

Variable rate nitrogen fertilizer response in wheat using remote sensing

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Abstract Nitrogen (N) fertilizer application can lead to increased crop yields but its use efficiency remains generally low which can cause environmental problems related to nitrate leaching as well as nitrous oxide emissions to the atmosphere. The objectives of this study were to: (i) to demonstrate that properly identified variable rates of N fertilizer lead to higher use efficiency and (ii) to evaluate the capability of high spectral resolution satellite to detect within-field crop N response using vegetation indices. This study evaluated three N fertilizer rates (30, 70, and 90 kg N ha⁻¹) and their response on durum wheat yield across the field. Fertilizer rates were identified through the adoption of the SALUS crop model, in addition to a spatial and temporal analysis of observed wheat grain yield maps. Hand-held and high spectral resolution satellite remote sensing data were collected before and after a spring side dress fertilizer application with FieldSpec, HandHeld Pro[®] and RapidEye[™], respectively. Twenty-four vegetation indices were compared to evaluate yield performance. Stable zones within the field were defined by analyzing the spatial stability of crop yield of the previous 5 years (Basso et al. in *Eur J Agron* 51: 5, 2013). The canopy chlorophyll content index (CCCI) discriminated crop N response with an overall accuracy of 71 %, which allowed assessment of the efficiency of the second N application in a spatial context across each management zone. The CCCI derived from remotely sensed images acquired before and after N fertilization proved useful in understanding the spatial response of crops to N fertilization. Spectral data collected with a handheld radiometer on 100 grid points were used to validate spectral data

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from remote sensing images in the same locations and to verify the efficacy of the correction algorithms of the raw data. This procedure was presented to demonstrate the accuracy of the satellite data when compared to the handheld data. Variable rate N increased nitrogen use efficiency with differences that can have significant implication to the N₂O emissions, nitrate leaching, and farmer's profit.

Keywords CCCI · Nitrogen uptake · NUE · Wheat yield · Spatial and temporal variability · Mediterranean environment · Precision agriculture

Introduction

Nitrogen (N) fertilization is an important agronomic practice. More than 50 % of the human population relies on N fertilizer for food production, and its global demand is about 7.3 million tons of N per year (FAO 2008; IFA 2008). Crops that grow in the presence of N deficiency present lighter green leaves, have reduced photosynthetic capacity, which lower yields and lower quality grains.

Dryland environments, where annual rainfall varies between 200 and 600 mm, are particularly susceptible to N fertilizer management because N fertilizer relies strongly on the amount of water stored in the soil, which is uncertain in these environments. Water available to plants is affected by precipitation amount and distribution, soil texture, structure, depth, position in the landscape and infiltration properties (Basso et al. 2011). In Mediterranean environments, farmers normally apply 30 % of the N fertilizer at sowing and the remaining 70 % at the stem elongation phase. If too much N fertilizer is applied early in the season and soil water is available, wheat can use most of the water before anthesis (flowering) leaving the soil dry during grain filling. This results in subsequent low yields and poor grain quality due to the lack of soil water available to fill the grain (Basso et al. 2012).

Precision agriculture allows farmers to take into account field spatial and temporal variability to increase the efficiency of N fertilizer use. Spatial and temporal variability analysis identifies areas within a field that demonstrate homogenous performance so that field can be divided into a number of zones that remain stable over time. N fertilizer can then be applied at a rate that is appropriate for each zone given its characteristics (Basso et al. 2013).

Remote sensing (RS) has been used to detect crop N deficiencies for more than a decade in various crops and in different environments (Blackmer et al. 1996; Daughtry et al. 2000; Gitelson and Merzlyak 1997; Mulla 2013). In-season spatial and temporal variability of N can be quantified using RS techniques over large geographic areas within a short period of time (Eitel et al. 2007; Flowers 2001; Gitelson et al. 1996; Long et al. 2000). In rainfed environments, the presence of both water and N stress can cause confounding effects on the remote estimation of crop N status because water deficiency can mask the crop spectral response for N stress through changes in reflectance patterns in the NIR and middle infrared spectral bands (Rodriguez et al. 2006). Recent studies have shown the ability of a narrow portion of the electromagnetic spectrum (Red-Edge) to detect canopy N content independent of water stress and canopy cover at the time of second N application (Cammarano et al. 2011a, b; Fitzgerald et al. 2006; Mulla 2013; Cammarano et al. 2014). The knowledge of canopy N content along with biomass would give producers more precise

information on the spatial variability of crop N uptake. The study aims at demonstrating this concept.

The hypothesis of this study was that wheat yield responds differently to N fertilizer rates, and that yield response to N may be spatially variable. In simpler words, 90 kg N ha^{-1} could give the same response as 30 kg N ha^{-1} , but the response may change spatially. The objectives of this study were to: (i) demonstrate that properly identified variable rate N fertilizer leads to higher use efficiency, and (ii) evaluate the capability of high spectral resolution satellite to detect within-field crop N response using remotely sensed vegetation indices; (iii) determine if the variability was more driven by the management zone or the N rate.

