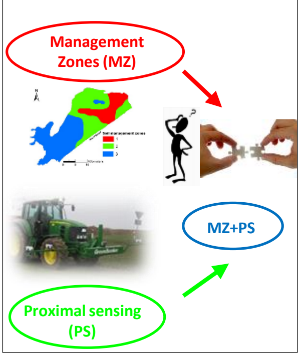
Spatial management strategies for nitrogen in maize production based on soil and crop data

Published version:

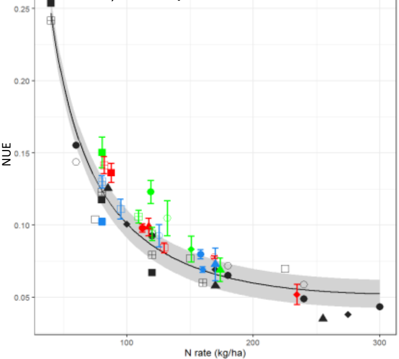
DOI:10.1016/j.scitotenv.2019.133854

(Article begins on next page)

Tested precision fertilisation practices



Improved NUE



Rule for choosing best practice

Spatial range in grain yield	Best N fertilisation practice
no	Uniform
High (>100 m)	MZ
Intermediate	MZ+PS
Small (<16 m)	PS

Title:

Spatial management strategies for nitrogen in maize production based on soil and crop data

Authors : Eleonora Cordero[1*], Louis Longchamps[2], Raj Khosla[3], Dario Sacco[1]

Affiliations :

[1] Department of Agricultural, Forest and Food Sciences, University of Turin, Grugliasco, Italy.*

[2] St-Jean-sur-Richelieu R&D Centre, Agriculture and Agri-Food Canada/Government of Canada, Saint-Jean-sur-Richelieu, QC, Canada.

[3] Department of Soil and Crop Sciences, Colorado State University, Fort Collins, CO 80523, USA.

Corresponding author: Raj Khosla, Raj.Khosla@colostate.edu

Abstract

Nitrogen (N) fertilisation determines maize grain yield (MGY). Precision agriculture (PA) allows matching crop N requirements in both space and time. Two approaches have been suggested for precision N management, *i.e*. management zones (MZ) delineation and crop remote and proximal sensing (PS). Several studies have demonstrated separately the advantages of these approaches for precision N application. This study evaluated their convenient integration, considering the influence of different PA techniques on MGY, N use efficiency (NUE), and farmer's net return, then providing a practical tool for choosing the fertilisation strategy that best applies in each agro-environment. A multi-site-year experiment was conducted between 2014 and 2016 in Colorado, USA. The trial compared four N management practices: uniform N rate, variable N rate based on MZ (VR-MZ), variable N rate based on PS (VR-PS), and variable N rate based on both PS and MZ (VR-PSMZ), based on their effect on MGY, partial factor productivity (PFP_N), and net return above N fertiliser cost (RANC). Maize grain yield and PFP_N maximisation conflicted in several situations. Hence, a compromise between obtaining high yield and increasing NUE is needed to enhance the overall sustainability of maize cropping systems. Maximisation of RANC allowed defining the best N fertilisation practice in terms of profitability. The spatial range in MGY is a practical tool for identifying the best N management practice. Uniform N supply was suitable where no spatial pattern was detected. If a high spatial range (>100 m) existed, VR-MZ was the best approach. Conversely, VR-PS performed better when a shorter spatial range (<16 m) was detected, and when maximum variability in crop vigour was observed across the field (range of variation=0.597) leading to a larger difference in MGY (range of variation=13.9 Mg ha^{-1}). Results indicated that VR-PSMZ can further improve maize fertilisation for intermediate spatial structures (43 m).

Keywords: precision fertilisation, variable rate N application, proximal crop sensing, management zones, data fusion

Introduction

Sustainable intensification of crop production is required to fulfil the growing consumption needs of humanity while reducing the environmental impact of agriculture (Cassman, 1999; Foley et al., 2011). Sustainable cultivation requires a more efficient resource use, including fertiliser applications. Nitrogen (N) is among the most important nutrients supplied to maize for obtaining the full yield potential, as it affects both grain yield and quality (Miao et al*.,* 2007). A proper N management should aim to meet maize N needs, to avoid exceeding crop requirements. An optimally tailored N fertilisation could increase maize production and maintain soil fertility, while limiting environmental concerns through the reduction of N imbalances and inefficiencies (Ma and Biswas, 2015). Excess N is subjected to losses in the environment, through leaching, surface run-off, denitrification and ammonia emissions (Cai et al., 2002; Ma and Biswas, 2015). Several studies reported that N losses in maize cultivation could range between 10 and 70% of the applied N, considering different environmental conditions and fertilisation management (Cai et al*.,* 2002; Delgado et al., 2005; Wang et al*.,* 2014; Prasad and Hochnut, 2016). Crop N demand varies spatially and temporally within a field, due to the inherent variations in soil N availability, soil properties and crop growing conditions (e.g.

edge effect) across the field (Khosla et al., 2002; Nawar et al., 2017). Two main approaches have been proposed in literature to adapt N fertilisation to the spatial variability: soil-based methods and plant-based methods. The former includes the concept of homogeneous management zones (Khosla and Shaver, 2001), while the latter relies on crop N status monitoring with crop canopy sensors during the growing season (Roberts et al., 2012). Few studies have compared these two approaches or assessed the possibility of using them in combination.

The identification of management zones (MZ) represents a cost-effective method to manage field variability, through field classification into areas of broad similarities (Khosla et al., 2002; Nawar et al., 2017). Management zones approach was originally suggested to overcome the limitation of intensive grid soil sampling for mapping the variance of soil properties, due to high cost and labour (Fleming et al., 2000). Therefore, it can be suggested as an alternative method to produce prescription maps for site-specific crop management, by identifying areas of similar productivity potential within a field (Hornung et al., 2006). Indeed, in the location of a field where yield potential is low, added N fertiliser profitability can be reduced (Ma and Biswas, 2015). Doerge (1999) defined MZ as sub-regions of a field that express a homogeneous combination of yield limiting factors. Therefore, MZ can be considered as homogeneous areas within a field that show similar characteristics in landscape and soil conditions, that should lead to a similar yield potential and input use efficiency (Schepers et al., 2004). However, the delineation of uniform sub-field regions may be challenging as different physical, biological and chemical processes acting simultaneously with different intensities and with complex interactions can affect crop yield potential (Moral et al., 2010). Several techniques have been proposed in literature to delineate MZ, using various soil and crop properties individually or in combination (Longchamps and Khosla, 2017). Topography, bare soil aerial imagery, apparent electrical conductivity (EC_a), farmers' management experiences together with yield maps have been extensively used to define the boundaries of MZ (Khosla et al., 2002; Schepers et al., 2004). Indeed, grain yield data, being a total reflection of all biotic and abiotic factors that can affect crop production, can be combined with other soil variables in order to explain field variability associated with both crop and soil properties (Hornung et al., 2006, Bunselmeyer and Lauer, 2015). However different weights should be attributed to the different data layers, on the basis of their contribution to crop production variability

(Hornung et al*.,* 2006). Moreover, yield patterns are often inconsistent across growing seasons (Hornung et al*.,* 2006). Therefore, it is important to also consider temporal variation of crop yield, which reflects climate variability across the growing seasons (Schepers et al., 2004) and is not necessarily correlated to soil properties variations (Nawar et al., 2017). The knowledge of yield history could improve MZ delineation through the identification of yield patterns at sub-field levels (Bunselmeyer and Lauer, 2015). Indeed, Maestrini and Basso (2018) built a spatial indicator that combines the processes that regulates yield by averaging the normalised values of each pixel over the yearly map, using the previous three-year data. Considering the complex interactions involved in yield variability, at least five or more years of yield data should be used to identify stable MZ (Nawar et al., 2017). Typically, traits such as low-lying topography, dark colour, and historic high yields were designated as zones of potentially high productivity, or high zones (Khosla et al., 2002). Soil-based information used alone to manage maize N fertilisation may not always lead to improvement in Nitrogen Use Efficiency (NUE, defined as the grain yield obtained at a certain level of N supplied with fertilisers). Such an approach fails to account for in-season micro-variability *(i.e.,* variability that occurs at shorter range*)* associated with crop N status, since the crop response in unstable zones has been demonstrated to be strictly dependent on weather (Maestrini and Basso, 2018). Consequently, the delineation of MZ alone does not characterise the entire representation for variable N applications (Shanahan et al., 2008). Crop monitoring, which exploits optical properties of leaf pigments, allows integrating soil, climate, agronomic management, and other environmental factors on crop N status (Shanahan et al., 2008; Muñoz-Huerta et al., 2013). Ground-based reflectance measurements have been proposed as promising tools to assess crop N status during the growing season (Roberts et al., 2012). Several vegetation indices can be determined combining reflectance data recorded at specific wavelengths (Bajwa et al., 2010). Among these, the most widely used is Normalised Difference Vegetation Index (NDVI), calculated as the difference between the NIR and red reflectance divided by the sum of these two values (Shanahan et al., 2008. NDVI values are positively correlated with leaf area index (LAI), green biomass and leaf N (Shaver et al*.,* 2010). Consequently, they provide a measure of canopy chlorophyll content in the field-of-view of the sensor. Maize growth stage at the moment of spectral data acquisition heavily affects NDVI values. Teal et al. (2006) demonstrated that NDVI readings acquired at V8 (8-leaf) maize growth stage showed the highest ability to distinguish in-field N variability. Shaver et al. (2010) found out that the best time for maize N status monitoring is between V10 and V12 growth stages. This is in line with the optimal sensing period reported in the Trimble's Greenseeker manufacturer's manual (https://www.manualslib.com/download/1485318/Trimble-Greenseeker-Rt-200.html), a sensor widely used for NDVI determination at field scale.

Several studies have demonstrated separately the potential advantages of soil-based and plant-based methods of driving variable N fertilisation in maize, while very few tried to investigate the possibility of integrating them (*e.g.* Longchamps and Khosla, 2015). The information from MZ delineation is potentially complementary to ground-based active sensors for crop N status monitoring, and could further improve NUE, economics and overall sustainability of maize cropping systems (Khosla et al*.,* 2010; Roberts et al*.,* 2012). The integration of the two approaches may allow tailoring N rate algorithms for each MZ independently, through the detection of both soil and crop properties correlated with crop productivity, then demonstrating the advantages derived by this data fusion, considering different information layers.

This study aimed at verifying the hypothesis that uniform N management practices can be improved through PA techniques, taking advantage of a) proximal crop sensing and b) MZ delineation, and overall c) combination of the two strategies. The specific objectives of this study were to assess the influence of precision N management practices on i) maize grain yield, (ii) NUE, and (iii) farmer's net return.

Materials and methods

Site and soil characteristics

The experiment was carried out over three crop growing seasons (2014, 2015 and 2016) in four different experimental sites in north-eastern Colorado (USA), located in Fort Collins, Ault Iliff, and Atwood (*Figure 1*). The climate of the area is classified as semi-arid (Moshia et al*.,* 2014), with a mean annual temperature of 10.1 °C and a mean annual rainfall of 408 mm (U. S. Climate Data, 2018).

Mean monthly temperature and cumulative monthly rainfall over the experimental period are shown in *Table 1*.

Prior to the start of the experiment, maize was continuously cultivated on all experimental sites for a period of at least three years.

