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REVIEW ARTICLE

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Abstract Conventional farming has led to extensive use of chemicals and, in turn, to negative environmental impacts such as soil erosion, groundwater pollution and atmosphere contamination. Farming systems should be more sustainable to reach economical and social profitability as well as environmental preservation. A possible solution is to adopt precision agriculture, a win–win option for sustaining food production without degrading the environment. Precision technologies are used for gathering information about spatial and temporal differences within the field in order to match inputs to site-specific field conditions. Here we review reports on the precision N management of wheat crop. The aims are to perform an investigation both on approaches and results of site-specific N management of wheat and to analyse performance and sustainability of this agricultural practice. In this context, we analysed literature of the last 10–15 years. The major conclusions are: (a) before making N management decisions, both the measurement and understanding of soil spatial variability and the wheat N status are needed. Complementary use of different sensors has improved soil properties assessment at relatively low cost; (b) results show the usefulness of airborne images, remote and proximal sensing for predicting crop N status by responsive in-season management approaches; (c) red edge and near-infrared bands can penetrate into higher vegetation fraction of the canopy. These narrowbands better estimated grain yield, crop N and water status, with R^2 higher than 0.70. In addition, different hyperspectral vegetation indices accounted for a high variability of 40–75 % of wheat N status; (d) various diagnostic tools and procedures have been developed in order to help wheat farmers for planning variable N rates. In-season adjustments in N fertilizer management can account for the specific climatic conditions and yield potential since less than 30 % of spatial variance could show temporal stability; (e) field studies in which sensor-based N management systems were compared with common farmer practices showed high increases in the N use efficiency of up to 368 %. These systems saved N fertilizers, from 10 % to about 80 % less N, and reduced residual N in the soil by 30–50 %, without either reducing yields or influencing grain quality; (f) precision N management based on real-time sensing and fertilization had the highest profitability of about \$5–60 ha^{-1} compared to undifferentiated applications.

Keywords Sustainable agriculture · Soil and crop variability · Wheat nitrogen status · Sensor-based assessment · Precision nitrogen fertilization

Contents

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1 Introduction

Next decades are likely to see the primary resources (i.e. soil, water and atmosphere) progressively worsening due to the excessive use of agro-chemicals, in the agricultural intensification context, to enhance food production. Conversely, sustainable agriculture could preserve these resources for the expected world population of 8.3 billion in 2030, achieving both high yields and acceptable environmental impact (Pitman and Läuchli 2002; Tilman et al. 2002). Sustainable agricultural development could preserve or improve land productivity, water availability and plant genetic resources (FAO 1995). Therefore, sustainability of agricultural practices has become a critical issue in farm management that is generating widespread interest (Abbott and Murphy 2007; Komatsuzaki and Ohta 2007; Montemurro et al. 2008). It can be referred to practices economically and environmentally viable that meet current and future society needs for food and feed, ecosystem services and human health (Diacono and Montemurro 2010; Lichtfouse et al. 2009).

Pierce and Nowak (1999) investigated the precision agriculture (commonly also known as 'precision farming' or 'site specific management') as a win–win solution both for improving crops yield and environmental quality of agriculture. This approach applied to wheat crop fertilization is the context of our review.

Nitrogen (N) is the largest agricultural input used by wheat farmers. They generally over-apply it because they want to ensure enough N for crop requirements increase. Fields spatially differ in crop requirements but are mostly managed as homogenous units, often receiving a single excessive uniform rate of N. The excessive use of N may cause weed problems and could result in an increased risk of lodging, delayed maturity and greater wheat susceptibility to diseases (Skjødt 2003). Moreover, this practice leads to greater N loss to ammonia volatilisation, denitrification, runoff and leaching (Montemurro 2009). To minimize potential N losses, N fertilizer should be applied according to the time and the needs of the crops. In addition, to solve these problems, farmers could have recourse to variable-rate N fertilization, accounting for the spatial patterns of N fertility, as suggested by precision agriculture applications. Precision agriculture is a set of methods and modern technologies introduced primarily in the soils of North America and, subsequently, spread in other countries with good infrastructure resources in agriculture (Ammann 2009; Seelan et al. 2003). It includes the use of information technology to tailor different inputs, to achieve the required outcomes and to monitor the results (Bongiovanni and Lowenberg-Deboer 2004).

According to Stafford (2000), the first application of precision agriculture was the 'on-the-go' fertilizer spreading and distribution system described by Fairchild (1988). It is interesting to note that fertilization improvement has always been considered a key factor in precision agriculture studies (Fiez et al. 1994; Mulla et al. 1992). Different level of inputs (e.g. fertilizers) is matched to localized spatial and temporal soil properties and crop requirements. Therefore, site-specific management generally consists in the management of agricultural crops at a spatial scale smaller than that of the whole field (Cassman 1999; Plant 2001). Two main general benefits of such methods could be synthesized as: (a) the economic margin from crop production may be increased by inputs reduction; (b) under or over fertilization (with risk of environmental pollution and degradation) can be avoided. These benefits can be obtained by using tools and sources of information continuously updated, such as: (a) global positioning system (GPS; Long et al. 2000) to record position information of within-field measurements (Fig. 1). It has recently been integrated with Inertial Navigation System technology in the algorithm known as 'AhrsKf' (Li et al. 2012). This algorithm has been introduced for the automated agriculture vehicle guidance and control, fulfilling the accuracy, reliability and availability requirements; (b) geographic information systems (GIS) to display, combine and manipulate spatial maps of field characteristics (McBratney et al. 2003). Recently, the Science Applications International Corporation introduced GeoRover® Mobile, a software solution which enables the collection of GIS data in the field without network connectivity (SAIC 2011); (c) soil and plant radiometric sensors for remote and proximal sensing (Adamchuk 2011; Humphreys et al. 2004; Fig. 2a, b); (d) yield monitoring devices and variable-rate technologies for site-specific inputs application (Johnson et al. 2003; Plant 2001; Fig. 3). However, it is well-known (Robert 2002) that precision agriculture is not just the use of new technologies, but it is rather an information revolution that results in a more precise and sustainable field management.

According to Pierce and Nowak (1999), the success of site-specific farm management can be determined by the

Fig. 1 Sampling location (point coordinates) and elevation can be recorded by using a differential global positioning system (DGPS, HiPer® 27 Pro, TOPCON). It enhances the quality of location data gathered using global positioning system (GPS) receiver. The figure shows base station of the instrument positioned in a wheat field

degree to which the spatial variability of factors affecting crop performance is temporally stable. The concept of site-specific management needs to be validated by testing the null hypothesis of precision agriculture, i.e. 'given the large temporal variation evident in crop yield relative to the scale of a single field, then the optimal risk aversion strategy is uniform management' (Whelan and McBratney 2000). Therefore, the adoption of differential treatments could be based on repeatable evidence of the rejection of null hypothesis. This might be obtained by researching the value of managing spatial variation in the light of temporal one.

Several challenges (socio-economical, agronomical and technological) could still limit the use of precision agriculture practices. This topic has been reviewed by Robert (2002) who highlighted that implementation of precision agriculture on farm generates additional costs, requires new skills and needs to improve and develop more precise application technologies. On the other hand, there is a new trend in ecological and organic agriculture for precision agriculture applications often with a less technological touch (Ammann 2009). Also, a considerable number of studies have demonstrated that the advantages outweigh the disadvantages when precision agriculture practices are used in cereal crop systems. This outcome appeared as particularly true in the case of site-specific fertilization practices (Bocchi and Castrignanó 2007; Li et al. 2009; Singh et al. 2011; Tubaña et al. 2008).

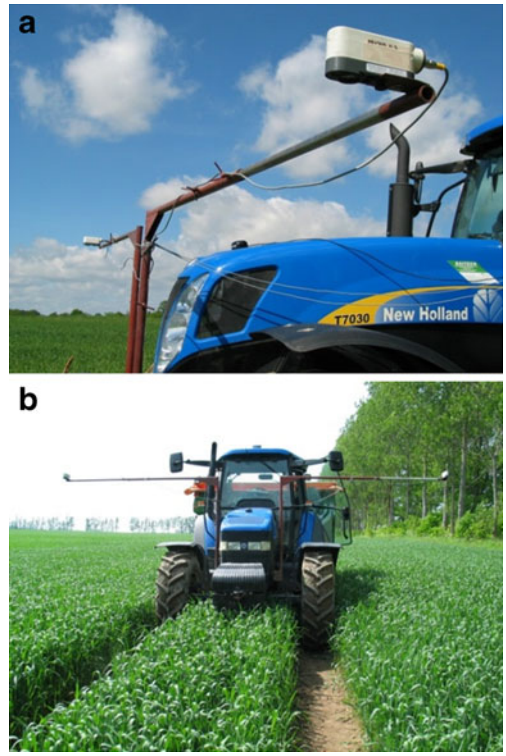

Fig. 2 **a**, **b** Active-light proximal sensors can be used to monitor wheat nitrogen status. These sensors could help farmers to plan variable nitrogen application rates. **a** This shows a particular of the system developed for using two Crop Circle™ (Holland Scientific, Lincoln, NE) sensors, while **b** shows an example of use of these sensors in a wheat crop in Poland (from Samborski S., Department of Agronomy, Faculty of Agriculture and Biology, Warsaw University of Life Sciences)

The precision agriculture techniques applied in cereal systems have been studied in different researches. However, to the best of our knowledge, there are no published review papers which focused the site-specific fertilization of wheat. The present manuscript attempts to address this issue by referring to more recent literature (particularly that of the

Fig. 3 Implementation of variable-rate technology for site-specific nitrogen application in a winter wheat field in southern Germany (From: Schmidhalter U., Life and Food Sciences Center Weihenstephan of the Technische Universität München)

last 10–15 years). The aims of our study are: (a) to perform an investigation on approaches and results of site-specific N management of wheat and (b) to analyse the sustainability of this modern agricultural practice.