Materials and methods

Site description and agronomic management

The study was carried out on a 12 ha field located in Foggia, Italy ($41^{\circ}27'47''\text{N}$, $15^{\circ}30'24''\text{E}$; 80 m a.s.l.) during the 2008/2009 and 2009/10 growing seasons. Durum wheat (*Triticum durum*, Desf.), cultivar Duilio, was planted each year in a deep silty-clay Vertisol of alluvial origin, classified as fine mesic Typic, Chromoxerert (Staff 1999). For each growing season, the seedbed was prepared in the first week of September with a minimum tillage (chisel plow) to a depth of 20 cm. Sowing was carried out in both years in the first week of December to a depth of 5 cm with a 17 cm distance between the rows and

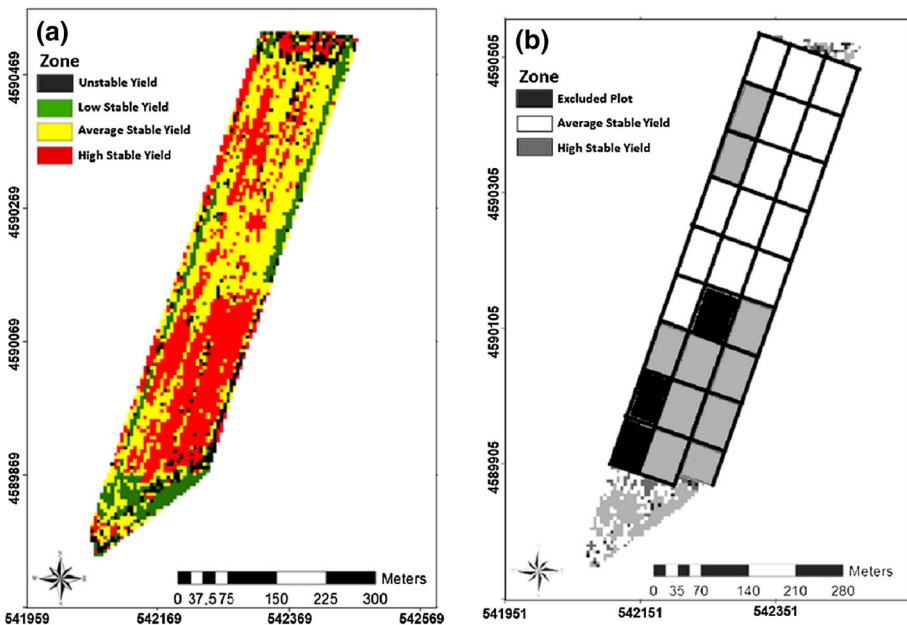


Fig. 1 **a** Spatial distribution of the homogeneous zones. **b** Plots of homogeneous zones, the *black plots* were excluded from the analysis because they had about the same number of pixels of Average (AS) and High (HS) zone

a density of 400 plants m^{-2} . ENTEC 25-15-0 was used as the N fertilizer and the dates for second N applications were 16 March 2009 and 17 March 2010.

Uniform management zones

Three homogenous zones were defined within the 12-ha field using 5 years of yield maps (2005–2010), spatial soil chemical and physical properties, remotely sensed data, and soil electric resistivity as described in detail in Basso et al. (2012, 2013). The three zones identified were a high stable zone (HS) characterized by high and stable yield, a low stable zone (LS) characterized by low constant low yield, and an average stable zone (AS) with average yields (Fig. 1). An Unstable Zone was identified and excluded from any further analysis because it included edges and small area of the field.

The field was divided into 27 rectangular and adjacent plots (50 × 75 m). The bottom portion of the field was excluded because the area was not sufficient large enough to be identified as a plot. No plots were associated to the LS zone because such pixels are located mostly at the bottom of the field, and excluded from the plots analysis along the boundaries of the field. The map of the management zones (Fig. 1) was superimposed on the plot map and each plot was assigned to a zone by applying a majority filter with a difference tolerance of 5 %. The majority filter computed the number of pixels associated to each zone that occurred within each plot, and then assigned the plot to the zone with the greatest number of associated pixels. A plot was assigned to one class only when its number exceeded the others by at least 5 %. The resulting maps are shown in Fig. 1b. However, the majority filter did not fulfill the criterion of tolerance of 5 % for three plots (black plots in Fig. 1b) so they were excluded from the analysis. The SALUS crop simulation model (Basso et al. 2006; Dzotsi et al. 2013; Senthilkumar et al. 2009; Basso et al. 2010) was used

