Optimising nitrogen use in cereal crops using site-specific management classes and crop reflectance sensors

Brett. M Whelan and Mario Fajardo

Sydney Institute of Agriculture, School of Life Sciences, The University of Sydney, Australia.

A paper from the Proceedings of the
14th International Conference on Precision Agriculture
June 24 – June 27, 2018
Montreal, Quebec, Canada

Abstract. *The relative cost of Nitrogen (N) fertilisers in a cropping input budget, the 33% Nitrogen use efficiency (NUE) seen in global cereal grain production and the potential environmental costs of over-application are leading to changes in the application rates and timing of N fertiliser. Precision agriculture (PA) provides tools for producers to achieve greater synchrony between N supply and crop N demand. To help achieve these goals this research has explored the use of management classes derived from historic field data and in-season crop reflectance sensors in an attempt to quantify, and manage the effects of, spatial and temporal variation in N uptake. This simple study combines the two techniques to try and quantify in-season variation in N requirements, and furthermore attempts to improve the predictive ability of in-season yield prediction functions through the inclusion of historic soil and yield data sets. Experiments from two example fields are used to quantify seasonal variations in N using in-season reflectance data. A process was designed to build site-specific N requirement algorithms from reflectance and historic input data. The variation in historic yields and current season reflectance indices across potential management classes indicates that the magnitude of variation in plant N requirements is sufficient to implement management classes in conjunction with in-season crop reflectance sensors. Furthermore the development of modified site-specific yield prediction functions according to management classes built from soil* EC_a *data, previous yield observations and calibrated yield prediction functions significantly enhanced yield prediction accuracy. These improved in-season yield predictions were used to construct N application strategies that proved more cost effective than traditional approaches. The combination of site-specific historic data and in-season reflectance information shows promise for the development of N application decision support to improve NUE in both economic and environmental terms.*

Keywords. *nitrogen, precision agriculture, crop reflectance sensors, management classes.*

Introduction

In the past 50 years average wheat (*Triticum aestivum* L.) yields have increased significantly, resulting in larger requirements for Nitrogen (N) to support greater crop growth and development. This, along with increases in the price of N drives a continuous review of N usage and the rate, mode of application, and timing of N fertilisation. All this is aimed at improving the approximately 33% nitrogen use efficiency (NUE) that is still observed globally in cereal grain production (Raun and Johnson 1999). The causes of low NUE have been extensively researched (Cassman *et al.* 2002; Fageria and Baligar 2005; Goulding *et al.* 2008; Raun and Johnson 1999; Thomason *et al.* 2000; Zebarth *et al.* 2007) with the conclusion that the main reasons for low NUE are due to the poor synchronisation of N supply with N crop demand. This, coupled with a poor knowledge of N uptake and spatial variability in resident soil N, means that current production practices may have high levels (70%) of N losses (Raun *et al.* 2002).

Precision agriculture provides tools for producers to achieve greater synchrony between N supply and crop N demand. The use of PA technology allows variability within a field to be sensed and management strategies generated to capitalise on spatial variability (Brennan *et al.* 2007). The use of site-specific management classes has been a major contributor to this advance. Site-specific management classes are defined as areas in which agronomically different production treatments may be required (Taylor *et al.* 2007). Identifying class boundaries typically relies on high spatial density historical crop production and landscape data. However such classes may be less consistent in characterising spatial variation in N uptake because of observed temporal variation attributed to seasonal weather and its effect on yield potential (Shanahan *et al.* 2008).

The development of in-season, real-time crop reflectance sensors (Raun *et al.* 2001; Scharf and Lory. 2009; Holland and Schepers 2010.) has allowed the effects of seasonal variation in climatic attributes, such as rainfall, photoperiod and temperature on N uptake to be explored. (Lukina *et al.* 2001). Using these tools has the potential to minimise N losses, by helping to monitor and meet changing plant nutrient requirements (in space and time) as they occur in-season. A recent review by Colac and Bramley (2018) provides an excellent account of the impact the reflectance tools have had on improving NUE. One of the major findings is the lack of inclusion of variability in soil derived contributions to both N availability and supply. While some research has been conducted into comparing and/or including soil/landscape information in the processes of N fertilizer decision making using reflectance sensors (e.g. Erbertseder *et al.* 2005; Kitchen *et al.* 2010; Tremblay *et al.* 2010) minimal research has targeted the incorporation of both site-specific management classes derived from multivariate historical data and on-the-go real-time crop reflectance to try and quantify in-season variation in N requirements. This study uses both techniques to try and quantify in-season variation in N requirements between management classes using real time reflectance measurements. This preliminary research attempts to highlight a simple approach to improve the predictive ability of the Australian yield prediction functions through the inclusion of previous soil and yield data sets. This should further optimise the level of N inputs practically and economically, thus potentially reducing N losses and assisting to overcome the increasing costs of N as a cereal crop input.

Materials and Methods

Site description and experimental design

Two fields in Gilgandra, northern NSW are used as examples in this study. The farm uses no-tillage, controlled traffic farming practices. The average rainfall for the area is 558mm with in-season winter rainfall averaging 307mm. However rainfall in the cereal growing season was 71mm below average, which when coupled with above average temperatures (average daily maximum 25.6°C and average daily minimum 10.9°C) meant that moisture stress became a limiting factor in dryland wheat production. The experiment was carried out in two adjacent fields, 'Diamond' (72 ha) and 'Mugs' (69 ha). 'Diamond' was sown with the wheat variety Ventura (short season spring wheat). 'Mugs' was sown with the wheat variety Strzelecki (long season spring wheat) on 21/5/2007. Both fields had no phosphorus (P) applied at sowing and no nitrogen (N) applied to the bulk of the field. Field-length N fertiliser treatment strips were established using urea fertiliser (46% N) in locations designed to include the extent of expected soil variability (Figure 1). Two treatment rates (non-limiting N and traditional) were replicated in each field. In 'Diamond' and 'Mugs' the non-limiting N and traditional rates were 250 kg / 80 kg urea ha^{-1} and 260 kg / 80 kg urea ha^{-1} respectively.

