with the usual Grower's N rate. Comparisons were conducted at three scales: across all sites, between fields, and within fields by delineating homogeneous zones.

Materials and Methods

Experimental data

To compare Adapt-N tool with usual grower N rates, nine on-farm field-scale experiments were conducted within the Nebraska on-farm research network (USA). Two trials were conducted in 2021, three were conducted in 2022, and four in 2023. The area of the fields ranged from 27.8 ha to 60 ha, with 50% of the trials having an area of 48.8 ha or less. A strip-plot design was implemented in each field. The width of each strip was determined by the width of the grower's machinery. Repetitions ranged from 4 to 21, depending on field size and variability.

All trials had irrigation, eight were irrigated using a pivot, and one by gravity (8_2023). The seeding rate ranged between 71,607 and 86,422 seeds ha^{-1}, 50% of the trials were seeding with 81484 seeds ha^{-1} or less. For all trials, the row spacing was 76.2cm. The planting date was between April 19th and May 12th. The previous crop was soybean in all fields except in 6_2023 where the previous crop was corn.

Nitrogen recommendation

For each trial, a nitrogen prescription was made using Adapt-N model. For each field, the expected yield was estimated for homogeneous zones. Layers available for the zone delineation varied among fields if available organic matter from grid samples, electroconductivity, NDVI, or historical crop yield were used as input for the zone delineation. Once the zones were delineated, their expected yield was adjusted based on the grower's experience.

Data processing

Yield and as-applied data were processed, cleaned, and aggregated following the protocol proposed by Puntel et al. (2024). A 15-meter inner buffer was applied to the boundaries of the fields to reduce border effects. All data was processed using R software (R Core Team 2024).

To compare treatments, nitrogen use efficiency (NUE) was calculated as Eq. (**1**

$$NUE = \frac{Y_N}{F_N} \tag{1}$$

where Y_N is the corn yield (kg ha^{-1}) with applied N, F_N is the amount of N applied (kg N ha^{-1}) (Cassman et al. 1998, 2002).

Zone delineation

Multispectral imagery data from Sentinel-2 Level-2A (L2A) of the European Space Agency (ESA) (Drusch et al. 2012) and digital elevation model (DEM) product from the U.S. Geological Survey (U.S. Geological Survey 2023) were used to delineate homogeneous zones in each trial. The L2A product provides atmospherically corrected Surface Reflectance (SR) images at a spatial resolution of 10m. The DEM data has a 1/3rd arc-second resolution, which is approximately 10m resolution. The data was downloaded using the *rstac* (Simoes et al. 2021) and *gdalcubes* (Pondi et al. 2024) R packages. The multispectral images (<5% cloud coverage) were obtained for 2018, 2019, and 2020 from July 15th to August 30th. The Normalized Difference Vegetation Index (NDVI) (2) and Normalized Difference Red-Edge (NDRE) (3) indices were calculated.

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{2}$$

$$NDRE = \frac{NIR - RE}{NIR + RE} \tag{3}$$

where NIR is Near-infrared spectral band (832.8-833.0 nm), RED is red spectral band (664.4-665.0 nm), and RE is red-edge spectral band (703.8-704.1 nm). From DEM elevation data, six DEM-derived variables were calculated: slope, aspect, Topographic Position Index (TPI), roughness, Terrain Ruggedness Index (TRI), and Topographic Wetness Index (TWI) were calculated.

Elevation data, the six DEM-derived variables, NDVI, and NDRE values from the downloaded imagery data were used to delineate homogeneous zones. The KM-sPC method was applied, which performs a fuzzy k-means cluster analysis on the spatial principal components obtained from the data (Córdoba et al. 2016). To characterize each delineated within-field zone, each was summarized by calculating the mean of all DEM-derived variables and the median and the coefficient of variation (CV) for the vegetation indices.

Treatment comparison

To explore the treatment effect on yield (t ha^{-1}), applied N (kg N ha^{-1}), and NUE (kg yield N^{-1}) linear mixed models were fitted for each trial (Pinheiro and Bates 2000). To account for within-field variability, the trial area was gridded. Each cell was within a repetition including both treatment strips and was approximately 15m wide. For each trial the model fitted was

$$Y_{ijkl} = \mu + \tau_j + c_{k|l} + s_l + \varepsilon_{ikl} \tag{4}$$

where Y_{ijkl} is the value of the response variable (yield, N, or NUE) for the j-th treatment in k-th cell in the l-th repetition, μ is a constant, τ_j represents the effect of treatment j. Assuming that observation i is in the repetition l and within the cell k, $c_{k|l}$ and s_l are random cell effect and random repetition effect, respectively.