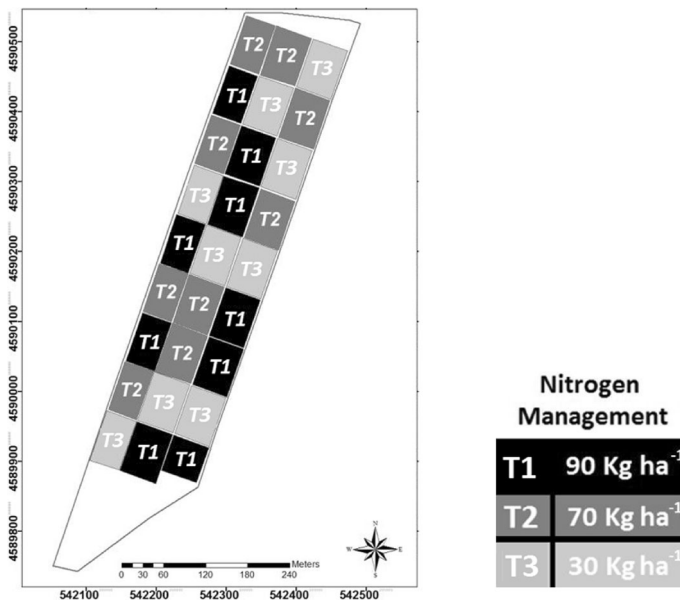


Fig. 2 Spatial distribution of the randomly determined N treatments for the growing seasons 2008/09 and 2009/10

to determine the amount of N fertilizer to apply in each zone and following the same approach as described in Basso et al. (2013, 2012, 2011). The approach consisted of selecting the optimal N rate for each zone that would increase yield without increasing nitrate leaching. The three N rates suggested by the model and applied spatially across field were 90 kg N ha⁻¹ (T1); 70 kg N ha⁻¹ (T2), and 30 kg N ha⁻¹ (T3) (Fig. 2). Fourteen plots were placed in the AS zone, of which, 6 plots had T1, 5 plots T2, and 3 plots T3. The HS zone included 10 plots: 2 plots associated with T1, 2 plots with T2, and 6 plots with T3 (Fig. 1). In this way, each stable zone had different N rates to be compared next to each other. This layout allowed us to determine if the variability was more driven by the zone or the N rate.

Field measurements

Grain yield was georeferenced using a yield monitor system (grain mass flow and moisture sensors). Site coordinates for each yield measurement were determined with a differentially corrected GPS (OMNISTAR signal) Trimble 132 receiver with 5 cm accuracy. The SMSTM software version 3.0 of AgLeader Technology was used to read raw yield data (expressed at 13.5 % dry matter). Yield data were then processed to eliminate outliers with values lower than 500 kg ha⁻¹ and greater than 6000 kg ha⁻¹. Yield maps were obtained by plotting the yield data, at the nodes of a regular grid of 5 m spatial resolution. The yield maps were then georeferenced and projected in UTM WGS 84 zone 33 N.

N use efficiency (NUE) was calculated using the partial balance approach. Inputs to this method consist of grain yield, and the amount of N applied. It is calculated as follows:

$$NUE = \frac{Yield(kgha)}{N_{app}} \quad (1)$$

where N_{app} is the N fertilizer amount.

Remote sensing images

RS spatial maps were obtained from RapidEyeTM satellite images. This platform collects data in five bands of the electromagnetic spectrum: Blue (440–510 nm), Green (520–590 nm), Red (630–685 nm), Red-Edge (690–730 nm) and Near Infrared (760–850 nm) at a spatial resolution of 5 m. Satellite acquisition dates were planned to correspond with the days before and after the second N fertilization. RS data were collected on 10 March 2009, 21 April 2009, 14 March 2010, and 7 April 2010. These dates correspond to 6 and 3 days before and 36 and 21 days after the second N application for the growing season 2008/2009 and 2009/10, respectively. Reflectance measurements acquired with a FieldSpec HandHeld ProTM portable spectroradiometer (Analytical Spectral Devices 2002) on the same dates of satellite images acquisitions were used for calibration of the satellite images. The instrument's spectral range is between 325 and 1075 nm with a 10 nm bandwidth with a field of view of 25°. Readings were taken under clear sky conditions and converted to reflectance by referencing a 99 % Spectralon white panel (Labsphere 1998). All satellite images were georeferenced and coregistered in UTM WGS84 reference system and atmospherically corrected.

Twenty-four vegetation indices (VIs) were calculated from the remotely sensed data. VIs are algebraic calculations of reflectance in the visible and near-infrared portion of the