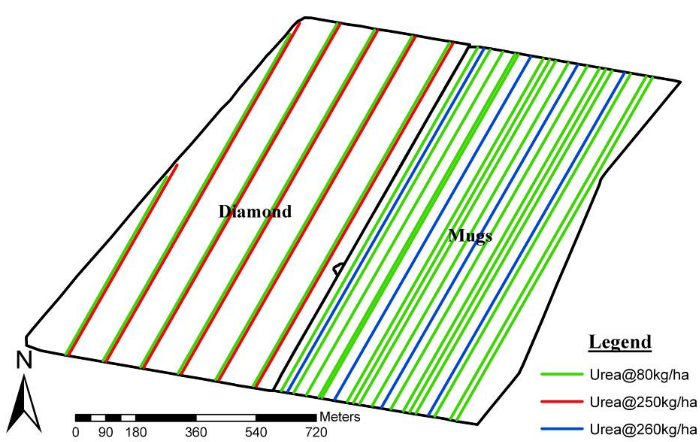

Fig. 1. Experimental design of N strips in 'Diamond' and 'Mugs' fields in the trial year.

Historical and in-season data

Soil apparent electrical conductivity (EC_a) data was collected pre-season using a Geonics EM38® (Geonics, Ontario, Canada) and a Veris 3100® (Veris Technologies, Kansas, USA) at 20m swaths. Elevation data was also collected using an RTK GPS. Historic grain yield data from 'Diamond' was available for year-2 and 'Mugs' (year-2, year-3 and year-4) collected using a Green Star® (John Deere, Illinois, USA) yield mapping system on 9m swaths. Normalized difference vegetation index (NDVI) data was collected using boom-mounted Green Seeker® sensors at 9 m swaths. Passes with the Green Seeker® were taken throughout the growing season.

Data analysis

Potential management class delineation

Potential management classes were derived from soil attribute data layers (EM38 and Veris 0–30 cm, 0–90 cm and 30–90 cm), previous seasons yield data and elevation data as available for each field. Class delineation was carried out using k-means cluster analysis in JMP (SAS) as per the protocol of Taylor *et al.* (2007). For each field, two and three potential management class options were constructed. This gave three monitoring combinations to be tested in each field: whole-field, two classes and three classes.

Allocating point data

In order to compare the in-season N response, NDVI readings and yield predictions with the final yield, the observations were colocated. End of season yield measurements from the yield monitor provided the location grid as it was the data set with the coarsest resolution and the common data requirement for all comparisons and analysis. All soil, previous yield, potential management class allocation, fertiliser rates and NDVI data was transferred to this location grid using a nearest neighbour procedure. Any sites on this grid that required an original observation to be moved from more than six metres away were removed from further analysis.

Yield prediction and nitrogen requirement algorithms

To predict yield in-season the NDVI data from the Green Seeker® passes was used in accordance with functions developed by NTech/Trimble. The process uses a series of generic functions (Eqns 1–5) within region-specific algorithms. The regionality is achieved by local calibration of the functions providing different coefficient values (k).

The series of functions forming the N application algorithm include:

$$YP\ 0 = \text{MIN}\left[k_a \cdot e^{\left(\frac{NDVI \cdot k_b}{DFP}\right)},\ \text{Max Yield}\right] \quad (1)$$

$$RI = \left(\frac{NDVI\ N\ Non\ Limited}{NDVI\ N\ Limited}\right) \quad (2)$$

$$RI_{adj} = \text{MIN}\left[k_c\left(\frac{NDVI\ N\ Non\ Limited}{NDVI\ N\ Limited}\right) - k_d,\ \text{Max}\ RI_{adj}\right] \quad (3)$$

$$YP\ \text{N} = \text{MIN}\left[YP\ 0\ \cdot RI_{adj},\ \text{Max Yield}\right] \quad (4)$$

$$\text{N}_{\text{applied}} = \frac{P_N}{NUE} \cdot \left(YP\ \text{N} - YP\ 0\right) \quad (5)$$

Where: 'YP 0' is the predicted potential grain yield with no added fertiliser in kg ha^{-1}; 'k_a', 'k_b', 'k_c', and 'k_d' are site-specific coefficients (an outline of the values for the proprietary algorithm being tested is seen in Table 1); 'NDVI' is the normalized difference vegetation index; 'DFP' is the cumulative days from planting where GDD > 0; 'Max Yield' is a defined maximum yield assumed as 6000 kg ha^{-1} for all algorithms; 'RI' is the response index; 'NDVI N Non limited' is the NDVI reading of the non limiting N strips; 'NDVI N limited' is the NDVI reading of the strips which may be limited by N; 'RI_{adj}' is the adjusted response index; 'Max RI_{adj}' is a defined maximum RI; 'YP N' the predicted potential grain yield with added fertiliser in kg ha^{-1}; '$N_{applied}$' is the amount of N fertiliser to be applied in kg ha^{-1}; 'P_N' is the percentage N in the grain; and 'NUE' is the nitrogen use efficiency which was assumed as 50% for all algorithms.

