How digital technologies will assist with nitrogen management

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Key messages

Nitrogen decision aids are evolving with the advent of machine learning and artificial intelligence.

Nitrogen inputs can be tailored to a paddock, based on whether the crop will respond to applied N.

N Rich and N Minus strips, combined with historical estimates of crop yield, leaf N concentration and soil moisture information enhance N decisions.

N Minus strips provide advanced warning of impending N stress, and can be used as a visual cue to top up N.

Aims

Conventional crop nitrogen (N) fertilizer decision aids provide a nitrogen fertiliser recommendation that requires information about the supply of N from the soil and the demand of N by the crop. These tools are often complex to implement, as farmers need to measure the starting soil N, account for N mineralisation and estimate the demand requirements of the crop. These factors all vary with the season and the soil type, and complicate the N decision. Given the uncertainties, Oliver and Robertson (2009) recommended that fertilising to the long term mean yield in Western Australia was an economically sensible approach to N fertiliser management.

Since that study, artificial intelligence and machine learning techniques have evolved and it is now possible to process large volumes of information about crops, using satellite imagery, or using information generated from crop models like APSIM. Furthermore, yield monitoring equipment can be used to run on-farm strip trials, and this information could in theory be used to parameterise crop models or decision aids to provide an N recommendation for a particular field. In essence, an on-farm trial, combined with a crop model and satellite imagery analysis could help farmers understand whether their crop will respond to an application of N, regardless of crop type, soil type or season. The aim of this study is to identify the variables that need to be monitored to help farmers make an N fertiliser decision. We do this to demonstrate how to bring aspects of crop modelling, satellite imagery and on-farm experimentation together to help farmers make an N fertiliser decision.

Method

The APSIM crop model was used to generate a substantial library of wheat N response trials for a wide range of seasons, soil types, starting N rates and locations. For each trial, the optimal N rate was calculated, again by way of simulation, where the N rate was steadily increased until no further economic yield increase was detected. The objective was to define what parameters could help enhance an N decision, thus for each location an N minus, N rich and standard management strip simulation was applied and simulated outputs on plant and soil attributes were generated for each experiment. The standard management treatment had 20 kg/ha of N applied at sowing. The N minus strip had 0 kg/N/ha applied at sowing. The N rich strip had 80 kg/N/ha applied at sowing. These rates were designed to ensure disparate N treatments within the first 6 weeks after sowing. It was expected after this time, a further application of N may be required.

A machine learning technique 'Random Forest' was then used to determine which variables were the most important to predict the optimal N rate for a field. The Random Forest methodology allows the relative importance of the variables that were extracted from APSIM simulations to be assessed. Nineteen crop and soil variables were extracted for each of the N minus, N rich and Standard management trial. The long term historical yield and starting soil N were also included as possible variables that may be of importance, resulting in a total of 59 variables that may help inform an N decision. With the exception of the historical yield and starting soil N, all other variables were assessed at between 45 and 65 days after sowing. The locations and soil types are described in table 1. The complete list of variables is described in table 2.

The random forest analysis was structured to identify variables that predicted the economically optimal N rate for a particular trial, in a particular season. This approach enabled information about the crop and soil to be drawn from the N minus strip, where the crop may be more likely to experience N stress, the standard management strip and the N rich strip, where the crop would have a luxurious supply of N.

The random forest analyses were structured to determine whether more data helped make a better N decision. A global analysis that considered all the data, from the N minus, N Rich and standard management treatment was compared to another where information about the starting soil N was ignored. A third analysis only considered information from the standard management strip. These analyses were compared to a control analysis that simply predicted the N requirement based on the long term historical yield, as proposed by Oliver and Robertson (2009). The performance of the different amounts of data was quantified with the residual mean squared error. Lower errors imply that the ability to predict the optimal N supply improved.

Further specific details about model simulations and the random forest analysis are available in Lawes et al (2019).

Table 1. Site Attributes including location, mean annual rainfall (MAR) soil description, plant available water holding capacity (PAWC) and mean optimal yield for a locally adopted wheat variety.

