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Integrating soil and plant tissue tests and using an artificial intelligence method for data modelling is likely to improve decisions for in-season nitrogen management

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Key messages

- The new approach of combining some simple and easily accessible soil, climate and plant information for an advisor tool may be more powerful than using a sophisticated, but soil and climate data limited research tool like APSIM for yield predictions and nitrogen recommendations
- Using an Artificial Intelligence (AI) method eliminates the need for model algorithms and emphasises dynamic programming functions instead, thereby reducing error and the need for model maintenance, model upgrades etc
- The proposed AI method is cost- and time-effective to develop and further calibrates or trains itself to local conditions to give even better customized advice over the years to come to improve the nitrogen use efficiency (NUE)

Aims

Nitrogen (N) is the most important driver of yield and is usually applied in-season to top-up any nitrogen at seeding. However, existing decision support tools to guide the required N rate are often lacking accuracy. Many tools work on identifying the gap between water-limited crop yield (potential yield) and yield estimates during the growing season. The data that those models use vary from just using soil test and climate data (Yield Prophet, APSIM, N Broadacre Soil, SYN, PYCAL, etc) to just using plant test data (Green Seeker, Minolta Spad, etc). Usually those tools process the data using traditional modelling like decisions trees and multi factorial regression analysis. The accuracy of models may be improved with a different, novel approach to N recommendations.

This paper hypothesizes that there is value in combining soil, climate and plant tissue data to give more reliable advice on nitrogen top-ups in-season when compared with models that are currently available. The benefit of soil and climate data is to factor in N mineralisation and potential yield while plant test data is a more direct approach of yield estimates when considering firstly plant N uptake from the whole soil profile and secondly biomass (important yield component). Plant test data are closer to yield in time and space than soil test data, shortening the time period for any yield prognosis by about 2-3 months, depending when plant testing occurred. A positive side-effect of plant testing is to check whether any other nutrients, apart from nitrogen, are limiting yield or an N response. Secondly, this paper explores an AI method as a comparison to the traditional modelling technique to further improve the accuracy and to turn the model into a self-calibrating model. Unlike a statistical autoregression technique, the tested AI method has dynamic functions that can be used not only on time series data but also on data such as used here.

Method

Twenty four wheat nitrogen responsive field research trials (with 3 random replicates each) from CSBP Ltd experimental program have been compiled into a database. These sites were selected because soil N supply was limiting wheat grain yield. Sites were planted in May and June and harvested in November and December. Table 1 presents the grain yield for the nil and maximum N fertiliser treatments which are used to calculate relative yield (%), RY%= yield nil fertiliser N/yield plus N fertiliser x 100. This enables evaluation of modelling to predict the yield in-season as well as the potential yield on that site and in that year over a wide range on locations, seasonal conditions and soil types. Potential yield is based on rainfall, soil and plant characteristics such as soil texture, rainfall-use efficiency of the crop and estimated biomass. The in-season yield is calculated from the Potential Yield (t/ha), which is adjusted for yield loss due to N deficiency. The gap between those two yield predictions is guiding the nitrogen recommendation. Results from APSIM (Agricultural Production Systems Simulator) model (Keating et al. 2003) predictions, which does not use plant tissue testing, , are taken for the same dataset as a benchmark comparison to the new approach for the adviser tool that uses climate, soil and plant test results, which is described here.

A principal component analysis (PCA) and a cluster analysis were done to investigate the dataset using GenStat.

Two modelling techniques were applied to the dataset. Traditional modelling was done using a combination of decision tree and multi factorial regression analysis of normalised data that had optimised coefficients using a squared error function. The yield potential model included a modified French & Schultz approach (Oliver et al., 2009). This approach is widely regarded as the traditional expert system.

