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Reducing topdressing N fertilization with variable rate does not reduce maize yield

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Abstract:

Background: Proximal sensing represents a growing avenue for precision fertilization and crop growth monitoring. In the last decade, precision agriculture technology has become affordable in many countries; Global Positioning Systems for the automatic guidance instruments and proximal sensors can be now used to guide the distribution of nutrients such as nitrogen (N) fertilization using real time applications.

Methods: A two-year field experiment (2017-2018) was carried out to quantify maize yield in response to variable rate (VR) N distribution, which was determined with a proximal vigour sensor, as an alternative to fixed rate (FR) in a cereal-livestock farm located in the Po valley (Northern Italy). The amount of N distributed for the FR (140 kg N ha^{-1}) was calculated according to the crop requirement and the regional regulation. ±30% of the FR rate was applied in the VR treatment according to the Vigour S-index calculated on-the-go from the CropSpec sensor.

Results: The two treatment of N fertilization did not result in significant difference of yield in both the years. The findings suggest that the application of VR is economically profitable than at FR application rate, especially under the hypothesis of VR application on farm scale.

Conclusions: The outcome of the experiment suggests that VR is a viable and profitable technique which can be easily applied at farm level by adopting proximal sensors to detect the actual crop N requirement prior to stem elongation. Besides the economic benefits, the VR approach can be regarded as a sustainable practice that meets the current European Common Agricultural Policy.

Keywords: Variable rate, nitrogen fertilization, maize, proximal sensing, organic fertilizers

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1. Introduction

Today, machinery and high technological devices used in agriculture are very heterogeneous throughout the world due to economic and environmental reasons. The wide range of environmental conditions, land use and suitability differences of agricultural fields make possible a wide diversification of the technical ameliorations. Precision Agriculture (PA) is commonly defined as the process of doing the right action at the right place at the right time; therefore, PA is not just a technology, but rather a management philosophy which is made possible by new technologies [1,2]. Advancements in remote sensing, machinery control systems, crop modelling, weather monitoring, decision making, cloud computing and big data analysis drive PA to the new revolution in agriculture named smart farming [3]. These advancements enhanced the accuracy of PA applications and made it available for a broader range of farmers, allowing to enhance practices through the possibility to predict the occurrence of water or nutrient stresses and take real-time supported decisions. Collaboration between public and private sectors towards research, education and innovation opportunities in precision agriculture are rising and under constant development [2]. Fertilization is one of the most relevant targets of this new approach [4]. Indeed, adjusting N rate to the measured crop requirement increases crop N use efficiency [5,6] and reduces environmental risks [7–9]. Delgado et al. 2005 [10] reported that applying N using VR can reduce NO_3 leaching losses by 25%. The VR application is recognized to effectively reduce the carbon footprint and the GHG emissions [11] who studied VR application in a pear orchard as case study.

The interaction between N rate, soil, weather and crop response is a complex system, in which these factors vary spatially within the same field and temporally over the season [12]. Managing this variability is the key aspect that distinguishing PA to conventional management [13]. Understanding of crop nutrition needs and supply balance should be the base for definition of optimum N fertilizer application. Different factors play a role on the optimum N rate, such as N supply from other sources, fertilizer costs, quality and quantity of final product and its price [13,14].

In a review paper about proximal sensing crop monitoring [15] it was analysed the feasibility of remote and proximal optical sensors to estimate N management-linked variables; it was pointed out that different factors can impact the perception of crop variability (e.g., sensor type, spatial resolution, standardization of sensor measurements), though they are strongly linked to location, year, and variety. Farmers frequently adopt proximal optical sensors rather than retrieving information from remote sensing due to the easier access to this technology (REF). Proximal sensing can be classified in Unmanned Aerial Vehicles UAVs with different cameras mounted on it, or tractor mounted sensors (TMS). The UAVs [16–20] are massively used is agricultural systems [16–20]. Proximal sensing equipment also used for VR fertilization is represented by Greenseeker [21–23] and OptRx [24].

The proximal sensing equipment are typically used to manage differently field homogeneous zones, also known as management zones. They represent subfield regions with same soil traits and hydrologic characteristics within which a single strategy (e.g fertilization rate) is appropriate [25–27]. Since it is now possible to map the maize yields and moisture level at the harvest with very high spatial resolution, the major challenge is modulating the amount of fertilizer equally to match the crop demand [28]. The VR fertilization is a key aspect of fertilization prescription in precision agriculture, which typically involves multiple criteria and objectives. Practical motivation embraces the optimization of the trajectories in the field with a consequent reduction in the use of fuel and fertilizer, waste of pesticides and labour hours [25,29]. In the present case study, located in eastern Lombardy (Italy), maize production is experiencing relevant variability, being caused mainly by the low price on the market and pests control regulations and limits, which results in increasing imports from countries outside the EU [30]. It was observed that dairy farmers hardly adhere to the organic recommended fertilizer application rates due to the high availability of manure and slurry [27,31–35]; however, to ensure high crop yields, largely use topdressing mineral N is used despite the purchase and environmental costs [36]. Even considering the current subsidized rates, mineral fertilizers still represent a substantial budget item in European farms [37].