In essence the algorithms begin with a function to predict yield (YP 0), and then use the RI to establish the crop yield response to added fertiliser and provide an N requirement. The main Australian function available from the sensor manufacturer for South Australia was used in this work (Table 1) as other manufacturer provided functions were tested and provided poorer predictions (data not shown). The yield predictions (YP 0) generated from within each algorithm using Equation 1 were correlated with actual observed yields to test their predictive ability.

Table 1. Coefficient values for standard algorithms used to generate yield predictions and N requirements.

Name	K_a	K_b	K_c	K_d	Max RI_{adj}	P_N	NDVI Range
Spring Wheat Rainfed South Australia (S.AU)	1800	85	1.69	0.7	2.2	0.02	0.25–0.88

Modified function development

Local farm functions were developed in an attempt to improve the predictive ability of the yield prediction functions. Development of new yield prediction functions was performed using two methods. The first involved the development of a calibrated yield prediction function for the farm ($YP0_{FARM}$). The protocol (Oklahoma State University (2008)) outlines a process that requires the investigation of 10 points across 10 fields where no N fertiliser is applied. At growth stage Z30, NDVI data is collected for each point and this is used to generate the in-season estimation of yield (INSEY). INSEY is calculated by dividing the NDVI at each point by the cumulative days from planting (DFP), where GDD is greater than zero. A regression of INSEY against final grain yield provides the coefficients (k) for the calibrated site-specific yield prediction function ($YP0_{FARM}$). The absence of previous season NDVI data meant that calibration was carried out on reflectance data from across the entire farm and the protocol was modified by randomly identifying 100 points, 1 from each centile of the reflectance distribution and obtaining a kriged estimate of yield at those points from the yield monitor data.

The second method involved the inclusion of historic production data form each field to assist in explaining variability in the current season yield. Two processes for including this historic data into the production of modified yield prediction functions were established. The first used the spring wheat rainfed S.AU YP 0 function plus historic information, and the second used the 'FARM' calibrated function ($YP0_{FARM}$) with the inclusion of historic data. Both processes used stepwise multiple regression to determine which historical data layers were significant in improving yield prediction. This process was carried out for each whole field, and also class-specific functions were developed for each of the potential management classes within both fields. The modified yield prediction functions were then run across the NDVI data in both fields allowing correlations to be drawn between the predicted and actual yields. The correlations for all algorithms were carried out at the whole field scale and also by calculating predictions separately within each potential management class to quantify any impact of segregating production classes on yield prediction. The Akaike information criterion (AIC) was calculated as per Webster and McBratney (1989) to determine which modified prediction function performed best.

Results

Management classes

The potential management classes for 'Diamond' (Fig. 2) and 'Mugs' (Fig. 3) show contiguity that suggests the spatial structure is suitable for implementing site-specific management classes (de Oliveira *et al.* 2007). An assessment of the optimal number of classes using the method of Whelan *et al.* (2002) suggests that the three management classes in 'Diamond' and two in 'Mugs' would be feasible (Table 2). For completeness, two and three management class delineations were used in each field to assess the yield prediction functions and N management approaches.

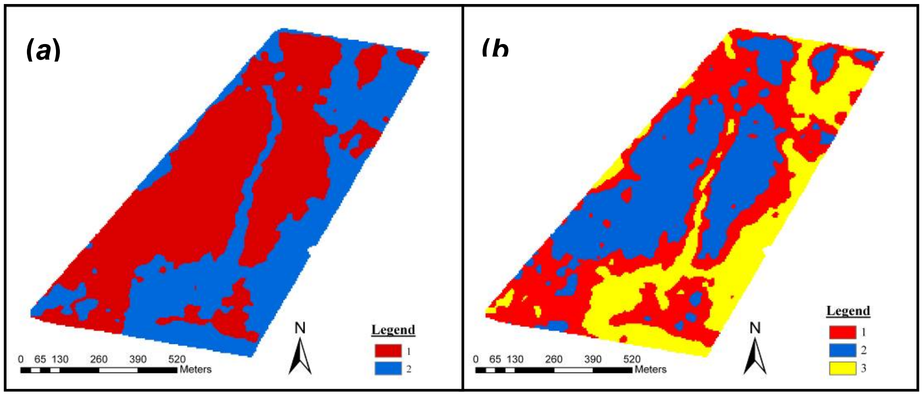

Fig. 2. 'Diamond' potential management classes based on soil sensor data (Veris 0–30 cm, 0–90 cm and 30–90 cm) and 2005 wheat yield. (*a*) two management classes, (*b*) three management classes.

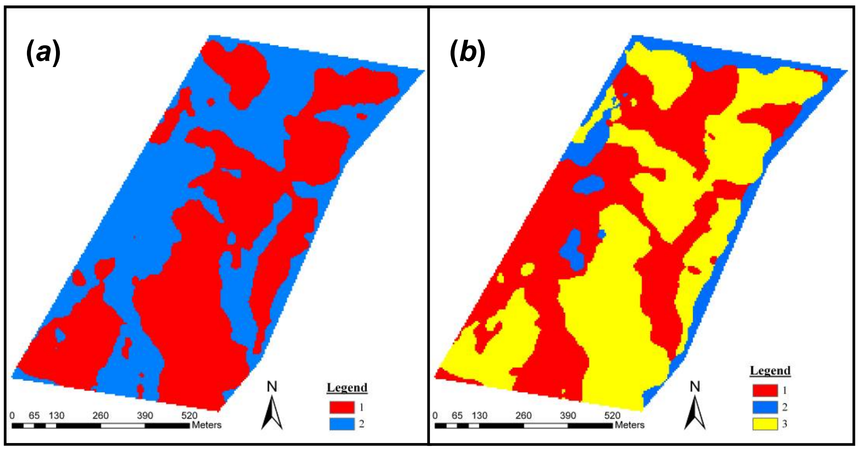

Fig. 3. 'Mugs' potential management classes based on soil sensor data (EM38, Veris 0–30 cm, 0–90 cm and 30–90 cm), 2001 and 2005 wheat yield, and 2004 canola yield. (*a*) two management classes, (*b*) three management classes.