As a contrast, the data was configured to apply an “artificial neural network with back propagation” technique (ANN-BP) using MatLab. This AI technique emerged in the field of machine learning and pattern recognition. It is inspired by biological neural networks like our brain, but in practice is increasingly based on statistics and signal processing. An important feature of ANN-BP includes learning ability, a fundamental trait of intelligence. Here we use the dataset from the field trials as training and testing data (Figure 1). ANN-BP’s ability to automatically learn from examples makes this technique attractive. Instead of following a set of rules specified by human experts, ANN-BPs appears to learn underlying rules like input-output relationships from the given collection of representative samples. This is one of the major advantages of neural networks over traditional expert systems.

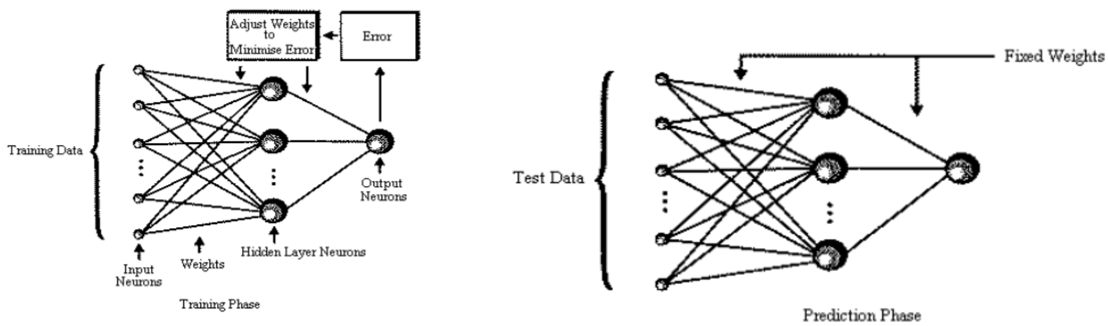

Figure 1 Schematic representation of a training and prediction phase in ANN-BP.

Daily meteorology data was obtained from the nearest town to the experimental site. APSIM simulations were done using the same varieties and seeding date as used in the experiments over the period 2000-2013. Currently, APSIM simulations are done on soils with defined soil plant available water holding capacities (PAWC) and measured soil profile inorganic status to derive site yield predictions. In this paper, APSIM simulations were done with known yield to derive PAWC and soil profile inorganic status. Impact of PAWC on yield was simulated using PAWC of 36, 48, 53, 76, 95, 120, 145 and 193 mm under high N supply (soil profile N set to 240 kg N/ha and 100 kg N/ha applied at sowing and on 30 July). A selected PAWC was used when predicted yield was within 15% of observed yield or maximum yield predicted was achieved by APSIM. For sites where APSIM simulations predicted yield within 15% of observed yields, a range of soil profile N levels (30, 60, 90, 120, 150 and 200 kg N/ha) were used to derive a predicted grain yield for the nil N fertiliser treatment. Also, various combinations APSIM simulations were conducted for site 4 to examine the impact water supply (PAWC and rainfall) and temperate on predicted yield.

Table 1 Wheat trials in WA that were soil and plant sampled as part of CSBP's field research program. Results from these soil and plant tests served as the database for developing a novel approach to in-season nitrogen recommendations.