In the integrated crop and livestock farm system, which is characterized by slurry availability over the year, it is required to improve the use of organic fertilizer to enhance the production efficiency and farmer net return [38], maximize grain yield mainly with the improvement of spatial homogeneity on the field, and improve the quality by increasing grain protein content [39]. A way to achieve these objectives is to implement a precision farming management with the adoption of proximal sensors, as supported by the rural development plan (PSR) of the Lombardy Region, which has recently partly subsidized the equipment purchase by farmers [40,41]. The use of organic N fertilizers from recycled digestate waste makes the agricultural system more environmentally sustainable [7,38,42,43], and improve net farmer return [44].

In this study, we compared the effect of topdressing FR derived from fertilization plan with VR nitrogen fertilization on maize yield in a 2-year field experiment in eastern Lombardy under the hypothesis that the N application at VR guided by an active optical TMS leads to: i) maintain the same productivity level, ii) allow for the reduction of mineral N supply, iii) improve intra-field spatial homogeneity of maize grain yield. The topdressing N rate was estimated according to the fertilization plan calculated by the current legislation and availability of organic fertilizer and in VR by the crop vigour status measured with an on-the-go approach.

2. Materials and Methods

2.1 Study area

The test fields are located on a crop and livestock farm (approximately 400 ha and 700 dairy cows); two maize cropping seasons (2017-2018) were monitored from sowing (in April) to harvesting (in August). The experiment was carried out in two adjacent fields over the experimental period. The fields at coordinates N 45 ° 12'43 '' 10 ° 48'27 '', E 45 ° 12'29 '' 10 ° 48'42 '', the fields are around 4 ha each **(figure 1)**.

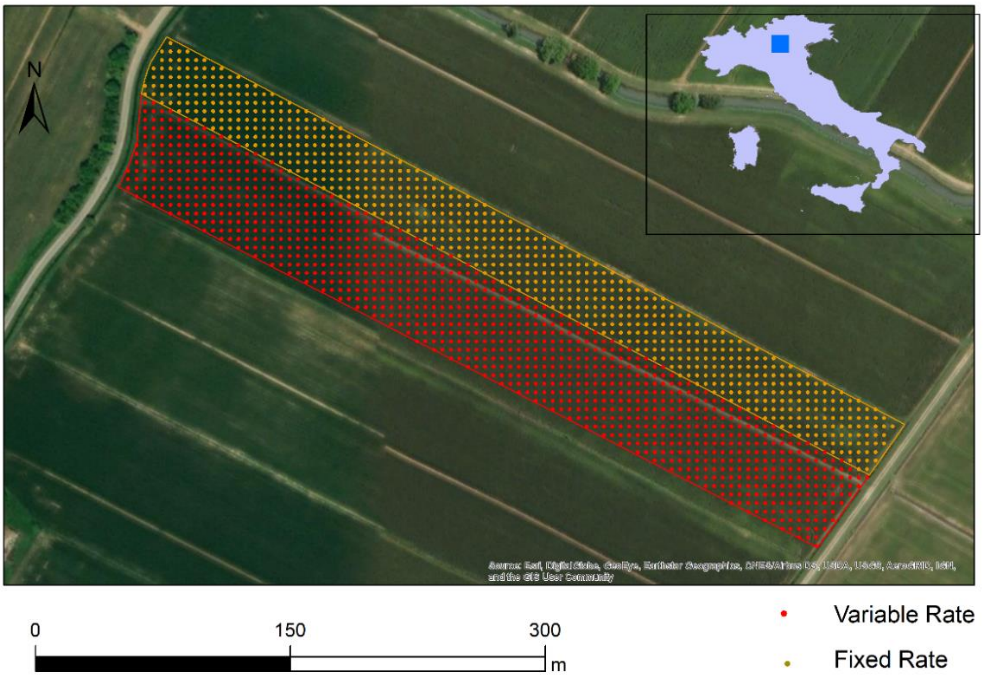

Fig.1 Map showing the location of the two adjacent fields on the experimental site.