Table 2. Partitioning of mean yields according to potential management classes in 'Diamond' and 'Mugs'. Confidence intervals (CI) provide an indication of the required magnitude in yield differences to quantify management class delineation.

		Grain Yield t ha^{-1}					95% Confidence Interval (CI)
		3 Classes			2 Classes		
		Class 1	Class 2	Class 3	Class 1	Class 2	
Diamond	Wheat YR-2	2.80	3.09	2.51	2.98	2.61	± 0.10
Mugs	Wheat YR-4	2.64	1.95	3.25	3.21	2.42	± 0.14
	Canola YR-3	1.60	1.00	1.56	1.56	1.46	± 0.04
	Wheat YR-2	3.83	2.94	3.77	3.77	3.61	± 0.12

NDVI and yield

In-season NDVI data for the two fields (Table 3) demonstrate that NDVI levels generally increase with season progression. The more detailed temporal scale in 'Mugs' shows that the general increase of NDVI over the growing season has a reduction in mid September. This reduction is to be expected as at this growth stage (Z60) of the wheat plant, grain filling starts to occur which results in N being redistributed from plant leaves (Hocking 1994) and the reduction of plant biomass and associated NDVI levels. There are observable differences in the NDVI between potential management classes in both fields. Observations of final yield across the two fields are shown in Figure 4a and Figure 4b.

Table 3. Average in-season NDVI readings of 0 kg N ha^{-1} treatments.

Field	Pass Date	DFP (GDD > 0)	Uniform Production	3 Classes			2 Classes	
				Class 1	Class 2	Class 3	Class 1	Class 2
Diamond	22/08	66	0.500	0.510	0.518	0.456	0.517	0.473
	21/09	96	0.678	0.688	0.691	0.643	0.691	0.658
Mugs	25/07	62	0.384	0.366	0.392	0.397	0.395	0.369
	21/08	89	0.775	0.765	0.734	0.790	0.789	0.757
	7/09	106	0.788	0.790	0.710	0.805	0.804	0.767
	13/09	112	0.753	0.750	0.699	0.761	0.761	0.741

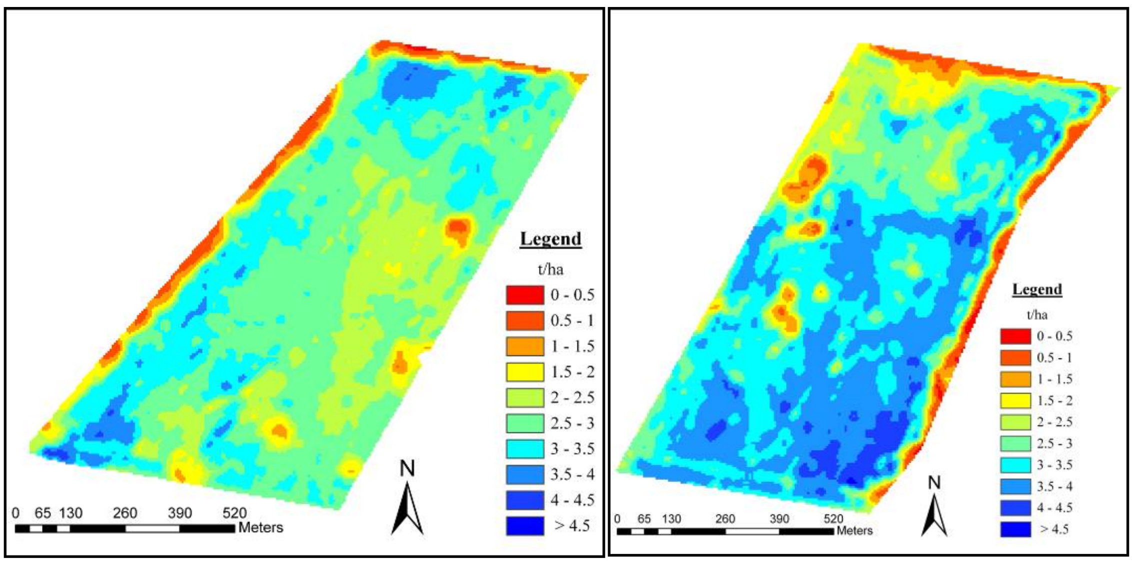

Fig. 4. (a) 'Diamond' 2007 wheat yield map; (b) 'Mugs' final wheat yield map.

Standard yield prediction

Yield prediction was higher than observed harvest yield across both fields, with a correlation value of 0.391 and 0.224 in 'Diamond' and 'Mugs' respectively (Table 4).

Table 4. Correlations (r) of current in-season yield prediction function with final yield.

