

CAN CROP SENSORS HELP MAKE NITROGEN MANAGEMENT DECISIONS?

GRDC PROJECT: 9176493 - FUTURE FARM PROJECT



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Introduction

- N is crucial nutrient for crops;
- Directly affects season profitability;
- It can be difficult to identify the N demand across an entire paddock;
- Crop sensors and information like normalised difference vegetation index (NDVI);
- Colaço & Bramley (2019) showed that such sensor calibration, i.e. the relationship between the vegetation index used (usually the NDVI) and the yield, is site-year specific.

Goal

- This work aims to create a reliable estimate N sufficiency or N deficiency, using sensors and machine learning, to inform an in-crop application of nitrogen (N) fertiliser.
- Ultimately, how much and where and when;
- Now, if needs or not.

Material & Methods

- Paddocks in WA and SA



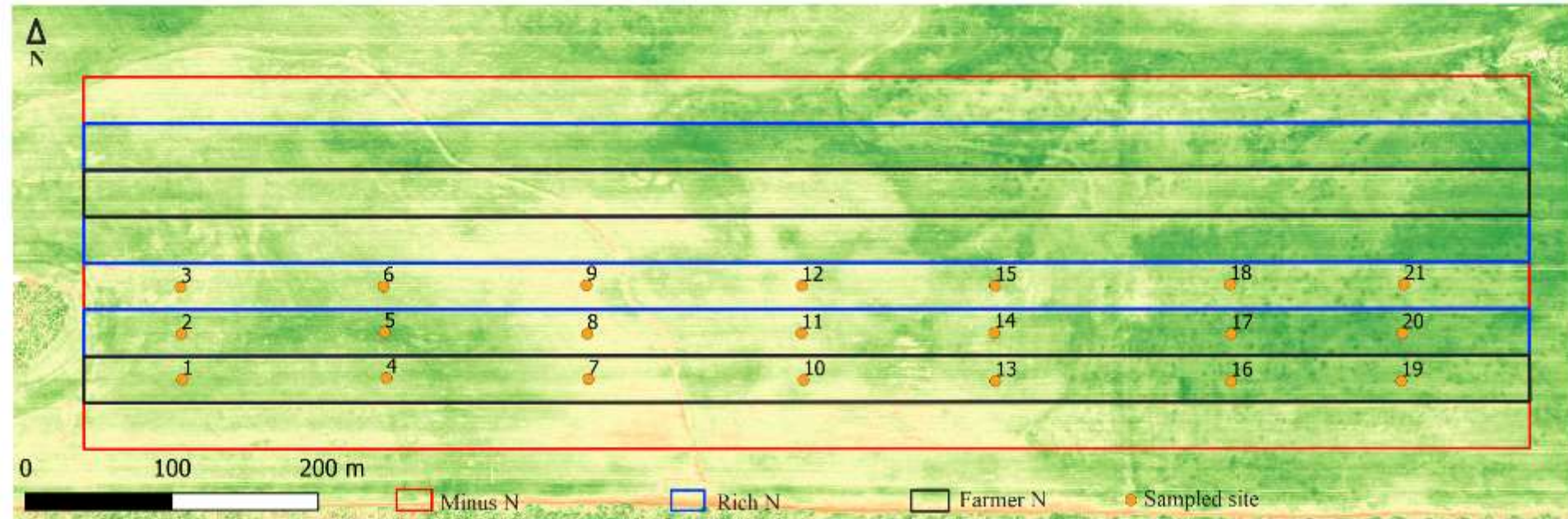
- How the paddocks look like?