The main soil properties of the experimental fields are summarised in *Table 2*. Soil samples were collected at 0-20 cm depth prior to planting within each field, following a random-grid (40 m) spatial survey sampling design within the study area (Heltshe and Ritchley, 1984). Soil samples were then dried and analysed at a commercial laboratory (Ag Harris, Lincoln, NE).

Management Zones delineation

Management zones were used to characterise in-field variability, identifying areas of high, medium, and low productivity potential within the experimental sites. At Ault, Atwood, and Iliff sites, the delineation of MZ boundaries was accomplished through the Management Zone Analyst (MZA) free software, developed by Fridgen et al. (2004). The MZA uses a fuzzy k-means clustering algorithm to delineate MZ from geo-referenced field information, that showed effective results for zone delineation in previous studies by Odeh et al. (1992). Different clustering variables were used in the delineation process, notably: elevation, bare-soil aerial imagery of the field, and soil apparent electrical conductivity (EC_a). Bare-soil imagery was acquired after field preparation and before sowing, using Google Earth Pro (Google LLC, Mountain View, CA) to select dates when there was no canopy cover in the selected field. The images exported from Google Earth Pro were georectified with at least six ground control points using the ArcMap software (ESRI, Redlands, CA). Soil EC_a was measured on each field prior to planting in spring through EM38 (Geonics Ltd., Mississauga, Ontario, Canada), an electrical conductivity meter that measures EC_a on the basis of the principle of electromagnetic induction at two depths. Data were collected in vertical dipole orientation. Sensor was combined with a GPS and data loggers, mounted on an all-terrain vehicle travelling in parallel transects. High-resolution soil EC_a readings were acquired when the soil was at field capacity. The EC_a data was overlaid with the satellite imagery from Google Earth Pro in the ArcMap software. The rough field topography was extracted from EC_a survey data using the elevation data recorded by a Trimble Ag114 DGPS (Trimble Navigation, Sunnyvale, CA) corrected by a VBS Omnistar (Omnistar, Houston, TX) signal providing a vertical resolution of about 2 m. Despite the low resolution for absolute topography measurements, the relative topography values were accurate enough to detect the overall spatial pattern of topography in each fields. A grid of points was laid on the entire surface of the study area using the Fishnet tool from ArcMap on a 2 m by 2 m cell. Using a raster sampling tool from ArcMap, each point was attributed to the corresponding information: the Red, Green and Blue pixel value from the geotiff extracted from Google Earth Pro (raster sampling), the deep and shallow EC_a value as well as the elevation value (nearest point algorithm) from the EC_a survey dataset. The point feature file was then converted into a table to be uploaded in the MZA software. The MZA software performed a fuzzy k-means clustering of the soil information used as input and provided simultaneously a range of cluster number. Mahalanobis distance was chosen as measure of similarity for allocating each individual observation to a particular cluster, as it is reported to be the most appropriate when correlation exists among variables (Fridgen et al*.,* 2004). Other option settings were defined, considering fuzziness exponent of 1.5, maximum number of iterations of 300 and convergence criterion of 0.0001 according to Fridgen et al. (2004). The minimum and maximum number of zones was set to 2 and 6 respectively, in order to allow a sufficient differentiation avoiding at the same time excessive fragmentation of zones' sub-areas. Moreover, after performing the clustering procedure, the software calculated two performance indices, i.e. Fuzziness Performance Index – FPI and Normalised Classification Entropy – NCE, that allowed the decision of the most appropriate number of MZ for each field. The FPI measures the degree of separation between the zones, while NCE indicates the amount of disorganisation of each partitioning (Fridgen et al*.,* 2004). Consequently, the best number of MZ is achieved when both indices have the minimum value, leading to the least membership sharing and the greatest amount of organisation as a result of the clustering process. Therefore, by evaluating both FPI and NCE values, the optimal number of MZ was chosen. Finally, each geo-referenced soil measurement point was assigned to a specific management zone. The vector containing MZ values was transferred to the ArcMap software and converted into polygon features representing the MZ. The attribution of low, medium or high productivity potential of each management zone was reflective of the historical yield performances according to farmers' knowledge of the field. In Fort Collins, MZ had already been defined prior to the project using bare soil imagery, coarse elevation, and yield and management history as layers for delineation. The Rapid Eye satellite imagery platform was used to acquire bare soil imagery of the field. It deploys the Jena-Optronik multi-spectral imager (Jena, Germany), in five distinct bands of the electromagnetic spectrum: Blue (440-510 nm), Green (520-590 nm), Red (630-690 nm), Red-Edge (690-730 nm) and Near-Infrared (760-880 nm). Zone clustering was done using the AgriTrak Professional software (Agritrak L.L.C, Fort Morgan, CO, USA) described by Fleming et al. (1999). This method consisted of enhancing the contrast of the bare soil image into various strata or zones using the AgriTrak Professional software. Following which, the actual farmer of that field designated the zones with low, medium, or high productivity potential. The designation of zones was based on the historical knowledge of management practices and yield performance of that field. The delineated MZ in each experimental site are shown in *Figure 2.* Afterwards, QGIS open source software (http://qgis.org) was used to assign each yield point from the yield map obtained during the experiment to the corresponding MZ, through Voronoi polygons delineation. Subsequently, the information about the MZ corresponding to each yield point was added to the original dataset using QGIS. This procedure aimed to link each yield value to the productivity potential of the yield sampling point, expressed by the MZ.

Experimental design and treatments

This experimental setup at each site-year aimed at comparing four fertilisation practices, characterised by different N management in maize production:

- traditional farmers' management, with a uniform N rate (UR);
- variable rate N management based on crop proximal sensing (VR-PS);
- variable rate N management based on MZ delineation (VR-MZ);
- variable rate N management based on both crop sensing and MZ delineation (VR-PSMZ).

In each site-year, several N rates were tested, as shown in *Table 3.* For each site, during the first year of experiment a standard N dose (in bold in *Table 3*) was selected based on farmer's business as usual. During the second and third years of the experiment, the reference dose was slightly adjusted, if needed, in order to cope with crop needs.

Moreover, in each site, other N rates were tested in order to fit with higher or lower productive MZs or NDVI responses. The respective rates were chosen according to expected levels of productivity based on expert knowledge derived from farm managers. Unfertilised treatments were added in site-years 1, 2, 3, 5, and 6.

In the other site-years, farmers preferred to add a minimal N fertilizer of 50% of their usual N rate to avoid further yield loss. Nitrogen treatment strips were imposed at each site-year, however, the size of the treatment strips varied across the site-years (Table 3). The width of the strip corresponded to the width of the fertiliser sprayer used by the farmer and the length corresponded to the entire length of the field when possible. When not possible, the strips were long enough to contain at least 15 yield data points (based on the assumption that a commercial combine harvester generates about one yield data point at every 2.5 m length) for each zone by treatment section. Nitrogen treatment strips were randomly distributed (randomised using the Sample function in R without replacement and with the seed of the number generator set to 123) within the field.

The comparison among the different fertilisation approaches was realised by selecting observations that fulfil specific conditions, then simulating the different fertilisation strategies. At each site-year the UR received various N rates distributed uniformly, without taking into account neither MZ, nor NDVI values obtained from PS.

The VR-PS was analysed selecting observations where increasing N rates were coupled with lower NDVI values and vice-versa, without accounting for MZ. Consequently, with the aim of identifying classes reflecting homogeneous crop vigour, NDVI values were clustered using k-means clustering to obtain NDVI classes. For each site-year, the number of NDVI classes was equal to the number of N levels. During data analysis, N rates were paired to NDVI classes, considering pairs where the highest N amount was coupled with the lowest crop vigour, then progressively considering lower N application at increasing crop vigour. The VR-MZ considered the observations where reduced N supply was coupled with lower productivity and increased N supply was coupled with higher productivity. Then, zones characterised by intermediate productivity received the standard N rate, while in high and low zones N rates was increased or reduced, respectively. The VR-PSMZ accounts for both soil productivity potential (through MZ) as well as crop N status (through in-season PS measurements). Three N rates were selected based on three NDVI classes (e.g. low NDVI received a high N rate), and these three selected N rates were modulated depending on which zone they were located in (e.g.

very low N, low N and medium N for the low productivity zone). Depending on the number of N treatments available, not all site-years allowed a complete set of combinations.

Crop agronomic management

In all site-years, maize hybrids belonging to FAO maturity class 300 were grown. Standard agronomic techniques were adopted for all the crop growing seasons at each location. All field sites were conventionally tilled for planting, as presented in *Table 4*. Likewise, details of the agronomic management are reported in *Table 5.* In each site-year, the total amount of N fertiliser was localised in strips close to plant rows, at the 6th leaf crop stage development of maize (V6, according to Reitsma et al*.,* 2009). All N was supplied using urea ammonium nitrate (UAN), a 32% N fertiliser. In order to prevent drought stress, irrigation was carried out by means of a centre - Pivot system in site-years 1, 2, and 3 (*Table 3*); and a surface furrow irrigation system in site-years 4, 5, and 7, and a lateral move irrigation system in site-year 6. Water was applied uniformly across the entire experimental area, until the end of the crop dough stage (R4). The irrigation scheduling was performed by collaborating with farmers, primarily on the basis of soil moisture measurements, previous occurrence of precipitation, and related weather data as well as visual assessment of the field. Adequate pesticide treatments were undertaken throughout the maize growth, enabling an optimal control of diseases and pests. Fields were treated with chemical herbicides to control weed development.

Field measurements

Ground-based crop reflectance measurements were performed on different dates, corresponding to maize growth stage between the development of the 2nd and the 12th leaf (V2 to V12) (*Table 6*). The Greenseeker (Trimble, Sunnyvale, California, USA) handheld active optical sensor was used to determine NDVI, detecting canopy reflectance in the visible red (wavelength 660 nm) and in the NIR (wavelength 770 nm) spectral regions. The measurements were taken by holding the instrument at a distance of about 0.8 m above the maize canopy, as suggested by the manufacturer’s instruction manual and reported in Solari et al*.* (2008). Reflectance measurements were acquired around noon, even though Padilla et al*.* (2019) demonstrated that radiation conditions did not alter NDVI values measured with active sensors. Being an active sensor not influenced by the sunlight (Solari et al*.,* 2008; Schmidt et al*.,* 2009), reflectance data was acquired walking at a constant speed alternatively along the crop rows. NDVI readings were acquired continuously on one of the central rows of each strip. Each NDVI measurement was georeferenced.

Grain yield, adjusted to a moisture content of 15.5%, was determined at harvest. At physiological maturity maize was harvested with a combine harvester equipped with a GPS receiver and a yield monitor, ensuring that all grain yield sampling points are geo-referenced. Experimental plots were located on commercial fields, then a different combine harvester was used at each location except for the Atwood site, where data was collected by hand. In Fort Collins, the grain was harvested using a 6-row Case combine harvester model Case IH 1660 (Case Corporation, Racine, WI) equipped with an AgLeader (AgLeader Technology, Ames, IA) yield-monitoring system. In Ault, the grain was harvested using an 8-row John Deere 9670 STS (Deere and Company, Moline, IL) combine harvester model equipped with a GreenStar yield-monitoring system. In Iliff, the grain was harvested using a 2-row John Deere 3300 (Deere and Company, Moline, IL) combine harvester model equipped with an AgLeader yield-monitoring system. Yield data was then cleaned following the procedures described in Khosla and Flynn (2008). In Atwood, a combine harvester equipped with a yield-monitoring system was not available and therefore, the yield values were harvested by hand on a 3 m length of maize row at 75 locations regularly distributed throughout the study area and evenly distributed across N treatments. Hand harvested maize ears were then transported to a facility where kernels were separated from the maize ears, weighted and analysed for moisture content using a Dickey-John GAC 2100b (Dickey-John Corp., Auburn, IL) grain analysis computer.