It is common knowledge that the basic components of precision agriculture are: (a) soil–plant system variability assessing, (b) managing such a variability and (c) evaluating efficiency and efficacy of the procedures applied (Bocchi and Castrignanó 2007; Pierce and Nowak 1999). Within the framework of these criteria, the topic of spatial and temporal variability assessment is defined in section 2 of this review, whereas section 3 outlines the site-specific fertilizers application strategies, to manage variability in wheat fields and section 4 investigates the sustainability of such precision N management. Some concluding remarks on challenges and future research needs are drawn in the final section 5.

2 Recent advances in the assessment of wheat field variability

The measurement and the understanding of field variability are the first steps of the precision agriculture approach, which can become more profitable as factors underlying spatial variability of crop growth and yield can be assessed (Fitzgerald et al. 2010; Vrindts et al. 2003). In any case, it is necessary to identify those processes and scales of variation of crop performance that are most critical, given the difficulty of modelling every variation and its effects (Lark 2001).

As regards the soil, it varies spatially in physical, biological and chemical characteristics. Jenny (1941) was the first author who found that variability in such characteristics derives from the following soil-forming factors: (a) climate, (b) organisms, (c) relief, (d) parent material and (e) time. Moreover, several studies have documented that the spatial distribution of soil properties differently interacts with weather conditions and farming practices, so determining both a within-field spatial variation in crop growth and productivity potential variability from year to year (Batchelor et al. 2002; Mzuku et al. 2005). Factors influencing yield variability in a field are those over which farmer has less control (e.g. topography and climate) and others more easily controllable, such as soil structure, available water, nutrient contents, weeds and pests (Godwin and Miller 2003). In particular, Whelan and McBratney (2003) indicated that in dry-land environments, the spatial variability of different factors may affect within-field variability of cereals yield. These factors are those that contribute to nutrient supply, soil moisture and soil–water movement.

The measurement of variability in wheat productivity by yield monitoring is a way to infer soil variability. The yield-monitoring combine harvesters can provide yield maps by means of their vehicle positioning system integrated with a yield recorder (Fig. 4). The maps document the spatial variability of wheat yield, but they do not give information on the reasons of the observed variability (Johnson et al. 2003). To explain such variability, other factors must be taken into account, i.e. permanent features of the field (soil type, topology, etc.) and variable features (management history and the weather). Therefore, sampling and analysing soil to assess field variability are needed before designing variable-rate fertilization, as well as irrigation or sowing (Iqbal et al. 2005). Among the most critical aspects of sampling, there is soil samples collecting with adequate spatial density at the proper depth and during the appropriate time (Adamchuk et al. 2004). Random soil sampling even at high density (Stewart et al. 2002) and soil cores extracting and analysing from points in the field within a grid (Shahandeh et al. 2011) are commonly used to assess soil characteristics. Composite sampling to obtain the field average of a soil property is used to guide uniform applications and management at the field level. On the other hand, the site-specific inputs management requires the spatial distribution of soil information (Havlin and Heiniger 2009). A mathematical scheme must be used to interpolate values between sample points with the objective of constructing a map which indicates the values of soil parameters at all locations in the field (Plant 2001). Therefore, after recording the position information of each soil measurement by a GPS, the network of points can be interpolated and mapped by using geostatistical procedures (e.g. kriging, multivariate factorial kriging, kriging with an external drift, etc.), non-geostatistical interpolators (e.g. nearest neighbours, splines and local trend surfaces, regression tree, etc.) or combined procedures (e.g. trend surface analysis combined with kriging, linear mixed model, etc.). Actually, there are large numbers of

Fig. 4 Precision harvest of durum wheat in southern Italy. The data of yield are recorded with a *John Deer* combine equipped with a yield monitor system (with grain mass flow and moisture sensors)

spatial interpolation methods that could alternatively be used as reported in a survey by Li and Heap (2008). Sampling, analysing and interpolating data can then be repeated over time to estimate temporal variability of sampled variables (Diacono et al. 2012).

The process of modelling measured spatial variation is commonly used to assess the spatial dependence between sampled soil and crop attributes. This is the foundation of soil geostatistics and it is based on the concept that spatial variation of soil is not random, but it reveals a structured variance, and the variability decreases as distance diminishes between points in space (Iqbal et al. 2005; Isaaks and Srivastava 1989). Castrignanò et al. (2012) pointed out that multivariate geostatistics can improve the estimation of one variable by taking into account the spatial relationships among variables. McBratney et al. (2003) supported this concept highlighting that soil could be better predicted by using co-kriging of denser sets of secondary variables (e.g. remote sensing data). These variables must be correlated with the primary variable at neighbouring locations. Indeed, since precision agriculture technologies were introduced, the research has been aimed to develop new techniques to collect more useful data to determine within-field variability. Among these techniques, the approach of sensor-based gathering of crop and soil data has had the widest use (Babar et al. 2006; Thomason et al. 2011; Wong and Asseng 2006). The subject has been reviewed by Adamchuk et al. (2004). They reported as electrical and electromagnetic sensors have been widely used for giving valuable information about field heterogeneity. It is relevant to note that this kind of information is more intensive and generally cheaper compared with conventional sampling of soil or crop variables and their analysis (Adamchuk et al. 2011).

Therefore, starting from a brief overview on the sensor-based diagnosis of soil variability, in the next subsections the past and current strategies for estimating wheat N status are more deeply investigated. This last assessment represents the important basis for the in-season recommendations of N rate.

2.1 Sensor-based assessment of soil variability

As for soil data gathering, geophysical methods provide indirect fine-scale and continuous information on various physical properties both of topsoil and subsoil. The most commonly used methods for agricultural purposes are: electromagnetic induction, electrical conductivity/resistivity based on rolling electrodes and ground penetrating radar (De Benedetto et al. 2012; McBratney et al. 2003). Ground conductivity meters are typically employed for obtaining apparent electrical conductivity measurements. These measurements are usually related to different physical and chemical soil properties, such as: water content, clay, soluble salts, soil cation exchange capacity and soil organic matter (Humphreys et al. 2004).

In Australia, spatially detailed soil maps were obtained from electromagnetic induction sensors and were combined with the APSIM wheat model (Wong and Asseng 2006). This combination allowed to support N management since the main causes of spatial variability in wheat yield were determined. The method could aid in fertilization planning because it also indicated the field locations which may be affected by N loss through nitrate leaching. Actually, in some circumstances, the electromagnetic induction sensors could not be able to distinguish between contrasting soils encountered across some fields even if a calibration is always needed. In a recent study, Castrignanò et al. (2012) demonstrated that the complementary use of different geo-electrical sensors in a multi-sensor platform can overcome the limits of the electromagnetic induction in order to distinguish among contrasting soils. This approach was applied on wheat in a 80-ha field trial in Western Australia. Sensor fusion has the potential to improve the measurement accuracy of agronomically important stresses in the crop, integrating canopy reflectance sensing with other sensors which measure soil parameters (Adamchuk et al. 2011; Fig. 5). Moreover, the described methods for automatic information gathering on field should be jointly combined with traditional soil sample analysis and crop observations to give better insight to within-field temporal and spatial variation. Several authors (Castrignanò et al. 2012; Johnson et al. 2003; Vrindts et al. 2003) supported this hypothesis when they determined soil properties by chemical and textural analysis of mixed samples, complemented with soil or canopy reflectance measurements and maps as additional information source.

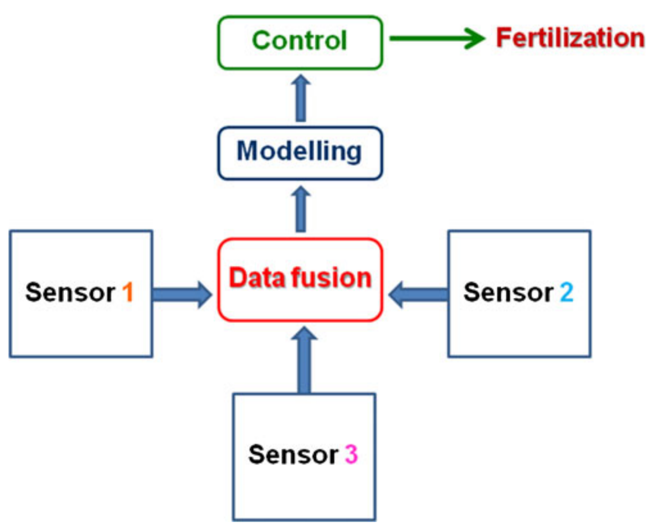

Fig. 5 Sensors fusion can integrate canopy reflectance sensing with other sensors. This fusion is important for the acquisition of data about water stress in the plants and water and nitrogen available in the soil to target fertilization to specific field conditions

According to Pierce and Nowak (1999), the deficiencies and excesses of N can occur within the same wheat field and during the same year due to overall spatial variability. As a consequence, making precision N management is much more difficult than phosphorous and potassium management. Although the assessment of soil properties variability is crucial, since the proper N fertilization strategy should supply N at the right time, the evaluation of the wheat N status is a matter of priority.