Table 1 Vegetation Indices used in this study

Single indices		
Structural indices	Formula	
NDVI	$(\text{NIR} - \text{Red})/(\text{NIR} + \text{Red})$	
MTVI	$1.2 \times [1.2 \times (\text{NIR} - \text{Green}) - 2.5 \times (\text{RED} - \text{Green})]$	
MTVI2	$(1.5 \times (1.2 \times (\text{NIR} - \text{Green}) - 2.5 \times (\text{Red} - \text{Green}))) / ((2 \times \text{NIR} + 1)^2 - (6 \times \text{NIR} - 5 \times (\text{Red}^{0.5})) - 0.5)^{0.5}$	
GC	Computed as reported in Maas et al. 2010 [32]	
OSAVI	$(1 + 0.16) \times (\text{NIR} - \text{Red})/(\text{NIR} + \text{Red} + 0.16)$	
Chlorophyll indices		
	Formula	
NDRE1	$(\text{NIR} - \text{RE})/(\text{NIR} + \text{RE})$	
NDRE2	$(\text{RE} - \text{Red})/(\text{RE} + \text{Red})$	
CRM	$\text{NIR}/\text{RE} - 1$	
CGM	$\text{NIR}/\text{green} - 1$	
CVI	$(\text{NIR}/\text{green}) \times (\text{Red}/\text{green})$	
MTCI	$(\text{NIR} - \text{RE})/(\text{RE} - \text{Red})$	
CARI	$(\text{RE} - \text{Red}) - 0.2 \times (\text{RE} - \text{Green})$	
TCARI	$3 \times ((\text{RE} - \text{Red}) - 0.2 \times (\text{RE} - \text{Green})) \times (\text{RE}/\text{red})$	
MCARI	$((\text{RE} - \text{Red}) - 0.2 \times (\text{RE} - \text{Green})) \times (\text{RE}/\text{red})$	
MCARI2	$1.5 \times (2.5 \times (\text{NIR} - \text{Red}) - 1.3 \times (\text{NIR} - \text{Green})) / ((2 \times \text{NIR} + 1)^2 - (6 \times \text{NIR} - 5 \times \text{Red}^{0.5} - 0.5))^{0.5}$	
Combined indices		
NDRE/NDVI		
NDRE2/NDVI		
TCARI/OSAVI		
MCARI/OSAVI		
MCARI/MTVI		
MCARI/MTVI2		
CCCI _{NDVI}	$\text{CCCI} \times \text{NDVI}$	This study
CCCI _{GC}	$\text{CCCI} \times \text{GC}$	This study

electromagnetic spectrum. The indices were divided into structural indices, chlorophyll indices, and combination indices (Table 1). VIs were computed by considering only the inner pixels of each plot, excluding a buffer of 5 m from the computation. Spectral data collected with the handheld radiometer on the 100 grid points were used to validate the spectral data from the RS images in the same locations and to verify the efficacy of the correction algorithms of the raw data. This procedure was presented to evaluate the accuracy of the satellite data when compared to the handheld data.

CCCI is a 2-dimensional index derived from the and NDVI. The CCCI index estimates the chlorophyll content of vegetation and, indirectly, its N content. The index CCCI must be normalized to take account for biomass and to compare the rate of N applied in a specific plot with the crop N uptake.

Statistical analysis

In this study, the crop response to different N fertilizer rates was evaluated indirectly by the response of remotely sensed data acquired before and after the N application, through the

computation of a difference VIs (Δ VI). The Δ VI were obtained by calculating the difference between the VIs acquired before and after N application. The N plots were large enough (about 3750 m²) to be treated as independent replications for statistical analysis using the conventional analysis of variance (ANOVA).

The ANOVA was performed on the mean Δ VI per plot values during both study years (2008/09 and 2009/2010) with a significance value of 0.05 and was performed separately for the two homogenous zones. The ANOVA test was used to evaluate the influence of the homogenous zones on the VIs response to applied N.

In order to compare the Δ VI maps to N rates, a segmentation analysis was performed. This analysis consists of partitioning the Δ VI maps into sub-groups or clusters. Three classes were obtained by minimizing the inner variance of each cluster: Class 1 (low index values as a surrogate for 30 N), Class 2 (medium index value as a surrogate for 70 N) and Class 3 (high index value as a surrogate for 90 N). The confusion matrix was computed to understand if a Δ VI accurately predicts the crop N response for each N treatment. This analysis involves the creation of a matrix with columns representing the instances of predictions (the three classes), while rows represent the instances of the actual class (N treatments). Overall accuracy was calculated as the ratio between the correct prediction and the total number of instances in the matrix (Congalton 1991). Pearson correlation coefficients between Δ VI and harvested yield were calculated for both growing seasons. Pearson analysis, ANOVA analysis, accuracy analysis and VI classification analysis were performed in Matlab software (The MathWorks Inc. 2010). The confusion matrix visualizes the accordance between a predicted variable and an observed (or measured) values, at the same time and location. Each column of the matrix represents the instances in a predicted class, while each row represents the instances in an actual class. The name derives from the fact that it makes it easy to see if the system is “confusing” two classes. In our study, we compared the difference value between the VI before and after the N application with the rate of N applied in a specific plot.

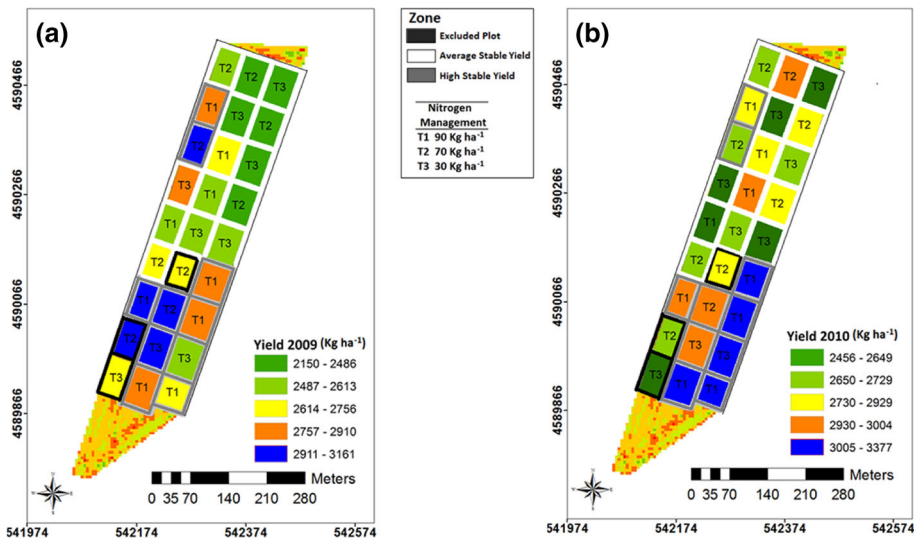


Fig. 3 a Map of mean grain yield for each N plot for the 2008/09 growing season, and b the 2009/10 growing season

