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(Article begins on next page)

Tested precision fertilisation practices

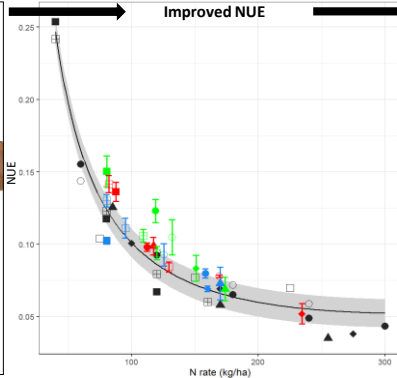
Management Zones (MZ)



MZ+PS

Proximal sensing (PS)

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

1 **Title:**

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

3
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13 **Abstract**

14 Nitrogen (N) fertilisation determines maize grain yield (MGY). Precision agriculture (PA) allows matching crop
15 N requirements in both space and time. Two approaches have been suggested for precision N management,
16 *i.e.* management zones (MZ) delineation and crop remote and proximal sensing (PS). Several studies have
17 demonstrated separately the advantages of these approaches for precision N application. This study
18 evaluated their convenient integration, considering the influence of different PA techniques on MGY, N use
19 efficiency (NUE), and farmer's net return, then providing a practical tool for choosing the fertilisation strategy
20 that best applies in each agro-environment. A multi-site-year experiment was conducted between 2014 and
21 2016 in Colorado, USA. The trial compared four N management practices: uniform N rate, variable N rate
22 based on MZ (VR-MZ), variable N rate based on PS (VR-PS), and variable N rate based on both PS and MZ (VR-
23 PSMZ), based on their effect on MGY, partial factor productivity (PFP_N), and net return above N fertiliser cost
24 (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*.

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

131 The main soil properties of the experimental fields are summarised in *Table 2*. Soil samples were collected at
132 0-20 cm depth prior to planting within each field, following a random-grid (40 m) spatial survey sampling
133 design within the study area (Heltshe and Ritchley, 1984). Soil samples were then dried and analysed at a
134 commercial laboratory (Ag Harris, Lincoln, NE).

135 ***Management Zones delineation***

136 Management zones were used to characterise in-field variability, identifying areas of high, medium, and low
137 productivity potential within the experimental sites. At Ault, Atwood, and Iliff sites, the delineation of MZ
138 boundaries was accomplished through the Management Zone Analyst (MZA) free software, developed by
139 Fridgen et al. (2004). The MZA uses a fuzzy k-means clustering algorithm to delineate MZ from geo-
140 referenced field information, that showed effective results for zone delineation in previous studies by Odeh
141 et al. (1992). Different clustering variables were used in the delineation process, notably: elevation, bare-soil
142 aerial imagery of the field, and soil apparent electrical conductivity (EC_a). Bare-soil imagery was acquired after
143 field preparation and before sowing, using Google Earth Pro (Google LLC, Mountain View, CA) to select dates
144 when there was no canopy cover in the selected field. The images exported from Google Earth Pro were
145 georectified with at least six ground control points using the ArcMap software (ESRI, Redlands, CA). Soil EC_a
146 was measured on each field prior to planting in spring through EM38 (Geonics Ltd., Mississauga, Ontario,
147 Canada), an electrical conductivity meter that measures EC_a on the basis of the principle of electromagnetic
148 induction at two depths. Data were collected in vertical dipole orientation. Sensor was combined with a GPS
149 and data loggers, mounted on an all-terrain vehicle travelling in parallel transects. High-resolution soil EC_a
150 readings were acquired when the soil was at field capacity. The EC_a data was overlaid with the satellite
151 imagery from Google Earth Pro in the ArcMap software. The rough field topography was extracted from EC_a
152 survey data using the elevation data recorded by a Trimble Ag114 DGPS (Trimble Navigation, Sunnyvale, CA)
153 corrected by a VBS Omnistar (Omnistar, Houston, TX) signal providing a vertical resolution of about 2 m.
154 Despite the low resolution for absolute topography measurements, the relative topography values were

155 accurate enough to detect the overall spatial pattern of topography in each fields. A grid of points was laid
156 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
157 sampling tool from ArcMap, each point was attributed to the corresponding information: the Red, Green and
158 Blue pixel value from the geotiff extracted from Google Earth Pro (raster sampling), the deep and shallow EC_a
159 value as well as the elevation value (nearest point algorithm) from the EC_a survey dataset. The point feature
160 file was then converted into a table to be uploaded in the MZA software. The MZA software performed a
161 fuzzy k-means clustering of the soil information used as input and provided simultaneously a range of cluster
162 number. Mahalanobis distance was chosen as measure of similarity for allocating each individual observation
163 to a particular cluster, as it is reported to be the most appropriate when correlation exists among variables
164 (Fridgen et al., 2004). Other option settings were defined, considering fuzziness exponent of 1.5, maximum
165 number of iterations of 300 and convergence criterion of 0.0001 according to Fridgen et al. (2004). The
166 minimum and maximum number of zones was set to 2 and 6 respectively, in order to allow a sufficient
167 differentiation avoiding at the same time excessive fragmentation of zones' sub-areas. Moreover, after
168 performing the clustering procedure, the software calculated two performance indices, i.e. Fuzziness
169 Performance Index – FPI and Normalised Classification Entropy – NCE, that allowed the decision of the most
170 appropriate number of MZ for each field. The FPI measures the degree of separation between the zones,
171 while NCE indicates the amount of disorganisation of each partitioning (Fridgen et al., 2004). Consequently,
172 the best number of MZ is achieved when both indices have the minimum value, leading to the least
173 membership sharing and the greatest amount of organisation as a result of the clustering process. Therefore,
174 by evaluating both FPI and NCE values, the optimal number of MZ was chosen. Finally, each geo-referenced
175 soil measurement point was assigned to a specific management zone. The vector containing MZ values was
176 transferred to the ArcMap software and converted into polygon features representing the MZ. The
177 attribution of low, medium or high productivity potential of each management zone was reflective of the
178 historical yield performances according to farmers' knowledge of the field. In Fort Collins, MZ had already
179 been defined prior to the project using bare soil imagery, coarse elevation, and yield and management history
180 as layers for delineation. The Rapid Eye satellite imagery platform was used to acquire bare soil imagery of
181 the field. It deploys the Jena-Optronik multi-spectral imager (Jena, Germany), in five distinct bands of the