2.2 From past to current strategies for estimating plant nitrogen status

The methods for making N fertilizer recommendations to crop are commonly based on plant N status testing. Different methods have been used to obtain information about wheat N status by plant analysis and, indirectly, by soil analysis. The soil samples analysis consists of an evaluation of mineral N remaining in the soil as a reserve for the crop after winter leaching and of organic form which will be slowly mineralized in the plough layer (Houlès et al. 2007). Nevertheless, the activity of microorganisms involved in the mineralization process in the soil is particularly restricted under too wet or too dry conditions. Since the weather can be difficult to predict, also predicting both mineralization of organic forms of N and other nutrients into plant available mineral forms and the wheat demand remains a challenge (Walley et al. 2002). It is the case particularly of rain-fed regions of the world, which are characterized by limited and unpredictable rainfall during the growing season, making difficult to synchronize fertilizer application with wheat demand, available N and water supply (Basso et al. 2010). Walley et al. (2002) suggested that a solution for predicting wheat N requirements can be to combine soil N availability indices with additional information about field scale variability. In fact, the authors observed that less than 40 % of the yield variability can be explained merely by soil indices.

To make fertilizer recommendation, the alternative widespread method consists in plant analysis. The plant N content depends on several factors i.e. the N and water contents of soil, mineralization of crop residues, root growth and efficiency of N uptake by plants (Basso et al. 2009). Typically, laboratory tests are performed on fresh plant organs or dry plant material to determine crop N status. There are methods for measuring the nitrate content of the sap at the base of the stem (Liu et al. 2003) and those giving relative measurements of leaf N content by using different hand-held chlorophyll meters, such as SPAD-502 (Konica Minolta, Tokyo, Japan) and Hydro N Tester (Yara International ASA, Oslo, Norway; Ladha et al. 2005; Montemurro et al. 2006). As reported by different authors, in wheat SPAD readings are commonly determined in one point at mid-length on fully expanded leaves (Mistele and Schmidhalter 2008; Montemurro et al. 2007). When sunlight reaches the crop, part of the light energy is transmitted through the crop canopy and another part is reflected from the canopy. The readings are adsorbed red light (at 650 nm) through the leaf blade, compared with transmittance of near-infrared light (at 940 nm) at which no absorption occurs. Using these two transmittances, the hand-held chlorophyll meter calculates a numerical value which is linked to the chlorophyll content of the leaf. In fact, light reflected by vegetation in the visible region of the electromagnetic spectrum is predominantly influenced by chlorophyll pigments in the leaf tissues, which have been found to relate to the N concentration (Haboudane et al. 2002; Rodriguez et al. 2006). In particular, chlorophyll-content reduction can increase light reflectance in the visible range (400–700 nm). Furthermore, Cartelat et al. (2005) proposed the use of leaf polyphenolics content to indicate crop N status due to their absorption features in the visible and in the UV part of the spectrum. The authors used the leaf-clip device Dualex® (FORCE-A, Orsay, France) on two winter wheat cultivars grown with different levels of N supply. Under low N availability, the crop secondary metabolism is activated and the polyphenolic substances content increased. The findings of this research showed that the ratio between chlorophyll and flavonols contents can be measured by the proposed non-destructive optical method for the assessment of crops N status. More recently, in a research on wheat, Martinon et al. (2011) used the new proximal optical sensor Multiplex® (FORCE-A, Orsay, France). Due to the utilization of fluorescence, the sensor can be used to monitor crop canopy density and crop N status, optimizing management of agricultural technical practices. Fluorescence-based technologies allowed for highly sensitive plant N status information, independently from soil interference, leaf area or biomass status (Tremblay et al. 2011). According to Tremblay et al. (2011), these technologies allow the probing of both the chlorophyll status and other physiological parameters, which react to N fertility conditions. Schächtl et al. (2005) reported exponential regression between laser-induced chlorophyll fluorescence measurements and wheat N uptake.

Unfortunately, most of the plant-based analyses mentioned above are generally time-consuming, and only a few plants can be sampled inaccurately representing spatial variation of crop N status in-season and within the entire field (Fitzgerald et al. 2010). As Miao et al. (2011) suggested, the commonly adopted prescriptive approach to fertilizer management could be rightly replaced by a responsive in-season management approach. This approach is mainly based on in-season diagnosis of crop growth, N status and demand by means of spectral devices. In fact, the reflectance characteristics of plants are related to the physiological status and crop growth (Erdle et al. 2011). Therefore, Miao et al. (2011) made an important observation since modern non-contact sensors to spatially diagnose canopy N status have received increasing attention to match N supply with wheat requirement at the correct rate, place and time (Fitzgerald et al. 2006a; Li et al. 2010).

2.3 Use of sensors to spatially diagnose in-season crop conditions

Sensors on aircraft or satellite can collect the reflected electromagnetic radiation from the canopy at small scales of space and time. These remote sensors can assess changes in growth environments from location to location and have the potential to give a synoptic view of an entire field (Song et al. 2009).

Wood et al. (2003) demonstrated the possibility of using airborne data in wheat production. Calibrated aerial digital photography was used to assess shoot population and canopy green area index. Nitrogen application rates were then varied below or above the planned amount where growth was above or below the target, respectively. In North Carolina, Sripada et al. (2007) obtained aerial color infrared photographs at growth stage 30 (Zadoks et al. 1974) before N applications over a wide range of soil conditions. The authors reported that when winter wheat biomass at this growth stage was more than 1,000 kg ha^{-1}, the best predictor of optimum N (R^2 of 0.85) was a quadratic model. This useful model was based on measured wheat radiance relative to mean radiance in the green band for a non-limited N reference area.

As for satellite, Quickbird is an example of a commercial one that records high-resolution imagery globally with on-board sensor that has a multispectral scanner at a 60- and 70-cm spatial resolution (Song et al. 2009). On the other hand, the Landsat series have a spatial resolution of 30 m and can provide reflectance data from different spectral bands. Lobell et al. (2003) successfully used Landsat data in yield estimation of wheat. An innovative approach applied the multi-temporal Landsat Thematic Mapper satellite images and the Envisat Advanced Synthetic Aperture Radar satellite images to monitor wheat crop condition and forecast both grain yield and protein content (Liu et al. 2006). Other results confirmed the usefulness of remote sensing techniques (as broadband RapidEye™ data) for predicting wheat N status (Eitel et al. 2007). Blondlot et al. (2005) focused on Farmstar, a commercial remote sensing service which use space-based remote sensing and airborne images for the N fertilization management of wheat. The first step was the retrieval of biophysical and biochemical parameters of the crop canopy from reflectance data. Then these parameters were linked to agronomic indicators (i.e. N absorption). Such indicators can be used as input for existing agronomic models helping the N fertilization recommendations.

Both passive and active-light proximal sensors can also be used to collect the reflected radiation. The passive non-contact sensors depend on sunlight, whereas the active sensors, with their own light sources, enable assessing crop status irrespective of ambient light conditions (Samborski et al. 2009). The most commonly used commercial proximal sensors are: (a) the passive Yara N-Sensor®/FieldScan (Yara International, ASA, Oslo, Norway) and FieldSpec® Portable Spectroradiometer (ASD Inc., Boulder, CO, USA) and (b) the active sensors GreenSeeker® (N Tech Industries, Inc., Ukiah, CA) and Crop Circle™ (Holland Scientific, Lincoln, NE). These sensors were used in different researches on wheat crop (Erdle et al. 2011; Havránková 2007; Singh et al. 2011; Xavier et al. 2006). According to Samborski et al. (2009), the problem is that any diagnostic feature of vegetation will be subjected to confounding factors so that preliminary calibration for different genotypes, plant growth stages and environmental conditions is strongly required.

2.3.1 Use of crop status indices

Spectral data collected by sensors can then be converted into measurements of canopy green area by calculating several vegetation indices based on simple operations (e.g. ratios and differences) between the reflectance at given wavelengths (Aparicio et al. 2000). The most widely known normalized difference vegetation index (NDVI) is determined by dividing the difference of reflectance in the red (670 nm) and near-infrared (780 nm) by the sum of reflectance at these two wavebands (Drissi et al. 2009; Tucker 1979). Green vegetation has a NDVI more than 0.5 while dead vegetation, generally, has a NDVI less than 0.3 (Dang et al. 2011). Therefore, canopy sensing enables detailed, spatially referenced indirect measurements of chlorophyll content and can provide rapid identification both of wheat N status and water stress. According to Tilling et al. (2007), the identification of these growth conditions could help to target the N fertilizer to areas with sufficient plant available water. In addition, Christensen et al. (2005) introduced the prediction of wheat N status under the influence of water deficiency using spectral and thermal information. This study showed that the identification of water deficiency areas in a given field is crucial before predicting the actual N content. On the other hand, Rodriguez et al. (2006) showed that water stress was a confounding factor when trying to draw empirical predictive relationships between the spectral indices and the shoot N content of wheat. To overcome this problem, the authors developed a nitrogen stress index, which adjusted shoot N content for plant biomass and area. In this way, it could take into account the environmental conditions that affect growth (e.g. crop water status).

Also the effect of soil reflectance, besides water stress, is one of the recurring problems in the assessment of canopy N with sensor-based vegetation indices, particularly in rain-fed environments (Basso et al. 2009). Soil has reflectance spectra in the 1,100–2,500 nm range and its absorption features are the result of overlapping bands from different mineral components and organic matter (Ladoni et al. 2010). Broge and Mortensen (2002) highlighted that at early growth stages, when the wheat canopy is not closed, soil background exposure reduces the reliability of using reflectance for the estimation of crop N status. To adjust for different brightness of background soil, the most commonly used index is the soil-adjusted vegetation index, which uses a single constant to minimize soil interference effects changing with differences in percent canopy closure (Havránková 2007). In any case, the crop growth stage is an important parameter that has to be considered when using sensors to investigate in-season crop conditions.