Field	Prediction Functions	Whole Field	3 Classes			2 Classes	
			Class 1	Class 2	Class 3	Class 1	Class 2
Diamond	Spring Wheat Rainfed S.AU	0.39	0.50	0.31	0.25	0.40	0.35
	No. of observ.	*34941*	*13559*	*12846*	*8536*	*21198*	*13743*
Mugs	Spring Wheat Rainfed S.AU	0.22	0.15	0.001	0.154	0.141	0.16
	No. of observ.	*27895*	*11116*	*2826*	*13953*	*15821*	*12074*

Improved yield prediction

Site-specific YP 0

The $YP0_{FARM}$ function is shown in Equation 6.

$$YP0_{FARM} = 2309.81 + (138107.84 \times \mathrm{INSEY}) - 84409266(\mathrm{INSEY} - 0.0078)^2 \quad (6)$$

Where: ‘Site YP 0’ is the predicted potential grain yield with no added fertiliser in kg ha^{-1}; and ‘INSEY’ is the in-season estimation of yield.

Modified site-specific yield prediction functions

The development of modified site-specific yield prediction functions including soil EC_a data and previous yield observations further enhanced yield prediction accuracy. Significant increases in correlations across both fields and all classes indicate that the prediction accuracy of the modified functions is an improvement in yield prediction accuracy compared to the standard algorithms (Table 5 and Table 6). The higher correlation values and the lower AIC indicates that the modified 3 class site-specific function is the best yield predictor for both fields (Table 6). The improvement in yield prediction accuracy using the modified functions is further demonstrated by comparing actual yield maps (Fig. 4) with those built using the standard spring wheat rainfed S.AU function and the modified 3 class site-specific functions for both fields (Figures 5 and 6).

Table 5. Correlations (r) of standard yield prediction function and modified site-specific yield prediction functions with final yield, per field and per potential management class. NB Spring Wheat Rainfed S.AU is the standard prediction function used.

Field	Prediction Functions	3 Classes Class 1	3 Classes Class 2	3 Classes Class 3	2 Classes Class 1	2 Classes Class 2	Whole Field Uniform Function
Diamond	Spring Wheat Rainfed S.AU	0.50	0.31	0.25	0.40	0.35	0.39
	Modified (S.AU)	0.52	0.34	0.27	0.42	0.37	0.40
	Site-Specific YP 0 ($YP0_{FARM}$)	0.55	0.35	0.31	0.45	0.40	0.43
	Modified ($YP0_{FARM}$)	0.57	0.38	0.32	0.47	0.41	0.44
	Number of observations	*13559*	*12846*	*8536*	*21198*	*13743*	*34941*
Mugs	Spring Wheat Rainfed S.AU	0.15	0.001	0.15	0.14	0.16	0.22
	Modified (S.AU)	0.31	0.49	0.38	0.40	0.62	0.49
	Site-Specific YP 0 ($YP0_{FARM}$)	0.18	0.17	0.16	0.19	0.27	0.24
	Modified ($YP0_{FARM}$)	0.32	0.50	0.38	0.40	0.63	0.49
	Number of observations	*11116*	*2826*	*13953*	*15821*	*12074*	*27895*

Table 6. Whole field correlations (r) and Akaike information criterion (AIC) of standard yield prediction function and modified site-specific yield prediction functions with final yield, per field. Note: The whole field correlation for the class-specific functions was computed by recombining separate class predictions into a whole field.

Prediction Function	Whole field correlation (r)		Akaike information criterion (AIC)	
	Diamond	Mugs	Diamond	Mugs
Spring Wheat Rainfed S.AU	0.39	0.22	326210	274972
Site-Specific YP 0 ($YP0_{FARM}$)	0.43	0.24	324863	274722
Modified Uniform Function (S.AU)	0.40	0.49	325588	268522
Modified 2 Class-Specific Function (S.AU)	0.42	0.58	325068	264974
Modified 3 Class-Specific Function (S.AU)	0.43	0.66	324564	260133
Modified Uniform Function (Site)	0.44	0.49	324272	268639
Modified 2 Class-Specific Function (Site)	0.46	0.58	323362	264641
Modified 3 Class-Specific Function (Site)	0.48	0.66	322653	260013
Number of observations	*34941*	*34941*	*27895*	*27895*