182 electromagnetic spectrum: Blue (440-510 nm), Green (520-590 nm), Red (630-690 nm), Red-Edge (690-730
183 nm) and Near-Infrared (760-880 nm). Zone clustering was done using the AgriTrak Professional software
184 (Agritrak L.L.C, Fort Morgan, CO, USA) described by Fleming et al. (1999). This method consisted of enhancing
185 the contrast of the bare soil image into various strata or zones using the AgriTrak Professional software.
186 Following which, the actual farmer of that field designated the zones with low, medium, or high productivity
187 potential. The designation of zones was based on the historical knowledge of management practices and
188 yield performance of that field. The delineated MZ in each experimental site are shown in *Figure 2*.
189 Afterwards, QGIS open source software (<http://qgis.org>) was used to assign each yield point from the yield
190 map obtained during the experiment to the corresponding MZ, through Voronoi polygons delineation.
191 Subsequently, the information about the MZ corresponding to each yield point was added to the original
192 dataset using QGIS. This procedure aimed to link each yield value to the productivity potential of the yield
193 sampling point, expressed by the MZ.

194 ***Experimental design and treatments***

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

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

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

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

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

217

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

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

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

236 ***Crop agronomic management***

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

250 ***Field measurements***

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

260 a constant speed alternatively along the crop rows. NDVI readings were acquired continuously on one of the
261 central rows of each strip. Each NDVI measurement was georeferenced.

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

278

279 ***Data analysis***

280 A database was built for each site-year. The databases reported the list of geo-referenced observations, each
281 one referred to an area of 2*4 m². For each area, N rate, belonging to a specific MZ, NDVI value and grain
282 yield were provided.

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

285
$$PFP_N = \frac{Y}{N_T} \quad (1)$$

286 where Y represents grain yield and N_T is the total amount of N applied, both expressed in kg ha^{-1} .
 287 Consequently, it was not possible to calculate PFP_N where no fertiliser was applied. Considering the
 288 agronomic output that can be obtained at a certain level of all N resources in the cropping system, PFP_N could
 289 be considered a useful integrative NUE index. Indeed, PFP_N takes into account total available N derived from
 290 both soil and N applied fertiliser (Cassman et al., 1996; Ladha et al., 2005).
 291 Additional data columns containing NDVI classes were added to the original dataset, with the aim of
 292 identifying classes reflecting homogenous crop vigour. The NDVI classes were created using k-means
 293 clustering with the *k-means* function in the R *stats* package (R Core Team, 2018). For each site-year, the
 294 number of NDVI classes was equal to the number of N levels established for the experimental site.
 295 A statistical procedure was applied in order to check the significance of the difference in grain yield among
 296 precision fertilisation practices and uniform practices. As grain yield depends mostly on N rate, the check of
 297 the significance was performed based on the same N rate for both practices. Average field grain yield and N
 298 rate for each precision fertilisation practices were calculated as the total grain yield or supplied N divided by
 299 the corresponding strip area. Corresponding values of grain yield in uniform practice were derived from
 300 interpolation of a linear model applied to the different site-years. The linear model was applied only to
 301 uniform N application data and expressed grain yield as a function of N rate accounting for an additive
 302 component due to site-year effects (*Equation 2*).

$$\text{Yield} = \mu + (\text{site_year}) + \beta * \text{Nrate} \quad (2)$$

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

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

311

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

315 In order to underline the Nrate effect, both grain yields represented by \bar{X} and fitted values were shifted by
 316 site-year to be represented on a single equation, according to *Equation 4*.

$$\text{grain yield}_{\text{shifted}} = \text{grain yield} - (\text{site_year}) \quad (4)$$

317

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

320

$$PFP_N = \mu + (\text{site_year}) + \gamma_1 * \text{Nrate} + \gamma_2 * \frac{1}{\text{Nrate}} \quad (5)$$

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

323 Finally, an economic evaluation was conducted, with the aim of assessing the influence of precision N
 324 management practices on farmers' net return. Net return above N fertiliser cost (RANC) was calculated as
 325 the difference between grain yield market value and N fertiliser cost (Bachmaier and Gandorfer, 2009). The
 326 calculation was computed as previously reported in Casa et al. (2011). Maize grain prices were based on
 327 Agricultural Statistics (2017) published by USDA. The values employed were 0.15 \$ kg⁻¹, 0.14 \$ kg⁻¹, and 0.13
 328 \$ kg⁻¹, for 2014, 2015, and 2016, respectively. The price of UAN fertiliser was obtained from a fertiliser retail
 329 dealer in Colorado which was equal to approximately 16 000 \$ metric ton⁻¹ (15.70 \$ kg⁻¹). Then, aiming at
 330 assessing the influence of precision N management practices PFP_N , grain yield, and RANC, radar charts were
 331 created for each location and year of the experiment. The considered variables (*i.e.* PFP_N , grain yield, and
 332 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*.

356 The linear model used in the study was suitable at fitting the experimental data ($R^2=0.61$). Nrate was
357 significant ($P(F) = 0.000$, df numerator = 1, df denominator = 4139); site-year was significant as well ($P(F) =$
358 0.000 , df numerator = 6, df denominator = 4139).