To evaluate crop N requirements, another diagnostic tool is the nitrogen nutrition index. This is calculated as the ratio between the measured and the critical N content, which indicates the minimum N content required for the maximum biomass production. The index is greater than one in canopies in an ample N state and less than one in ones lacking N (Mistele and Schmidhalter 2008). An integrated approach consists in calculating the nitrogen nutrition index by using remote sensing (Fitzgerald et al. 2010). Mistele and Schmidhalter (2008) examined the relationship between the index and the canopy reflectance intensity in a 3-year field experiment of winter wheat showing an overall average R^2 of 0.95. This information about the N status of crop stands by using spectral reflectance measurements can be useful to support precision N fertilizer applications.

Plant sensing techniques to spatially diagnose crop N status are usually based on a vegetation index used in conjunction with a reference area of the field with non-limited N supply. By using this approach, the differences between hybrids, soil and other environmental conditions are normalized to a fixed optimal situation (Dellinger et al. 2008; Vrindts et al. 2003). The subject has been reviewed in detail by Samborski et al. (2009), focusing on sensing tools available and procedures for data normalization. In-season measurements of vegetation indices, like the NDVI, could discriminate wheat N uptake between well-fertilized areas in the field and those receiving normal rates (Raun et al. 2005). The information obtained can then be used to calculate a response index, and integrated in an algorithm which may help to optimize in-season fertilization.

In a ramped calibration strip system, 16 incremental N rates were given by increasing rate from one end of the strip to the other (Raun et al. 2008). The authors suggested that farmers can measure NDVI by using hand-held sensors over the entire ramped calibration strip system. Furthermore, they can read the output data with the Ramp Analyzer program, and the optimum N rate will then be computed accordingly (identifying where NDVI peaks within the strip system). Recently, Roberts et al. (2010) studied whether similar predictions from the program were replicable in Oklahoma hard red winter wheat. The predictions were derived from 36 individual strips from on-farm experiments, and each strip was analysed three times during growing season. Unfortunately, this case study showed that the ramped calibration strips were unlikely to produce accurate N requirement predictions at any spatial scale.

A major drawback, as suggested by Fitzgerald et al. (2006b), is that estimating leaf N status may be more difficult when vegetation indices are scaled up to the canopy also due to shadows and structural differences. The indices may calculate the same amount of green both for an area of crop with low cover and high N concentration, and vice versa. The NDVI is particularly sensitive to changes in the wheat canopy when leaf area index (total one-sided area of photosynthetic tissue per unit ground surface area) is low, then works well for early season estimation, becoming saturated as wheat canopy closes and with the decline of plant pigmentation (Aparicio et al. 2000; Dang et al. 2011; Havránková 2007). According to different authors, reflectance indices that utilize the red band usually saturate at leaf area index above 3, which is due to the lack of sensitivity of red light at the higher vegetation fractions (Erdle et al. 2011; Prasad et al. 2007). By contrast, Babar et al. (2006) indicated that the near-infrared bands can penetrate into the higher vegetation fraction of the canopy and assess both the crop water status and the amount of green biomass. Therefore, in attempting to overcome the limitations of vegetation indices obtained from broad-waveband sensors, new narrow-waveband instruments have been designed. They are expected to provide more detailed information, as reviewed in the next subsection.

2.3.2 Advantages and drawbacks of hyperspectral proximal sensing

The narrowbands provided by hyperspectral sensors are able to measure the precise characteristic absorption peaks of plant pigments and, thereby, to provide better information, related to plant health, than broadbands (Ray et al. 2010). In particular, the hyperspectral proximal sensing technique, based on reflectance measurements acquired in a high number of contiguous spectral bands, have been successfully used to derive biophysical variables related to plant status such as water content, chlorophyll and N concentrations (Fava et al. 2009; Thenkabail et al. 2004; Vigneau et al. 2011). Xavier et al. (2006) performed field reflectance measurements, over 80 wheat plots (randomized, complete-block design with four wheat cultivars, five levels of N fertilizer and four replicates), with the FieldSpec® hyperspectral radiometer (ASD Inc., Boulder, CO, USA). Their work confirmed that hyperspectral indices can provide an overall better estimate of biophysical variables when compared to broadbands vegetation indices. In fact, the Optimum Multiple Narrow-Band Reflectance index, with four bands, had the highest R^2 values to estimate both grain yield (R^2 of 0.74; booting and heading stages at Zadoks 40 and 71, respectively; Zadoks et al. 1974) and plant height (R^2 of 0.68; heading stage).

However, there is still a need to study and define optimal wavebands to estimate crop biophysical parameters by using hyperspectral crop reflectance data (Xavier et al. 2006). Extracting useful information from hyperspectral sensing can be much more complex than the multispectral ones. This is because of the large amounts of data collected in a short time and the analysis and interpretation that these data require. Multivariate statistical analysis techniques can play a crucial role in analysing hyperspectral data set because they allow both to eliminate the redundant information by reducing the data set at fewer components and to identify synthetic indices which maximize differences among levels of nutritional stress (Ray et al. 2010; Stellacci et al. 2012; Thenkabail et al. 2004).

Barnes et al. (2000) showed that the spectral region (on the reflectance S-shaped curve) between the red absorption feature and high near-infrared reflectance, termed the 'red edge', changes in shape and position when the plant undergoes N deficiency. As a consequence of lower amounts of green biomass, vegetation under nutrient stress shows a decrease in reflectance in the near-infrared bands and the point of inflection on the red edge shifts to shorter wavelengths (Aparicio et al. 2000; Broge and Mortensen 2002; Fig. 6). Other authors more specifically observed that the spectral reflectance was negatively correlated to N rate in the visible (460–710 nm) and near-infrared long wavebands (1,480–1,650 nm), whereas in the near-infrared short wavebands

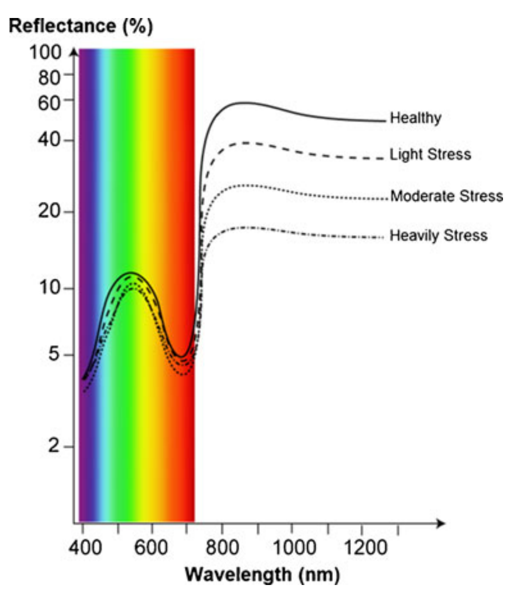

Fig. 6 Generalized reflectance curves for plants under different levels of environmental stress (from Keiner L.E., Coastal Carolina University)

(760–1,220 nm) the reflectance tended to increase with N rate (Zhu et al. 2006). Therefore, the normalized difference red edge index, which takes the form of the NDVI but substitutes the red band with a band in the red edge, can be used as a reliable measure of chlorophyll or N status (Fitzgerald et al. 2006b). Tilling et al. (2007) calculated this index from airborne image and showed that it accounted for 41 % of the variability in wheat crop N status.

Li et al. (2010) reviewed various papers about other hyperspectral vegetation indices for estimating plant N concentration of winter wheat in the North China Plain, during different growth stages and cropping seasons. The authors found that the combination of wavelengths at 370 and 400 nm, as either simple ratio or normalized difference index, performed most consistently (in terms of the relationship with the plant N concentration) in both experimental (R^2 of 0.58) and farmers' fields (R^2 of 0.51). Also the red edge and near-infrared bands were more effective for N concentration estimation when canopy was not closed, whereas ultraviolet, violet and blue bands were more sensitive when canopy was fully closed. Recently, Erdle et al. (2011) found that the most powerful and temporarily stable index, indicating the N status of wheat, was the near-infrared-based index obtained by dividing the reflectance at 760 nm by that at 730 nm. This index was provided by testing and comparing different sensors to discriminate the influence of four N levels (ranging from 0 to 220 kg ha^{-1}) on various wheat N-status parameters. The active sensors were the GreenSeeker RT100® (NTech Industries, Inc., Ukiah, CA), the Crop Circle ACS-470® (Holland Scientific Inc., Lincoln, Nebraska) and a flash sensor similar to the N-Sensor ALS® (YARA International, ASA). The passive device was a bi-directional radiometer with modified electronics (tec5, Oberursel, Germany) to enable hyperspectral readings.

Another index, the canopy chlorophyll content index, has been designed from canopy-level hyperspectral data to detect canopies N in irrigated and rainfed wheat (Tilling et al. 2007). The index accounted for a high percent of variability (76 %) of crop N status just prior to stem elongation at Zadoks stage 24 (Zadoks et al. 1974). In Fitzgerald et al. (2006b), derivation of this index led to an R^2 relationship of 0.53 with chlorophyll after stage 43 showing the potential for mid-season fertilizer recommendations. Then, the canopy chlorophyll content index was also combined with the canopy N index, which was developed to normalize for crop biomass and correct for the N dilution effect of crop canopies (Fitzgerald et al. 2010). The obtained 'combined index' was a powerful tool to predict canopy N. It was able to give prediction from Zadoks 14–37 with an R^2 of 0.97 and root mean square error of 0.65 g N m^{-2}, when dry weight biomass by area was also considered.