To study the treatment associated with site-specific site characteristics, a model accounting for treatment and homogeneous zone interaction was fitted for each trial.

$$Y_{imjkl} = \mu + \tau_j + \gamma_m + \tau\gamma_{jm} + c_{k|l} + s_l + \varepsilon_{imkl} \quad \textbf{(5)}$$

were Y_{imjkl}, μ, τ_j, $c_{k|l}$, s_l, ε_{imkl}, are defined as in equation (4, and $\gamma_j$is the effect of j-th zone on variable Y, $\tau\gamma_{jm}$ is the interaction effect between treatment j and zone m. For all the linear mixed models, the term ε_{ikl} was assumed normally distributed with mean zero and heteroscedastic variances for each treatment and repetition. The models were estimated by Restricted Maximum Likelihood (REML) using the function *lme* from the *nlme* package (Pinheiro et al. 2023) in R software (R Core Team 2024).

The output of the model fitted in equation (4) was used to compare the overall treatment effect for yield, N, and NUE via a meta-analysis. The nine adjusted means differences between treatments (Adapt-N - Grower) with their fitted standard error (SE) were used as input for the function *rma* from the *metafor* package (Viechtbauer 2010). The analysis was performed with a random-effect model estimated by REML.

A Principal Component Analysis (PCA) was conducted to describe the relationships between zone characteristics and the observed differences between treatments for grain yield, N rate, and NUE. To standardize the site characteristic variables between trials, the within-zone summarized values (x_i) were scaled by the field mean ($x_i - \bar{x}$).

Results

Grain Yield

The overall difference, a result of the metanalysis including all trials, was not statistically significant. The average difference was -0.02 t ha^{-1}, with a confidence interval of 95% ranging between -0.13 and 0.08 t ha^{-1} (Figure 1). The median grain yield of the nine mean differences (Adapt-N - Grower) was -0.05 t ha^{-1}, indicating that in at least 50% of the trials, the grower's yields were higher than the Adapt-N yields. The minimum value was -0.30 t ha^{-1} and the maximum value was 0.17 t ha^{-1}. In four fields (44%), the yield values observed for Adapt-N treatment were higher than those observed for the growers' regular practice. The mean difference ranged from 0.05 t ha^{-1} to 0.17 t ha^{-1}, with a median value of 0.10 t ha^{-1}. In two trials (1_2021 and 6_2023) the differences between treatments were not statistically significant. In three trials (33%), the growers' practice yielded superior results than Adapt-N. The average between the differences for these trials was -0.20 t ha^{-1}, the values ranged between -0.30 t ha^{-1} and -0.03 t ha^{-1}.

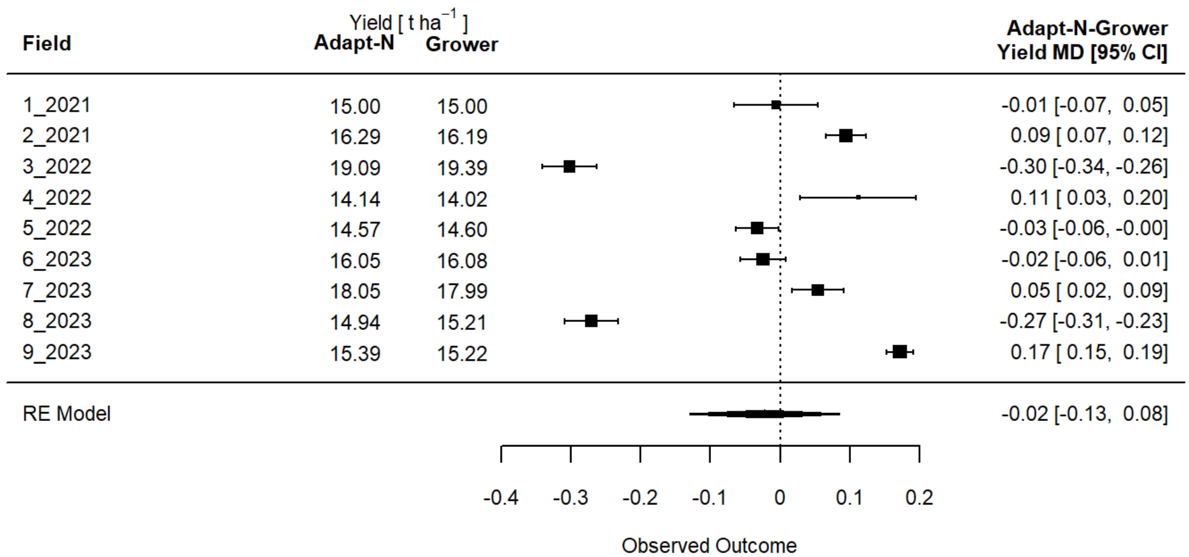

Figure 1. Forest plot of grain yield means between treatments and means differences in t ha^{-1} between Adapt-N and Grower treatments for nine On-Farm experiments. Differences (observed outcomes) are expressed as Adapt-N minus Grower yield. Positive values indicate yield advantage for Adapt-N. In brackets 95% confidence interval (95% CI) for the means differences.