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

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

368 The linear model referred to uniform N application and used to express PPF_N as a function of N rate properly
369 fitted PPF_N values obtained in the present experiment ($R^2=0.92$). Nrate and $1/Nrate$ were significant ($P(F) =$
370 0.000 , df numerator = 1, df denominator = 3390); site-year was significant as well ($P(F) = 0.000$, df numerator
371 = 6, df denominator = 3390)

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

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

378 In site-years 1 and 5, precision fertilisation practices did not positively affect grain yield, it resulted in similar
379 grain yield as compared to the uniform application of the same N rate. In the other site-years, the impact on
380 grain yield was different, depending on both site-year and the precision N management practice. In
381 particular, in site-year 2, VR-MZ reduced grain yield by approximately 9% compared to uniform supply of the
382 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

410 model was the best fit for the experimental semivariogram on the basis of AIC, apart from grain yield data
411 acquired in site-year 2 that were best described through a Gaussian model. The range of spatial structure,
412 setting the limit of the autocorrelation and beyond which spatial structure does not exist anymore, varied
413 among the different site-years. In particular, the range of spatial dependency was 9 m in site-year 6 while in
414 site-year 2 and 3 it was 11 m and 16 m, respectively. In site-year 4 and 5, spatial range values were higher
415 and estimated to be 102 and 43 m, respectively. The range of spatial autocorrelation indicated the scale of
416 spatial variability detected in the field. Higher range values are related to large scale variability, and vice
417 versa. Semivariograms of grain yield, together with their approximate theoretical models, are reported in
418 *Figure 6*.

419

420 **Discussion**

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

433 In general, PFP_N decreased with increasing N rates, confirming previous results reported by Barbieri et al.
434 (2008) and Ma and Biswas (2016). This may indicate that maize was unable to absorb or utilise N at higher N

435 rates. Another possible explanation is that higher N amount increased also N losses in the environment,
436 which exceeded crop N uptake (Delgado et al., 2005). In this study, the total amount of N fertiliser was applied
437 in experimental strips around the 6th leaf crop growth stage development. Splitting N application so that N
438 supply is synchronised with maize uptake may improve nitrogen use by the crop, as suggested by Sharma
439 and Bali (2018).

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

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

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

458 On the whole, N application based on crop proximal sensing during the growing season was shown to be the
459 best precision N management practice when the range of spatial variability is lower than 16 m. Conversely,
460 for higher range, up to 102 m, N supply based on MZ delineation performed better. These results agree with
461 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 al. (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

488 and 5, the factor that induced grain yield variability may have a range longer than the range that can be
489 optimal for using proximal crop sensing to drive N fertilisation.

490 The delineation of management zone defines sub-field regions with similar yield-limiting factors, for which a
491 single rate of a specific crop input is appropriate (Schepers et al., 2004; Vrindts et al., 2005).

492 However, in site-year 7, grain yield did not vary across the management zone (data not shown), assessing
493 that, despite different yield-limiting factors, the yield potential is similar across the field. In such a situation,
494 uniform N supply was proven to be the most profitable practice.

495 In site-year 4, N supply on the basis of MZ delineation achieved the best compromise between high grain
496 yield and PFP_N values, evaluated on the basis of RANC. This can be mainly attributed to the reduction of N
497 supply in the low productivity areas, according to a previous study by Koch et al. (2004). In site-years 4 and
498 5, furrow irrigation method was adopted over multiple years. Furrow irrigation transports soil particles and
499 subsequently nutrients, inducing an important soil macro-variability that creates areas with different fertility
500 within the field. This large-scale variability is confirmed by the presence of a spatial range of 102 m.
501 Consequently, N management on the basis of the different MZ is able to better consider soil macro-
502 variability. However, in site-year 5, the uniform application of 40 kg N ha^{-1} led to the highest PFP_N , combined
503 with a negligible grain yield loss. Interestingly, the synergic use of MZ delineation and PS for driving N
504 application improved both PFP_N and grain yield with respect to PS alone. A possible explanation is that crop
505 proximal sensing during the growing season can well assess crop micro-variability, but is less effective in
506 evaluating field macro-variability. Conversely, VR-MZ is an optimal N management practice when the field
507 exhibit a strong macro-variability, with areas with similar yield limiting factors. Consequently, the
508 combination of proximal sensing and MZ delineation can be a promising tool to consider both large and small
509 scale sources of variability. Therefore, the integration of soil-based and plant-based methods to drive
510 fertiliser applications can be considered a promising tool for N use efficiency without impacting grain yield,
511 strengthening the hypothesis that supported the present study. Then, the present study confirmed the
512 potential of precision fertilisation to improve maize cultivation sustainability, but also highlighted that the
513 choice of the optimal N fertilisation strategy needs to be related to the range of spatial variability detected
514 in the field.

515

516 **Conclusions**

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

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

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

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

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Fort Collins Site (2014-16)
Type: Research field
Study area: 1.3 ha
Slope: <1%
Soil type: Aridic Argiustolls

