A spatially distributed on-farm experimental approach for the development of a sensor-based nitrogen decision model

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Abstract
Classical small plot experimental designs are limited in the number of factors they can sensibly consider and so may not be the best experimental strategy for developing and validating multivariate sensor-based N decision models. In this paper, we present a spatially distributed on-farm experimental approach being implemented to develop a sensor-based N decision model for the Australian grains industry; this model will be used for targeted (site-specific) mid-season N application. The experimental design features N-rich and N-minus strips, the calibration of crop sensors with data collected from different zones of a paddock and the on-farm assessment of optimum N application rates. Such an approach may also support other sensor-based decision aids besides those aimed at N management.

Key Words
Precision agriculture, digital agriculture, crop sensors

Introduction
Sensor-based strategies for the delivery of site-specific nitrogen (N) recommendations have been developed since the mid-1990s to improve the profitability and sustainability of N fertiliser application. Since then, crop reflectance sensors such as the N-sensor®, GreenSeeker®, and Crop Circle™ have been both commercially available and generally regarded as potentially useful tools in informing in-season crop N requirements. However, despite extensive research, a recent review concluded that there is little robust evidence supporting the success of the different sensors and algorithms developed (Colaço and Bramley, 2018). Common sensor-based N approaches developed in the USA often rely on calibrated models to transform sensor vegetation indices (VI), such as the normalized difference vegetation index (NDVI), into N recommendations. For example, in the NFOA approach (Nitrogen Fertilisation Optimization Algorithm; Raun et al. 2005), the NDVI sensor is calibrated to predict yield potential as the starting point for calculating N requirement based on an N balance method. In the approach of Scharf and Lory (2009), sensor measurements normalized against readings taken from an 'N-rich' strip are calibrated directly to an optimum N rate (ONR). The development of such algorithms and their validations have, in the main, relied on N response plot experiments, an approach that is still commonly used (e.g. Kitchen et al. 2017). In such cases, the N plot experiments are used for two purposes: to create a range of yields and biomass for sensor calibration; and to allow calculation of crop N response and optimum N rate (ONR) to calibrate and validate the sensor N rate recommendation.

The review by Colaço and Bramley (2018), supported by a recent reinvestigation of sensor calibration data from Oklahoma plot trials (Colaço and Bramley, 2019), suggests that classical plot experiments may not be the optimum design for providing the necessary data for modelling and validating sensor algorithms. The reasons for this conclusion, reasons that are further discussed below, are the limited ability of plot trials to account for important covariates to fertiliser response (e.g. soil water availability), likely to be valuable in generating a generalized N decision model, and the limited range of conditions over which the recommendations are validated (for example, small plot experiments cannot accurately simulate the spatial variability of key soil properties such as texture or depth). The purpose of this paper is to present a spatially distributed on-farm experimental approach to the development and validation of sensor-based N management strategies. Such an approach is being implemented in the GRDC-funded Future Farm project, which aims to develop a sensor-based N decision and application platform for the Australian grains industry.

Crop sensor calibrations and N recommendations are multivariate problems
Many factors may influence soil N availability and the crop demand for N. Colaço and Bramley (2018) and Lawes et al. (2019) have highlighted the importance of a multivariate approach that combines information from different types of sensors (e.g. for crop reflectance and soil characteristics such as available water) as inputs for a robust N decision model. As with most N decision models, the calibration of crop reflectance sensors to predict relevant variables for N recommendation may also require the measurement of multiple variables (i.e. not just the mid-season crop vegetation index, Colaço and Bramley, 2019).

The relationships between mid-season vegetation indices and crop parameters (e.g. grain yield, N uptake or crop biomass) may vary significantly between different regions and different seasons. Given such variation, one important question is the extent to which calibrations derived from specific locations in specific seasons can be confidently extrapolated to other locations in future seasons. A recent study re-analysed 19 years of N plot experimental data that were previously used to derive calibrations between mid-season sensor NDVI and wheat grain yield for the NFOA approach in Oklahoma, USA (Colaço and Bramley, 2019). The analysis showed that, for any particular year, the relationships between sensor and crop parameters can have good precision ($R^2 > 0.90$). However, these calibrated models can change markedly between years, leading to poor ex-ante validations; i.e. when the calibration from one year is validated with independent datasets from other years. In other words, the fact that there is a relationship between mid-season crop VI and yield in one year does not guarantee that such relationship can be used to predict grain yield in future years or in different locations. Moreover, results showed that for this Oklahoma dataset, soil moisture at depth, measured at around 50 to 90 days after sowing, had a strong influence on both the equation coefficients and fit (R^2) of sensor calibrations, which indicates that incorporating site-year covariates (such as soil moisture information) could help in building generalized sensor calibrations. Below, we describe an on-farm spatially distributed experimental design being used in Future Farm which we believe can better accommodate the multivariate nature of sensor and N model calibrations than the current classical plot designs being traditionally used in N sensor research.