2.2 Weather condition

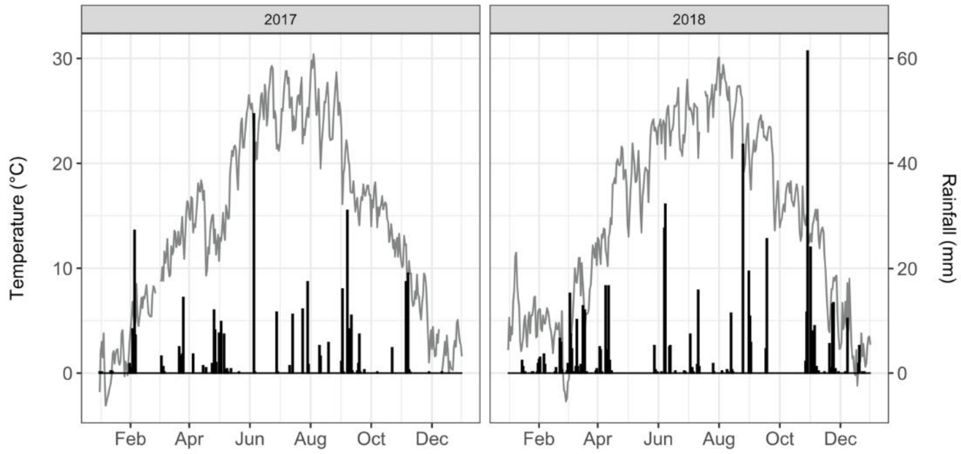

Figure. 2 Monthly variations in temperature (°C) and rainfall (mm) of the experimental site during the two years experiment 2017/2018.

The pedoclimatic conditions were comparable between the two experimental years. At the time of maize sowing (April), the mean daily temperature was on average greater than 10 °C in both years, **(figure 2)**. Before the maize sowing (March), soil accumulated 31 mm in 2017 and 78 mm in 2018. In the first maize vegetative stages, indicatively from April to May, the rainfall was 60 mm in both 2017 and 2018.

2.3 Soil Sampling

During sowing and after harvesting, we carried out a sampling mesh to evaluate the soil physical and chemical soil properties in the two fields so that their background conditions were comparable. The soil analysis also allowed for mapping pedological discontinuities, which were likely to cause low production in certain areas, which were identified by the farmer in previous years. The sampling mesh was made with a density of 4 samples per hectare; soils were sampled at a depth of 0.3 m depth. Three soil cores per site were sampled and dried first at air conditions and subsequently sieved and homogenized [42]. The analysis highlighted poor SOC area as shown in **Figure 2**.

The sampling scheme was implemented taking into account an experimental design that ensure at least 4 samples per hectare (USDA guidelines). The sampling was done following the soil sampling guidelines (methods of detection and computerization of pedological data, Costantini et al 2011) [45]. The examined properties were soil organic carbon (SOC), total soil Nitrogen (N), Carbonates ($CaCO_3$), Nitrate ($NO3^-$), Phosphorus (P_2O_5) and Potassium (K_2O) see table 1.

Table 1. Classification of the soils according to the SOC concentration.

Classification based on SOC g kg^{-1}	**Medium content of particles (F-FL-FA-FSA)**
Very poor	<10
Poor	10-18
Averagely amount	19-25
Rich	25

To obtain soil properties surfaces to be used for spatial modelling, the data were interpolated through the Inverse Distance Weighting IDW algorithm in ArcMap 10.7, ESRI. The map of SOC in 2017 (**Figure 3**), displayed using 10 quantile classes, shows two spots with higher SOC % and comparable content between the two fields.

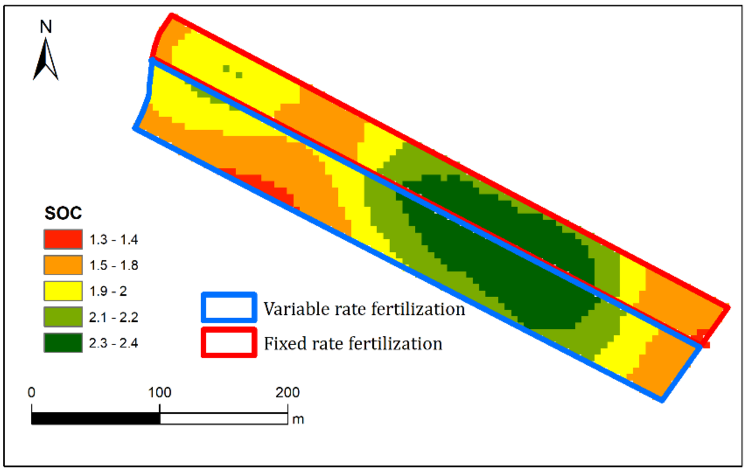

Figure 3. Percentage content of soil organic carbon (SOC) map obtained with IDW. Red areas have the lowest SOC concentration.