Site	Soil Description	PAWC	Mean Yield and Cultivar
Mingenew; MAR 400 ± 106 mm	Clay Sand	245 77	3391 (cv Yitpi) 1987 (cv Yitpi)
Wongan Hills; MAR 364 ± 92 mm	Sand Sand (constrained)	98 68	2204 (cv Wyalkatchem) 2419 (cv Wyalkatchem)
Cunderdin; MAR 359 ± 90 mm	Loam Duplex	240 208	2560 (cv Wyalkatchem) 2419 (cv Wyalkatchem)
Esperance; MAR 515 ± 99 mm	Sand Sand (constrained)	68 53	3583 (cv Yitpi) 2569 (cv Yitpi)
Minnipa; MAR 324 ± 85 mm	Sandy clay loam Sand clay loam (constrained)	139 74	1882 (cv Wyalkatchem) 1137 (cv Wyalkatchem)
Hart; MAR 410 ± 101 mm	Clay Loam	183 212	3251(cv Espada) 3127(cv Espada)
Walpeup; MAR 325 ± 98 mm	Dune Loamy Sand Swale Loamy Sand	105 183	1486 (cv Wyalkatchem) 1562 (cv Wyalkatchem)
Birchip; MAR 351 ± 103 mm	Sandy clay loam Clay loam	146 168	2079 (cv Yitpi) 2017 (cv Yitpi)
Condobolin; MAR 424 ± 138 mm	Medium clay Light clay	233 131	2130 (cv Wyalkatchem) 2087 (cv Wyalkatchem)
Temora; MAR 516 ± 150 mm	Red Chromosol Red Dermosol	147 189	3423 (cv Espada) 3622 (cv Espada)

Table 2. List of variables used for the random forest analysis to predict the optimal N rate required by a wheat crop.

Variable	Description	N-rich and N-minus included*
Site	Location	No
Start Nitrogen	Start N (0,10,20,50,100)	No
Soil Water 15 cm	Total soil water to 15 cm	Yes
Soil Water 30 cm	Total soil water to 30 cm	Yes
Soil Water 60 cm	Total soil water to 60 cm	Yes
Soil Water 90 cm	Total soil water to 90 cm	Yes
Soil Water 120 cm	Total soil water to 120 cm	Yes
Soil Water 150 cm	Total soil water to 150 cm	Yes
Extractable Soil Water 15 cm	Available soil water to 15 cm	Yes
Extractable Soil Water 30 cm	Available soil water to 30 cm	Yes
Extractable Soil Water 60 cm	Available soil water to 60 cm	Yes
Extractable Soil Water 90 cm	Available soil water to 90 cm	Yes
Extractable Soil Water 120 cm	Available soil water to 120 cm	Yes
Extractable Soil Water 150 cm	Available soil water to 150 cm	Yes
Wheat Leaf LAI	Leaf Area Index	Yes
Wheat Leaf CoverGreen	Cover	Yes
Wheat Leaf Live NConc	N concentration of leaf	Yes
Wheat AboveGround Wt	Above ground biomass	Yes
Wheat AboveGround N	Total above ground N	Yes
Wheat Zadok Stage	Growth stage	Yes
Main Stem Leaf Number	Leaf number	Yes

*19 variables were present in the standard management strip, N rich and N minus strip. 2 variables were only present in the standard management strip. A total of 59 variables were evaluated in the random forest analysis.

Results

The control model, that predicted the optimal N supply based on historical yield generated an RMSE of 54 kg/N/ha with an r^2 of 0.27 between the observed and predicted optimum. When variables from the strip trials were used, the RMSE declined to just 22 kg/N/ha. If the starting soil N was ignored this increased slightly to 23 kg/N/ha. When information from the strip trials was ignored, this increased further to 26 kg/ha. Infield trialling therefore improved the ability to predict the optimal N rate. Starting soil N provided a small improvement as well, but was less valuable than infield trialling.

The random forest analysis identified which variables where the most important and useful for predicting the optimal amount of N required. The most important variable was the long term historical mean site yield, as estimated from the by crop simulation. This was expected, as it means the algorithm is setting the demand side of the equation with this variable. Extractable soil water to 150cm and leaf nitrogen content from the N minus strip were the two next most important variables. Leaf nitrogen and extractable soil water in the standard management zone were almost as important. Finally, starting soil N and total above ground N in the N minus strip were of moderate importance.