Results

Grain yield for both growing seasons is shown in Fig. 3. Overall, wheat yield ranged between 500 and 5000 kg ha⁻¹ with an average yield of 3000 kg ha⁻¹ for the growing season 2008/09 and 3500 kg ha⁻¹ for the growing season 2009/10. The HS zone was more productive than the AS zone during both years (Fig. 3); but the plots showing higher production in 2009 had lower yields in 2010. In the HS zone the 30 and 90 N yields for the growing season 2009/10 had the same yield range, while the AS plots showed high yield variability, except for some plots in 2009 located in the north-east area of the field.

Table 2 Pearson correlation coefficients between vegetation indices difference taken after and before the second N application (Δ VI) and mean yield per plot in 2010

Δ Vegetation indices	Pearson correlation between yield and Δ VI	
	2008/2009	2009/2010
WDVI	0.574	0.602
GNDVI	0.523	0.756
TVI	0.204 ^{n.s.}	-0.309 ^{n.s.}
CRM	0.690	0.682
CVI	0.522	0.642
CGM	0.565	0.658
PVI	-0.550	-0.646
SAVI	0.613	0.669
TSAVI	0.633	0.710
SAVI2	0.639	0.604
MSAVI	0.622	0.590
OSAVI	0.598	0.691
NDVI	0.701	0.707
NDRE	0.690	0.777
NDRE2	0.444	0.305 ^{n.s.}
MTCI	0.710	0.765
CARI	0.245 ^{n.s.}	-0.296 ^{n.s.}
TCARI	-0.398	-0.205 ^{n.s.}
TCARI/OSAVI	-0.670	-0.747
MCARI	0.121 ^{n.s.}	0.294 ^{n.s.}
MCARI2	0.467	0.549
MTVI	0.487	0.529
MTVI2	0.555	0.554
MCARI/OSAVI	0.143 ^{n.s.}	0.277 ^{n.s.}
MCARI/MTVI	0.222 ^{n.s.}	0.293 ^{n.s.}
MCARI/MTVI2	0.231 ^{n.s.}	0.293 ^{n.s.}
NDRE1/NDVI	0.522	0.663
NDRE2/NDVI	-0.433	-0.330 ^{n.s.}
CCCI	0.644	0.663
CCCI*NDVI	0.730	0.820
CCCI*gc	0.624	0.698
GC	0.723	0.745

n.s. not significant at $p > 0.05$

Δ VIs were positively correlated with harvested yield except for PVI, TCARI, TCARI/OSAVI, and NDRE2/NDVI, and 9 other indices that had no significant correlation at $p > 0.05$ (Table 2). The Δ NDVI, Δ GC, Δ MTCI, Δ NDRE and the Δ CCCI_{NDVI} were significantly correlated to harvested yield for both growing seasons with higher overall coefficients among the other indices tested (0.70).

The only significant response of the Δ VIs to N fertilization was found in the AS zone for the growing season 2009/10, while the other zone and growing season were non-significant (Table 3). Among the Δ VIs the CCCI_{NDVI}, MTCI, CCCI_{GC}, NDRE1, and CRM were significantly different (Table 3).

The CCCI_{NDVI} and the MTCI were therefore chosen to build the confusion matrix for the AS zone as well as harvested yield (Table 4). The CCCI_{NDVI} was classified Class 1 (low index value) 4 times for the 30 N and 0 for the other 2 N treatments, but 2 times was classified as Class 2 (medium index value) while it should have been in Class 1. Its overall accuracy was 71 % (Table 4). The MTCI had confounding effects between Class 1 and 2 for estimating 30 N, and Class 2 and 3 for 70 N and had an overall accuracy of 50 %. Grain yield response to N fertilizer can be also used as a proxy for crop response to N fertilization, and its overall accuracy was 65 % with the response for each class being very close to the normalized CCCI_{NDVI} response (Table 4).

The spatial CCCI_{NDVI} maps before and after the N applications are shown in Fig. 2 for the growing season 2008/09 and in Fig. 3 for growing season 2009/10. Before the second N application CCCI- values were lower for the whole field, ranging between 0.052 and 0.092, and between 0.09 and 0.151, for the first and second growing season, respectively (Figs. 4, 5).