No	Year	Location	SR (mm)	GSR (mm)	Cultivar	Soil texture	OC (%)	pH_{Ca}	Previous Crop	Sowing Date	Date of Plant Tissue Sample	Min. Yield (t/ha)	Max. Yield (t/ha)	RY(%)
1	2009	Bolgart	53	229	Wyalkatchem	sandy loam	2.30	5.0	canola	4-Jun	18 Aug, 10 Sep	2.3	4.2	46
2	2003	Boyup Brook	107	377	Calingiri	gravelly loam	4.57	5.2	canola	29-May	18 Jul, 27 Aug, 23 Sep	4.8	7.1	33
3	2003	Boyup Brook	107	377	Wyalkatchem	gravelly loam	4.57	5.2	canola	29-May	27 Aug, 23 Sep	4.5	5.1	12
4	2011	Broomehill	104	368	Mace	sandy loam	1.20	4.8	canola	2-Jun	8-Aug	3.6	4.6	22
5	2002	Condingup	83	251	Camm	sandy loam	2.50	4.7	canola	19-Jun	14-Aug	2.4	3.0	20
6	2003	Corrigin	159	266	Wyalkatchem	clay loam	1.26	4.6	pasture	29-May	3 Jul, 14 Aug	1.9	3.4	46
7	2011	Cunderdin	116	283	Mace	loamy sand	1.80	5.0	wheat	24-May	29 Jun, 26 Jul, 4 Aug	3.6	4.7	23
8	2011	Cunderdin	116	283	Mace	loamy sand	1.80	5.0	canola	24-May	29 Jun, 26 Jul, 4 Aug	4.0	5.0	20
9	2005	Dowerin	37	295	Calingiri	clay	2.00	4.8	wheat	17-May	12-Jul	2.0	2.8	29
10	2003	Eneabba	44	428	Wyalkatchem	loamy sand	1.18	5.5	wheat	21-May	14 Jul, 5 Aug	2.0	3.6	43
11	2011	Gutha	75	191	Mace	loam	0.70	4.5	wheat	17-May	20-Jul	1.7	2.9	41
12	2010	Hopetoun	138	258	Sapphire	sand	1.10	5.1	canola	25-May	8 Jul, 30 Jul	1.5	4.0	63
13	2003	Moora	72	337	Wyalkatchem	loam	1.25	5.7	pasture	27-May	3 Jul, 20 Aug	4.7	6.0	21
14	2008	New Norcia	108	358	Calingiri	gravelly loam	2.00	5.2	wheat	16-May	8-Jul	2.5	5.0	50
15	2011	Perenjori	29	227	Mace	clay	1.40	4.9	wheat	18-May	13-Jun	1.9	3.2	41
16	2003	Salmon Gums	43	239	Wyalkatchem	clay	1.30	7.8	wheat	5-May	25 Jun, 7 Aug	3.9	5.0	23
17	2003	Strawberry Hill	55	336	Wyalkatchem	loamy sand	0.91	5.9	oats	16-May	6-Aug	4.1	4.8	14
18	2003	Toodyay	123	435	Wyalkatchem	loam	0.98	4.7	pasture	30-May	11-Jul	4.2	5.2	20
19	2005	Wagin	114	315	Wyalkatchem	loamy sand	1.46	4.7	lupins	26-May	21-Jul, 23-Aug	1.2	3.4	65
20	2010	Walebing	79	181	Magenta	loam	4.50	5.8	barley	19-May	3-Sep	2.1	3.4	38
21	2010	Walebing	79	181	Magenta	loam	4.50	5.8	canola	19-May	14-Jul, 3-Sep	2.7	3.7	28
22	2009	Wongan Hills	49	240	Wyalkatchem	sand	0.90	6.1	pasture	2-Jun	17-Aug	2.8	3.4	18
23	2003	Yerecoin	72	272	Carnamah	loamy sand	0.66	4.9	wheat	29-May	10 Jul, 21 Aug	2.1	4.0	47
24	2003	Yerecoin	72	272	Calingiri	loamy sand	0.66	4.9	wheat	29-May	10 Jul, 21 Aug	2.0	3.5	44

SR = Summer Rainfall (mm), GSR = Growing Season Rainfall (May to October) (mm), pH_{CaCl}

Results

About the dataset

Yield varies with management factors. In summary, the PCA of experimental data revealed that plant tissue testing is important, because plant N%, plant NO_3 (mg/kg) and above-ground plant dry weights (=> plant vigor due to N supply) is determining the yield more than pH_{CaCl}, seeding rate, previous crop and emergence day (=> grower management decisions). A cluster analysis revealed a distinct pattern (cluster profile and weights not shown) for yields relating to climatic zone, organic carbon (%) and pH_{CaCl}. The cluster analyses suggest these factors could be used to predict growing season N mineralisation. Currently, only organic carbon (%) is used to predict growing season N mineralisation (Diggle and Bowden 2003).