The SOC and N were determined by dry combustion using ThermoQuest NA1500 elemental analyzer (Carlo Erba, Milano, Italy). The instrument determines both total nitrogen and total carbon on 0.4 g samples (two replicates for each sample). The measured values were subtracted from the C-carbonate content, which was determined by with the acid titrimetric method [46]. Phosphorus and Potassium content were obtained by a previous sampling collection (2015); they were determined at field level with 4 samples per hectare.

Tab. 2 Soil properties.

Parameter	Mean	SE±
Sand (%)	24	1.32
Silt (%)	38	1.22
Clay (%)	38	1.43
pH H2O	7.8	0.41
Salinity (dS m)	0.02	0.00
Total CaCO3	7.3	0.08
Active CaCO3	0.01	0.00
Cation-Exchange Capacity (cmol/kg soil)	28.6	3.42
C/N	10.5	0.85
Mg/k	3.1	0.05
Organic Carbon (g kg^{-1})	19	2.33
Total Nitrogen (g kg^{-1})	1.8	0.09
Assimilable P (mg kg^{-1})	48	3.57
Exchangeable K (mg kg^{-1})	422	15.36
Exchangeable Ca (mg kg^{-1})	3880	54.65
Exchangeable Mg (mg kg^{-1})	343	10.22

2.4 The experimental setup

The dates of maize sowing were 07-04-2017 and 7-04-2018 with the use of tanned seed. Variety and seeding density at the Field 2 were DEKALB 6728, the sowing density 8 plants m^{-2}. **Figure 1** reports fields scheme. In both field 1 and field 2, dairy slurry was distributed at the beginning of Autumn at a rate of 50 Mg ha^{-1}, with a N input of 150 kg ha^{-1} (Table 3).

Tab. 3 Nitrogen concentration and nitrogen forms in the digestate.

Compounds	Units	Value × 1000	Methods
Total Nitrogen	g kg^{-1} N	3.1	IRSACNR vol3/6 r 00/86
NH_3	g kg^{-1} N	2.2	IRSACNR vol3/7 r 00/87
Organic Nitrogen	g kg^{-1} N	0.9	
NO_3^-	mg kg^{-1} N-NO_3	12	IRSACNR vol3/8 r 00/86
Dry matter at 105° C	%	4.2	IRSACNR vol2/2 r 00/84

This experimental setup aimed to compare the VR and FR application at side-dressing using urea (46%N) (Table 4).

Tab. 4 Nitrogen applied as topdressing fertilization.

		N application rate (kg ha^{-1})			
		Application of digestate on bare soil in Autumn	NPK[(1)] at sowing	Topdressing	VR/FR
2017	FR			138	1
	VR			from 92 to 135	0.7 – 1
2018	FR	150	50	138	1
	VR			from 90 to 147	0.7 – 1.1

(1) N content = 24%

The management of the two fields differed regarding the topdressing fertilization rate (Table 4). The application of N during Autumn and at sowing did not vary between the two treatments. Based on the last five-year grain yield data of adjacent fields, N crop uptake as well as phosphorus and potassium were calculated using a fertilization plan following the Lombardy rules [42].

2.5 Equipment and working sensors

The farm equipment accounts for: satellite guidance, crop vigour sensors and precision fertilizer spreader. The yield map of the two years obtained from the harvester IoT system.

2.5.1 The vigour sensor

The sensor used in this experiment is an active optical sensor developed by Topcon Agriculture that evaluates the canopy vigour for the site-specific N fertilization of the most common field crops (e.g., winter wheat, barley, oat, maize, soybean, rice). Canopy vigour was sensed through CropSpec and expressed as a synthetic vegetation index S, which is computed as follows:

$$s = \left(\frac{R2}{R1} - 1\right) \cdot 100 \quad (1)$$

Where R2 and R1 represent the red and infrared bands, respectively. CropSpec consisted of two sensors, i.e. the left and right sensors, which both return the S index value with a spatial resolution of less than 3m.

CropSpec was used at two times per year: during the fertilization at (V3), at the phenological phase of raising at the sixth leaf (V6). The sensor operated at a short distance from the crop (approximately 20 cm) and at a height which varies between 2 and 2.3 m.

The rationale of the VR consisted in giving the higher amount of N (N-max) defined by the fertilization plan at the less favourable zones in terms of vegetation vigour at the moment of the topdressing fertilization. In contrast the most vigorous received the smallest amount of N (N-min), and in between various conditions receiving N between (N-max and N-min) at 10kg step.