Data analysis

A database was built for each site-year. The databases reported the list of geo-referenced observations, each one referred to an area of 2*4 m^2. For each area, N rate, belonging to a specific MZ, NDVI value and grain yield were provided.

Then, partial factor productivity (PFP_N) was determined for each area, as an indicator of maize NUE, according to Cassman et al. (1996):

$$PFP_N = \frac{Y}{N_T} \quad (1)$$

where Y represents grain yield and N_T is the total amount of N applied, both expressed in kg ha^{-1}. Consequently, it was not possible to calculate PFP_N where no fertiliser was applied. Considering the agronomic output that can be obtained at a certain level of all N resources in the cropping system, PFP_N could be considered a useful integrative NUE index. Indeed, PFP_N takes into account total available N derived from both soil and N applied fertiliser (Cassman et al*.,* 1996; Ladha et al*.,* 2005).

Additional data columns containing NDVI classes were added to the original dataset, with the aim of identifying classes reflecting homogenous crop vigour. The NDVI classes were created using k-means clustering with the *k-means* function in the R *stats* package (R Core Team, 2018). For each site-year, the number of NDVI classes was equal to the number of N levels established for the experimental site.

A statistical procedure was applied in order to check the significance of the difference in grain yield among precision fertilisation practices and uniform practices. As grain yield depends mostly on N rate, the check of the significance was performed based on the same N rate for both practices. Average field grain yield and N rate for each precision fertilisation practices were calculated as the total grain yield or supplied N divided by the corresponding strip area. Corresponding values of grain yield in uniform practice were derived from interpolation of a linear model applied to the different site-years. The linear model was applied only to uniform N application data and expressed grain yield as a function of N rate accounting for an additive component due to site-year effects (*Equation 2*).

$$Yield = \mu + (site\_year) + \beta * \ Nrate \qquad (2)$$

where μ is the grand mean of all data, site_year is the fixed effect representing the shift from the grand mean of each site-year, Nrate is the covariate representing the N rate uniformly supplied, while β is its coefficient. The statistical assumptions of homogeneity of variances and normality hypothesis of the residuals were graphically checked, as suggested by Zuur et al*.* (2010). Moreover, Laara (2009) stated that for large datasets the central limit theorem implies approximate validity of the statistical methods that require normality. Therefore, with the aim of comparing precision N fertilisation practices with uniform application of the same N amount, t tests were calculated for each PA approach against the corresponding value fitted on the LM model using the following *Equation 3:*

$$t = \frac{\bar{x} - fitted\ value}{\sqrt{SE_{uniform} + SE_{PA\ approach}}} \qquad (3)$$

Where $\overline{x}$ is the average grain yield of a given PA approach, fitted values are the grain yields for uniform N application predicted by the LM for the same N rate, and $SE_{uniform}$ and $SE_{PA\ approaches}$ are the standard errors of uniform and precision agriculture approaches, respectively.

In order to underline the Nrate effect, both grain yields represented by $\overline{x}$ and fitted values where shifted by site-year to be represented on a single equation, according to *Equation 4*.

$$grain\ yield_{shifted} = grain\ yield - (site\_year) \qquad (4)$$

The same procedure was applied to PFP_N values, but including also the reciprocal of N rate as covariate, with the aim of introducing the hyperbolical components into the model (*Equation 5*).

$$PFP_N = \mu + (site\_year) + \gamma_1 * Nrate + \gamma_2 * \frac{1}{Nrate} \qquad (5)$$

where again μ is the grand mean, site_year is the effect related to the site-year, while Nrate represents the N rate uniformly supplied, and γ_n are its coefficients.

Finally, an economic evaluation was conducted, with the aim of assessing the influence of precision N management practices on farmers' net return. Net return above N fertiliser cost (RANC) was calculated as the difference between grain yield market value and N fertiliser cost (Bachmaier and Gandorfer, 2009). The calculation was computed as previously reported in Casa et al. (2011). Maize grain prices were based on Agricultural Statistics (2017) published by USDA. The values employed were 0.15 $ kg^{-1}, 0.14 $ kg^{-1}, and 0.13 $ kg^{-1}, for 2014, 2015, and 2016, respectively. The price of UAN fertiliser was obtained from a fertiliser retail dealer in Colorado which was equal to approximately 16 000 $ metric ton^{-1} (15.70 $ kg^{-1}). Then, aiming at assessing the influence of precision N management practices PFP_N, grain yield, and RANC, radar charts were created for each location and year of the experiment. The considered variables (*i.e.* PFP_N, grain yield, and RANC) were standardised by centring on zero (by subtracting the mean) and further scaling them dividing by the standard deviation, so that they have a standard deviation equal to 1. This procedure allowed incorporating the different variables on a comparable scale.

Lastly, the presence or absence of a spatial pattern in grain yield data was investigated through Moran's *I* test (Moran, 1950); following which, the spatial structure was described with a semivariogram, which is a plot of semivariances as a function of distances between the observations. Geostatistical methods implemented in the library *GeoR* (Ribeiro and Diggle, 2016) were used for the estimation of the empirical semivariogram. After that, standard theoretical variogram models (exponential, Gaussian, and spherical) were fitted to the empirical semivariogram. With the aim of assessing the theoretical model that best fitted the empirical semivariogram, the goodness of fit was evaluated through the Akaike's Information Criterion (AIC), then taking into account also the complexity of the given model. For each year and location, the model that showed the lowest AIC value was considered the most appropriate to represent the experimental semivariogram, according to McBratney and Webster (1986). Semivariograms were described using range (*i.e.* the distance at which observations are no longer spatially autocorrelated), sill (representing the maximum variance of the field relative to grain yield, disregarding the spatial structure), and nugget (*i.e.* the microscale variation or measurement error). Statistical analysis was performed using R software version 3.4.3 (R Core Team, 2018) and R Studio version 1.1.183 (RStudio Team, 2016).

Results

Mean temperature during the growing season correlates with the obtained grain yield, with higher values in site-year 3 and lower in site-years 1, 4, 5 (*Table 1*). Also annual total precipitation highlighted a different amount among the site-years (*Table 1*).

Figure 3 shows the overall yield response to N rates, expressed as the average N application at field scale, across the site-years and the N management strategies. Site-year effect was removed according to *Equation 4*.

The linear model used in the study was suitable at fitting the experimental data (R^2=0.61). Nrate was significant (P(F) = 0.000, df numerator = 1, df denominator = 4139); site-year was significant as well (P(F) = 0.000, df numerator = 6, df denominator = 4139).

In general, for uniform N management practices maize grain yield increased with increasing N rates. The application of the linear model to uniform treatments allowed to parametrise the crop response function to increasing N rates. Precision N management yields were then compared with uniform application, considering the average amount of N applied on the whole treatment. A general trend cannot be highlighted. In particular, VR-PS and VR-PSMZ maintained grain yield with respect to the uniform application of the same N amount in five site-years, while VR-MZ did in six. Moreover, in three site-years, VR-PSMZ improved grain yield, while VR-PS and VR-MZ did in other one site-year.

Figure 3 shows PFP_N values obtained through the different N management practices in each site-year, corresponding to each N supply after removing site-year effect.

The linear model referred to uniform N application and used to express PFP_N as a function of N rate properly fitted PFP_N values obtained in the present experiment (R^2=0.92). Nrate and 1/Nrate were significant (P(F) = 0.000, df numerator = 1, df denominator = 3390); site-year was significant as well (P(F) = 0.000, df numerator = 6, df denominator = 3390)

Overall, PFP_N values decreased with increasing N rates. As expected, in all site-years the lowest PFP_N was obtained with the highest uniform N supply. *Figure 4* clearly highlights the potential of precision fertilisation techniques to increase $PFP_{N.}$ Hence, in most site-years, PFP_N values obtained through precision fertilisation practices lay over the curve fitted on uniform N rates.

Table 7 shows grain yield and PFP_N values obtained with precision fertilisation practices, compared to uniform supply of the same N amount through Student's t test, as described in *Equation 3*.

In site-years 1 and 5, precision fertilisation practices did not positively affect grain yield, it resulted in similar grain yield as compared to the uniform application of the same N rate. In the other site-years, the impact on grain yield was different, depending on both site-year and the precision N management practice. In particular, in site-year 2, VR-MZ reduced grain yield by approximately 9% compared to uniform supply of the same N amount. Conversely, both VR-PS and VR-PSMZ raised grain yield, by 16% and 8%, respectively. In site-year 3, VR-MZ increased grain yield by 11%, while VR-PSMZ led to a grain yield reduction (-12%). Moreover, N supply based on proximal sensing did not affect grain yield. In site-year 4, VR-MZ obtained a grain yield value similar to that of the same uniform N supply, while both VR-PS and VR-PSMZ led to a moderate reduction, approximately equal to 7% and 10%, respectively. In site-year 6, VR-PSMZ improved grain yield by 9%, while the other precision N fertilisation practices did not affect grain yield. Lastly, in site-year 7, VR-PSMZ increased grain yield with respect to uniform application of the same N amount (+12%), while both N supply based on proximal sensing or MZ delineation obtained similar grain yield levels. Then, despite differences among the site-years, maize grain yield improvement seems to not to be the main outcome of precision fertilisation practices.

In general, precision N fertilisation practices increased PFP_N compared to uniform supply of the same N amount (*Table 7*). However, only in site-years 2 and 4, PFP_N improvement resulted to be significant. In particular, in site-year 2, VR-PS increased PFP_N by approximately 52%. In site-year 4 VR-MZ and VR-PS improved PFP_N by 25% and 27% respectively.

Radar charts were used to represent the positioning of each N fertilisation practices according to their respective contribution to PFP_N, grain yield, and RANC for each year and location (*Figure 5*).

A rational N management would lead to reductions in N losses and improvement in crop yield and PFP_N. In each year and location of this study, the N fertilisation management that allowed to obtain the highest RANC was considered the best N fertilisation practice. Indeed, RANC value is a useful indicator that takes into account the effect of N management both on grain yield and PFP_N. The highest RANC coupled with the highest PFP_N values were observed in site-years 1, 5, and 6. In the other site-years, RANC value was shown to be mostly related to the grain yield levels, achieving the highest value corresponding to higher grain yield levels. Moreover, in site-year 6, VR-PSMZ resulted the most profitable N fertilisation practice, leading to the highest PFP_N coupled with a negligible, but significant, grain yield decrease (2%).

Finally, theoretical semivariogram models were used to analyse the spatial patterns in grain yield data in each site-year, with the aim of linking the presence of a spatial structure in grain yield data with the application of precision N fertilisation strategies. Results reported in *Table 8* showed the presence of spatial structure in most (5 out of 7 site-years) of the site--years in this study, with the exception of site-year 1 and 7. Exponential model was the best fit for the experimental semivariogram on the basis of AIC, apart from grain yield data acquired in site-year 2 that were best described through a Gaussian model. The range of spatial structure, setting the limit of the autocorrelation and beyond which spatial structure does not exist anymore, varied among the different site-years. In particular, the range of spatial dependency was 9 m in site-year 6 while in site-year 2 and 3 it was 11 m and 16 m, respectively. In site-year 4 and 5, spatial range values were higher and estimated to be 102 and 43 m, respectively. The range of spatial autocorrelation indicated the scale of spatial variability detected in the field. Higher range values are related to large scale variability, and vice versa. Semivariograms of grain yield, together with their approximate theoretical models, are reported in *Figure 6*.