Table 3 Analysis of variance (ANOVA) results of the difference between vegetation indices taken after and before the second N application (Δ VI) and the overall accuracy in detecting the amount of N applied for each N treatment

Average stable zone	
Δ Vegetation indices	ANOVA significance level (2009/2010)
CRM	0.032*
CVI	0.521
CGM	0.069
NDRE1	0.026*
NDRE2	0.217
MTCI	0.004*
CARI	0.385
TCARI	0.299
TCARI/OSAVI	0.705
MCARI	0.512
MCARI2	0.053
MCARI/OSAVI	0.502
MCARI/MTVI	0.501
MCARI/MTVI2	0.507
NDRE1/NDVI	0.927
NDRE2/NDVI	0.574
CCCI	0.927
CCCI _{NDVI}	0.007*
CCCI _{GC}	0.034*

* Significant at $p < 0.05$

Table 4 Confusion matrix for the $CCCI_{NDVI}$ and MTCI and their accuracy in discriminating the three different N treatments

	Class 1 (Low VI values)	Class 2 (Medium VI values)	Class 3 (High VI values)	Total
$CCCI_{NDVI}$				
30 N (30 kg N ha ⁻¹)	4	2	0	6
70 N (70 kg N ha ⁻¹)	0	3	2	5
90 N (90 kg N ha ⁻¹)	0	0	3	3
	Overall accuracy = 71 %			
MTCI				
30 N (30 kg N ha ⁻¹)	3	3	0	6
70 N (70 kg N ha ⁻¹)	0	1	4	5
90 N (90 kg N ha ⁻¹)	0	0	3	3
	Overall accuracy = 50 %			
Yield				
30 N (30 kg N ha ⁻¹)	4	2	0	6
70 N (70 kg N ha ⁻¹)	0	3	2	5
90 N (90 kg N ha ⁻¹)	1	0	2	3
	Overall accuracy = 65 %			

The columns represent the indices classification, class 1 (low index value), class 2 (medium index value) and class 3 (high index value). The rows represent the N treatments

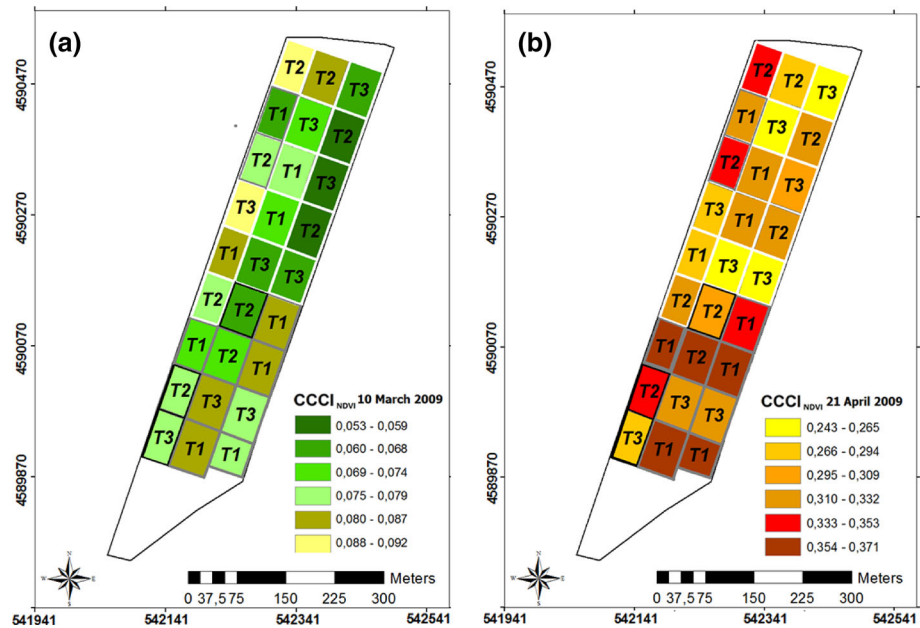


Fig. 4 a Normalized canopy chlorophyll content index ($CCCI_{NDVI}$) maps obtained from RapidEye™ satellite the 10 March 2009 (second N application) and b the 21 April 2009

After N application the $CCCI_{NDVI}$ values increased for all the plots, but, as shown in Table 3, only the AS zone showed significant response to N fertilizer.

The difference between the two $\Delta CCCI_{NDVI}$ and $\Delta MTCI$ readings for 2009/10 (April reading minus March reading) is shown in Fig. 6. The $CCCI_{NDVI}$ had higher difference in the south-west portion of the field in the plots that had the highest yield for the same growing season and lower values in plots that had lower yields (Figs. 6a, 3b). The MTCI showed similar difference values between the N plots, but its overall accuracy was 20 % lower than the $CCCI_{NDVI}$ (Table 4; Fig. 6b).

NUE on average was 30 kg of grains per kg of N applied fertilizer for the 90 N treatment, 45 kg of grains per kg of N fertilizer for the 70 N treatment, and 89 kg of grains per kg of N fertilizer for the 30 N treatment.