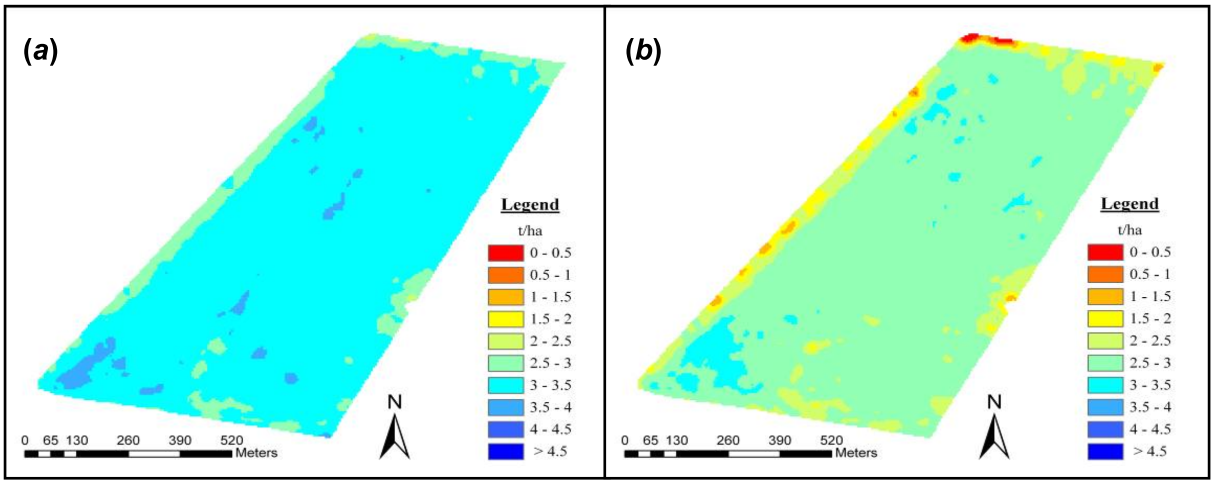

Fig. 5. Interpolated maps of predicted potential grain yield with no fertiliser (YP 0) in ‘Diamond’ using: (*a*) Spring wheat rainfed S.AU function, (*b*) Modified 3 class-specific function (Site).

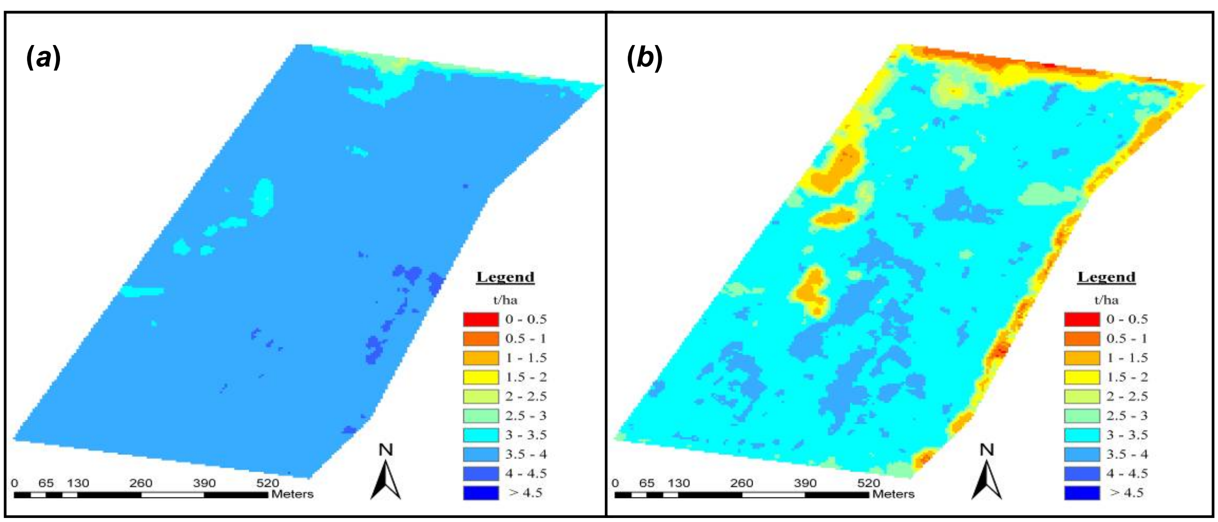

Fig. 6. Interpolated maps of predicted potential grain yield with no fertiliser (YP 0) in ‘Mugs’ using: (*a*) Spring wheat rainfed S.AU function, (*b*) Modified 3 class-specific function (Site).

Discussion

Enhancing NUE using in-season crop reflectance sensors requires spatial variability to be sensed accurately and N applications tailored to meet spatial N requirements. Using potential management classes in SSCM further requires the presence of sufficient magnitude and spatial structure in the variation. The observed variability in historical yield across both fields (Table 3) suggests that it may be viable to implement SSCM to maximise input efficiency. Adding weight to this is the variability in average in-season NDVIs between potential management classes (Table 4) which indicate that there is also significant difference in current season yield potential (Raun *et al.* 2005). Using in-season NDVI in standard yield prediction algorithms has shown a correlation with final yield values (0.21–0.39) across both fields, supporting the findings of Raun *et al.* (2002) and Raun *et al.* (2005). The minimal yield response to applied fertiliser (Tables 4 and 5) indicate that soil N levels were not a limiting factor on grain yield. Moisture stress is proposed as a major contributor to the small correlations between predicted and observed yields for the monitored season in this study as compared with previous studies (Berntsen *et al.* 2006; Lukina *et al.* 2001; Raun *et al.* 2001).

A calibrated site-specific yield prediction function ($YP0_{FARM}$), developed in an attempt to incorporate some local response information resulted in improved correlations at the whole field scale in both fields (0.39 to 0.43 in 'Diamond' and 0.22 to 0.24 in 'Mugs') compared to the standard prediction function currently in use on the farm (spring wheat rainfed S.AU). But given the expectation that moisture stress may play a role in the majority of seasons in Australia, a process to predict potential yield more accurately in-season may be improved by considering past production information in the estimation. Modified yield prediction functions that incorporate either the standard or the site-specific calibrated yield prediction functions (Raun *et al.* 2002) and include previous season data layers and potential management classes were developed and compared.

A modified prediction function created using the standard yield prediction function (spring wheat rainfed S.AU) coupled with soil and previous yield data provided improvements in yield predictions. Correlations with actual yields using a uniform function at the whole field scale increased from 0.39 to 0.40 and 0.22 to 0.49 in 'Diamond' and 'Mugs' respectively. These improvements are further enhanced via the prediction of yield using modified class-specific functions (Table 6). The modified class-specific functions further increased correlations in both fields ('Diamond' 2 classes = 0.44, 3 classes 0.43 and 'Mugs' = 2 classes 0.58, 3 classes = 0.66).