Total Nitrogen rate

The overall difference for the total nitrogen applied was not statistically significant, the overall mean was -0.05 kg ha^{-1} and the 95% confidence interval ranged from -15.42 kg ha^{-1} to 15.32 kg ha^{-1} (Figure 2). Differences in N rates between Adapt-N and the Grower rate ranged from -27 kg ha^{-1} to 46 kg ha^{-1}, positive values in the differences indicate a higher N rate in Adapt-N. The total Nitrogen applied was lower for Adapt-N prescriptions in four fields (44%), on average 10.3% lower than the Grower rate. In these fields, changes relative to the Grower rate varied from 14.6% to 5.7% lower. In the five remaining fields, the changes ranged from 0.2% to 37.3% higher for Adapt-N. In field 5_2022, the Adapt-N rate was 340 g ha^{-1} higher than the Grower rate. On field 7_2023, the grower rate was 46.56 kg ha^{-1} lower than Adapt-N, representing a 37.3% higher rate for Adapt-N. The mean for the five fields was 13% more than the grower.

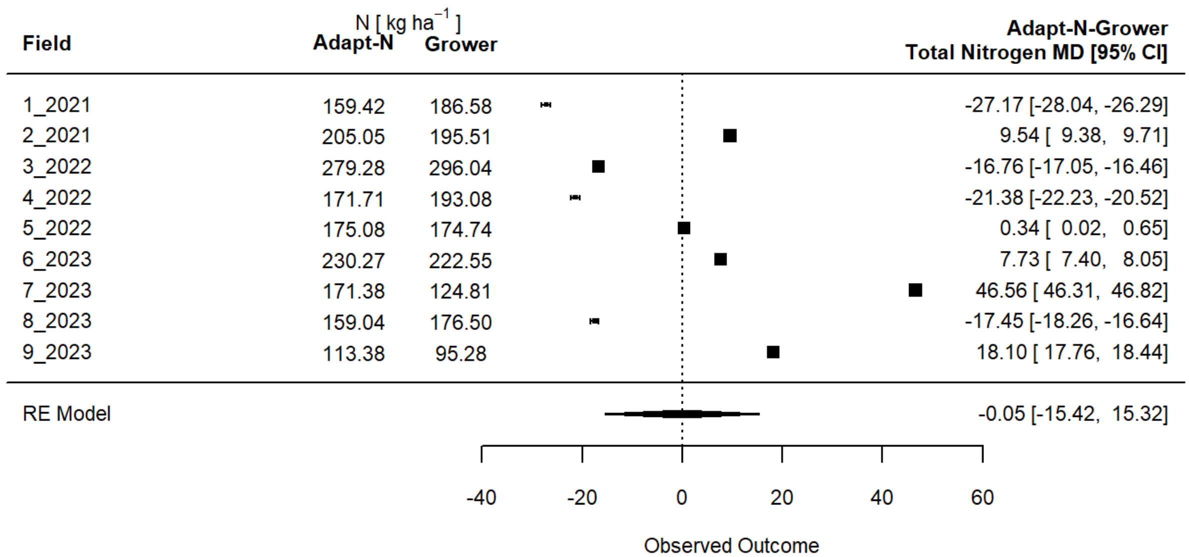

Figure 2. Forest plot of nitrogen rate (N) means between treatments (Adapt-N and Grower) and means differences in kg ha^{-1} between Adapt-N and Grower treatments for nine On-Farm experiments. Differences (observed outcomes) are expressed as Adapt-N minus Grower rate. Positive values indicate a higher N rate for Adapt-N. In brackets 95% confidence interval (95% CI) for the means differences.

