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Review

Do crop sensors promote improved nitrogen management in grain crops?

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ABSTRACT

Crop sensing technologies to aid nitrogen management in grain crops have been the focus of an important element of Precision/Digital Agriculture research. We review sensor-based application research to explore the outcomes from this technology and provide guidelines for future developments in its application. Most studies report N fertilizer savings of 5–45% with little effect on grain yield, but a lack of consistent evidence of economic benefits limits adoption by farmers. Reported impacts on profit usually ranged between losses of US\$ 30 ha^{-1} and profits of US\$ 70 ha^{-1}, with an overall average profit of US\$ 30 ha^{-1}; about 25% of studies reported economic losses from sensor-based N applications. Sensor-based N applications which reduced environmental impacts were often not profitable compared to current N practices. Some methodological aspects of the research have also made interpretation of the benefits difficult as the value of the information used to recommend N rates and improved agronomy was often confounded with the value of sensor-based variable rate technology itself. Traditional plot experiments adopted in most studies are not the ideal method to evaluate variable rate technologies implemented to accommodate the effects of spatial variability. Neither simple fertilizer redistribution functions nor calibrated sensor algorithms, with or without the use of reference N-rich strips, were necessarily successful across a range of field conditions. New approaches to sensor-based site-specific N management are needed and it is likely the best approaches will arise from the use of multiple sensors.

1. Introduction

Optimal nitrogen (N) fertilizer use should be based on an understanding of the nutrient demand and supply balance. Although it might sound simple, this is a complex task as both sides of the equation are hard to predict. From a biological perspective, the optimum N rate depends on many variables such as the expected quantity and quality of the final product, the N supply from other sources besides fertilizer and N losses to the environment. Pragmatically, economics (price of N fertilizer and of crop produced) are also fundamental to identification of optimal rates. Crop response curves to applied N empirically derived from N rate experiments are alternatives to determine the optimum rate without the necessity of predicting all the variables affecting the crop-soil N system. Yet, due to their simplicity, recommendations derived from these cannot be confidently generalized to conditions beyond those of the experiment (Bramley et al., 2013). Alternatively, simulation models predicting crop, soil and climate variables have been developed in many parts of the world to support more robust recommendations (Keating et al., 2003; Kersebaum, 2007; Pampolino et al., 2012; Sela et al., 2016; Setiyono et al., 2011).

An added complexity in recommending N fertilizer rates is the fact that all parameters affecting nutrient dynamics in the cropping system can vary both spatially (between fields and within a single field) and temporally (between cropping seasons and/or during one season). The capacity to account for the variability of both crop N demand and soil supply is the key aspect distinguishing Precision Agriculture (PA) strategies from traditional methods of N management in which uniform application is assumed to be the optimal strategy. In the context of PA, the use of electronic sensors is common for providing site-specific diagnostics of various soil and crop parameters (Heege, 2013). During the past two decades, non-destructive proximal canopy reflectance sensors have been identified as potentially valuable tools for site-specific N management (Ali et al., 2017; Mulla, 2013). These have been developed to assess plant nutritional status and guide variable rate N application for different grain crops (e.g. Cao et al., 2016; Raun et al., 2002; Shanahan et al., 2008), cotton (e.g. Oliveira et al., 2013; Vories et al., 2014) and sugar-cane (e.g. Amaral et al., 2015a,b; Portz et al., 2012), and have been one of the most heavily investigated topics in PA.

Typically, proximal canopy sensors make measurements of reflected light at selected wavelengths in the electromagnetic spectrum and convert these to vegetation indexes (VI, e.g. NDVI – normalized difference vegetation index) representing the amount of photosynthetically active biomass (Heege et al., 2008). Based on calibration against crop biomass, N nutritional status or yield potential, these

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sensors are typically used to provide insight into the 'demand' side of the equation and, assuming other factors are non-limiting, in-season N prescriptions can be generated and applied site-specifically. After decades of development, several commercial sensors are available as well as different methods to transform their readings into N rates.

Recent nation-wide surveys in Australia, Brazil and USA indicate that the adoption of variable rate fertilizer application (VRA) is around 15–25% of grain growers (Llewellyn and Ouzman, 2014; Molin, 2017; Schimmelpfennig and Ebel, 2016). However, the adoption of sensor-based technology to support VRA (not specified in these studies) can be expected to be much lower (R Bramley, CSIRO − unpublished data, 2017; Franzen et al., 2016; Lowenberg-Deboer, 2013; Scharf et al., 2011). Such low adoption indicates that more development is needed and/or that research has failed to demonstrate the usefulness of the technology to farmers; perceived usefulness is pointed as one of the main drivers for the adoption of PA technologies (Aubert et al., 2012; Pierpaoli et al., 2013; Robertson et al., 2012). Thus, in order to fully explore the factors driving adoption, some important questions should be asked: has current sensor-based N application been able to increase profit and improve environmental protection? Is there enough evidence to support its potential and if not, what can be learned from two decades of development?

Several studies have compared sensor-based N approaches against other methods of N recommendation. However, evaluating studies individually does not help answer the key questions. Current reviews are based on summaries of different sensors and methods available and not on the outcome from their use (Ali et al., 2017; Franzen et al., 2016; Mulla, 2013; Muñoz-Huerta et al., 2013; Samborski et al., 2009). Our objective was to review the outcomes from the use of crop sensors for site-specific N management, focusing on studies that have tested whether the technology can improve yield, N use efficiency (NUE), profitability and environmental protection. We also sought to identify the main limitations of the current technology and the experimental methods used in developing and evaluating it, to provide guidelines for future investigations and technology enhancement.