Discussion

In traditional maize cropping system in Colorado, N fertiliser is usually applied uniformly and at high rates (around 225 kg ha^{-1}), as farmers want to ensure that N is not the limiting factor in their maize production system. Mean N fertilisation in the region varied between 100 and 250 kg ha^{-1} depending on the different locations, with a mean annual uptake of about 215 kg N ha^{-1} (Inman et al*.,* 2005). Although N requirements become larger with increasing grain yield, crop production and N application are not linearly correlated. In general, the results obtained in this study highlighted a trend where the highest N supply is combined with the lower PFP_N. This was anticipated as in theory, a field where no nitrogen is added would result with an infinite PFP_N (i.e. divided by zero) even though yield could be very low. In order to appeal farmers, N application should be conveniently reduced in order to maintain grain yield, thus increasing PFP_N. This finding was particularly evident in the experiment conducted in site-years 1, 2, and 3 where, by reducing uniform N supply to 180 kg ha^{-1}, PFP_N significantly improves by 25 to 49%, against a grain yield reduction varying approximately from 1.5 to 11% with respect to the value recorded supplying the highest N rate.

In general, PFP_N decreased with increasing N rates, confirming previous results reported by Barbieri et al. (2008) and Ma and Biswas (2016). This may indicate that maize was unable to absorb or utilise N at higher N rates. Another possible explanation is that higher N amount increased also N losses in the environment, which exceeded crop N uptake (Delgado et al., 2005). In this study, the total amount of N fertiliser was applied in experimental strips around the 6th leaf crop growth stage development. Splitting N application so that N supply is synchronised with maize uptake may improve nitrogen use by the crop, as suggested by Sharma and Bali (2018).

Overall, variable rate N management did not increase grain yield with respect to uniform N application when the same total N amount was used. This finding agrees with previous results by Ma et al. (2014). Indeed, where statistical differences in grain yield were detected, precision fertilisation practices increased or reduced maize grain yield of approximately 10%, corresponding to about 1 Mg ha^{-1}. However, crop yield and N efficiency should both be considered for agroecosystem improvement (Jin et al., 2012). Results from this study clearly demonstrated the potential of precision fertilisation techniques for increasing PFP_N.

The economic evaluation suggests that the optimisation of N management not only improved the environmental sustainability of the agricultural system, but also positively affected farmers' economic return above N fertiliser cost. Improving PFP_N is a promising tool to also increase the profitability for the farmers. Farmers choose the best fertilisation practice on the basis of RANC maximisation. However, it appears evident that RANC is largely affected by maize grain yield, due to the large influence of fertiliser application on maize production value. Consequently, the results strengthened the hypothesis that a compromise between achieving high yield and increasing PFP_N is essential.

Variable rate input application requires to quantitatively assess spatial variability of grain yield at a field scale (Kravchenko et al., 2005). The analysis of semivariogram models determined the range of spatial dependency, allowing the link between the spatial structure of grain yield and the performance of the different N management practices. Indeed, range determination allowed choosing the best fertilisation practice, that can maximise RANC.

On the whole, N application based on crop proximal sensing during the growing season was shown to be the best precision N management practice when the range of spatial variability is lower than 16 m. Conversely, for higher range, up to 102 m, N supply based on MZ delineation performed better. These results agree with previous findings by Schepers et al. (2004), that have reported that MZs are a promising tool to identify spatial variability in grain yield for spatial range higher than 16 m, leading to the identification of distinct spatial patterns. Uniform N application was the best approach where no spatial dependency was detected. As shown in site-year 5, for intermediate range value (43 m), the integration of crop proximal sensing and MZ delineation improved both PFP_N and grain yield with respect to PS alone, but negatively affected RANC.

In general, the high level of spatial structure corresponds to a high potential for variable rate N application to increase the profitability for the farmer. The only exception was represented by site-year 3, where the most profitable N management was uniform N application of 240 kg ha^{-1}, despite the presence of spatial autocorrelation. Therefore, in these situations where spatial patterns were not highlighted or the variability in crop vigour across the field led to a moderate difference in grain yield, site-specific management is not suitable. Indeed, in site-year 5, despite a range equal to 43 m, the best fertilisation practice was uniform application of 40 kg N ha^{-1}.

Furthermore, N application based on crop proximal sensing during the growing season was shown to be suitable especially when maximum grain yield difference among the NDVI classes was substantial (CV>20%). In this experiment, such high value has been recorded only in site-year 2 and 5 (data not shown), where the best N management were VR-PS and VR-PSMZ respectively, confirming that crop N status monitoring can be used to more efficiently apply N inputs. Both in site year 4 and 7, as well as in site-year 3, grain yield difference among the NDVI classes showed CV values varying between 10 and 15%. In these situations, VR-PS could not potentially be a promising tool to manage in-field micro-variability. However, in site-year 3, VR-PS has shown to be a promising fertilisation practice to increase PFP_N. But considering the moderate variation of grain yield among NDVI classes, the increment of N rate used in the present study should have been fairly large to compensate for small differences in crop vigour, leading to low yield level. Hence, this approach needs to be further tested with finer levels of N supply. Indeed, Kitchen et a*l.* (2010) and Roberts et al. (2010) have stated that crop sensing can be used to more efficiently tune N inputs. However, they have considered N increments of 34 kg ha^{-1} while in the present study the experimental setup established 60 kg N ha^{-1} increments. In site-year 1 and 5, grain yield did not vary among the NDVI classes, showing a high uniformity across the field. Consequently, N supply based on crop proximal sensing is not a suitable approach. Moreover, in site-year 4 and 5, the factor that induced grain yield variability may have a range longer than the range that can be optimal for using proximal crop sensing to drive N fertilisation.

The delineation of management zone defines sub-field regions with similar yield-limiting factors, for which a single rate of a specific crop input is appropriate (Schepers et al., 2004; Vrindts et al., 2005). However, in site-year 7, grain yield did not vary across the management zone (data not shown), assessing that, despite different yield-limiting factors, the yield potential is similar across the field. In such a situation, uniform N supply was proven to be the most profitable practice.

In site-year 4, N supply on the basis of MZ delineation achieved the best compromise between high grain yield and PFP_N values, evaluated on the basis of RANC. This can be mainly attributed to the reduction of N supply in the low productivity areas, according to a previous study by Koch et al. (2004). In site-years 4 and 5, furrow irrigation method was adopted over multiple years. Furrow irrigation transports soil particles and subsequently nutrients, inducing an important soil macro-variability that creates areas with different fertility within the field. This large-scale variability is confirmed by the presence of a spatial range of 102 m. Consequently, N management on the basis of the different MZ is able to better consider soil macro-variability. However, in site-year 5, the uniform application of 40 kg N ha^{-1} led to the highest PFP_N, combined with a negligible grain yield loss. Interestingly, the synergic use of MZ delineation and PS for driving N application improved both PFP_N and grain yield with respect to PS alone. A possible explanation is that crop proximal sensing during the growing season can well asses crop micro-variability, but is less effective in evaluating field macro-variability. Conversely, VR-MZ is an optimal N management practice when the field exhibit a strong macro-variability, with areas with similar yield limiting factors. Consequently, the combination of proximal sensing and MZ delineation can be a promising tool to consider both large and small scale sources of variability. Therefore, the integration of soil-based and plant-based methods to drive fertiliser applications can be considered a promising tool for N use efficiency without impacting grain yield, strengthening the hypothesis that supported the present study. Then, the present study confirmed the potential of precision fertilisation to improve maize cultivation sustainability, but also highlighted that the choice of the optimal N fertilisation strategy needs to be related to the range of spatial variability detected in the field.

Conclusions

The achievement of both high yield and high NUE is needed to increase sustainability without negatively impacting crop productivity.

Precision fertilisation practices have been shown to be promising tools for improving PFP_N without negatively impacting maize grain yield, thus increasing farmers' profitability. However, adaptation to specific agro-environments is needed.

The quantitative evaluation of the spatial patterns in grain yield has been demonstrated to be an important tool to guide precision agriculture application. Variable rate N management based on MZ delineation is the best practice when large-scale variability is detected. Conversely, variable rate N management based on crop proximal sensing is more suitable when the yield-limiting factors are related to a small-scale variability. Their integration can be helpful to manage both macro and micro-variability that may exist in a crop field, further improving maize fertilisation, and enhancing the overall sustainability of the cropping system.

However, the need of considering whether the higher economic revenue can compensate for added cost for services or technologies required for variable rate N supply appears evident.

Acknowledgments

This research project was funded by Colorado Corn Board and USDA-NRCS-CIG grant. Authors want to thank the students Marcelo Chan, Alfonso DeLara, Rafael Siqueira, Tawney Bleake and Jeffrey Siegfried of Colorado State University for their helpful collaboration in the data acquisition.

References

Bachmaier M., Gandorfer M., 2009. *A conceptual framework for judging the precision agriculture hypothesis with regard to site-specific nitrogen application*. Precis. Agric.10:95-110.

Bajwa, S.G., Mishra, A.R., Norman, R.J. (2010). *Canopy reflectance response to plant nitrogen accumulation in rice*. Precision Agric. 11: 488-506.

Barbieri, P. A., Echeverría, H. E., Saínz Rozas, H. R., Andrade, F. H. (2008). *Nitrogen Use Efficiency in maize as affected by nitrogen availability and row spacing*. Agron. J, 100:1094–1100.

Bunselmeyer, H. A., Lauer, J. C. (2015). *Using corn and soybean yield history to predict subfield yield response.* Agron. J. 107: 558–562.

Cai, G. X., Chen, D. L., Ding, H., Pacholski, A., Fan, X.H., Zhu, Z. L (2002). *Nitrogen losses from fertilizers applied to maize, wheat and rice in theNorth China Plain.* Nutrient Cycling in Agroecosystems 63: 187–195.

Casa, R., Cavalieri, A., Locascio, B (2011) *Nitrogen fertilization management in precision agriculture: A preliminary application example on maize*. Italian Journal of Agronomy, 6:23-27.

Cassman, K. G., Gines, G. C., Dizon, M. A., Samson, M. I., Alcantara, J. M. (1996). *Nitrogen-use efficiency in tropical lowland rice systems: contributions from indigenous and applied nitrogen*. Field Crops Research 47: 1-12.

Cassman, K. G. (1999). *Ecological intensification of cereal production systems: yield potential, soil quality, and precision agriculture.* Proc. Natl. Acad. Sci. USA 96: 5952-5959.

Delgado, J., Khosla, R., Westfall, D. G., Bausch, W., Inman, D. (2005). *Nitrogen fertilizer management based on site-specific management zones reduces potential for NO_3-N leaching*. J. of Soil & Water. 60: 402-410.

Doerge, T. (1999). *Defining management zones for precision farming*. Crop Insight, 8, 21. Pioneer Hi-Bred International Inc.

Fleming, K. L., Westfall, D. G., Wiens, D. W., Rothe, L. E., Cipra, J. E., Heermann, D. F. (1999). *Evaluating farmer developed management zone maps for precision farming.* In Robert, P. C. et al. (ed.) Precision agriculture. Proc. Int. Conf., 4th, Bloomington, MN. 19-22 July 1998. ASA, CSSA, and SSSA, Madison, WI, 335-343.

Fleming, K. L., Westfall, D. G., Wiens, D. W., Brodhal, M. C. (2000). *Evaluating farmer defined management zone maps for variable rate fertilizer application*. Precision Agriculture, 2:201-215.