2.5.2 Fertilizer spreader

The fertilizer spreader which was used in the experiment was the Kverneland Exacta TL GEOSPREAD, which has two actuators on each dosing unit. An actuator controls the setting of the discharge point for the correct placement of the fertilizer inside the disk, while the other controls the distribution rate. The GEOSPREAD system makes it possible to set the specific fertilizer amount and distribute for both discs directly from the tractor cab. The working width (7 maize rows, 4.5 m) can be quickly and easily adjusted with the ISOBUS terminal. The correct position of the sections and the overlap is guaranteed by the satellite guide operating with differential corrections Network Real Time Kinematic (RTK).

2.5.3 Harvester and yield data collection

The crop was harvested using The CLAAS harvester CORIO model series specific for maize harvest. The harvester allowed for a high-precision yield and humidity mapping. The system allowed to record in each area (7x7m) the weight of the grain yield and the moisture concentration in the biomass.

2.5.4 Data treatment, statistical analysis, and economic analysis

Descriptive statistics for the VR and FR fields comprising the mean, standard deviation (SD), and coefficient of variation (CV) were calculated. Different fertilization rates were than separated in three different groups: "Low" with less than 100 kg N ha^{-1}, "Medium" with nitrogen application ranged between 100 and 125 and "High" with more than 125 kg N ha^{-1}.

As a preliminary elaboration, yield data were analysed to automatically detect outliers to exclude in the subsequent analysis. The data were tested for normality using the Kolmogorov-Smirnoff test.

Data of S index, which were measured by the sensors with a spatial resolution of 5 m x 5 m, were transformed from point to raster using inverse distance weighted (IDW), the same procedure was adopted for the dry yield data, which were measured at variable spatial resolution, therefore was useful to convert the vectors to a fixed spatial resolution the one closest to the real spatial resolution of the N that can be achieved with the equipment (spreader).

A bootstrap ANOVA was then carried out with the aim of testing the effect of the two treatments (FR vs. VR) on maize yield, SOC, and the N fertilization rate. After this stage, the analysis of variance was carried out to assess the effect SOC and S-index on the grain yield. The samples obtained from the fertilization and used for the analysis were 201 (Yield, S-index, SOC) annually.

The cost savings due to VR were computed annually as follow:
(1) the dataset of the 201 variable rates was split into ascendant 25 ranks, which were characterized by an increasing dose of urea equal to 5 kg ha^{-1};
(2) the field coverage (%) for each rank (i.e., the percentage of field that has been fertilized with that specific amount of urea) was computed as: (total observations / observations $rank^{-1}$)·100;
(3) the mean of each rank was utilized as a representative value to compute the urea cost (€ ha^{-1}) as a sum of each rank cost:

$$\sum(\text{mean rank value [kg urea ha}^{-1}] \cdot \text{urea cost [€ kg}^{-1}] \cdot \text{field coverage [\%]}$$

(4) the annual cost saving was then calculated as the difference between FR and VR.

3. Results

3.1 Descriptive statistics

For each variable considered in the present study, the mean, the standard deviation and the coefficient of variation are computed (Table 5).

The crop was harvested at the 18-22% of humidity (15-09-2017, 21-09-2018) respectively.

Tab.5 descriptive statistic of the S-index, Topdressing N rate and yield in 2017 and 2018.

Variable	mean	sd	cv
CropSpec S index May 2017	28.15	2.54	0.09
CropSpec S index May 2018	26.61	3.63	0.14
Topdressing N 2017	123.65	8.20	0.07
Topdressing N 2018	120.10	6.33	0.05
Yield 2017	14.19	1.64	0.11
Yield 2018	12.34	1.91	0.15

3.2 Differences between years and fields

The pedoclimatic condition were stable during the two years. In particular, before the maize irrigation, the similar amount of rainfall did not justify differences in productivity among years since irrigation was performed to supply the water demand.