- What are the paddocks :

Region	Av. Year Rain (mm)	2019 Rainfall	Soil (Avg. NO ₃ & NH ₄ [mg/kg])	N management
Dandaragan* – WA	604	344.5	Tenosol - Loamy Sand (1.49 & 1.93)	0N minus 40N farmer 80N rich
Kalannie – WA	316	226.5	Kandosol - Sandy loam (1.69 & 3.27)	0N minus 40N farmer 80N rich
Tumby Bay* – SA	338	286.2	Calcarosols – Silty loam (2.56 & 1.62)	0N minus 50 and 80N farmer 100 and 150N rich
Wauraltee – SA	423	246.4	Calcarosols – Clay loam (22.17 & 3.85)	50N farmer 100N rich 150 and 200N rich
Snowtown – SA	399	191.2	Calcarosols – Clay loam (7.29 & 3.20)	35N farmer 85N rich
Booleroo –SA	334	167.9	Calcarosols – Silty loam (11.22 & 2.19)	0N minus 60N farmer 120N rich
Veitch – SA	270	154.3	Calcarosols – loamy sand (9.38 & 2.40)	0N minus 20-50N** farmer 100N rich

- N-minus, N-farmer, and N-rich



- What was done:



Data:

- from sensor
- calculated

***If %N<4% then Yes, otherwise No
(Brennan & Scanlan, 2017)**

- N-minus, N-farmer, and N-rich

Variable	Description		Source
%N	Nitrogen content	%	Laboratory
Apply	Apply N	(yes or no)	determined*
NDRE	Normalised difference red edge		Sensed
NDVI	Normalised difference vegetation index		Sensed
LAI	Leaf area index		Sensed
CCC	Canopy chlorophyll content		Sensed
NIR	Near infra-red		Sensed
Red	Red		Sensed
RE	Red edge		Sensed
RPAR	Reflected photosynthetic active reflectance		Sensed
CNI	Canopy nitrogen index		$CNI = 1.86 * CCC - 0.346$
SCCCI	Simplified canopy chlorophyll content index		$SCCCI = NDVI / NDRE$
PAR	Photosynthetic active reflectance		Calculated*
CRE	Chlorophyll red edge		Calculated*

**From sensor manual

- What was done:



Data:
-from sensor
-calculated

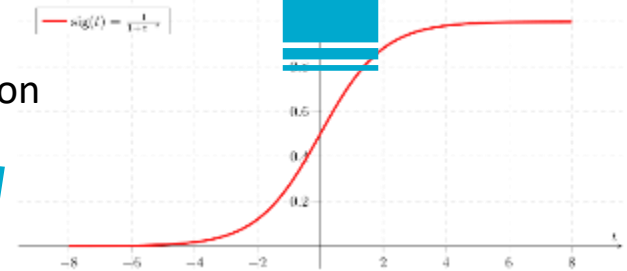
Next step:
-When and How much?



Apply mid-season N:
-Yes
-No



Machine Learning:
-Recursive Feature Elimination
-Random Forest



Traditional Statistics
-Logistic Regression

Results

- Machine Learning most important variables to predict N requirement:
 - Red Edge (RE) and Simplified Canopy Chlorophyll Content Index (SCCCI).
- Logistic regression most important variables to predict N requirement:
 - Simplified Canopy Chlorophyll Content Index (SCCCI).
- When tested against Lab data an overall accuracy of 96%

Results

- Only 6% (3 out of 48 samples) of the test data (lab data following recommendation) was **NO** – i.e. there is N sufficiency
- **One** case the model did **NOT** recommended application of N where it should be;
- **Two** cases the model recommended application of N where it was not needed.

Discussion

- We used the ‘smarts’ of the machine learning algorithm to identify which predictor is more relevant to assess a mid-season N decision and then used a classical statistical approach to do the decision process.
- This means a *quasi*-real-time ability, as soon as the field is scanned, an important information is obtained, specially when the recommended decision from the model is to not apply N.

Discussion

- When the model does not recommend mid-season N application a decision on applying less N can be taken reducing costs and possible N waste, leach and its environmental implications.
- Other problems in the area or focus on other problematic areas.

Conclusion

- Methodology to determine if there is a need of mid-season N application in wheat in *quasi*-real time with proximal Red Edge reflectance and Simplified Canopy Chlorophyll Content Index, that provided 96% of accuracy.
- Now we are developing a way to predict the optimum amount.
 - APSIM simulations
 - Satellite data
 - Future scenarios (the Good, the Bad, or Ugly weather)
 - Nitrogen cost vs. Yield profit

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Thank you! Questions?

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