Recently, Zhao et al. (2011) developed a method based on the relationship between winter wheat canopy vertical chlorophyll distribution and canopy reflectance. The canopy chlorophyll density (i.e. total amount of chlorophyll in the canopy per unit ground area) was combined with the contribution of wheat leaves in three layers of the canopy and related to canopy reflectance. The authors reported that the combined prediction model according to the contribution of leaves in the first two uppermost layers explained most of the variability in the chlorophyll status (R^2 of 0.73 at elongation stage) when early predicting it. Combined canopy chlorophyll was better related to difference vegetation index (difference of reflectance in the near-infrared (890 nm) and in the red (670 nm)) which could be used to quantify chlorophyll status.

From all the above, it can be summarized that spectral measurements of wheat canopy with high spatial resolution, collected by hyperspectral proximal sensors, proved to be quite promising to indirectly detect crop status. In fact, narrowbands better estimated (R^2 more than 0.70) grain yield, crop N and water status. Also, different hyperspectral vegetation indices accounted for a high percent variability (40–75 %) of wheat N status.

3 Precision nitrogen management of wheat: tools and approaches

The spatial variability of N availability justifies to study the methods to apply N rates in a site-specific way (Kitchen et al. 2010). This variability is a consequence of different level of soil N mineralization, together with potential N losses (by nitrate leaching, volatilisation of ammonia and nitrous oxide emissions). However, Lark (2001) indicated that the spatial variation of soil properties only justifies precision agriculture if it causes a spatial variation of the optimum N rate, which is large enough to be of practical significance. This observation would support Pierce (1995) who stated that, for site-specific management, the variation must be not only spatially structured (non-random) but also of sufficient magnitude and manageable.

Different diagnostic tools and procedures have been developed in order to help wheat farmers to plan variable N rate. They are discussed in the later subsections to identify their principal advantages and drawbacks.

3.1 Treatment maps, in-season determinations and homogeneous areas

Generally, precision N management can be employed when a yield-influencing factor (e.g. wheat N status) have been assessed by means of the sampling and analysing methods described above. Statistical techniques can then be used to identify correlations among N and the others grain yield-influencing factors. The goal is to produce a site-specific N treatment map that shows the precise location and rate of the treatment within the field. The map must be implemented by crop producers and consultants. This method can be used to control variable-rate applicators, thus responding to the variation across the site. Long et al. (2000), for instance, tested the variable-rate input by means of a programmable rate controller (Rawson Accu-Plant, Rawson Control Systems Inc., Oelwein, IA) linked to a variable speed motor that regulated the flow of urea fertilizer. Therefore, the map-based fertilization method may match fertilizer application rate to yield, as indicated by yield-map output, as well as to changes in soil conditions in each part of the field (Plant 2001).

As an alternative method to the prescriptive treatment maps, the sensors use enables to vary the N input without prior extensive data analysis involved. Canopy reflectance sensors can be mounted on fertilizer applicators, equipped with computer processing and variable rate controllers. These tractor-mounted systems allow on-the-go sensing of crop growth in real-time, throughout the growing season, and fertilization can be accomplished in one pass over the crop (Ammann 2009; Kitchen et al. 2010). Based on continuous information, a control system calculates the input needs and transfers this information to a controller, which delivers the input to the location measured by the sensor. Some examples of system for on-the-go control of N top-dressing are outlined in Heege et al. (2008).

Furthermore, the use of remote sensing to forecast crop yields is worldwide spread and, in this case, the yield maps can validate sensor-based predictive technology (Li et al. 2009; Prasad et al. 2007). Generally, spectral data are used to estimate crop yields by means of simple regression equations (Raun et al. 2001). Prasad et al. (2007) found that indices based on the minor water absorption band provided high correlations with winter wheat grain yield, explaining up to 74 % of the yield variation. Moreover, multiple-additive model described by Dang et al. (2011) related rainfed wheat yield as a function both of Landsat-derived NDVI (observed at crop anthesis) and of post-anthesis rainfall. Aparicio et al. (2000) showed that under similar environmental conditions, spectral reflectance indices measured at any durum wheat growth-stage were positively correlated with leaf area index and yield. Under irrigation, the correlations were only significant during the second half of the grain filling, thus suggesting the impact of different water status. Otherwise, Singh et al. (2011) observed robust relationships between in-season GreenSeeker®-based estimates of irrigated wheat yield, at Feekes 5–6 and 7–8 stages (Large 1954), and actual yields. According to Washmon et al. (2002), since the within-field coefficient of variations for wheat yield can be predicted with mid-season satellite

Landsat scenes of crop growth, the potential response to added nutrients may also be established. Then, in-season fertilizer applications can be accordingly adjusted. Also Robertson et al. (2007) highlighted the usefulness of using mid-season NDVI, taken before canopy closure, to identify low yielding areas within a field associated with either high or low mid-season biomass. Poor performing areas that had high mid-season biomass may reveal a subsoil constraint. This could hamper early biomass production to be turned into high yield.

Another approach of managing fertilization of wheat consists in assessing spatial variability and sorting out the factors most influencing yield across the field, to delineate homogeneous sub-field areas (Taylor et al. 2007; Vrindts et al. 2003). Each sub-region of a field become a management zone (or class) within which, due to a homogeneous combination of yield-limiting factors, a single rate of a crop input can be applied uniformly (Lark 1998; Mzuku et al. 2005). According to Taylor et al. (2007), a management class may consist of numerous zones, whereas a management zone can contain only one management class. Then, stratified random sampling can confirm significant differences in soil properties between the delineated management zones (Whelan and McBratney 2003). It is difficult to design these homogeneous field areas because their boundaries can change over time. Nevertheless, various authors (Castrignanò et al. 2006, 2008; Ferguson et al. 2003; Franzen et al. 2002; Guastaferro et al. 2010; Miao et al. 2006) have proposed different criteria for delineating them. The widest used criteria are: (a) overlay of different thematic spatial maps (of soil properties, crop growth and yield); (b) multivariate geostatistical approach to take into account the complexity of the interactions among the factors that affect wheat grain yield and quality.

Song et al. (2009) delineated management zones on the basis of soil and yield data, remote sensing information (Quickbird imagery) and the combination of these two information (soil with yield and remote sensing data). All these three methods decreased the variance of the crop nutrients, wheat spectral parameters and yield within the different delineated zones. The results of this study suggested that management zone delineation using satellite remote sensing data was reliable and feasible, since these data can reflect the spatial variation in wheat growth during the early growing stage, the spatial variation in soil properties and the yield. Recently, Zhang et al. (2010) developed a valuable web-based decision support tool to automatically determine the optimal number of management zones and delineate them using satellite images and field data. A stepwise protocol has been developed for non-irrigated broadacre Australian grain production systems, promoting a cost-effective approach to class delineating and management at a grower and consultant level (Taylor et al. 2007). In the same environment, Stewart et al. (2002) proposed another method, starting from calculating a regression tree structure for a 11-ha wheat field to predict three rising grain quality grades of durum wheat. The production of the first grade was favoured by coarser textured soil, lower organic carbon levels and available water holding capacities, so farmers could use this information to divide the field into management zones to be managed site-specifically. A different approach was used in southern Italy to delineate homogeneous areas in a 12-ha durum wheat field. Some semolina quality parameters (protein content, dough strength and tenacity/extensibility ratio) were analysed in 100 georeferenced locations (Diacono et al. 2011). Homogeneous within-field areas were delineated by geostatistical procedure called factorial co-kriging. In reverse order compared with the Australian authors, Diacono et al. (2011) suggested that the delineation of homogeneous areas should allow to segregate the harvested grain into various grades on the basis of the field-scale semolina qualitative parameters. This separation can enhance grain production of a higher quality on heterogeneous fields, and could obtain uniform grain lots useful for to the pasta industries.

The diagnostic tools and procedures previously described can help to plan variable N rate application. On this matter, it can be underlined, once again, how important is canopy sensing. Furthermore, the different proposed methods for management zones delineation seem to be a useful tool to reach uniform grain yield quality.

3.2 Temporal factor in the nitrogen management decisions

Since soil N supply and crop N demand are two cropping parameters with high temporal dependence, canopy temporal status should to be considered in developing fertilizer strategies.

In different studies, treatment strips have been investigated, which ran through the main areas of soil variation within each field (Godwin et al. 2003a; Welsh et al. 2003). The aim was to identify an experimental methodology to determine an optimal N application strategy. To achieve this goal, it was important to use standard farm machinery, so moving away from the traditional randomized block experimental design. Estimates of yield potential have been used by means of historic yield data and shoot density data approaches to divide the experimental treatment strips into management zones (Godwin et al. 2003a). The first approach was based on several-years yield data, whereas the second one was based on real-time information derived from airborne digital photographic images. According to Washmon et al. (2002), although the first approach is interesting, it fails to take into account the environment conditions within the current crop year of interest. This observation would support Godwin et al. (2003a) who demonstrated that decisions to treat field variability have to be made in-season to control N requirement by using real-time assessment of shoot density variation. Otherwise, decisions based upon historical data are generally based on probability rather than certainty. Spatial variability in the yield maps of the fields, in fact, was inconsistent from 1 year to the next, and these maps were not useful for determining a variable N application strategy in a particular season. This result is consistent with the findings of Diacono et al. (2012), who applied a novel multivariate geostatistical approach to analyse attributes related to the yield and quality of durum wheat production collected during a 3-year field study. The spatial data sets were analysed by factorial co-kriging analysis. The first regionalized factors (with eigenvalues greater than one) were retained to aid in delineating management classes of such a size to be manageable by a farmer. The classes obtained from the factorial co-kriging analysis output were compared with the yield maps in order to assess their production potential. The first factors relating to each year were also compared, by using contingency matrices, to estimate the temporal consistency of field delineation. The authors found that only 26 % (on average) of the total spatial variance was characterized by temporal stability. This also confirms the great influence of climatic conditions over the persistence of wheat crop responses (Montemurro 2009).