The site-specific modified functions further enhanced yield prediction ability. The correlation values for the uniform function at the whole field scale improved from 0.40 for the modified standard to 0.44 in Diamond. In Mugs, the uniform site-specific modified function did not greatly improve yield prediction. The modified class-specific functions resulted in increases in correlations over the uniform functions in both fields ('Diamond' 2 classes = 0.46, 3 classes = 0.48 and 'Mugs' 2 classes = 0.58, 3 classes = 0.66) suggesting that the prediction of yield according to modified class-specific functions should be considered for in-season potential yield prediction in the future.

It is evident that the improvement in predictions resulting from the introduction of historical production data is greater in 'Mugs' than 'Diamond'. The best prediction functions for 'Mugs' were based on the inclusion of three previous seasons yield data and soil EC_a data layers. In 'Diamond' the best prediction functions only contained one previous seasons yield data and soil EC_a data. The availability of more historical data may have a bearing on this result. Previous studies undertaken by Raun *et al.* (2001) state that the inclusion of two previous seasons NDVI data improved predictions and explained 83% of variability in grain yield. Given an expected correlation between grain yield and NDVI (Berntsen *et al.* 2006; Lukina *et al.* 2001; Raun *et al.* 2001), the inclusion of at least two previous seasons yield data may be necessary to significantly improve the prediction of yield predictions. Further reseach into in-season yield prediction needs to incorporate both previous season NDVI and grain yield to test for further improvements.

Using the simple stepwise regression process to determine the optimum modified functions resulted in the universal inclusion of soil EC_a data. The spatial variability in soil EC_a is strongly influenced by changes in soil texture and the effect on soil moisture holding capacity (Sudduth *et al.*, 1996). The presence of soil EC_a in each modified function suggests that soil texture and soil moisture are major factors influencing the variability in yield. In all of the modified functions (24 in total – data not shown), soil ECa measured over the profile depth or from the 'subsoil' was included as a significant predictive parameter. This is not unexpected as in dryland cereal production throughout Australia subsoil moisture provides a major contribution to crop water supplies (Kirkegaard *et al.* 2007). The inclusion of information relevant to subsoil moisture levels (such as soil EC_a) into future modified prediction functions may allow an accurate minimum potential yield to be predicted and would provide producers with an estimate of expected yield without any further in-season rainfall. In addition, in-season yield prediction accuracy may increase with the inclusion of direct soil attributes, such as plant available water capacity (PAWC).

Improved accuracy of in-season yield prediction via modified site-specific functions also results in significant improvements in projected N input costs compared with pre-plant N application (data not shown). Widespread adoption of in-season crop reflectance sensors coupled with nitrogen fertiliser optimisation algorithms (NFOA) in Australia will be dependent on increased financial returns from improved N management. Financial analysis of in-season yield prediction demonstrates that across both fields in-season N application via the modified 3 class site-specific yield prediction functions in the cropping season monitored would have resulted in a saving of $1268 and $1790 in 'Diamond' and 'Mugs' respectively.

For the monitored season the average saving per ha across both fields was $22 ha^{-1}. If savings of this magnitude were attained across 1000 ha this would equate to a saving of $22,000 per season resulting in the capital expenses of the crop reflectance sensors being recovered in under one season. In addition to the direct savings seen from in-season N fertilisation there is the potential to minimise the loss of N to the environment by avoiding over-application. (Daigger *et al.* 1976; Chichester and Richardson, 1992; Raun and Johnson 1999). This aspect has less impact on management in Australia at present.

The creation of modified class-specific yield prediction functions using historic production information has been shown in this preliminary study to improve the in-season prediction of variation in yield potential, especially in water-limited environments. Further exploration of the concept across a range of environments is warranted.

Conclusions

Variation in current season mean NDVI readings was identified between potential management classes derived from historic production information. This indicates that the use of NFOA in conjunction with in-season crop reflectance sensors may be enhanced by considering the construction of individual NFOA for identifiably different potential management classes. Improvement in correlations between predicted and harvested crop yield were obtained through the use of modified yield prediction functions in the NFOA. The inclusion of soil EC_a data, and previous yield observations into the in-season yield prediction functions (YP 0) significantly enhanced yield prediction accuracy in these two fields. Calculating class-specific, modified yield prediction functions provided the greatest correlation between predicted and achieved crop yield. In-season application of N fertiliser in response to accurately predicted crop yield potential shows substantial financial benefit over the traditional method of applying N fertiliser pre-season in response to a target yield goal.

Acknowledgements

The involvement and support of James Hassall, the innovative farmer who established and managed the trials on his property is gratefully acknowledged. The financial assistance of the Grains Research and Development Corporation is also acknowledged.

References

Berntsen, J., Thomsen, A., Schelde, K., Hansen, O.M., Knudsen, L., Broge, N., Hougaard, H., & Horfarter R. (2006). Algorithms for sensor-based redistribution of nitrogen fertilizer in winter wheat. *Precision Agriculture,* **7**, 65–83.

Brennan, L.E., Robertson, M.J., Dalgliesh, N.P. & Brown, S. (2007). Pay-offs to zone management in a variable climate: an example of nitrogen fertiliser on wheat. *Australian Journal of Agricultural Research,* 58, 1046–1058.

Cassman, K.G., Dobermann, A. & Walters, D.T. (2002). Agroecosystems, nitrogen-use efficiency, and nitrogen management. *Ambio,* 31, 132–140.