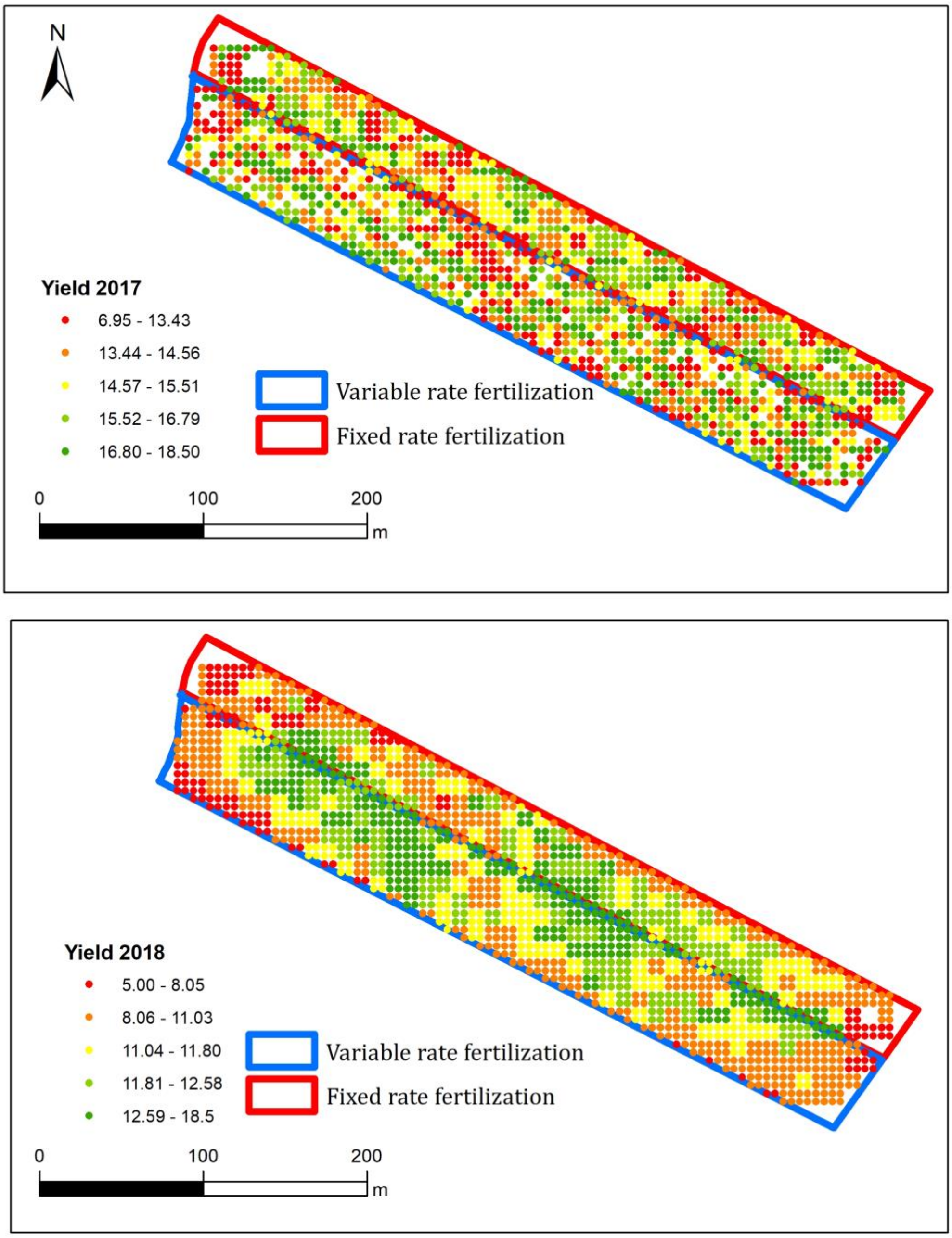

Figure. 4 Maize grain yield observed in 2017 and 2018 under the two treatments of N fertilization rate (variable and fixed).

In 2018, larger contiguous areas having homogeneous yield were observed in both FR and VR (figure 4). Conversely, in 2017 the yield observations were more scattered under the two treatments.

Table. 6 The results of the bootstrap ANOVA that was carried out to evaluate the effect of N fertilization rate on grain yield in 2017/2018.

SUMMARY				
	Groups	Count	Average	Variance
2017	Variable rate	201	14.69	6.32
	Fixed rate	218	14.14	8.91
2018	Variable rate	201	12.50	2.23
	Fixed rate	216	12.19	3.77

ANOVA							
	Source of Variation	SS	df	MS	F	P-value	F crit
2017	Between Groups	22.9	1	22.93	2.99	0.08	3.86
	Within Groups	3198.2	417	7.67			
	Total	3221.1	418				
2018	Between Groups	8.1	1	8.12	2.68	0.10	3.86
	Within Groups	1257.5	415	3.03			
	Total	1265.7	416				

The ANOVA showed that in 2017 the average yield production was not significant different between VR and FR ($P > 0.05$), with a production of 14.69 and 14.14 Mg ha^{-1} respectively.

In 2018, the average yield production was lower compared to 2017 with on average 12.50 and 12.19 Mg ha^{-1} for VR and FR, respectively. In 2018, the ANOVA test did not show significant differences between the two treatments ($P > 0.05$).