Predicting potential and in-season yield at the time of plant tissue sampling

The best performing method of predicting potential and in-season yield (and therefore the best guideline for N recommendations in-season) was the integrated approach of combining climate, soil and plant tissue tests using ANN-BP (Figure 3). The N deficiency at the time of plant sampling was similarly predicted between the traditional and the AI modelling technique (Figure 2).

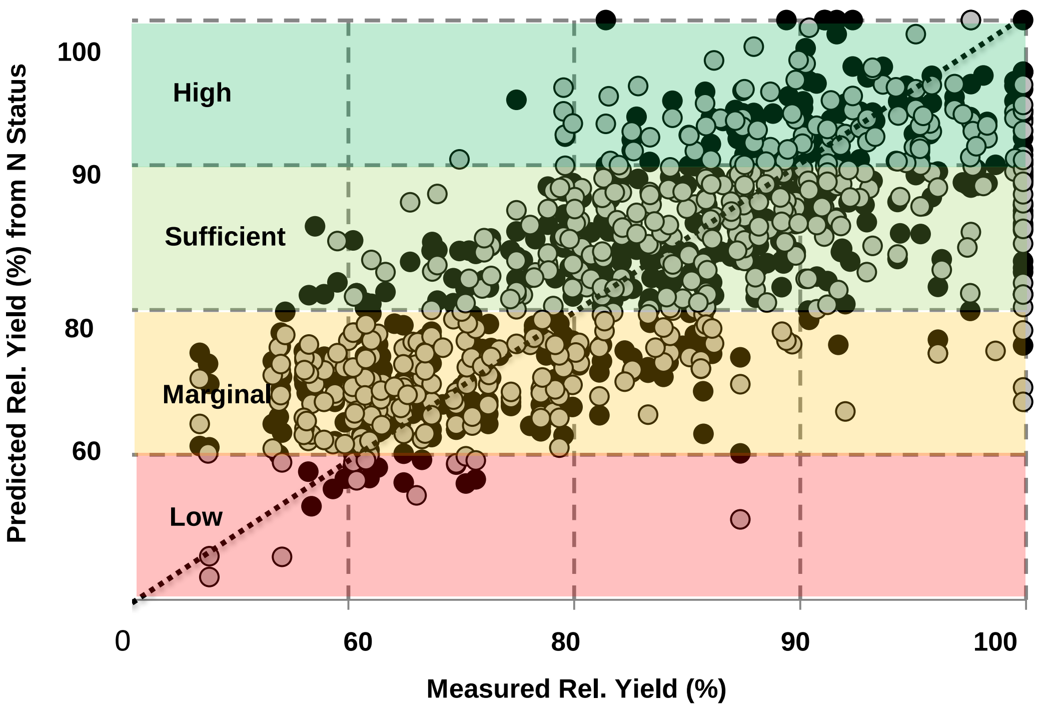

Figure 2 Measured and predicted relative yield displayed on a familiar scale of NUlogic statuses of “Low”, “Marginal”, “Sufficient” and “High”. The statuses with its colour indicate the N responsiveness in-season, based on the yield loss from the potential yield (=100% relative yield). Graph compares results from traditional modelling (●, r^2 =0.75) with results from ANN-BP modelling (○, r^2 =0.70).