Foley, J. A., Ramankutty, N., Brauman, K. A., Cassidy, E. S., Gerber, J. S., Johnston, M., Mueller, N. D., O'Connell, C., Ray, D. K., West, P. C., Balzer, C., Bennett E. M., Carpenter, S. R., Hill, J., Monfreda, C., Polasky, S., Rockstro, J., Sheehan, J., Siebert, S., Tilman, D., Zaks, D. P. M. (2011). *Solutions for a cultivated planet.* Nature 478: 337-342.

Fridgen, J. J., Kitchen, N. R., Drummond, K. A. S., Wiebold, S. T., & Fraisse, C. W. (2004). *Software Management Zone Analyst (MZA): Software for subfield management zone delineation*. Agronomy Journal, 96, 101–107.

Heltshe, J. F., Ritchey, T. A. (1984). Spatial pattern detection using quadrat samples. Biometrics 40:877-885.

Hornung, A., Khosla, R., Reich, R., Inman, D., Westfall, D. G. (2006). *Comparison of site-specific management zones: soil-color-based and yield-based.* Agron. J. 98:407–415.

https://www.manualslib.com/download/1485318/Trimble-Greenseeker-Rt-200.html

Inman, D., Khosla, R., Westfall, D. G., Reich, R. (2005). *Nitrogen uptake across site specific management zones in irrigated corn production systems.* Agron. J. 97:169–176.

Jin, L., Cui, H., Li, B., Zhang, J., Dong, S., Liu, P. (2012). *Effects of integrated agronomic management practices on yield and nitrogen efficiency of summer maize in North China*. Field Crops Research 134:30–35.

Kitchen, N. R., Sudduth, K. A., Drummond, S. T., Scharf, P. C., Palm, H. L., Roberts, D. F., Vories, E. D. (2010). *Ground-based canopy reflectance sensing for variable-rate nitrogen corn fertilization.* Agron. J. 102:71-84.

Khosla, R., Shaver, T. (2001). *Zoning in on nitrogen needs*. Colorado State University Agronomy Newsletter 21 (1): 24-26.

Khosla, R., Fleming, K., Delgado, J. A., Shaver, T. M., Westfall, D.G. (2002). *Use of site-specific management zones to improve nitrogen management for precision agriculture*. Journal of soil and water conservation 57(6):513-518.

Khosla, R., Flynn, B. (2008). *Understanding and cleaning yield monitor data*. Soil Science Step-by-Step Field Analysis:113-130.

Khosla, R., Westfall, D. G., Reich, R. M., Mahal, J.S., Gangloff, W.J. (2010). *Spatial variation and site-specific management zones*. In *Geostatistical applications for precision agriculture* 8:195-219.

Koch, B., Khosla, R., Frasier, W. M., Westfall, D. G., Inman, D. (2004). *Economic feasibility of variable-rate nitrogen application utilizing site-specific management zones*. Agron. J. 96:1572–1580.

Kravchenko, A. N., Robertson, G. P., Thelen K. D., Harwood, R. R. (2005). *Management, topographical, and weather effects on spatial variability of crop grain yields*. Agron. J. 97:514–523.

Laara, E. (2009). *Statistics: reasoning on uncertainty, and the insignificance of testing null*. Annales Zoologici Fennici 46: 138–157.

Ladha, J. K., Pathak, H., Krupnik, J., Six, T., Van Kessel, J. (2005). *Efficiency of fertilizer nitrogen in cereal production: retrospects and prospects*. Adv. Agron. 87, 85–156.

Longchamps, Louis, Khosla, Raj (2015). Improving N use efficiency by integrating soil and crop properties for variable rate N management. In: J. Stafford (Ed.), Precision Agriculture 2015, Proceedings of the 10th European Conference on Precision Agriculture (pp. 249–255). Wageningen Academic Publishers, Wageningen.

Longchamps, Louis, Khosla, Raj (2017). *Precision maize cultivation techniques*. In *Achieving sustainable cultivation of maize*, Burleigh Dodds Science Publishing., 2: Cultivation techniques, pest and disease control:450. Cambridge, UK: Dave Watson.

Ma, B. L., Biswas, D. K. (2016). *Field-level comparison of nitrogen rates and application methods on maize yield, grain quality and nitrogen use efficiency in a humid environment*. Journal of Plant Nutrition, 39(5): 727-741.

Ma, B. L., Biswas, D. K. (2015). *Precision nitrogen management for sustainable corn production.* In *Sustainable Agriculture Reviews* 16: 33-62 (edited by Eric Lichtfouse and Aakash Goyal).

Ma, B. L., Wu, T. Y., Shang, J. (2014). *On-farm comparison of variable rates of nitrogen with uniform application to maize on canopy reflectance, soil nitrate, and grain yield*. J. Plant Nutr. Soil Sci., 177: 216–226.

Maestrini, B., Basso, B. (2018). *Predicting spatial patterns of within-field crop yield variability.* Field Crop Research 219: 106-112.

Mc Bratney, A. B., Webster, R. (1986). *Choosing functions for semi-variograms of soil properties and fitting them to sampling estimates*. Journal of Soil Science, 37, 617439.

Miao, Y., Mulla, D. J., Hernandez, D. J., Wiebers, M., Robert, P. C. (2007). *Potential impact of precision nitrogen management on corn yield, protein content, and test weight.* Soil Sci. Soc. Am. J. 71:1490–1499.

Moral, F.J., Terrón, J.M., Marques da Silva, J.R. (2010). *Delineation of management zones using mobile measurements of soil apparent electrical conductivity and multivariate geostatistical techniques*. Soil and Tillage Research 106: 335–343.

Moran, P. A. P. (1950). *Notes on continuous stochastic phenomena.* Biometrika 37 (1/2): 17–23.

Moshia, M. E., Khosla, R., Longchamps, L., Reich, R., Davis, J. G., Westfall, D. G. (2014). *Precision manure management across site-specific management zones: grain yield and economic analysis.* Agronomy Journal 106(6):2146-2156.

Muños-Huerta, R. F., Guevara-Gonzalez, R. G., Contreras-Medina, L. M., Torres-Pacheco, I., Prado-Olivarez, J., Ocampo-Velazquez, R. V. (2013). *A review of methods for sensing nitrogen status in plants: advantages, disadvantages and recent advances*. Sensors 13: 10823-10843.

Nawar, S., Corstanje, R., Halcro, G., Mulla, D., Mouazen, A. M. (2017). *Delineation of soil management zones for variable-rate fertilisation: a review.* Advances in Agronomy 143: 175-245.

Prasad, R., Hochmuth, G. J. (2016). *Environmental nitrogen losses from commercial crop production systems in the Suwannee River Basin of Florida*. PLoS ONE 11(12): e0167558. doi:10.1371/journal.pone.0167558.

R Core Team (2018). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/.

RStudio Team (2016). RStudio: Integrated Development for R. RStudio, Inc., Boston.

Reitsma, K. D., Clay, S., Hall, R. G. (2009). *Best management practices for corn production in South Dakota: corn growth and development*. SDSU Extension Circulars. 491.

Ribeiro, P. J., Diggle, P. J. (2016). *geoR: Analysis of Geostatistical Data*. R package version 1.7-5.2.

Roberts, D. F., Ferguson, R. B., Kitchen, N. R., Adamchuk, V. I., Shanahan, J. F. (2012). *Relationships between soil-based management zones and canopy sensing for corn nitrogen management.* Agron. J. 104: 119–129.

Roberts, D. F., Kitchen, N. R., Scharf, P. C., Sudduth, K. A. (2010). *Will variable-rate nitrogen fertilization using corn canopy reflectance sensing deliver environmental benefits?* Agron. J. 102:85–95.

Schepers, A. R., Shanahan, J. F., Liebig, M. A., Schepers, J. S., Johnson, S. H., Luchiari, A. J. (2004). *Appropriateness of management zones for characterizing spatial variability of soil properties and irrigated corn yields across years*. Agron. J. 96:195–203.

Schmidt, J. P., Dellinger, A. E., Beegle, D. B. (2009). *Nitrogen recommendations for corn: an on-the-go sensor compared with current recommendation methods*. Agron. J. 101:916–924.

Shanahan, J. F., Kitchen, N. R., Raun, W. R., Schepers, J. S. (2008). *Responsive in-season nitrogen management for cereals*. Computers and electronics in agriculture 61: 51–62.

Sharma, L. K., Bali, S. K. (2018). *A review of methods to improve Nitrogen Use Efficiency in agriculture*. Sustainability, 10, 51.

Shaver, T. M., Khosla, R., Westfall, D. G. (2010). *Evaluation of two ground-based active crop canopy sensors in maize: growth stage, row spacing, and sensor movement speed*. Soil Sci. Soc. Am. J. 74:2101–2108.

Schepers, A. R., Shanahan, J. F., Liebig, M. A., Schepers, J. S., Johnson, S. H., Luchiari, A. J. (2004). *Appropriateness of management zones for characterizing spatial variability of soil properties and irrigated corn yields across years*. Agron. J. 96:195–203.

Solari, F., Shanahan, J., Ferguson, R., Schepers, J., Gitelson, A. (2008). *Active sensor reflectance measurements of corn nitrogen status and yield potential*. Agron. J. 100:571–579.

Teal, R. K., Tubana, B., Girma, K., Freeman, K. W., Arnall, D. B., Walsh, O., Raun W. R. (2006*). In-season prediction of corn grain yield potential using normalized difference vegetation index.* Agron. J. 98:1488–1494.

Trimble's Greenseeker manufacturer's manual available at https://www.manualslib.com/download/1485318/Trimble-Greenseeker-Rt-200.html. (last accessed on May 28, 2019).