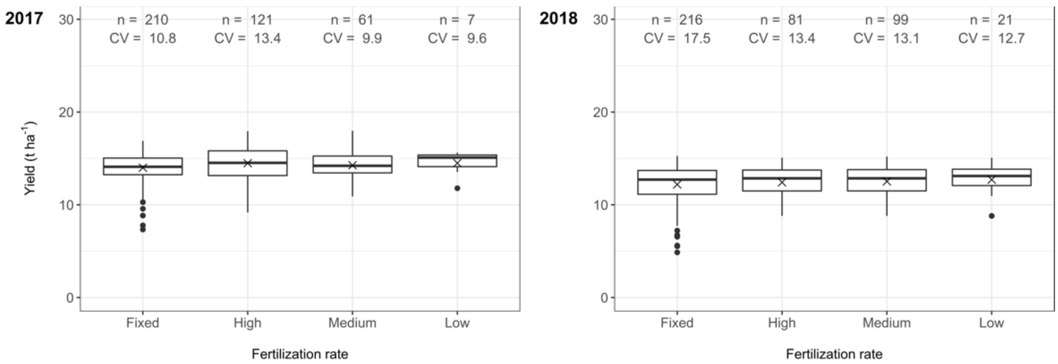

Figure. 5 Maize grain yield observed in 2017 and 2018 and divided by fertilization rate groups. Sample size (n) and the coefficient of variation (CV %) of each group is reported at the top of the graph, while "X" symbol represents the mean. Black dots indicate outliers (cases between 1.5 and 3 times the interquartile range).

The fertilization rate groups division allowed to better estimate the impact of the variable fertilization rate on maize yield. In 2017, data showed higher differences between the fertilization rates than in 2018. Compared to the fixed rate, the variable rates had a lower CV (except for "High") with a higher yield (**figure 5**). In general, in the first year the coefficient of variation ranged between 9 and 13 % among different fertilization rates. The "High" fertilization rate in 2017 had a CV of 13.4%, greater than all the other rates. Conversely, in the second year, the greatest CV was found in the fixed rate (17.5%), while the different variable rate had a stable CV around 13%. The yield remained stable around 12 Mg ha^{-1}.

Moreover, in 2017, data showed a higher sample size of the "High" fertilization rate (n = 121) compared to the "Medium" and "Low" groups. This sample size variation was less evident in 2018 when the "Medium" and "Low" group had similar sample sizes to the "High" group.

3.1 Cost estimation (Farmer Net Return)

Since all VR yielded equal or greater than FR in both years, it was reasonable to investigate the savings in reducing the amount of urea with VR. Therefore, based on the local market price (http://www.borsamerci.mn.it) of urea at the time of the experiment (0.361 € kg^{-1} in April 2018), we estimated the possible costs-benefit which can be achieved by applying

Tab. 6. On farm cost and saving with the application of VR on the farm area potentially cultivated with grain maize (400 hectares).

Lower limit (kg urea ha^{-1})	Upper limit (kg urea ha^{-1})	Field coverage (%)		UREA Cost (€ ha^{-1})	
		2017	2018	2017	2018
195	200	-	0.5	-	0.4
200	205	3.0	3.5	2.2	2.6
205	210	0.5	2.0	0.4	1.5
210	215	-	2.5	-	1.9
215	220	-	1.5	-	1.2
220	225	-	3.0	-	2.4
225	230	-	3.0	-	2.5
230	235	1	5.5	0.8	4.6
235	240	1.5	6.5	1.3	5.6
240	245	3.5	3.0	3.1	2.6
245	250	4.0	3.5	3.6	3.1
250	255	2.0	5.0	1.8	4.6
255	260	2.5	5.0	2.3	4.6
260	265	12.9	8.5	12.2	8.1
265	270	2.0	5.5	1.9	5.3
270	275	12.4	4.5	12.2	4.4
275	280	7.5	6.0	7.5	6.0
280	285	46.3	6.0	47.2	6.1
285	290	0.5	4.5	0.5	4.7
290	295	0.5	9.0	0.5	9.5
295	300	-	3.0	-	3.2
300	305	-	4.0	-	4.4
305	310	-	2.5	-	2.8
310	315	-	0.5	-	0.6
315	320	-	2.0	-	2.3
Sum of variable rate cost (€ ha^{-1})				97	95

Fixed rate cost (€ ha^{-1})	108	108
Saving (€ ha^{-1})	11	13
Farm saving (€ yr^{-1})	4320	5320

the VR on the 400 ha^{-1} available for the grain maize production, assuming similar pedoclimatic conditions.

With the approximation used in the present work, and the FR set to 138 kg N ha^{-1}, the saving reached 11 and 13 € ha^{-1} for 2017 and 2018 respectively. When this result was extended to the entire surface potentially cultivated with grain maize, the revenue of using the variable rate is 4320 and 5320 € ha^{-1} in the first and second year, respectively (Table 6).