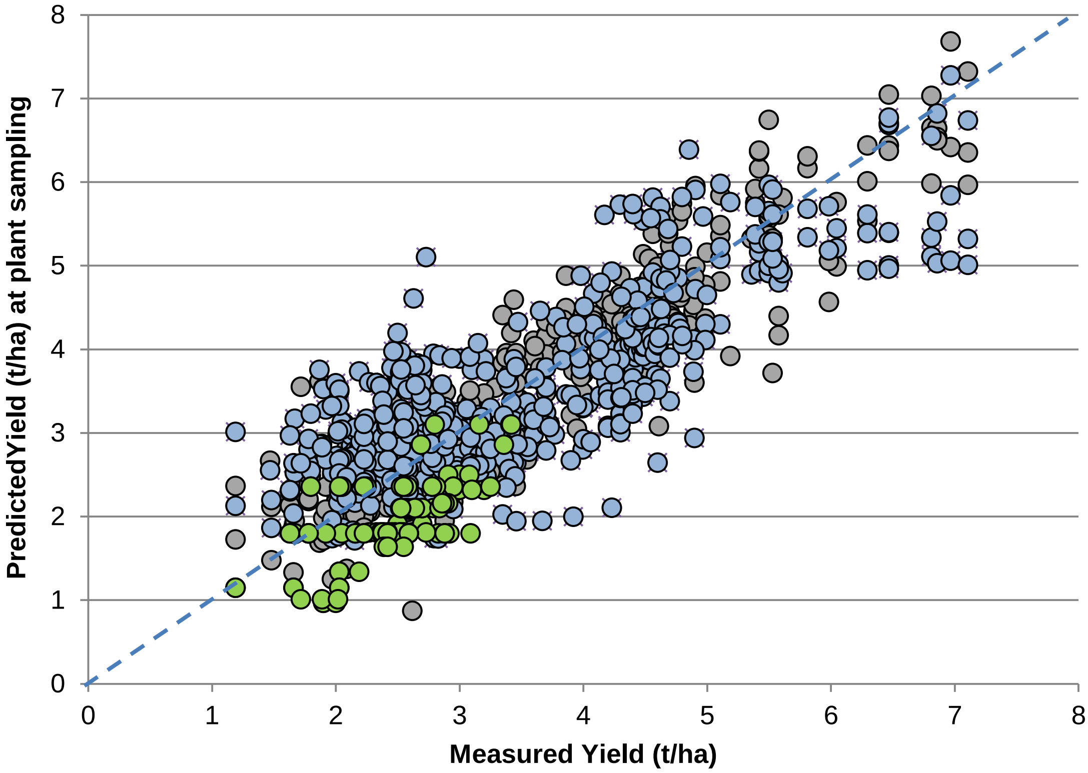

Figure 3~~:~~ Yield predictions in-season improved using AI (grey circles, r^2 =0.93) when compared with traditional modelling (blue circles, r^2 =0.79). Due to a high volume of data input and less precise prediction of high yields, only 112 lower yielding samples out of the 522 samples have been run through the APSIM model (green circles, r^2 =0.64), which does not use plant test data.

The AI potential yield model used here takes site-specific soil, climate and crop data into account. Its prediction by ANN-BP (r^2 **=**0.90) is better than with the traditional method (r^2 **=**0.72). In contrast, APSIM was only able to predict maximum yield for only 8 sites (Figure 3) due to mostly underpredicting shoot biomass. For the other 16 sites APSIM either under predicted yield (14 sites) by 18-46% and over predicted yield (2 sites) by 34 and 44%. For the 8 sites, the required soil profile N predicted the observed yield for the nil N fertiliser treatment when soil profile N ranged between 60-150 (kg N/ha). These levels of soil profile inorganic N contents are observed to occur within the wheat belt of WA (Anderson et al. 2014). For site number 4, Wyalkatchem grown near Boyup Brook in 2003, the reason for the under prediction appears to be related to a temperature limitation and not is due to a water limitation in APSIM. All correlation coefficients were established in comparison with the highest yielding treatment measured in each field trial, which was taken as the yield potential on that site in that season.

Conclusion

This proof-of-concept study is showing promising results for a more accurate tool to guide N recommendations that will lead to increased profitability for grain growers. This concept will need further testing in field trials. Additional functional and data enhancements for such a tool described here may be the implementation of augmented reality to replace the estimated biomass with a measured biomass in the field. The grower could also display of trend analysis data using soil and plant test and biomass data from the same GPS referenced site over the coming years. The aim is to increase N use efficiency (soil and fertiliser) by reducing nitrogen losses by the processes of leaching and nitrous oxide emissions, thereby contributing to more sustainable and profitable farming operations.

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Key words

nitrogen, soil test, plant test, model

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