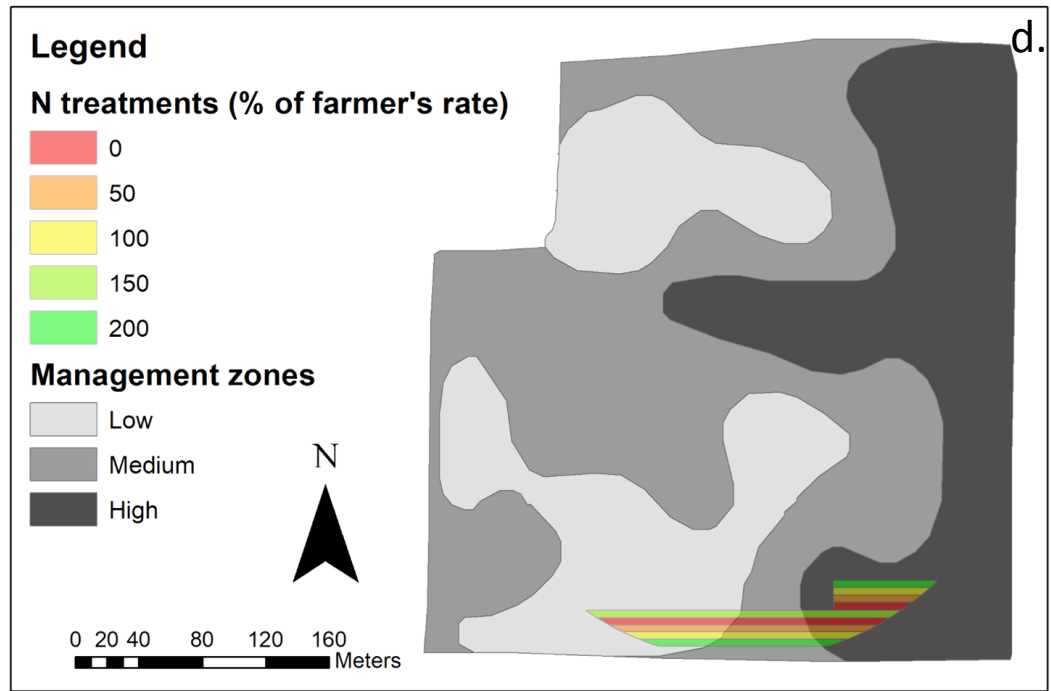
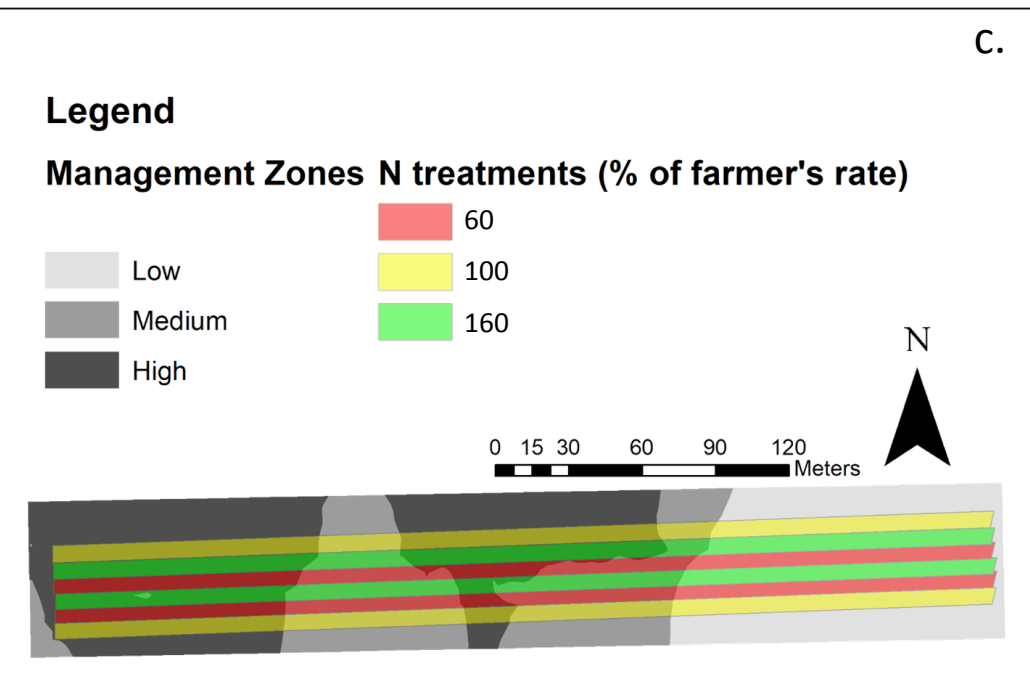
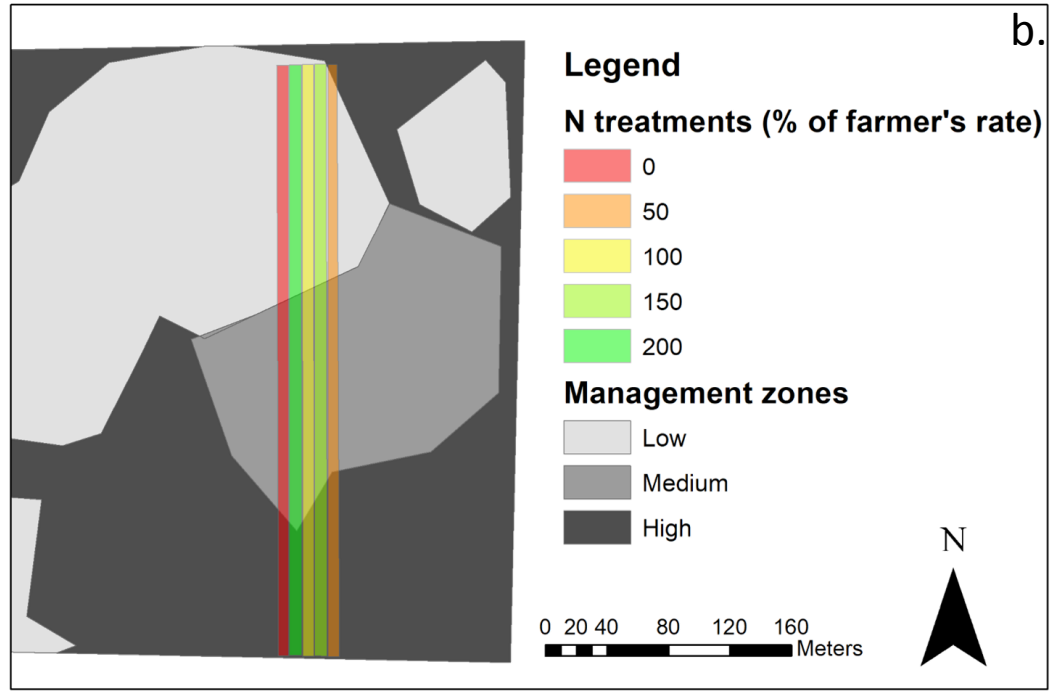
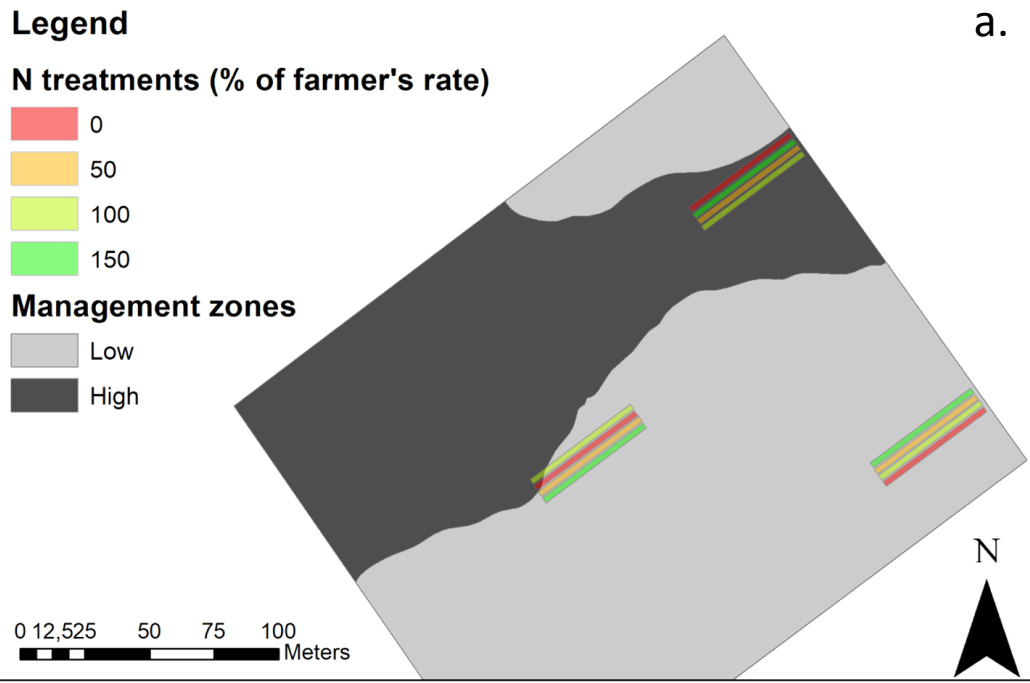
Iliff Site (2014)
Type: Commercial field
Study area: 0.2 ha
Slope: <1%
Soil type: Fluvaquentic Endoaquolls