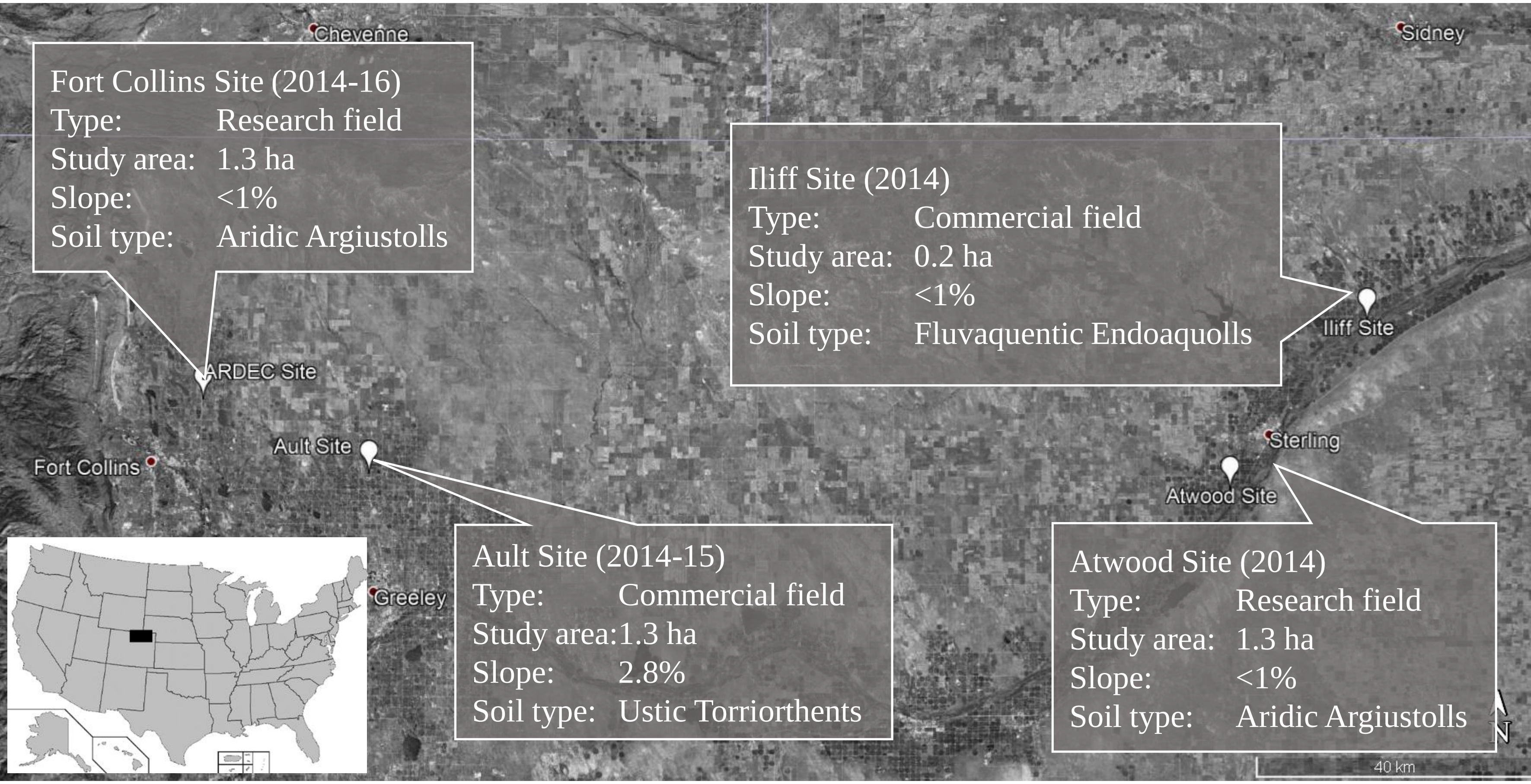
U. S. Climate Data (2018) available at https://www.usclimatedata.com/ (last accessed on May 28, 2019).

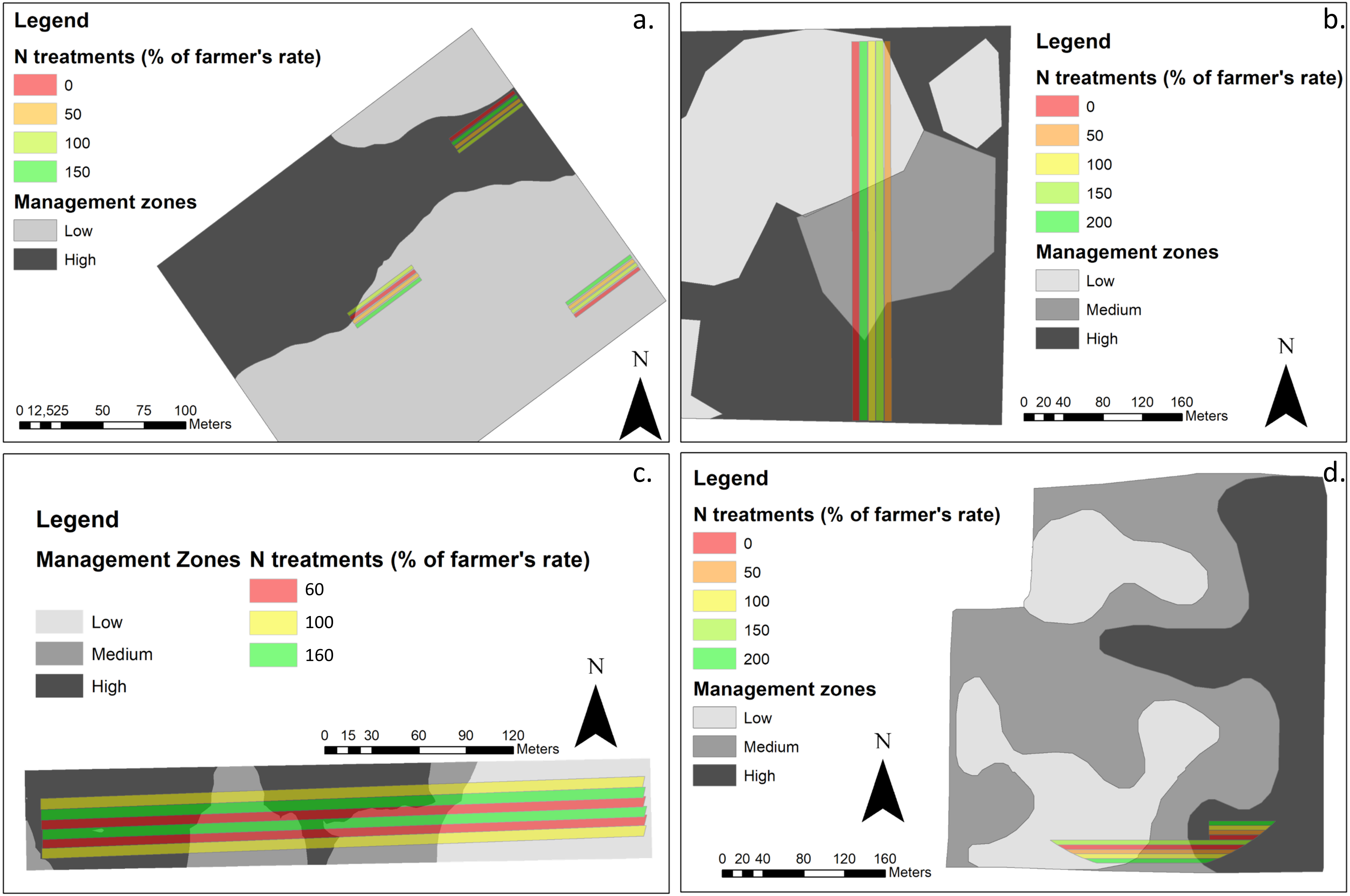
USDA (2017) Agricultural Statistics. Available at https://www.nass.usda.gov/Publications/Ag_Statistics/2017/index.php (last accessed on May 25, 2018).

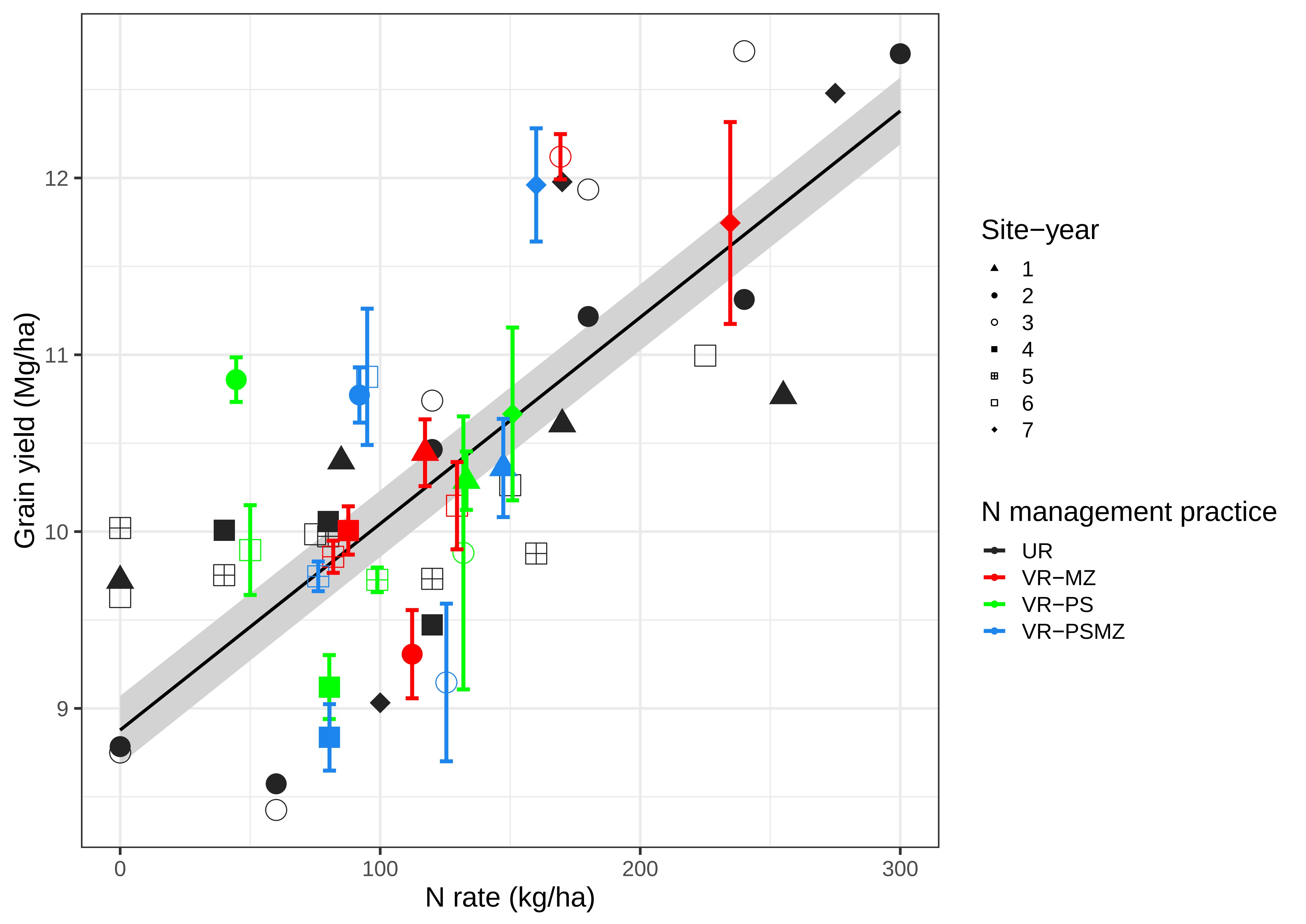
Vrindts, E., Mouazen, A.M., Reyniers, M., Maertens, K., Maleki, M.R., Ramon, H., De Baerdemaeker, J., (2005). *Management zones based on correlation between soil compaction, yield and crop data*. Biosyst. Eng. 92: 419–428.