When the same computation was extended to the N saving, the results suggest that VR can reduce the N supply in a range between 13 and 17 kg N ha^{-1} depending on the growing season.

4. Discussion

This field experiment allowed to test the effectiveness of proximal sensor of high and available technology in reducing N fertilizer with no negative impact on maize grain yield. The regional and EU incentives make the technology accessible thanks to a discounted purchase because the correct use of the sensor aims at reducing the mineral N fertilization targeting to limited N leaching and volatilization losses [37,39]. This experiment offered the opportunity to operate on actual field conditions being characterized by high SOC and N content due to the long-term application of on-farm available manure. Such condition is frequent in the Po plain, where crop and livestock farms need to valorise the available manure to return N and organic matter to soils [35, 46]. In such condition of high soil fertility, the VR fertilization may not express its potential of reducing the total N amount. On the contrary, this potential was observed in this study: an average of 15 kg N ha^{-1} was saved annually in VR compared to FR. Moreover, VR resulted in comparable yield as no significant differences were detected between the two treatments ($P>0.05$). This outcome suggests that VR was able to balance the differences between heterogeneous area (crop vegetation status) and result in a positive economic opportunity due to the concurrent fertilizer reduction and yield gain. The homogenous areas where similar S-index was estimated with proximal sensor technology reflected the spatial variability of soil properties and soil cover status [46, 47]. This result agrees with [25,49] in which comparable experiments were conducted on maize.

In our study, the S-index, Topdressing N and yield in 2017 and 2018 showed different average yields between the two years. This was observed throughout the region [50] because of severe biotic stress due to European corn borer (Ostrinia nubilalis) and fungal diseases causing the declining rate of crop production. In general, the FR often results in maize grain yield increase in response to increasing N rates if no water stress occurs [25]. However, unlimited N doses is recognize to cause the crop luxury consumption which is a process to avoid in sustainable farming [5,49]. Generally, in the first year the mean maize yield was consistent with the one observed by the farmer in the previous years. Conversely, in 2018 both fixed and variable rate treatments resulted in lower yield than the one observed in previous year. In 2017, VR increased grain yield by approximately 4% compared to uniform supply of the same N amount, even if such an increase was non statistically significant. The high yield in the first year of the experiment was likely to cause a large amount of crop residue production [51], which required more N to start C decomposition processes and therefore a consistent part of the N distributed in the second year was sequestered by the microbial community and not directly available to maize. In 2018, the VR application raised grain yield by 3%. A rational N management associated with good agronomic practices would lead to a better use of organic N and the reductions in N losses resulting in avoiding losses [27] or improvement of crop yield [52]. The soil variability (i.e., SOC content) did not significantly interact with treatments (Figure 4). This result confirms the hypothesis according to which livestock and crop farming are peculiar systems where the large availability of slurry applied at sowing masks any possible effect of SOC variability [35,38]. In this context, the N fertilization rate at topdressing is an ca be effectively reduced leading to economic and environmental sustainability.

The results obtained in the two years of experiment encourage the VR application even though the economic benefit is limited when the estimation is carried out at field scale (~10 € ha^{-1}). However, the application of the VR on the whole farm surface enhances the costs saving (~4500 € ha^{-1}). These findings highlight that this technology is appropriate only for large scale adoption, when no external economic incentives are provided by supporting programs. The net saving computed in this study is consistent with data reported in other studies regarding the variable N rate application on maize [13,53]. At field scale, Jin et al. (2019) reported that VR application on fields with high spatial heterogeneity and varying yields over time could be a potentially effective approach for raising revenues.

In the present study, economic savings were determined without considering any additional costs. Although canopy sensing has been shown to be a potentially profitable technology, it is recognized that more comprehensive approaches that include weather, soil and landscape information would improve the confidence of N recommendations.

5. Conclusions

The present study aimed at evaluating the effectiveness of the variable rate approach in reducing the N fertilization rate at topdressing while avoiding maize yield loss in intensive agricultural farming systems. The case study was a typical livestock and crop farm of the Po plain, where large amount of slurry is applied at sowing. In this context, the reduction of N fertilization rate at topdressing is a goal for enhancing economic and environmental sustainability. The reduction is possible thanks to the application of the variable rate approach, which can be pursued with the proximal optical sensor technology.

This study outcome suggests that the variable rate treatment results in an overall reduction of N amount without causing decrease in maize grain yield. In addition this treatment is responsible for reducing the yield variability within the field.

The study also highlights the economic profitability of the variable rate treatment under the hypothesis to adopt it at farm scale.

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