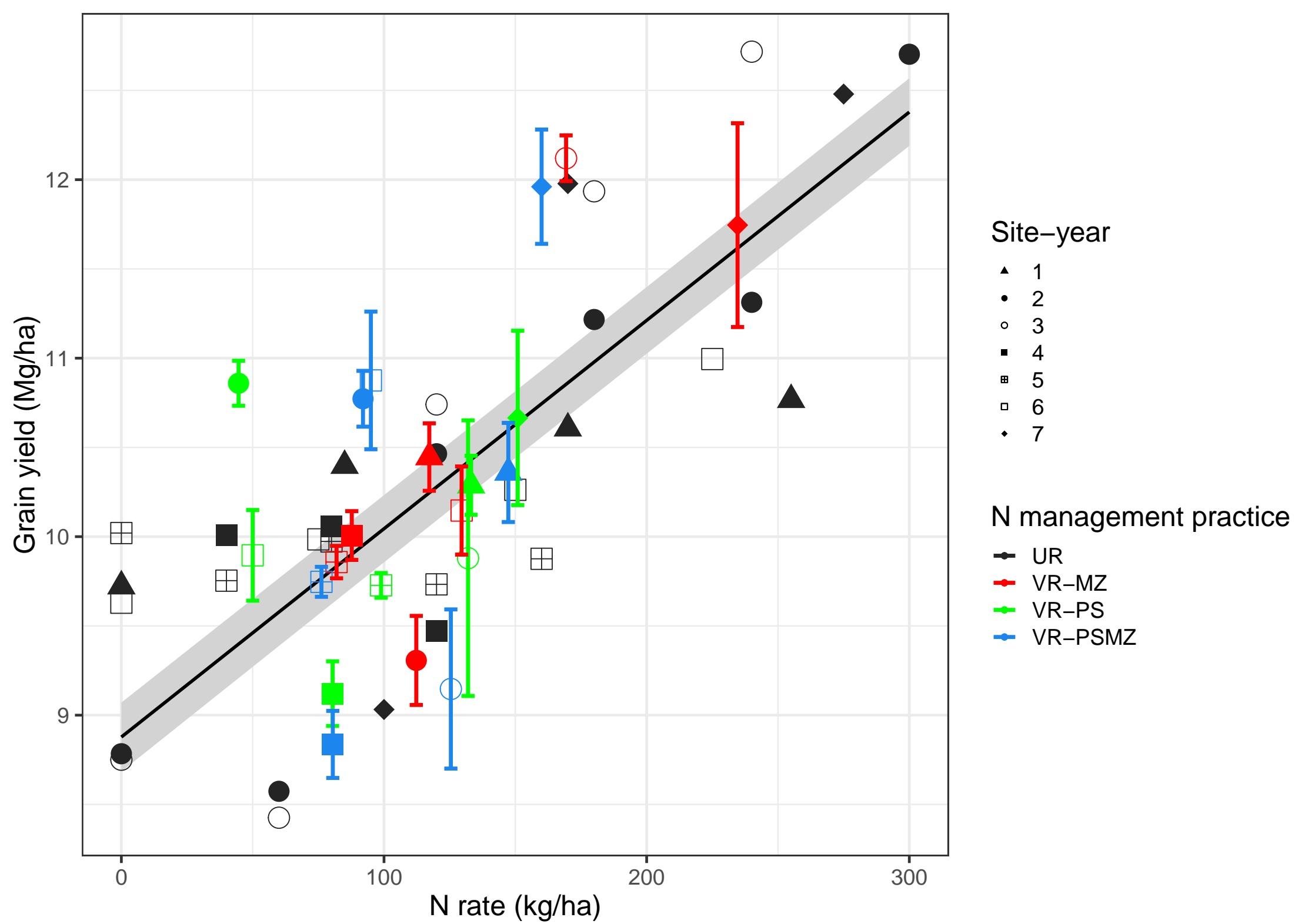
Ault Site (2014-15)
Type: Commercial field
Study area: 1.3 ha
Slope: 2.8%
Soil type: Ustic Torriorthents