2. Theoretical background to sensor-based N recommendations

The basis for in-season N prescription from crop sensors can be remarkably variable, from simple redistribution functions to complex calibrated algorithms. Simple redistribution functions around a predefined average rate are often available from the sensor's manufacturer. The user can pre-set the average or maximum and minimum N rates and take a sensor reading in parts of the field where given rates should be applied. In the case of simple linear functions, the user can choose an algorithm with either a positive or a negative slope. A positive slope will lead to application of higher N rates in areas of higher biomass, relying on the assumption that this area presents greater yield potential (probably due to higher water availability) and therefore needs more N to fulfil this potential. On the other hand, negative slopes (the most common form), are an attempt to save N where the crop has good performance and to boost yield where it is predicted to be low. This approach leads to less fertilizer being applied where the crop has higher biomass. The Yara N-sensor™ is an example of a commercial system that has both redistribution functions and associated proprietary algorithms available.

Aside from simple redistribution functions, more robust algorithms are available based on more complex agronomic theories. One is based on a 'mass balance' concept where N to be applied is back calculated from the total N demand needed to produce a target yield of given protein content (Meisinger et al., 2008). This approach may include crediting any additional N supply besides the N fertilizer and may also account for some level of N loss, which is usually considered to be between 35% and 75% (Meisinger et al., 2008). The sensor readings are used to estimate the expected yield based on previous calibration. In some cases, the N uptake at the time of sensing is also estimated from the sensor readings and subtracted from the total N demand (Lukina et al., 2001). An important weakness of many of these approaches is their primary focus on the 'demand' side of the N equation. The accurate estimation of the N credit from soil is dependent on soil and climate conditions which can be difficult to predict and, for that reason, the N supply from soil is often poorly considered or neglected. For example, higher soil organic matter tends to mean a larger soil microbial population and therefore potentially higher N supply through mineralization; higher temperature and soil moisture also leads to higher soil biological activity and N mineralization, as long as mineralizable N is present. Even when total N demand can be estimated with some confidence, the N supply from soil will ultimately determine the crop response to applied N (Kindred et al., 2015; Meisinger et al., 2008) and not accounting for this part of the equation can be a significant flaw in such an approach. The variability of soil N supply coupled with plant water stress are reasons why crop response to N and, consequently, optimum N rates can vary markedly temporally (Johnson and Raun, 2003; Kablan et al., 2017) and are often not related to expected yield (Doerge, 2005; Scharf et al., 2006).

Since the response to applied N may vary due to different soil and weather characteristics (i.e. it can vary spatially and temporally), one solution is to empirically verify how likely the crop in a particular location will respond to additional N at a particular time by implementing in-season, zone-specific calibration references, which is a clever strategy to infer information about the 'supply' side of the N equation without the need for direct measurements. This is done by establishing a reference location within the field to which the crop in the rest of the field will be compared. A reference strip, often referred to as an 'N-rich strip', supplied with a non-limiting amount of N, is the most common way to estimate field and season-specific N response. If the crop at a particular site is less vigorous than the reference strip, it is inferred that the crop at that location is likely to respond to additional N. Other similar techniques are also often reported such as the 'calibration stamps' (Raun et al., 2005b), 'ramped calibration strips' (Raun et al., 2008; Roberts et al., 2011b) or the 'virtual reference' concept (Holland and Schepers, 2013). Regardless of the specific type of reference, the strips or plots must be representative of the rest of the field or of the specific zone they are meant to represent (Lawes and Bramley, 2012), which is often the very weakness of such approaches. Because of spatial variability occurring across the field and within the reference area (especially if long strips are used), questions as to which VI value from the strip/plot to use as the reference or how many reference areas should be implemented in a field are matter of debate (see below). The N-rich reference has been used since early developments on handheld chlorophyll meters (Blackmer and Schepers, 1995, 1994; Schepers et al., 1992; Varvel et al., 1997) and is still used in many sensor-based N applications.

The 'Nitrogen Fertilization Optimization Algorithm' (NFOA) developed by Raun et al. (2002) and updated by Raun et al. (2005a) is based on the N-rich strip approach. Although some variations can be found in different studies, its basic recommendation concept is based on a 'mass balance' calculation of optimum N rate which is given as the additional N required to increase the expected yield at a particular location to the potential yield estimated from the N rich strip, or some fraction of it. Expected yield with no additional N (field) can be estimated from the sensor readings using calibration equations from other or prior experiments relating the INSEY (in-season estimate of yield, which is the NDVI divided by growing degree days at sensing) with grain yield. Yield with additional N (N rich strip) is given by multiplying the predicted yield in a particular spot of the field by the 'response index' (RI; where RI = NDVI from N rich strip divided by NDVI from non-rich parts of the field). This method later inspired many studies by other research groups, becoming one of the most commonly reported uses of crop reflectance sensors in cereals. It was also adapted and applied (often with collaboration of the original authors) by groups in Mexico (Ortiz-Monasterio and Raun, 2007), China (Li et al., 2009), India (Bijay-Singh