Nitrogen Use Efficiency

The NUE differences for the treatments ranged between -39.3 kg yield kg^{-1} N^{-1} to 21.3 kg yield kg^{-1} N^{-1}. In four out of nine fields (44%), the NUE was higher in plots with Adapt-N recommendations (positive values for mean differences). In these fields, the mean difference for NUE was 10.4 kg yield kg^{-1} N^{-1}, with a range of 2.9 kg yield kg^{-1} N^{-1} to 21.3 kg yield kg^{-1} N^{-1}. In fields where the grower had a higher NUE, absolute difference values ranged from 39.3 kg yield kg^{-1} N^{-1} to 3.4 kg yield kg^{-1} N^{-1}, representing a 27.3% to 4.1% lower efficiency than Adapt-N. The average absolute difference was 15.3 kg yield kg^{-1} N^{-1}. The overall NUE difference was -4.0 kg yield kg^{-1} N^{-1} with a 95% confidence interval ranging from -15.8 kg yield kg^{-1} N^{-1} to 7.9 kg yield kg^{-1} N^{-1} (Figure 3).

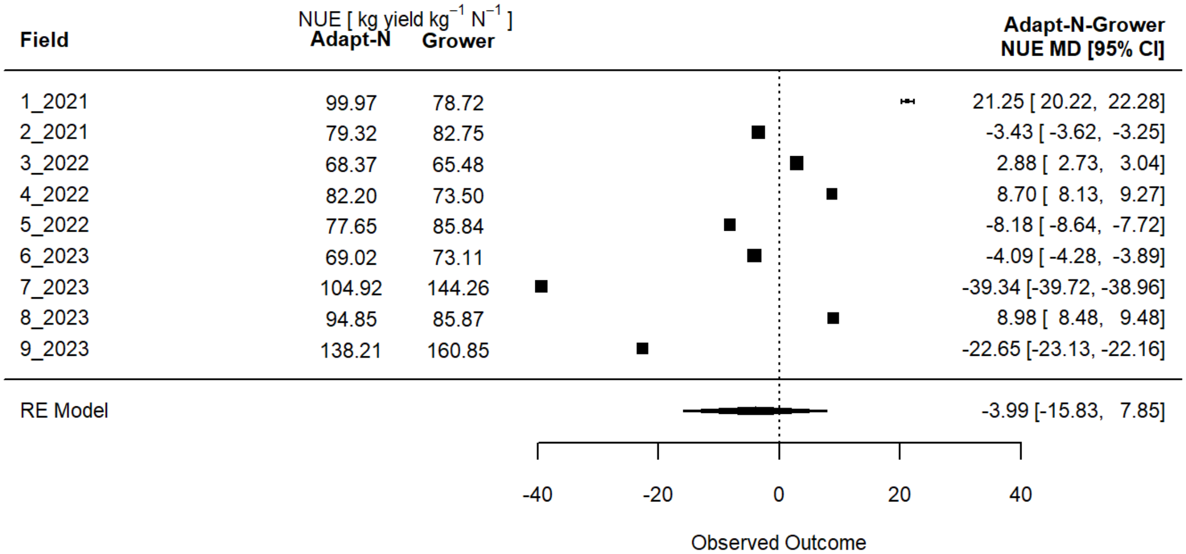

Figure 3. Forest plot of nitrogen use efficiency (NUE) means between treatments and means differences in kg grain yield kg^{-1} N^{-1} between Adapt-N and Grower treatments for nine On-Farm experiments. Differences (observed outcomes) are expressed as Adapt-N minus Grower rate. Positive values indicate a higher NUE for Adapt-N. In brackets 95% confidence interval (95% CI) for the means differences.

Within-field comparison

The Figure 4 presents a PCA biplot summarizing the association between DEM-derived variables, the vegetation indices (mean and CV), and differences between treatment for grain yield, N rate, and NUE, for homogeneous zones delineated for the nine fields. Different colored dots represent different fields. The first principal component (PC1) explains 39.2% of the total variability, while PC2 reflects 23.6%. Therefore, the two first components explain 62.8% of the variations in the variables. The four variables most important for the PC1 were Roughness, TRI, slope, and N differences (N_diff). The NDRE and NDVI coefficient of variation (NDRE_cv, and NDVI_cv), and the indices values (NDRE, NDVI), were the most important in the PC2. The loading effects showed that higher yield differences between Adapt-N and Grower (yield values for Adapt-N were higher than Grower values) were observed in zones where the TWI was high and slope, roughness, TRI, DEM, and TPI were low. The differences in N rate between Adapt-N and Grower were higher in zones where NDVI and NDRE values were higher. Consequently, the Adapt-N model prescribed a higher rate in those zones with higher vegetation indices values. In contrast, zones with low NDVI and NDRE values and higher variation in these indices had higher NUE differences.