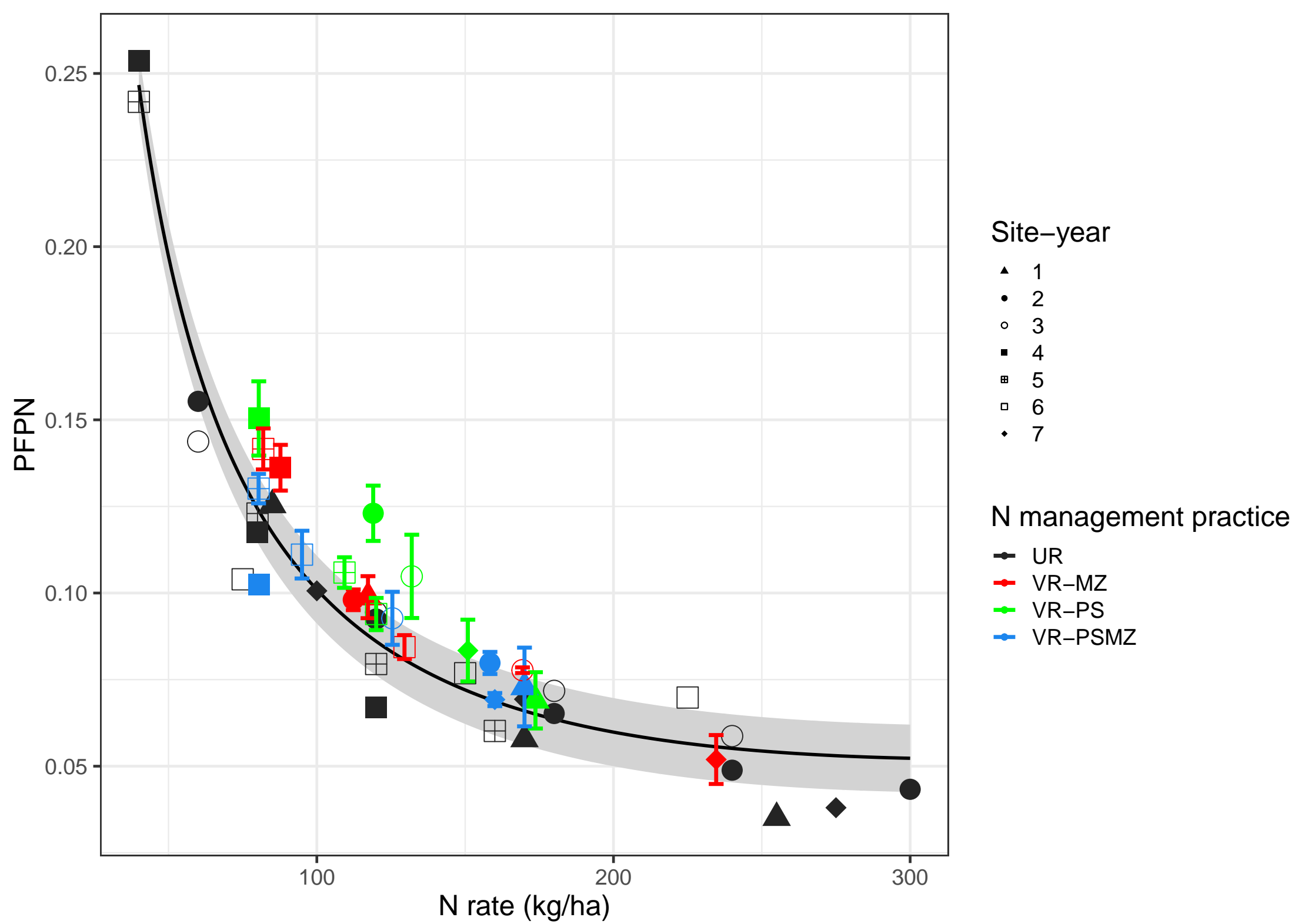
Atwood Site (2014)
Type: Research field
Study area: 1.3 ha
Slope: <1%
Soil type: Aridic Argiustolls



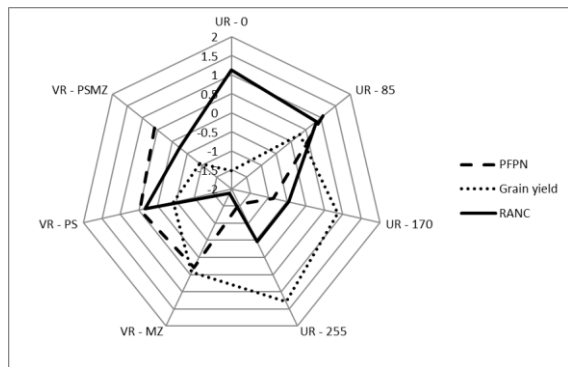
40 km



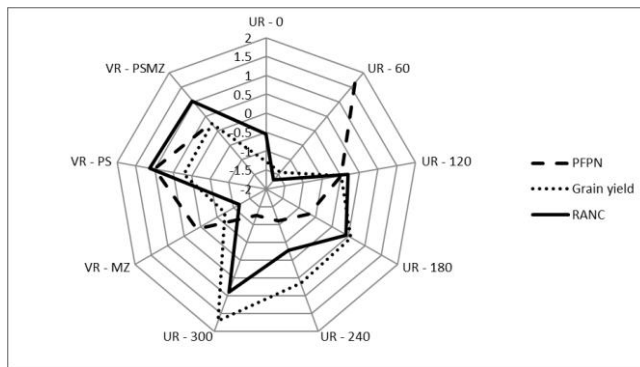




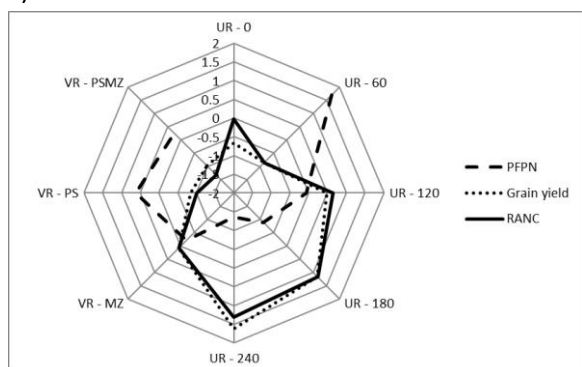
a)