Chichester, F.W. & Richardson, C.W. (1992). Sediment and nutrient loss from clay soils as affected by tillage. *Journal of Environmental Quality,* 21, 587–590.

Colaco, A.F. & Bramley, R.G.V. (2018). Do crop sensors promote improved nitrogen management in grain crops. *Field Crops Research,* 218, 126-140.

Daigger, L.A., Sander, D.H. & Peterson, G.A. (1976). Nitrogen-content of winter-wheat during growth and maturation. *Agronomy Journal,* 68, 815–818.

Erbertseder. Th, Schmidhalterm U., Gutser, R. Hege, U. & Jungert, S. (2005). Evaluation of mapping and on-line nitrogen fertiliser application strategies in multi-year and multi-location static field trials for increasing nitrogen use efficiency of cereals. In J. Stafford (Ed.), Precision Agriculture '05. pp. 281-288. Wageningen Academic Publishers: The Netherlands.

Fageria, N.K. & Baligar, V.C. (2005), Enhancing nitrogen use efficiency in crop plants. *Advances in Agronomy,* 88, 97–185.

Goulding, K., Jarvis, S. & Whitmore, A. (2008). Optimizing nutrient management for farm systems. *Philosophical Transactions of the Royal Society B-Biological Sciences,* 363, 667–680.

Hocking, P.J. (1994). Dry-matter production, mineral nutrient concentrations, and nutrient distribution and redistribution in irrigated spring wheat. *Journal of Plant Nutrition,* 17, 1289–1308.

Holland, K.H. & Schepers, J.S., (2010). Derivation of a variable rate nitrogen application model for in-season fertilization of corn. *Agronomy Journal*, 102, 1415-1424.

Kirkegaard, J.A., Lilley, J.M., Howe, G.N. & Graham, J.M. (2007). Impact of subsoil water use on wheat yield. *Australian Journal of Agricultural Research,* 58, 303–315.

Kitchen, N.R., Sudduth, K.A., Drummond, S.T., Scharf, P.C., Palm, H.L., Roberts, D.F. & Vories, E.D. (2010). Ground-based canopy reflectance sensing for variable-rate nitrogen corn fertilization. *Agronomy Journal*, 102, 71–84

Lukina, E.V., Freeman, K.W*., et al.* (2001), Nitrogen fertilization optimization algorithm based on in-season estimates of yield and plant nitrogen uptake. *Journal of Plant Nutrition,* 24, 885–898.

Oklahoma State University. (2008). Outline for generating new crop algorithms for N fertilization. http://www.nue.okstate.edu/Algorithm/Algorithm_Outline.htm, Accessed 30/04/2018.

Raun, W.R., Johnson, G.V. (1999). Improving nitrogen use efficiency for cereal production. *Agronomy Journal,* 91, 357–363.

Raun, W.R,, Solie, J.B., Johnson, G.V., Stone, M.L., Lukina, E.V., Thomason, W.E., & Schepers, J.S. (2001). In-season prediction of potential grain yield in winter wheat using canopy reflectance. *Agronomy Journal,* 93, 131–138.

Raun, W.R., Solie, J.B., Johnson, G.V., Stone, M.L., Mullen , R.W, Freeman, K.W., Thomason, W.E. & Lukina, E.V. (2002.) Improving nitrogen use efficiency in cereal grain production with optical sensing and variable rate application. *Agronomy Journal,* 94, 815–820.

Raun, W.R., Solie, J.B., Stone, M.L., Zavodny, D.L., Martin, K.L. & Freeman, K.W. (2005) Automated calibration stamp technology for improved in-season nitrogen fertilization. *Agronomy Journal*, 97, 338–342.

Scharf, P.C. & Lory, J.A.. (2009). Calibrating reflectance measurements to predict optimal sidedress nitrogen rates for corn. *Agronomy Journal*, 101, 615–625.

Shanahan, J.F., Kitchen, N.R., Raun, W.R. & Schepers, J.S. (2008) Responsive in-season nitrogen management for cereals. *Computers and Electronics in Agriculture,* 61, 51–62.

Sudduth, K.A., Drummond, S.T., Birrell, S.J. & Kitchen, N.R. (1996). Analysis of spatial factors influencing crop yield. In Robert PC, Rust RH, Larson WE (eds), Proceedings of the 3rd International Conference on Precision Agriculture, MN, USA. pp. 129-140. (ASA/CSSA/SSSA, Madison, Wisconsin, USA.)

Taylor, J.A., McBratney, A.B. & Whelan, B.M. (2007). Establishing management classes for broadacre agricultural production. *Agronomy Journal,* 99, 1366–1376.

Thomason, W.E., Raun, W.R. & Johnson, G.V. (2000). Winter wheat fertilizer nitrogen use efficiency in grain and forage production systems. *Journal of Plant Nutrition,* 23, 1505–1516.

Tremblay, N., Bouroubi, M.Y., Panneton, B., Guillaume, S., Vigneault, P. & Bélec, C., (2010). Development and validation of fuzzy logic inference to determine optimum rates of N for corn on the basis of field and crop features. *Precision Agriculture,* 11, 621–635.

Webster, R. & McBratney, A.B. (1989) On the Akaike Information Criterion for choosing models for variograms of soil properties. *Journal of Soil Science,* 40, 493-496.

Zebarth, B.J., Botha, E.J. & Rees, H, (2007), Rate and time of fertilizer nitrogen application on yield, protein and apparent efficiency of fertilizer nitrogen use of spring wheat. *Canadian Journal of Plant Science,* 87, 709–718.