Discussions

The Red-Edge is a very narrow portion of the wavelength between the visible (and therefore chlorophyll absorption) and the near-infrared (leaf scattering) (Demetriades-Shah et al. 1990) that has been found to be sensitive to small changes of canopy N. CCCI has been found to be correlated to canopy N content at the time of second N application (Cammarano et al. 2011b; Fitzgerald et al. 2010; Li et al. 2008). In other work, (Cammarano et al. 2011b; Rodriguez et al. 2006) CCCI was normalized with canopy biomass to take into account the dilution of N within the crop as growth and development progress (Justes et al. 1994) In this study, instead of relating CCCI with crop biomass, we normalized CCCI with NDVI which is used here as a surrogate for biomass ($CCCI_{NDVI}$).

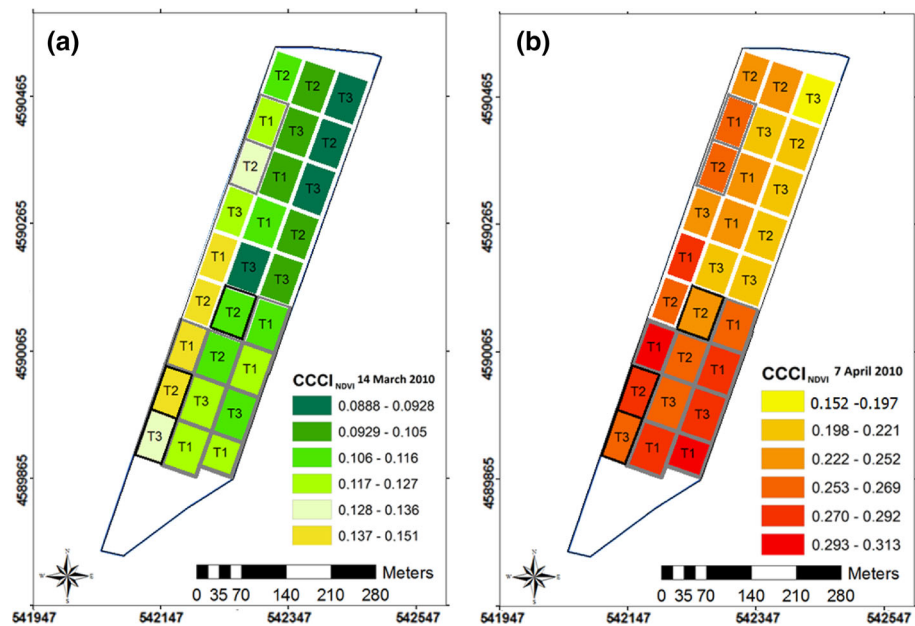


Fig. 5 a Normalized canopy chlorophyll content index ($CCCI_{NDVI}$) maps obtained from RapidEye satellite the 14 March 2010 (second N application) and b the 7 April 2010

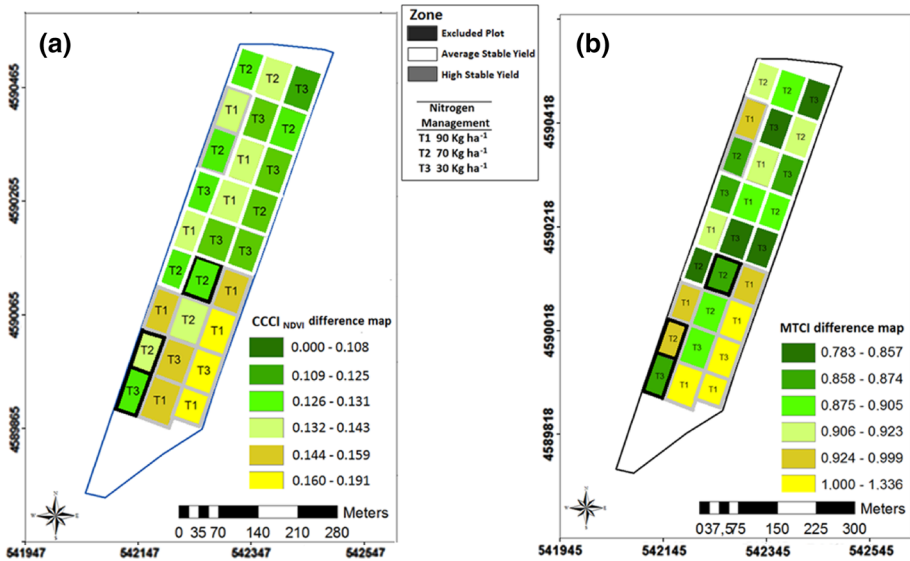


Fig. 6 **a** Difference map between the CCCI_{NDVI} taken the 7 April 2010 and 14 March 2010 and **b** difference map between MTCI taken the 7 April 2010 and March 2010

Several studies demonstrated (Baret and Guyot 1991; Wiegand et al. 1990) that NDVI is related to biomass by an exponential relationship which saturates at higher values of biomass. In this study, the vegetation index is applied at a time when biomass values are not high enough to saturate the NDVI. Therefore, CCCI_{NDVI} was developed into take into account the effects of canopy cover and N dilution within the crop (Justes et al. 1994).