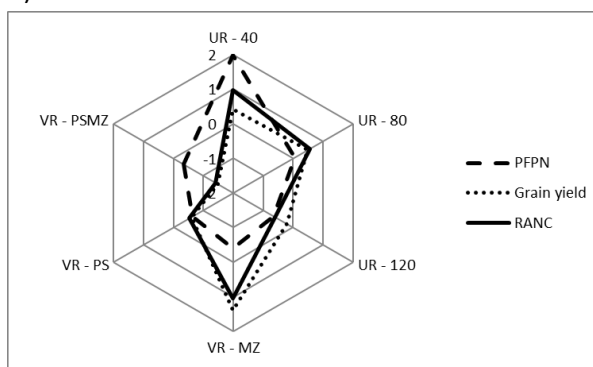
b)



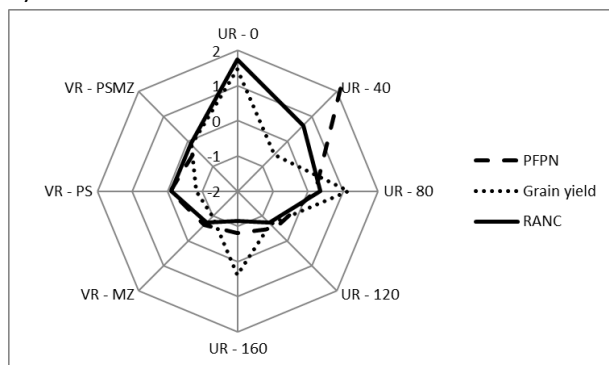
c)



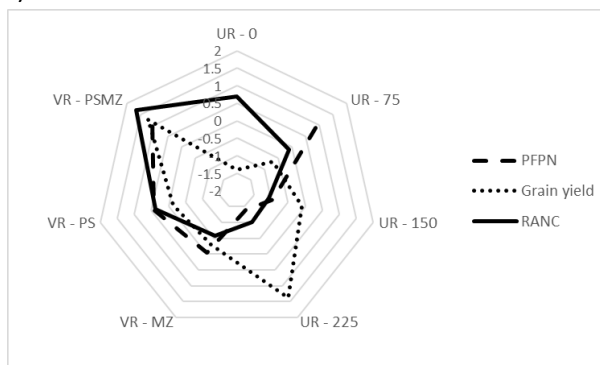
d)



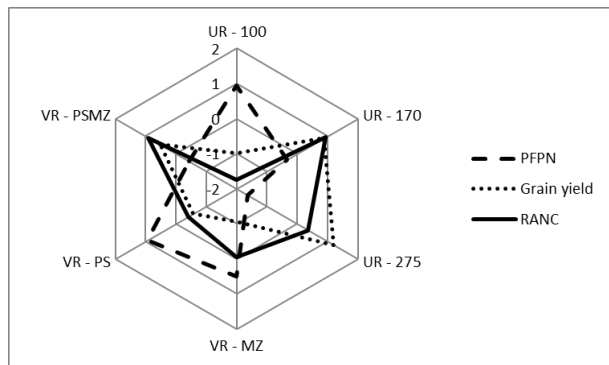
e)



f)



g)