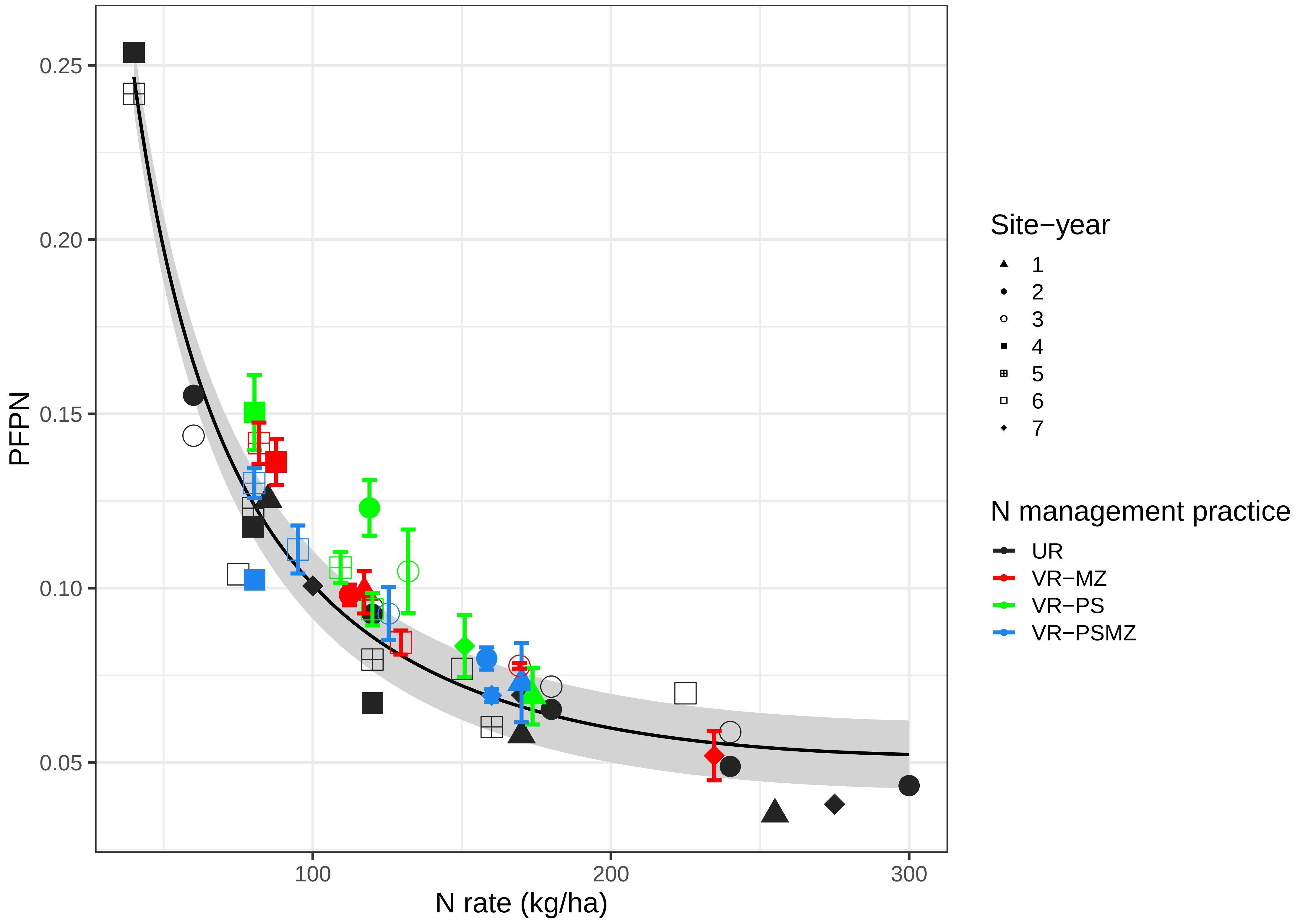
Wang, G., Chen, X., Cui, Z., Yue, S., Zhang, F. (2014). *Estimated reactive nitrogen losses for intensive maize production in China.* Agriculture, Ecosystems and Environment 197: 293–300.

Zuur, A. F., Ieno, E. N., Elphick, C. S. (2010). *A protocol for data exploration to avoid common statistical problems*. Methods in Ecology and Evolution 1: 3–14.

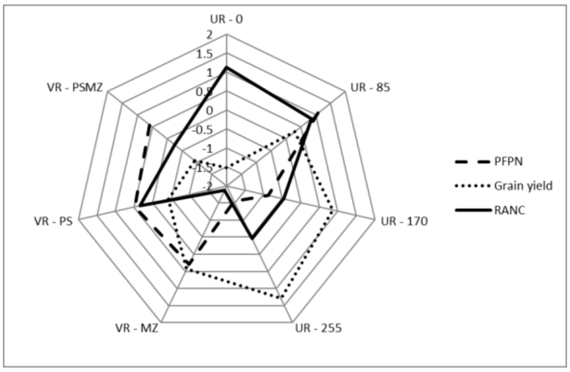

Cheyenne
Sidney
Fort Collins Site (2014-16)
Type: Research field
Study area: 1.3 ha
Slope: <1%
Soil type: Aridic Argiustolls
Iliff Site (2014)
Type: Commercial field
Study area: 0.2 ha
Slope: <1%
Soil type: Fluvaquentic Endoaquolls
Iliff Site
ARDEC Site
Ault Site
Fort Collins
Sterling
Atwood Site
Greeley
Ault Site (2014-15)
Type: Commercial field
Study area: 1.3 ha
Slope: 2.8%
Soil type: Ustic Torriorthents
Atwood Site (2014)
Type: Research field
Study area: 1.3 ha
Slope: <1%
Soil type: Aridic Argiustolls
N
40 km


a.
Legend
N treatments (% of farmer's rate)
0
50
100
150
Management zones
Low
High
N
0 12,525 50 75 100
Meters
b.
Legend
N treatments (% of farmer's rate)
0
50
100
150
200
Management zones
Low
Medium
High
N
0 20 40 80 120 160
Meters
c.
Legend
Management Zones
Low
Medium
High
N treatments (% of farmer's rate)
60
100
160
N
0 15 30 60 90 120
Meters
d.
Legend
N treatments (% of farmer's rate)
0
50
100
150
200
Management zones
Low
Medium
High
N
0 20 40 80 120 160
Meters

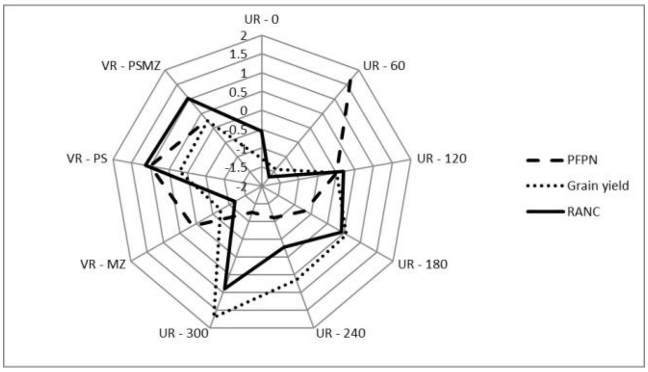

Grain yield (Mg/ha)
12
11
10
9
0
100
200
300
N rate (kg/ha)
Site−year
1
2
3
4
5
6
7
N management practice
UR
VR−MZ
VR−PS
VR−PSMZ


PFPN
0.25
0.20
0.15
0.10
0.05
100
200
300
N rate (kg/ha)
Site−year
1
2
3
4
5
6
7
N management practice
UR
VR−MZ
VR−PS
VR−PSMZ

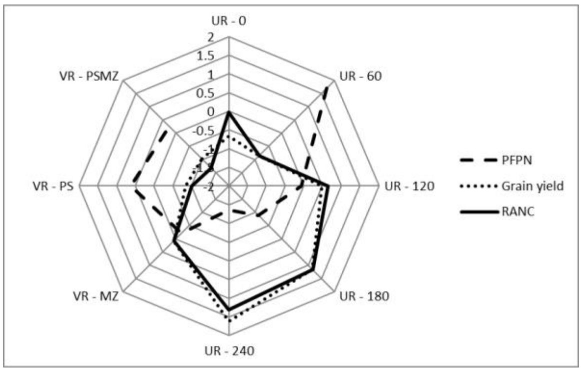
a)



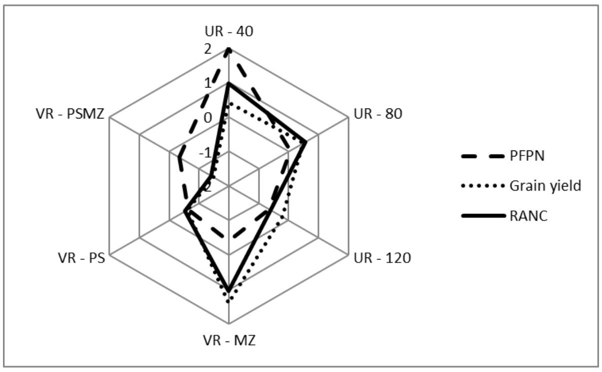
b)



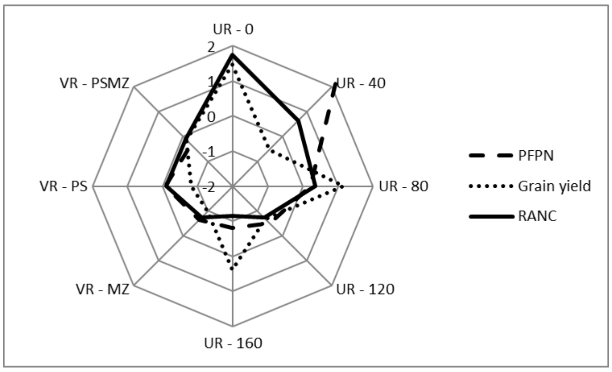
c)



d)

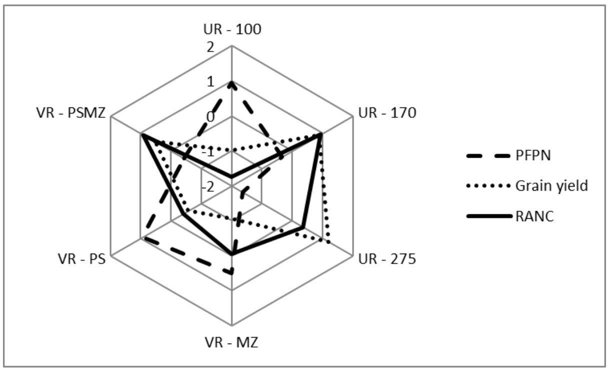


e)