Remotely sensed indices that included the Red Edge wavelength were able to discriminate wheat response to N fertilizer rate, but only for the growing season 2009/10. The lack of response of ΔVIs to N treatments in 2008/09 is related to the high amount of rainfall during the growing season, as previously demonstrated by Basso et al. (2013, 2012). In December there was 116 mm of rain which caused water logging in the upper right zone of the field moreover 100 mm rain fell between the second N application (16 March) and the acquisition of RS imagery. This high amount of rain in a short time might have caused high N leaching, especially for the 70 and 90 N treatments. A negative correlation between grain yield and growing season rainfall was found (Basso et al. 2012) due to water logging as a result of position in the landscape. That is why significant correlations were observed for the growing season 2009/10 when the rainfall was lower and better distributed in time as compared to the previous growing season.

The reason for the lack of ΔVI response in the HS zone for both growing seasons is found in the relationship between soil properties and growing season rainfall as explained in Basso et al. (2013). The study showed that there is no significant relationship between grain yield and N rates in the HS zone. The HS zone benefits little from high N rates because the high content of organic matter (>2 %) and deeper exploitable root zone allow more rainfall to be stored during the fallow period.

Grain yield response to different N rates within each management zone depends on the amount of fallow and growing season rainfall as well as the interaction between rainfall

and spatial distributions of soil properties within each zone. Rainfall in the 2008/09 growing season was 204 mm higher than the 2009/10 season, therefore the benefits of stored water prior sowing (fallow rain) were less evident (Basso et al. 2013). Short (July–September) fallow rainfall was higher in 2009/10 than the previous growing season, thus the benefits of stored water prior sowing were beneficial in obtaining a low yield variability within the field (Basso et al. 2013).

The AS zone of the field does not respond to short or long (July–November) fallow rainfall because its soil physical properties and yield were more sensitive to N rates (Basso et al. 2012). The soil has higher clay content in the first 50 cm over a compacted layer of soil and stones as the central transect was an old creek bed (Basso et al. 2012). In addition, the upper right area had a high electrical resistivity through the soil profile, high silt and coarse sand fraction and a descending slope in the direction of the upper right corner of the field that affected crop response to N fertilizer (Basso et al. 2012).

The $\Delta\text{CCCI}_{\text{NDVI}}$ map for the crop response to N treatments demonstrates that high values of this difference are associated with high values of grain yield later in the season (Figs. 3b, 6a). This can have important applications in order to evaluate the efficiency of the second N application. Within each uniform management zone there is an optimal amount of N that should be applied to optimize grain yield. Remotely sensed maps obtained before and after N fertilization are useful tools in understanding the spatial response of crops to N fertilization and provide an understanding of how management zones respond to environmental factors. The NUE was higher in the 30 N treatment. These differences have significant implications for N_2O emissions and nitrate leaching, as well as the overall profit of the farmer. By simply adopting the IPCC emission factor, the N_2O emissions of the VRN were reduced from 0.9 kg of N_2O per year to 0.3 kg of N_2O per year without significantly reducing yield. Variable N fertilizer showed that NUE can significantly be enhanced if the proper N fertilizer is applied spatially in the right amount.

The adoption of VRN remains low in this environment as well as others across the world, despite the obvious economic and environmental benefits of this management practice. This study demonstrated that the long-term assessment of spatial and temporal variability of crop yield through historical analysis of yield maps is crucial to determine whether N rates can have a positive response on grain yield. We showed that despite the additional N in T1 (90 kg N ha⁻¹), yield did not increase in areas where N was sufficient and in areas where other factors other than N dominated, the lower amount of T3 (Kg N ha⁻¹), did not penalize the yield when compared to higher N rates.

The use of a crop simulation model plays a critical role in the selection of the N fertilizer management and VRN as previously demonstrated by Basso et al. (2012, 2013). This study differs from others in the sense that the VRN benefits were demonstrated with field data and not just by crop model simulations. As far as we are aware of, this is one of the first studies to compare VRN impact on yield over space and time.

The advantages of using a crop model to select VRN across a field lies in the fact that N fertilizer dynamics are highly affected by other factors rather than just soil N or yield goal. To tackle the complexity of the problem, a systems approach is necessary to understand, simulate and predict the impact of N fertilizer application over space and time on crop yield. Furthermore, this study confirms that N response is field and season specific and can vary within a field. Side-by-side comparisons illustrated how much of the variability was due to inherent soil and weather conditions, versus the amount of N applied.

Conclusions

In this field study, we demonstrated that MTCI and CCCI are able to discriminate crop response to N fertilizer rates. The relative response of ΔVIs show that Red-Edge based VIs, such as the MTCI and CCCI, perform better in detecting the crop response to N applications than other VIs. The negative response observed in one growing season is a function of the rainfall amount within the growing season, while the negative response within a uniform management zone is due to the interaction between soil properties and rainfall.

The detection of crop response to N application based on spatial soil physical and chemical properties and on the temporal crop response (detected through the Red-Edge VIs) can have important practical outcomes in assessing the efficiency of the second N application and the response of crops to N fertilizer. Variable N fertilizer showed that NUE can significantly be enhanced if the proper N fertilizer is applied spatially in the right amount.

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