a) site-year 1

b) site-year 2

c) site-year 3

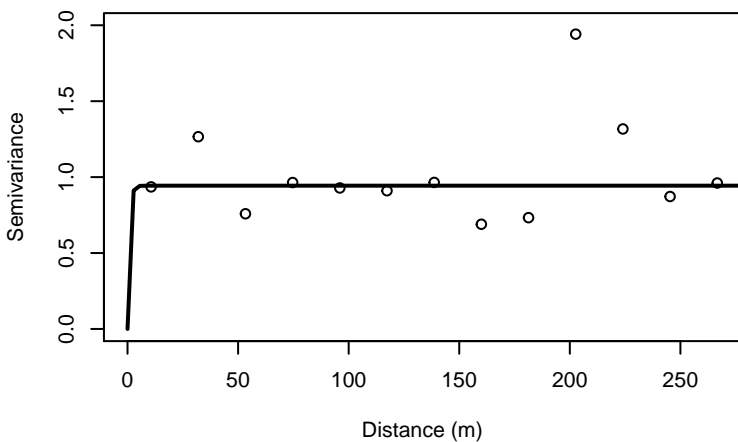
d) site-year 4

e) site-year 5

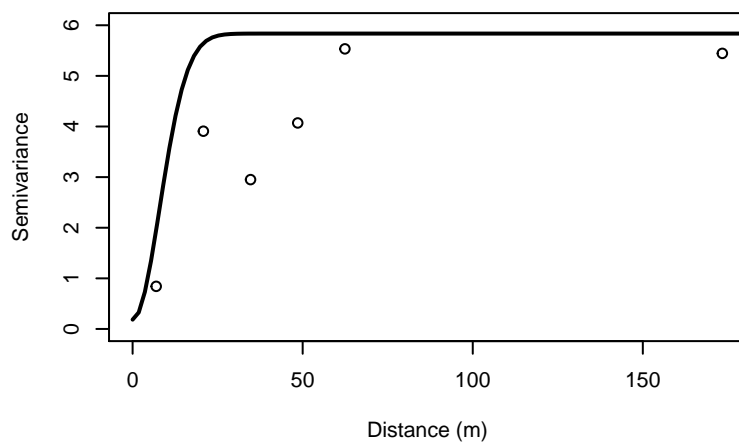
f) site-year 6

g) site-year 7

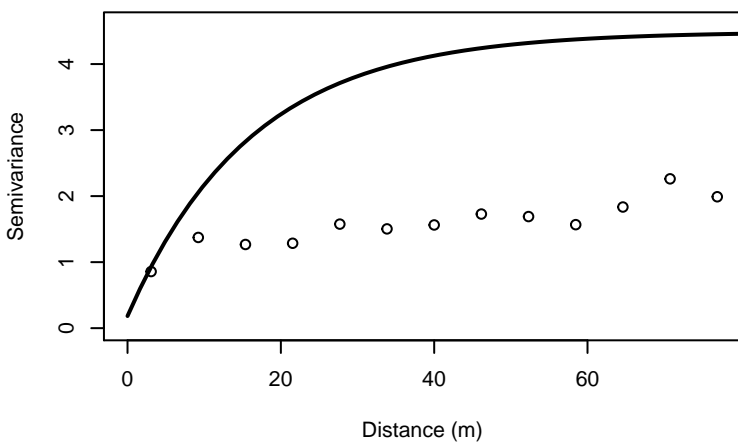
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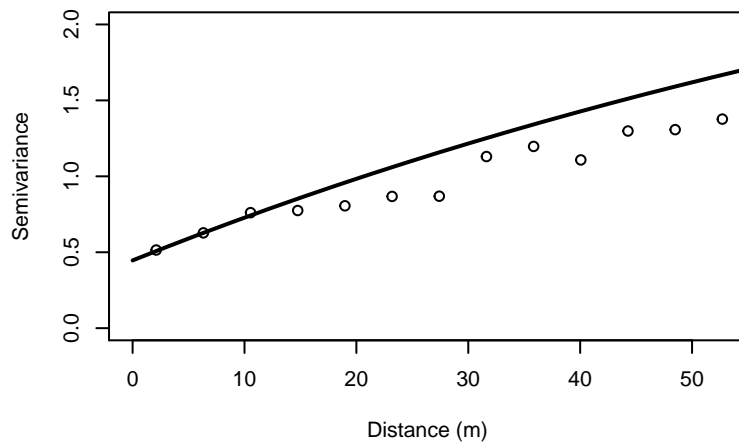
Site-year 2



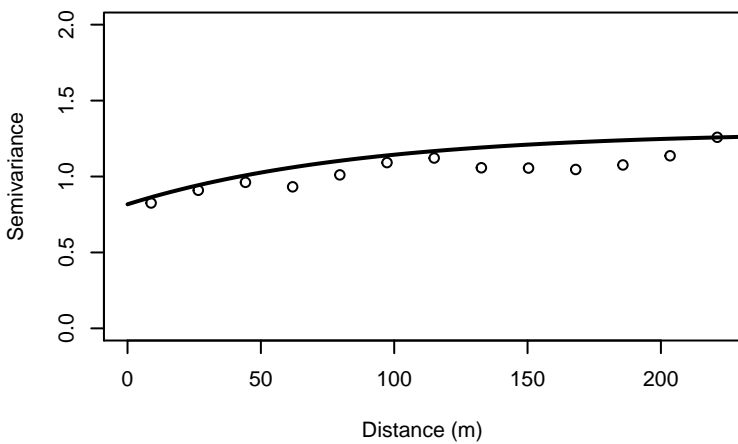
Site-year 3



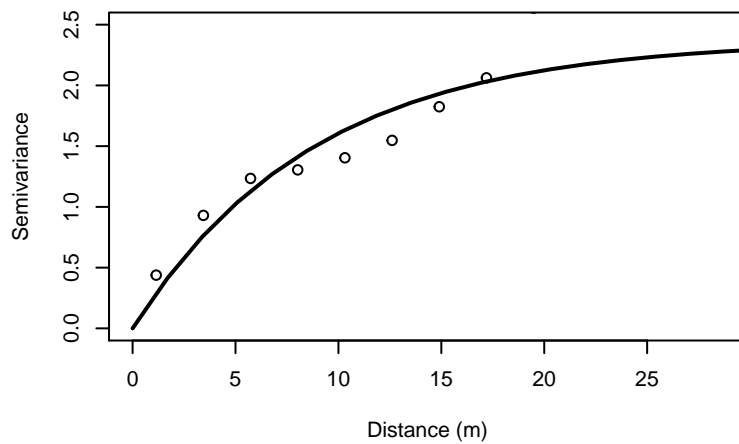
Site-year 4



Site-year 5



Site-year 6



Site-year 7

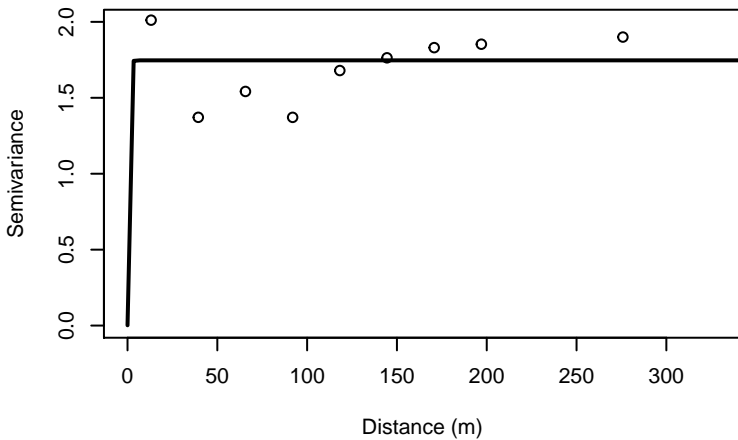


Table 1: Description of average climatic data for each site and each year for the crop growing seasons (May 1st to September 30th) of 2014-16. Table includes NOAA's normal weather conditions for the crop growing season from 1981 to 2010 for each location.

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

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	29 th April 2014	84 000	11 th June 2014	30 th October 2014
2	Dekalb DKC46-20RIB	96	27 th May 2015	84 000	30 th June 2015	19 th November 2015
3	Dekalb DKC46-20RIB	96	6 th May 2016	93 900	21 st June 2016	21 st October 2016
4	Pioneer P0474	104	5 th May 2014	84 000	17 th June 2014	24 th October 2014
5	Pioneer 35F48AM1	105	2 nd May 2015	93 900	23 rd June 2015	12 th November 2015
6	Pioneer P0157AM	101	19 th May 2014	84 000	24 th June 2014	23 rd October 2014
7	Pioneer P0474	104	7 th May 2014	84 000	17 th June 2014	26 th 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.

^aPNMP= precision N management practice; ^bPFP_N = partial factor productivity; ^cn.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