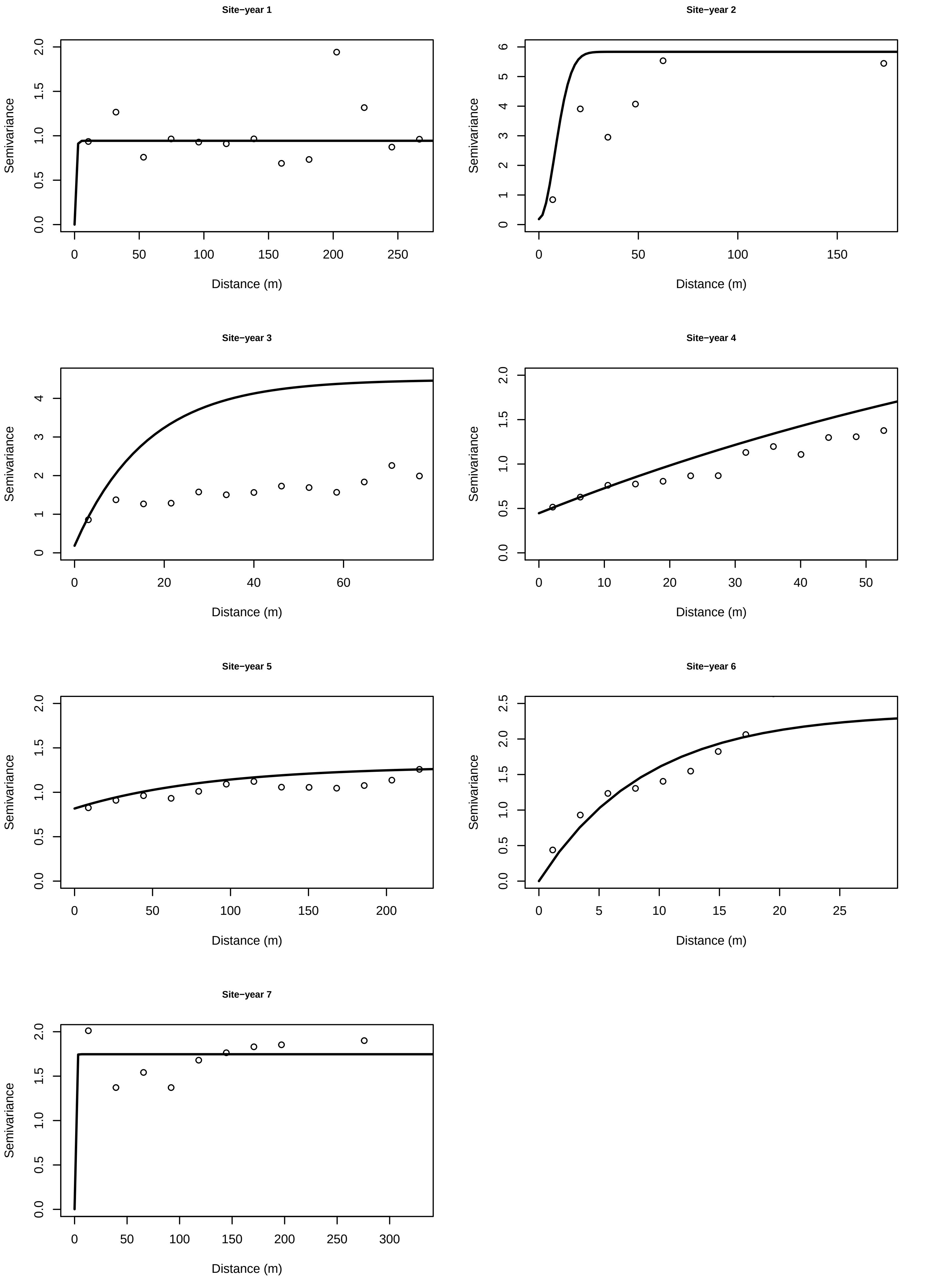


f)

g)



a) site-year 1
b) site-year 2
c) site-year 3
d) site-year 4
e) site-year 5
f) site-year 6
g) site-year 7



Site−year 1
Semivariance
Distance (m)
Site−year 2
Semivariance
Distance (m)
Site−year 3
Semivariance
Distance (m)
Site−year 4
Semivariance
Distance (m)
Site−year 5
Semivariance
Distance (m)
Site−year 6
Semivariance
Distance (m)
Site−year 7
Semivariance
Distance (m)

Table 1: Description of average climatic data for each site and each year for the crop growing seasons (May 1st to September 30th) of 2014-16. Table includes NOAA's normal weather conditions for the crop growing season from 1981 to 2010 for each location.

Site	Year	Average temperature (°C)	Total precipitations (mm)
Fort Collins	2014	17.4	236
	2015	17.9	254
	2016	18.2	89
	1981-2010	*17.9*	*227*
Ault	2014	17.7	259
	2015	18.1	227
	1981-2010	*19.8*	*215*
Iliff	2014	18.9	369
	1981-2010	*19.9*	*303*
Atwood	2014	18.2	435
	1981-2010	*19.0*	*290*

Table 2: Main soil properties of the four experimental sites. Mean, minima (Min.), maxima (Max.), median (Med.) and standard deviation (SD) values are reported. Sampling design consisted of random-within-grid inside the study area on a square grid of 40 m.

Soil properties	**Fort Collins (n=82)**					**Ault (n=6)**					**Iliff (n=13)**					**Atwood (n=12)**				
	Mean	Min.	Max.	Med.	SD	Mean	Min.	Max.	Med.	SD	Mean	Min.	Max.	Med.	SD	Mean	Min.	Max.	Med.	SD
Sand (%)[a]	539	47	63	53	3	64	58	69	63	4	39	29	47	41	5	56	50	59	56	2
Silt (%)[a]	14	8	20	14	2	14	4	24	15	8	23	20	26	24	2	21	17	24	21	2
Clay (%)[a]	33	25	35	33	2	22	18	27	23	4	38	31	47	37	4	23	22	26	23	1
Organic matter (%)[b]	2	1	2	2	0	1	1	1	1	0	2	2	3	3	0.2	1	1	1	1	0
pH[c]	8	8	8	8	0	8	8	8	8	0	8	8	8	8	0	8	8	8	8	0
Nitrate N (mg kg^{-1})[d]	14	4	39	11	8	8	7	9	7	1	16	10	24	16	4.3	10	7	14	9	2
CEC (meq /100 g)[e]	31	27	34	31	1	25	23	27	26	2	33	29	36	33	1.8	21	17	26	20	3
Available P (mg kg^{-1})[f]	19	5	73	11	14	46	7	86	450	40	26	16	37	25	7.6	55	18	124	50	32
Exchangeable K (mg kg^{-1})[g]	318	238	496	306	59	255	225	303	252	30	695	592	826	686	74	320	240	386	319	47

Superscript indicates the method of measurement: [a]: hydrometer, [b]: loss-on-ignition, [c]: 1:1 water-soil, [d]: Cd reduction, [e]: Summation of exchangeable K, Ca, Mg and neutralisable acidity, [f]: Olsen method, [g]: ammonium acetate

Table 3: Width of N strips and N rates (kg ha^{-1}) considered in the different locations and year of the experiment. Values in bold represent standard dose used by farmers.

Site-year	Location	Year	Width of N strips (m)	N rates (kg ha^{-1})
1	Fort Collins	2014	4.6	0 -85 – **170** – 255
2	Fort Collins	2015	4.6	0 – 60 – 120 – **180**- 240 - 300
3	Fort Collins	2016	4.6	0 – 60 – 120 – **180**- 240
4	Ault	2014	7.5	40 – **80** - 120
5	Ault	2015	7.5	0 – 40 – **80** – 120
6	Iliff	2014	2.3	0 – 75 – **150** – 225
7	Atwood	2014	6.9	100 – **170** – 275

Table 4: Date and type of tillage operation for each site-year.

Site-year	Date	Type of tillage operation
1	20^{th} November 2013	Disk harrow
	28^{th} March 2014	Brillion mulcher
	1^{st} April 2014	Brillion mulcher
2	30^{th} April 2015	Spring-tooth harrow
3	25^{th} November 2015	Disk harrow
	25^{th} April 2015	Brillion mulcher
4	15^{th} April 2014	Field cultivator
5	20^{th} April 2015	Field cultivator
6	11^{th} April 2014	Strip tillage
7	18^{th} November 2013	Disk harrow
	15^{th} April 2014	Brillion mulcher

Table 5: Details of the agronomic management.

Site-year	Maize hybrid	Relative days to maturity	Seeding date	Seed rate (seed ha^{-1})	Fertiliser application	Harvesting date
1	Dekalb DKC46-20RIB	96	29th April 2014	84 000	11th June 2014	30th October 2014
2	Dekalb DKC46-20RIB	96	27th May 2015	84 000	30th June 2015	19th November 2015
3	Dekalb DKC46-20RIB	96	6th May 2016	93 900	21st June 2016	21st October 2016
4	Pioneer P0474	104	5th May 2014	84 000	17th June 2014	24th October 2014
5	Pioneer 35F48AM1	105	2nd May 2015	93 900	23rd June 2015	12th November 2015
6	Pioneer P0157AM	101	19th May 2014	84 000	24th June 2014	23rd October 2014
7	Pioneer P0474	104	7th May 2014	84 000	17th June 2014	26th November 2014

Table 6: Dates of NDVI measurements in the different years and locations.

Site-year	Dates of NDVI readings	Maize growth stage
1	June, 26^{th}	V6-V7[a]
2	July, 10^{th}	V8-V10
	July, 14^{th}	V10
	July, 17^{th}	V10-V11
	July, 21^{st}	V11-V12
3	June, 27^{th}	V9
	July, 5^{th}	V12
	July, 8^{th}	V14
4	June, 26^{th}	V6-V7
	June, 17^{th}	V8-V10
5	June, 23^{th}	V10
	July, 1^{st}	V10-V11
	July, 7^{th}	V11-V12
6	July, 23^{rd}	V2
7	June, 17^{th}	V3-V4

[a]: Vn stage: development of the *n* leaf

Table 7: Grain yield and PFP_N values obtained with uniform or variable rate application of the same N amount, compared through Student's t test.

Site -year	PNMP[a]	N rate (Kg ha^{-1})	Grain yield (Mg ha^{-1})			PFP_N[b]		
			Uniform	PNMP	P(t)	Uniform	PNMP	P(t)
1	VR-MZ	117	10.2	10.4	n. s. [c]	0.082	0.099	n. s.
	VR-PS	174	10.4	10.3	n. s.	0.06	0.069	n. s.
	VR-PSMZ	170	10.6	10.4	n. s.	0.061	0.073	n. s.
2	VR-MZ	112	**<u>10.2</u>**	9.3	0.002	0.086	0.098	n. s.
	VR-PS	119	9.4	**<u>10.9</u>**	0.000	0.081	**<u>0.123</u>**	0.007
	VR-PSMZ	158	10	**<u>10.8</u>**	0.001	0.064	0.08	n. s.
3	VR-MZ	169	10.9	**<u>12.1</u>**	0.000	0.061	0.078	n. s.
	VR-PS	132	10.4	9.9	n. s.	0.074	0.105	n. s.
	VR-PSMZ	125	**<u>10.3</u>**	9.1	0.007	0.078	0.093	n. s.
4	VR-MZ	88	9.9	10	n. s.	0.109	**<u>0.136</u>**	0.047
	VR-PS	80	**<u>9.8</u>**	9.1	0.004	0.118	**<u>0.15</u>**	0.042
	VR-PSMZ	81	**<u>9.8</u>**	8.8	0.000	0.118	0.102	n. s.
5	VR-MZ	82	9.8	9.9	n. s.	0.116	0.142	n. s.
	VR-PS	109	10	9.7	n. s.	0.088	0.106	n. s.
	VR-PSMZ	80	9.8	9.7	n. s.	0.119	0.13	n. s.
6	VR-MZ	130	10.4	10.1	n. s.	0.075	0.084	n. s.
	VR-PS	120	9.5	9.9	n. s.	0.081	0.094	n. s.
	VR-PSMZ	95	10	**<u>10.9</u>**	0.038	0.101	0.111	n. s.
7	VR-MZ	235	11.6	11.7	n. s.	0.050	0.052	n. s.
	VR-PS	151	10.6	10.7	n. s.	0.066	0.083	n. s.
	VR-PSMZ	160	10.7	**<u>12</u>**	0.001	0.063	0.069	n. s.

[a]PNMP= precision N management practice; [b]PFP_N = partial factor productivity; [c]n.s. = not significant; bold underlined values highlight the highest values when comparing uniform and precision N management practices considering the same N supply.

Table 8: Moran I p value, best theoretical variogram model, partial sill, range of spatial dependency, and nugget recorded in each location and year of the experiment.

Site-year	**Moran *I* p value**	**Model**	**Partial sill**	**Range (m)**	**Nugget**	**Best N management practice [a]**
1	-	-	-	-	-	UR-85
2	<0.01	gaussian	5.7	11.3	0.2	VR-PS
3	<0.01	exponential	4.3	16.2	0.2	UR-240
4	<0.01	exponential	3.0	101.9	0.5	VR-MZ
5	<0.01	exponential	0.2	42.6	0.6	UR-40
6	<0.01	exponential	2.4	8.8	0.0	VR-PSMZ
7	-	-	-	-	-	UR-170

[a]: Nitrogen management practice that maximises Net return above N fertiliser cost (RANC), according to Figure 5