Methods

A five-year program of on-farm experiments (OFE) has been implemented in the northern, southern and western grain regions of Australia since 2018. These experiments were designed with three specific objectives in mind: to provide on-farm ONR information to which a multivariate sensor-based model can be calibrated; to allow investigation of the value of zone-specific reference areas ('N-rich' and 'N-minus' strips) for the in-season prediction of ONR; and to provide a range of crop and soil conditions from where sensor calibration data can be taken.

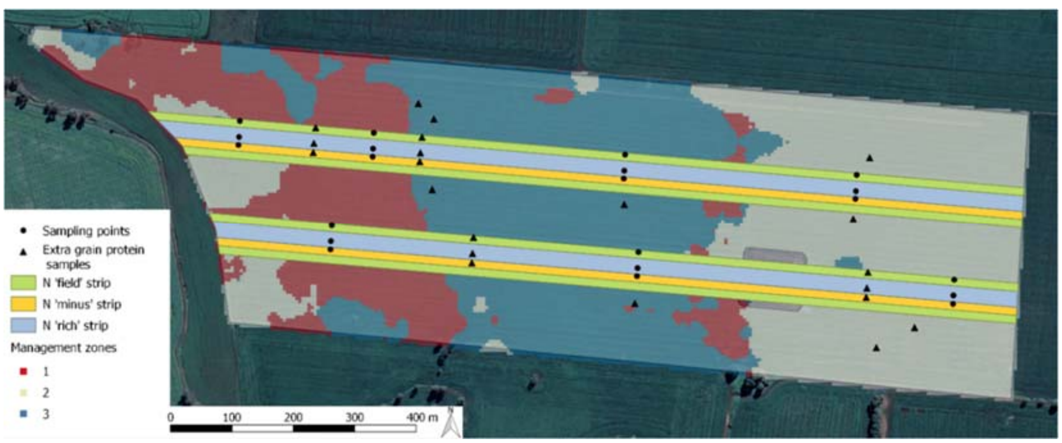

Figure 1. On-farm spatially distributed trial design in a 64 ha field near Tarlee, South Australia.

At our South Australian field site (Figure 1), N-rich and N-minus strips were applied across the paddock area in 2018 after emergence of the wheat crop using a liquid fertiliser sprayer. For this particular paddock, and after consultation with the farmer on how to best implement the strips, 13 m of the farmer's 39 m boom sprayer (13 m) was turned off for the N-minus strip whilst the rest of the boom applied almost double the N rate used in the rest of the field. In Figure 1, the N 'field' strips represent an adjacent strip area that received the same amount of N as the rest of the paddock. Strips crossed the different management zones in the field, which were previously defined based on a cluster analysis of historical yield and soil electrical conductivity maps. Sensor readings, biomass cuts and soil samples were collected between tillering and jointing crop stages at 21 target locations across strips and zones to calibrate the sensor VIs to variables that are relevant to the N decision (e.g. biomass, N uptake or grain yield). The spatial distribution of the sampling points was aimed at maximizing the variability of the measured attributes (Figure 1). During the season, the strips were monitored with proximal and remote sensing. The trial was then harvested using a header fitted with a yield monitor and on-board protein sensor. Response indices (ratios between adjacent N-rich, N-minus and N-field strips) were calculated, along with ONR calculated across the entire strip length based on the N removal difference between the N-rich and N-minus strips and a fertilisation efficiency factor.

Results

Table 1 displays a summary of the data being collected, some of which will commence in the 2019 grain season. Yield monitor data (Figure 2), along with protein monitor data, were used to calculate the N removal across the paddock and across the length of each strip. The differences in grain yield, protein concentration and N removal between N-rich and N-minus strips, along with results from a moving window t-test between strips (following the method of Lawes and Bramley, 2012) are reported in Figure 3.

Table 1. Summary of data collected in the experimental sites of Future Farm project.

Variables	Source	Spatial Resolution	Crop stage
Vegetation indices	Proximal and remote sensing	Across paddock	Tillering to jointing
Grain yield and protein	Yield and protein monitors	Across paddock	Harvest
Crop height and biomass*	Light detection and ranging	Across strip length	Tillering to jointing
Biomass, N uptake, etc.	Plant sampling	Selected points	Jointing and harvest
Soil N, texture, etc.	Soil sampling	Selected points	Pre-sowing, jointing and harvest
Soil moisture*	Soil moisture probe	For each zone	Daily across season
Soil electrical conductivity, historical yield, etc.	Historical data base	Across paddock	-