Plant variables can be ranked in order of Plant N concentration > Total N (above ground biomass × N concentration) > LAI > Cover > Leaf number. Deep extractable soil water measurements (> 120cm) were generally preferred to shallower (< 40cm) estimates. Data from the N-minus strip were favoured over data from the N-rich strip to predict the optimal N rate. N-rich strip information was still important, with data about soil water, leaf nitrogen and above ground N as the 10th, 11th and 12th most important variables.

How much advance warning does the N-minus strip provide?

The N-minus strip provided advanced warning of impending N stress. When data were averaged across all sites (Figure 1), the N-minus strip was already below a critical limit of 0.3 when starting N levels were 0 kg/ha. The standard N treatment was obviously N stressed with a leaf N concentration of 0.3 by day 57 after sowing. When 10 and 20 kg/ha of N was present in the soil, the N-minus strip provided 12.5 days advanced warning about impending N stress for the standard N treatment. When starting N levels were higher (> 50 kg/ha), the N-minus strip still acted as a lead indicator of N stress. It was only when the soil N levels were 100 kg/ha that the difference between leaf N concentrations for the various treatments was comparatively small (Figure 1).

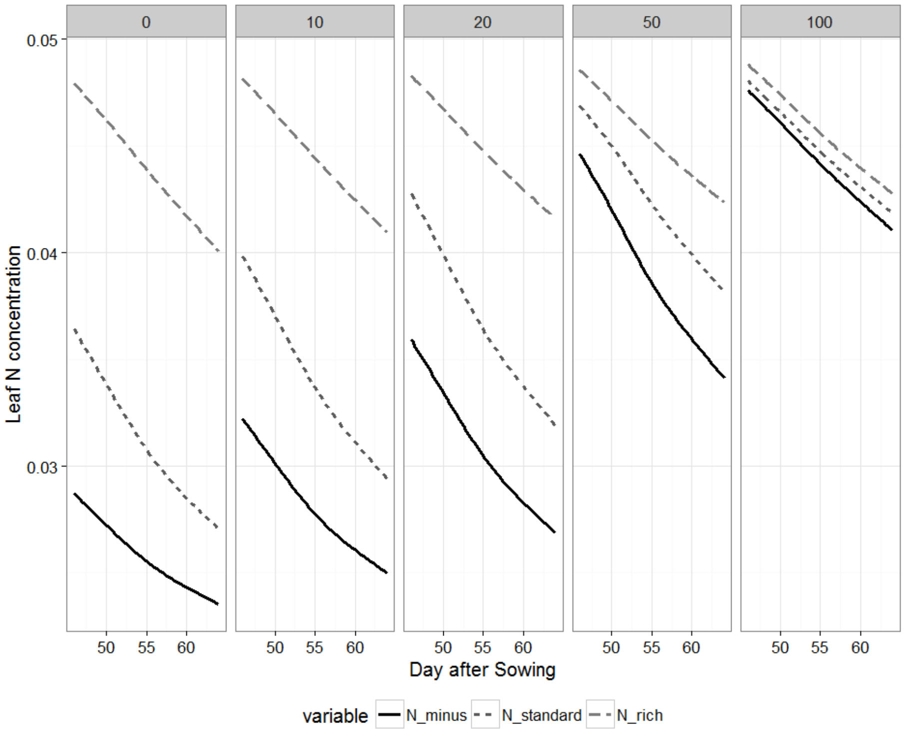

Figure 1. Average Leaf N concentrations for the N-minus, N Standard and N-rich strips vs days after sowing across soils with 0, 10, 20, 50 or 100kg/ha of starting soil N.

Conclusion

The random forest analysis of extensive APSIM output demonstrated that information about site mean yield, combined with information about plant and water status from an N-minus strip could improve N fertiliser decisions for wheat crops. This study provides the theoretical framework necessary to modernise N decisions using machine learning, remote sensing, on farm trialling and crop models. Future studies will integrate information from models, satellites and on farm trials to develop a farmer ready package to make N decisions as part of the GRDC Future Farm project. As the technology evolves, it could start to include other factors that influence an N decision such as risk and logistics.

References

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Key words

Nitrogen, On Farm Experimentation, Machine Learning,

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