Although the magnitude of temporal yield variation can be larger relative to spatial yield variation, Florin et al. (2009) suggested that large temporal variance of yield seems not necessarily to rule out the chance of site-specific crop management. This is possible if some kind of space–time variance equivalent magnitudes can be identified. This observation derived from spatio-temporal analysis undertaken for a dry-land farm of South Australia, with 3 and 4 years of wheat yield data (Florin et al. 2009). Temporal analysis included the calculation of semi-variance between pairs of years for creating semi-variance maps. These maps allowed to identify parts of the field where spatial management through time would be relatively easy by finding patches of low mean semi-variance. Interestingly, the authors observed that in the case of high positive rank correlations between pairs of years smaller spatial units can be managed. In fact, relative high yielding parts of the field are always relatively high regardless of the season.

Other authors found that understanding the optimal fertilization approach to manage field variability might require long-term studies since there are multiple temporal and spatial interactions of soil–plant–atmosphere (Basso et al. 2011). Crop simulation and calibration models can be useful to simulate long-term effects of N stress and its interactions on plant growth, in various climatic conditions, thus helping fertilizers application (Link et al. 2008). As an example, simulation scenarios with different N rates (0, 30, 60, 90, 120, and 180 kg N ha^{-1}) were performed in a long-term monoculture wheat system by using the SALUS crop model (Basso et al. 2010). The study suggested that the fertilization with 60 kg N ha^{-1} was the most appropriate one due to the lowest nitrate leaching and higher economic return. Also, Bannayan et al. (2003) reported that CERES-Wheat model was able to predict the upper and lower limit of observed wheat yield across all sites and years, with a significant correlation at grain milk stage. However, these models could not simulate every spatial information in a field, as required by precision agriculture, because of the costs associated with gathering data and the availability of detailed inputs. A solution to this issue was proposed, as an example, by Basso et al. (2011), who used a 25×25-m grid to identify 25 georeferenced sampling points for determining soil input data. In this case, the measurements were taken on the point of sampling, at three different distances (1, 3 and 5 m) from the grid node. Godwin et al. (2003b) recommended targeted sampling based upon significant variations in yield or soil type. Management zones can also be used to direct GPS-guided soil sampling.

From the discussion in this subsection it became evident that managing the temporal variation is as important as managing the spatial one.

Selected recent studies are indicated in Table 1. They focus on benefits of application of site-specific wheat fertilization as compared to conventional treatments. In particular, different methods have been developed for the in-season application of N rates, taking into account the canopy temporal variability. This aspect is dealt with in more detail below.

3.3 Sensor-based recommendation of nitrogen rates

In recent years, there has been growing interest in sensor-based application of N rates. Godwin et al. (2003a) summarized the results of a 6-year study, involving five principal fields in England. Firstly, the work has focused on identifying the in-field yield variability by applying uniform treatments to the 'key' fields. Then, spatially controlled and uniform N applications were compared in treatment strips. These strips consisted of different N rates, uniformly applied along their length, to provide an indication of crop response to different N levels in the various zones of the field. The treatment strips tested the following strategies: (a) increasing the N rate by 30 % than the standard (125 kg N ha^{-1}) to the highest yielding parts of the field, whilst reducing the application by 30 % to the lower yield zone and (b) reducing the N rate by 30 % to highest yielding parts of the field, whilst increasing it by 30 % to the lower yield zone. The same two strategies described for N rates based on historic yield data were also defined on shoot density basis. The approach which used the real-time assessment of the crop status to apply more N to the areas of low shoot density offered the greatest potential for crop production among these approaches, similarly to Welsh et al. (2003). On the contrary, the strategy based on historic yield maps showed

Table 1 Recent studies regarding site-specific N fertilization of wheat species

Study	Site	Wheat species	Approach applied	Benefits vs conventional treatments
Basso et al. (2011)	Foggia (Italy)	Durum wheat	Management zones (high, medium and low yielding zones)+SALUS crop model to select optimal nitrogen fertilizer rates. The N rates were simulated as split applications	High yielding zone had a maximum economic return and minimal nitrate leaching by annually applying 90 kg N ha^{-1}. Low yielding zone had little economic returns for application higher than 30 kg N ha^{-1}. When plant available soil water was low at the second time of N application, a lower N rate increased profit and decreased N leaching both in the medium and high yielding zones
Basso et al. (2009)	Foggia (Italy)	Durum wheat	Management zones (high, medium and low yielding zones)+crop simulation model CERES	Model helped to find the best management option for the N rate among the zones. In this way it is possible to maximize economic return by the farmers and also reduce the risk of environmental pollution
Biermacher et al. (2006)	Oklahoma (USA)	Winter wheat	Precise in-season system (top-dressing) to achieve the plateau yield	Reduction of the overall N application level by 59–82 % depending on the site. Maximum net benefit was \$22–33 ha^{-1}
Biermacher et al. (2009)	Oklahoma (USA)	Winter wheat	N precise-rate system based both on real-time plant sensing (top-dress N rate) and field-level precision system (uniform N rate based on plant sensing)	Real-time sensing and fertilization had net expected return on average about \$16 ha^{-1} more than the conventional uniform pre-plant application
Ehlert et al. (2004)	Potsdam (Germany)	Winter wheat	Late fertilizer rate varied according to wheat plant biomass, indirectly measured by a mechanical sensor-pendulum meter	Fertilizer was reduced in the study area in the range of 10–12 % without either reducing yields or influencing grain quality
Flowers et al. (2004)	North Carolina (USA)	Soft red winter wheat	For the site-specific system, the N rates at 25 and 30 Zadoks stages were determined for individual subplot management units	At sites where site-specific or field-specific systems were compared with the practices usually applied by farmers, grain yield benefits of in-season N optimization (up to 2,267 kg ha^{-1}) were apparent. A large reduction in N inputs (up to 48.6 %) was found by using in-season N rate optimization, compared with normal practices applied by farmers. A further reduction (up to 19.6 %) was possible through site-specific application, which maximized spring N fertilizer use efficiency and reduced within-field grain yield variance
Godwin et al. (2003b)	Southern England	Winter wheat	Variable rate application of N depending on crop canopy structure determined by using aerial digital photography techniques (to measure shoot density and green area index)	The variable rate application of N provided an average improvement of £22 ha^{-1}, compared to a standard uniform rate
Johnson et al. (2003)	Northeastern Colorado (USA)	Winter wheat	Management zones based on equal ranges of electrical conductivity	Shallow electrical conductivity-based management zones can be used for wheat fertilization management. Site-specific N rate determination can be based on maximum potential yield within shallow electrical conductivity class
Li et al. (2009)	North China Plain	Winter wheat	Sensor-based N management strategy	Nitrogen-use efficiencies were 61.3 and 13.1 % for the sensor-based management strategy and the practices applied by farmer, respectively. Residual N content in the soil from sensor-based and farmer N management strategies was 115 and 208 kg N ha^{-1}, respectively. Apparent N loss was 4 and 205 kg N ha^{-1}, respectively

Table 1 (continued)

Study	Site	Wheat species	Approach applied	Benefits vs conventional treatments
Link et al. (2008)	Southwestern Germany	Winter wheat	Two fields were divided into two different management grids. Each grid was subdivided into two areas. These two areas were treated with an uniform control prescription and a crop growth model-derived (APOLLO model), applied in side-by-side strips	Till about 60 % of the grids treated with the model-based nitrogen prescription had higher yields, compared with current farming practice. The model-based fertilizer prescription lead to N use efficiency increase and enabled the design of N prescriptions adapted to plants demand
Long et al. (2000)	Montana (USA)	Spring wheat	Five management zones were obtained from the N-recommended range (mapped values of the N-removed+the N-deficit), by specifying cut-off values. Uniform and variable-rate N treatments were randomly assigned in a randomized block design	Proteins were significantly enhanced by spatially variable N application and variability in protein levels was reduced within the whole field
Morris et al. (2006)	Oklahoma (USA)	Winter wheat	A randomized complete block design was carried out with 15 treatments and 4 replications. Top-dress N rate was determined utilizing the algorithm of Raun et al. (2002) and measuring spectral reflectance by means of a hand-held sensor	Among treatments, the top-dress N rate at Zadoks 30 resulted in maximum or near-maximum yields, as compared with treatments receiving both the pre-plant and the top-dress N
Robertson et al. (2008)	Western Australia	Spring wheat	Management zones	There was a greater economic benefit from zone management (from less than \$5 to 44 ha^{-1}) when the difference in potential yield between zones was larger. The cost savings were obtained on the low yielding zone with less N applied than the uniform field rate
Singh et al. (2011)	Northwestern India	Irrigated wheat	Optical sensor-guided, site-specific N management strategy	A combination of moderate prescriptive dose of N and a corrective sensor-based can improve N-use efficiency. This combination induced no reduction in yield, through savings in total N application as compared with prevalent blanket recommendations
Thomason et al. (2011)	Virginia (U.S.A)	Soft red winter wheat	Real-time variable rate prescriptions: (a) application of increasing N rates, as NDVI increased to near the level of N-rich strip; (b) recommendation of low N rates if the NDVI in the area to be fertilized was equal to (or exceeded) that of the N-rich strip	No crop sampling or laboratory tissue analysis is required by this method. The consequent time and labor savings should result in more accurate and appropriate rates of top-dress N being applied
Tubaña et al. (2008)	Oklahoma (USA)	Winter wheat	Treating spatial variability by using an in-season N fertilization optimization algorithm	Almost half of the fixed N rate (90 kg ha^{-1}) was prescribed. The algorithm approach resulted in 41 % N use efficiency, compared with 33 % of the conventional rate applied mid-season
Welsh et al. (2003)	Bedfordshire (UK)	Winter and spring wheat	Estimates of yield potential, produced from either historic yield data or shoot density maps (from airborne digital photographic images), were used to divide experimental strips into management zones	Applying additional N to areas with a low shoot density and maintaining the standard N rate to areas with an average shoot population resulted in an average yield increase of 0.46 t ha^{-1} compared with standard farm practices