*Commence in the 2019 grain season

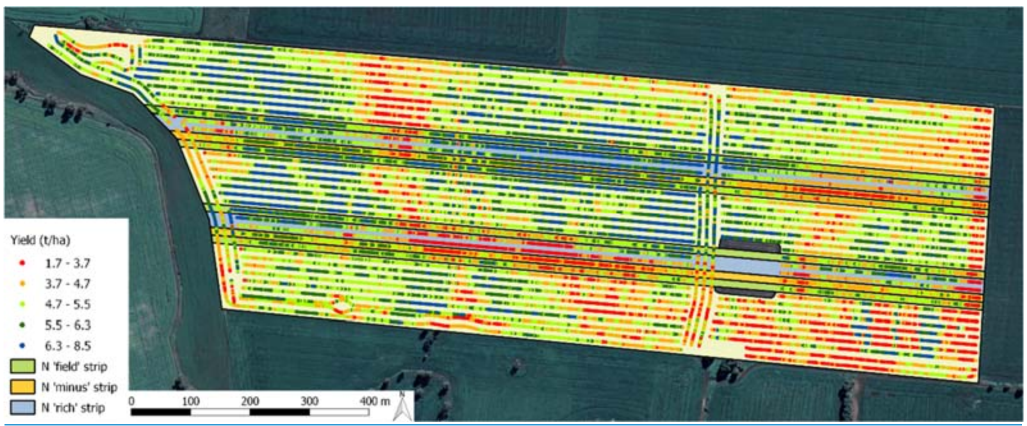

Figure 2. Grain yield information and N strips in an on-farm trial near Tarlee, South Australia.

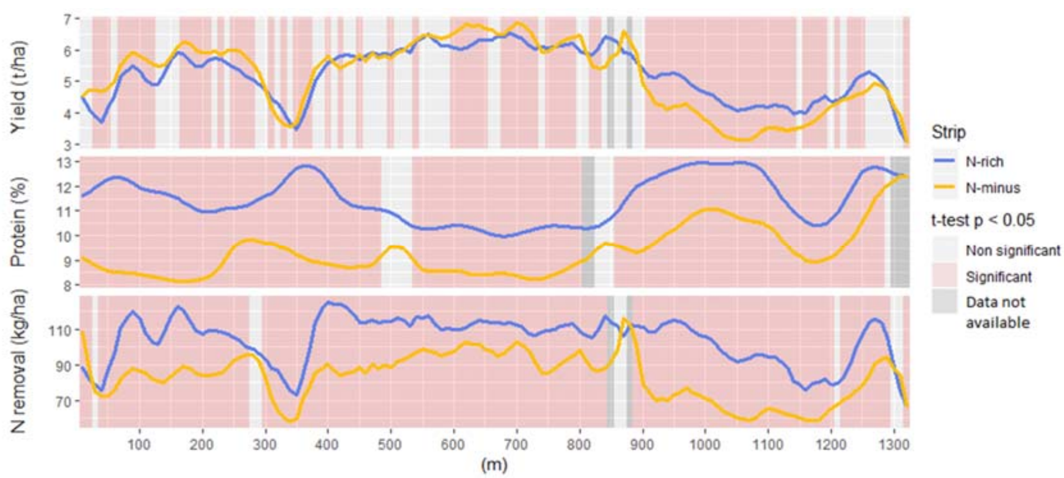

Figure 3. Grain yield, grain protein and N removal at N-rich and N-minus strips and moving window t-test.

The next step will be to arrange datasets at each sampling point, pixel, or at virtual points distributed along the strip length, forming different databases with different spatial scales from which sensor calibration and N recommendation models can be generated. Model validations can be conducted with the different types of datasets, testing the value of each source of information; such validations can be conducted across the different zones of the field, indicating where any particular crop or soil parameter might be more relevant to the N decision model.

Discussion

Given the multivariate nature of N recommendations and of sensor calibrations, we suggest that classical plot designs may not be the best form of experimentation to develop sensor-based N approaches. Such designs were developed to eliminate variation beyond that being accounted for in the experiment treatments (i.e. 'factors' in the factorial design). We believe spatially distributed OFE designs may offer benefits to sensor-based N research, because they capitalise on the spatial variation in the paddock rather than attempting to eliminate or control it. Multiple variables for modelling and validation can be measured across a range of conditions within the same field. Of course, such trials should also be spread across sites and years to maximize the variability in the data, given that variation in conditions such as soil moisture across years and sites may be more significant than variation within one paddock in one year. Spatially distributed OFE approaches have been available since the initial development of equipment such as variable rate applicators and yield monitors (Cook and Bramley, 1998). More recent technological improvements in equipment performance (accuracy of application and positioning) and the adaptation of classical statistics for spatial data analysis (e.g. Lawes and Bramley, 2012) have made such experiments even more practical and reliable. We believe these approaches will take an important role as agricultural research shifts from knowledge-based methods to more data-driven science. Nevertheless, some points around OFE are still worth attention. As seen in Table 1, compiling spatial databases from such trials might be a challenging task as the necessary data for the experiment might come from different platforms at differing spatial resolution (i.e. different sensor types with different footprints). Whilst interpolation using kriging may offer a possible solution to stitch high-density data layers based on a common spatial grid (e.g. Bramley and Trengove, 2013), it is often the case that some variables need to be measured manually and/or in limited number, with restricted opportunity for kriging/interpolation. It is therefore critical that more types of on-the-go soil and plant sensors are developed to facilitate development of sensor-based decision models using OFE.

Acknowledgements

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