The biplot suggests that fields 4_2022, 6_2023, and 8_2023 had highly contrasting delineated zones compared to the remaining fields. For fields 4_2022 and 6_2023, zones associated with high Yield and N differences showed low Roughness, TRI, Slope, and Aspect values. Therefore, compared to Grower's, Adapt-N had higher yield values and more N rate in areas with higher slope and aspect values. In the field 8_2023, the differences were associated with variables with more importance in the PC2. Zones associated with high NDVI and NDRE values were correlated with low NUE difference values. On the other hand, in these zones, the N recommended rate from Adapt-N was higher than the growers' rates. Consequently, in comparison to the Gower management approach, Adapt-N had lower NUE values and higher N application rates in zones with high vegetation indices.

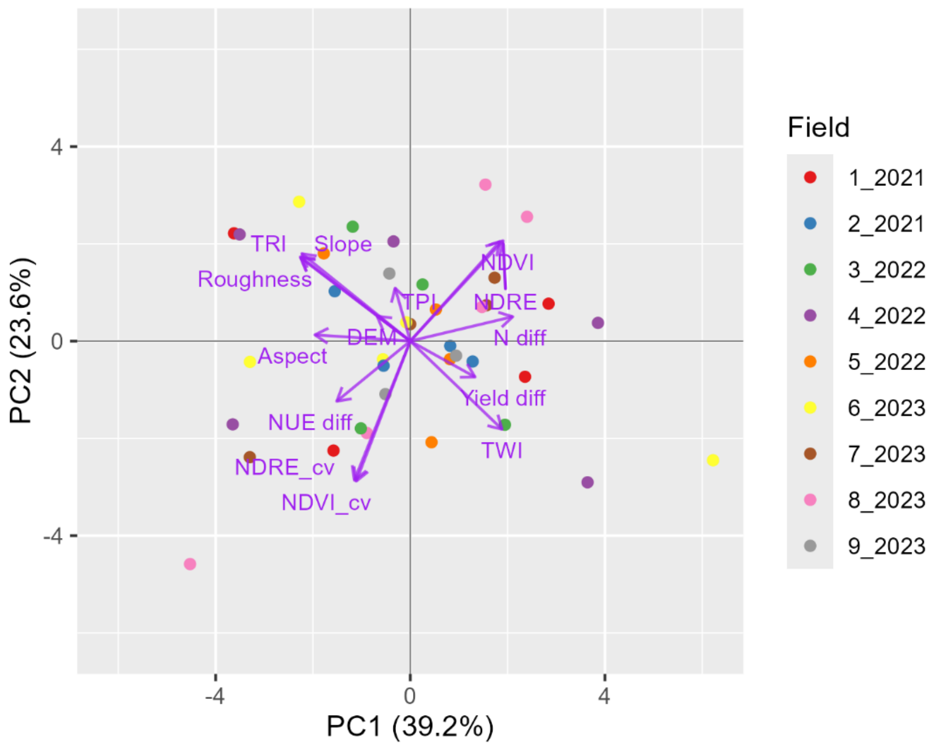

Figure 4. Biplot of within-field homogeneous zones in nine fields with zones characterized by 11 variables: Elevation obtained from digital elevation models (DEM) and DEM-derived variables (slope, roughness, aspect, topographic position index (TPI), terrain ruggedness index (TRI), and topographic wetness index (TWI)), vegetation indices (NDVI and NDRE) with their coefficients of variation (NDVI_cv and NDRE_cv), and differences between two treatments for three traits: Yield (Yield_diff), N (N_diff), and NUE (NUE_diff).

Summary

This study compares the Adapt-N tool, which is used to obtain adaptive N prescriptions, and growers' N management based on their experience and field knowledge. The analysis focused on assessing yield, total N rate, and NUE between treatments. The overall differences were not statistically significant. This could be because treatment performance depends on the characteristics of each field. Moreover, the interaction between soil-plant-environment may cause management strategies to change over time. These high-level interactions and changes make it more difficult to generalize the VRT. Adapt-N recommended rates were lower than the growers' rates in zones with low vegetation indices values. Therefore, Adapt-N had higher NUE compared with the grower in these zones. Consequently, Adapt-N has the potential to be a valuable tool in fields where there is a contrast in the properties within different zones. More On-Farm research in different environments and an assessment of within-field spatial variability are necessary to explore site characteristics and model performance.

Acknowledgments

This project is funded by USDA-NRCS Conservation Innovation Grants, On-Farm Conservation Innovation Trials, award number NR203A750013G014. We want to express our gratitude to the

participating growers and industry partners for their support in this project.

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