no or very little benefit, confirming that wheat yield data may be greatly influenced by seasonal rainfall differences (Diacono et al. 2012; Montemurro 2009). Thomason et al. (2011), studying 15 site-years, used an algorithm for grain yield prediction and variable N fertilizer rate determination of winter wheat. This algorithm enhanced N as NDVI increased to near the level of the N-rich strip, then recommended lower N rates if the NDVI in the area to be fertilized was equal to or exceeded that of the N-rich strip. In North Carolina, Flowers et al. (2004) developed a field-specific N management system for soft red winter wheat based on an in-season evaluation of N requirement of crops. If the average tiller density of wheat at growth stage 25 (Zadoks et al. 1974) was below a critical threshold (540 tillers m^{-2}), an N rate of 67 kg ha^{-1} was applied according to the Weisz and Heiniger (2000) N recommendation system. Otherwise, at growth stage 30, the average whole-plant N concentration was used to determine the N rate. Moreover, for the site-specific system, the N rates were determined for individual subplot management units at both growth stages (25 and 30 Zadoks). The latter strategy gave the best results compared with the practices commonly applied by farmers (Flowers et al. 2004). Interestingly, these results demonstrated that incorporating the in-season estimation of the optimum N rates have improved the site-specific management benefits vs conventional treatments.

In contradiction with the previous evidences, mapped values of wheat yield and protein were used in a field experiment in northern Montana to derive site-specific N fertilizer recommendations (Long et al. 2000). The amount of N-removed in hard red spring wheat and the N deficit (amount of additional N needed for raising protein concentration to a target level) were estimated. Then, the total N recommendation was obtained by summing the mapped values of the N removed and the N deficit. A map for variable-rate application of fertilizer was obtained by specifying cut-off values to divide the N recommended into five classes (representing N management zones). Uniform- and variable-rate N treatments were randomly assigned in a randomized block design arranged as pairs of strip plots. By using this approach, Long et al. (2000) showed that mapped values of yield and protein can support precision N fertilizer recommendations. Also these latter may improve protein level on average by 11 %. Despite this non-alignment with research on in-season determination of N rates, the statistical results of this study were of a preliminary nature and the analysis methodology should be improved before definite conclusions can be made.

On the other hand, Johnson et al. (2003) suggested that complementary data layers could be used, including a shallow electrical conductivity-classified map, ground-truth soil test information and accumulated yield maps. These data sets appear to address both actual yield and intrinsic soil productivity factors. The authors found a strong linear relationship (R of −0.97 to −0.99) between shallow electrical conductivity and wheat yields. This finding indicated that delineated management zones, based on equal ranges of shallow electrical conductivity, can provide an excellent framework for site-specific management. Nutrient inputs can then be based on maximum potential yield within shallow electrical conductivity class. Also, the integration of yield maps, ground truth measurements, electrical resistivity and remote sensing imagery allowed for the identification of three distinct management zones (high, medium and low yielding zone) on a 10-ha wheat monoculture field (Basso et al. 2009). Seven N rates, from 0 to 180 kg N ha^{-1} with 30 kg N ha^{-1} of increase, were simulated. The results demonstrated that the crop simulation model CERES was a useful tool in selecting the N management as 120, 90 and 60 kg N ha^{-1} for the high-, medium- and low-yielding zone, respectively. In particular, the model gave more information to find the best management option regarding the N rate that maximizes yield and reduces costs and environmental impacts. Another method was used by Link et al. (2008) that virtually divided two fields into two different management grids, for calculating and broadcasting the site-specific N rate. Each grid was subdivided into two areas treated with an uniform control prescription or a crop growth APOLLO model-derived one, applied in side-by-side strips. The calibrated model was run for different N rates (0–200 kg N ha^{-1} with 10 kg N ha^{-1} of increase) for each grid and for 30 years of weather data. The simulation searched site-specific N prescription to maximize the marginal net return, while reducing the amount of N losses to surface and groundwater. For agronomical, environmental and economic aspects, no significant differences were identified between both treatments. Nevertheless, till about 60 % of the grids, which were treated with the model-based N prescription, reached higher yields, compared with current farming practice (Link et al. 2008). According to the authors, the main weakness in the study was that the model needs to be updated with actual information on the current growing conditions.

A less time-consuming approach was defined by Ehlert et al. (2004) who varied the late fertilizer rate according to wheat plant growth indirectly measured by a mechanical sensor (i.e. pendulum meter). Strip trials were set up with three and four replications, to compare uniform and sensor-based site-specific fertilization. In the parts of plot with low plant biomass, due to water stress, the application rate was reduced (7 kg N ha^{-1}), and in the parts with high biomass, it was increased (68 kg N ha^{-1}).

On the whole, the reviewed results showed how different are the methods used in precision agriculture for site-specific N management. Our literature analysis also highlighted the advantages of the sensor-based application of N rates in wheat crops.

In next section, the in-season N application, the homogeneous sub-field areas and the crop simulation models are better analysed for their performance and sustainability characteristics.

4 Sustainability of precision nitrogen management in wheat crop

The knowledge of the eco-physiological processes governing crop response to environmental factors is not so deep to make accurate predictions of nutrient requirements (Cassman 1999). On the other hand, it is generally accepted that the use of a fixed N rate for the whole field could be neither economically nor environmentally sustainable. Precision fertilization has the potential to solve over- or misapplications of fertilizers (Fitzgerald et al. 2010), which decrease N use efficiency (NUE) and increase risk of N losses by leaching or volatilisation (Montemurro et al. 2007). The success of precise fertilization may depend on how well the processes that regulate N availability in soils (e.g. mineralization and immobilization by microorganisms) and the crop N requirements can be predicted and, also, controlled (Ladha et al. 2005). As an example, the NDVI can predict N uptake in the early wheat growth season. In the mid-season readings, this index is also positively correlated with final grain yield (Humphreys et al. 2004; Li et al. 2009). Therefore, the fertilization can be done at a time when crop needs are high by using the information obtained by a vegetation index. This approach reduces N losses from the soil-plant system, thus improving NUE and crop yield.

4.1 Impact on wheat yield and nitrogen use efficiency

The study by Carr et al. (1991) is known as the pioneering one about increasing profitability through the site-specific management of wheat fertilization (James and Godwin 2003). In particular, this management strategy could raise profitability of crop production thanks to the increased efficiency of N recovery by the crop. Morris et al. (2006) determined in-season top-dress N rate by means of an active hand-held sensor and an algorithm developed at Oklahoma State University. The results proved that top-dress N rate generally could obtain maximum wheat yields, compared to other treatments that received both pre-plant and top-dress N rates, even when early-season N stress was present. This is consistent with the previously mentioned study that applied a site-specific fertilization according to plant growth measurements (Ehlert et al. 2004). The authors underlined that N rate might be saved in the range of 10–12 %, without either reducing yields or influencing grain quality. On the other hand, other authors demonstrated that N efficiency and wheat yield, but not always crude protein, could be improved and fertilizer N saved with site-specific fertilization (Delin et al. 2005). Li et al. (2009) in the North China Plain showed that, compared with conventional farmer practice (372 kg N ha^{-1}), sensor-based N management strategy (67 kg N ha^{-1}) decreased residual soil mineral-N content after harvest on average by 44 % (across 2 years). Furthermore, NUE was considerably greater (by 368 %) for the sensor-based fertilizer recommendation than for common farmer practice. Also this strategy produced comparable grain yields. Similarly, Liang et al. (2005) found that, compared to traditional uniform application, variable-rate fertilization (based on the reflected spectrum from wheat canopy) reduced the variation of yield, ear numbers and dry biomass, but it did not increase crop yield and grain protein content significantly. An improved fertilizer NUE with comparable yield was also achieved in irrigated wheat by replacing blanket fertilizer recommendation by an optical sensor-based N management strategy (Singh et al. 2011). More specifically, this strategy consisted of applying moderate prescriptive dose of fertilizer N at planting and crown root initiation stages, and a corrective sensor-guided application at two stages corresponding to 2nd or 3rd irrigation events. Raun et al. (2002) also showed that winter wheat NUE improved when mid-season fertilization was based on optically sensed in-season estimates of grain yield. Nitrogen use efficiency, in fact, increased by more than 15 % compared with the mid-season flat rate of 45 kg N ha^{-1}.

As NUE increases, generally the ability of site-specific fertilization to maintain profitability with lower average N applications is expected to be improved (Bongiovanni and Lowenberg-Deboer 2004). The previously described research by Link et al. (2008) indicated that the model-based fertilizer prescription lead to NUE increased in about 53 % of the grids and enabled the design of N prescriptions adapted to plants demand. In different studies, lower N doses were applied on winter wheat based on crop reflection methods, producing the best efficiency in terms of grain production (as highest ratio: yield/applied N) and grain yields equivalent to the current standard method (Thomason et al. 2011; Vrindts et al. 2003). These results were obtained despite differences between N treatments were not always significant. Flowers et al. (2004) found that a large reduction in N inputs (up to 48.6 %) was due to in-season system to evaluate the crop and optimize N rates compared with the practices normally applied by farmers. A further reduction (up to 19.6 %) was possible through site-specific application. This method maximized spring N fertilizer use efficiency and reduced within-field grain yield variance, compared with field-specific management. Similarly, in a field trial in the UK, the application of N by using sensors saved 15 kg N ha^{-1} without a negative influence on yield, which increased the NUE (Havránková 2007). In addition, there were potential environmental benefits through a 52 % reduction of the residual N in the soil. The author reported a cost of sensing of £11 ha^{-1} which could be offset by the N rate reduction together with a small (by only 1 %) increase of yield. On this matter, Mullen et al. (2003) found that the higher the yield level a soil will support without N fertilization, the lower the additional N that will be needed to reach maximum yields. In other words, the lower the value of NDVI response index (calculated as the ratio: highest mean NDVI of N treatment/mean NDVI of check treatment), the lower the additional N required. Also, the NDVI response index was found to provide good prediction (R^2 higher than 0.56) of wheat harvest response index (calculated as the ratio: highest mean yield of N treatment/mean yield of check treatment). Results showed that supplying fertilizer N only when a crop response is expected may improve use efficiency and also profitability (Mullen et al. 2003). More recently, Arnall et al. (2009) have used winter wheat yield data, from a long-term fertility study established at Oklahoma, to explore the relationship between NUE and harvest response index. Regression analysis showed a weak relationship for all years across six N rates (R^2 of 0.37), which significantly improved with increased pre-plant N rates. The regression of NUE both on harvest index and NDVI response index (which was determined from mid-season sensing measurements) improved the relationship (R^2 of 0.45). This outcome was obtained when data were combined over N rates for all years data. Interestingly, the use of the response index allowed to measure crop responsiveness to N fertilizer by including the effects of environmental factors (i.e. temperature and moisture). Therefore, the response index could be a powerful tool to predict NUE (Arnall et al. 2009).

Raun et al. (2005) proposed an in-season N fertilizer optimization algorithm. Tubaña et al. (2008) reported that by using this algorithm, 40 % less of the fixed N rate (90 kg ha^{-1}) was prescribed. On average by sites and years, the algorithm approach resulted in 41 % NUE compared with 33 % of the fixed rate applied at the mid-season crop growth stage. The highest NUE values were achieved treating spatial variability at 13.4 m^2 resolutions. LaRuffa et al. (2001) confirmed a NUE increase by treating the variation at a finer resolution. In any case, Bongiovanni and Lowenberg-Deboer (2004) highlighted that if soil fertility for the entire field is already above agronomic need, then precision fertilization does not have great effect. Nitrogen additions to sites with high soil nitrate levels resulted in yield reductions up to 30 %, probably due to the increased lodging and lower grain test weights (Bundy and Andraski 2004). This seems to indicate that a range in average soil fertility is necessary for having positive outcomes by using precision agriculture approaches.

From all the above, it can be summarized that field studies in which sensor-based N management systems were compared with common farmer practices have indicated significant increases in the NUE (till to 368 %). These systems saved N fertilizers (from 10 % to about 80 % less N) and reduced residual N in the soil (by 30–50 %), without either reducing yields or influencing grain quality.

4.2 Profitability of variable nitrogen applications

The key to the acceptance of variable N applications is the profitability of the methods used. Therefore, research projects have been conducted in order to assess the economical efficiency of precision N management approaches applied on wheat crop.

Costs, measurement errors and, as was mentioned in the section 3, variation of wheat yields from year to year, have limited the usefulness of N recommendations based on yield monitors and soil sampling of small grids (Arslan and Colvin 2002). On the other hand, recently Biermacher et al. (2009) has determined the expected profit from using the plant sensing system of Raun et al. (2002; it was detailed in Morris et al. 2006), to define winter wheat N requirements in Oklahoma. The authors found that the precise-rate technology based on real-time sensing and fertilization had the largest net expected return. This latter was approximately 6 % greater than the uniform pre-plant 90 kg N ha^{-1} rate. In the same environment, Boyer et al. (2011) tested null hypotheses if yields, the N use and the profit differed between applying different levels of N (based on real-time optical reflectance measurements) and conventional applications of pre-determined 90 kg N ha^{-1}. The conventional top-dress N treatment produced the largest yield, on average, and it was the most profitable, despite no statistical difference among treatments was found. However, the pre-plant N (anhydrous ammonia) showed a cost advantage relative to top-dress N fertilizer (urea and ammonium nitrate). Although other agronomic results in the same area have shown that the optical sensing system used substantially less total N (59–82 % than conventional pre-plant application), this system required the use of nutrient in a liquid form which proves to be more expensive than the commonly used anhydrous ammonia (Biermacher et al. 2006). Therefore, these findings seemed to explain why adoption has been slow in the study area, showing that a practical solution is needed for fertilizers use.

As for management zones profitability, Robertson et al. (2007) demonstrated benefits of \$29–63 ha^{-1} for on farm trials in the Western Australia. These authors suggested that the full benefits of this management approach could only be realized by defining homogeneous sub-field areas that are consistent in performance. In the same area, Robertson et al. (2008) showed that when the difference in potential yield between zones is larger, there is greater economic benefit from zone management (from less than \$5 to \$44 ha^{-1}). This benefit increases with higher grain and fertilizer prices and depending on levels of soil nutrients in the different zones. In addition, in the case of high yield variation, a benefit accrues from cost savings on the low yielding zone with less N applied than the uniform field rate. To provide accurate estimates of the benefits and risks of site-specific fertilization vs. conventional one, the demand for crop growth simulation models has increased (Booltink et al. 2001). Basso et al. (2011) used the SALUS crop model on three previously identified management zones showing that the high-yielding zone had a maximum economic return and minimal environmental impact (in terms of nitrate leaching) by annually applying 90 kg N ha^{-1}. Conversely, the low-yielding zone had little economic returns for application higher than 30 kg N ha^{-1}. The most remarkable result was that lower fertilizer rate increased profit and decreased N leaching in the medium and high yielding zones, when simulated soil root zone water was low at side dressing.

Varying fertilizer cost, crop price and sampling costs greatly influence net return from non-uniform application (Skjødt 2003). On the whole, several studies (Havlin and Heiniger 2009; Meyer-Aurich et al. 2010) found that the greater is the degree of heterogeneity in the property influencing the input rate, the greater is the potential economic return from precision application compared to the uniform one. Also Robertson et al. (2008) findings supported this observation. By surveying yield monitor data from 199 wheat fields in Western Australia, the authors observed that both small and large (10–172 ha), and low and high (0.6–4.9 t ha^{-1}) yielding fields exhibited variation that was potentially worth managing from an economic standpoint. In England, Godwin et al. (2003b) reported an average improvement of £22 ha^{-1} from the variable rate application of N (based upon crop canopy management using aerial digital photography) compared with standard uniform rate in eight different experimental strips of two wheat fields. The authors stated that applying N fertilizer based upon the variations in historic yield was not economically justified.

Meyer-Aurich et al. (2010) aimed at modelling economic potentials of the combination of site-specific fertilization and quality specific harvesting for wheat in Germany. The authors found that this combination, simulated as 'separate management', had an economic advantage of up to €30 ha^{-1} for the gross revenue. Conversely, the site-specific fertilization alone had only marginal economic effects. Separation of different grain qualities, which were measured by protein content at harvest by near infrared sensors, enhanced the opportunity for site-specific management to be profitable. In addition, the profit-maximizing N application rate, accounting for wheat yield and quality, was higher than the rate that maximized yield. Then, it can be concluded that fertilizing for grain quality (as discussed in subsection 3.1) is justified if the quality price differential can compensate for the grain yield loss and the additional fertilizer use.

The reviewed results suggest that economic benefits are not always obtained by using precision N management, because they depend on the degree of heterogeneity in the different factors influencing the fertilizer rate. Nonetheless, precision N management based on real-time sensing and fertilization had the highest profitability (about \$5–60 ha^{-1}) compared to undifferentiated applications.

5 Conclusions

More sustainable agricultural practices are required in farm management for improving crops yield performance and reduce the environmental risks of agriculture. Precision agriculture can satisfy these requirements. As it is generally accepted, it can help farmers to apply the right input, in the right amount, to the right place, at the right time and in the right manner.

Significant results have has been obtained in spatially managing nutrients across crop fields. However, to date no review papers have addressed the issue of precision N management of wheat crop. Therefore, our work investigated recent studies in order to fill this gap.

The within-field variability is the major source of uncertainty for making decisions in wheat crop production. Variability must be interpreted and managed at the spatial and temporal scales. Innovative experimental approaches, remote and proximal sensing and crop simulation models, will play an increasing role in assessing field variability, at relatively low cost, in order to make variable wheat N fertilization.

Researchers and farmers can obtain huge amounts of information. Anyway, assessing the quality of the collected information to transform it into N management decisions, which are economically and environmentally sustainable, has proven to be difficult. Studies at multiple sites and with standardized methodologies must be further conducted, to improve knowledge of wheat yield determinants.

In most wheat field studies, sensor-based N management systems were compared with common farmer practices, indicating significant increases in N use efficiency with either no or only small increases in yield. This result was mainly due to the reduction of N amounts of fertilizers. Although examples of success of precision N fertilization of wheat have been reported, the improvements in yields, profitability or environmental quality still appear questionable.

In any case, there is a possibility to increase the profitability and reducing negative environmental impacts of wheat N management. This can be obtained by integrating the real-time crop N status acquisition methods (by remote and proximal sensing) with the soil and yield maps. These maps could be obtained with the traditional soil sample analysis and crop observations. This solution takes into account canopy spatial and temporal variability in order to determine crop performance and input use efficiency. The final aim is to implement in-season adjustments of N rate for the specific climatic conditions and yield potential.

Future directions for precision N management researches in wheat may include better sensors, more user-friendly software and decision support models. The challenge is to find cost effective and easy to use precision agriculture systems, as well as simple ways of delivering spatial information to farmers.

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