Proximal sensing technologies on soils and plants on Eyre Peninsula

RESEARCH

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Location
Minnipa Agriculture Centre, paddock N10, 2017 & 2018
Rainfall
Av. Annual: 325 mm
Av. GSR: 241 mm
2018 Total: 269 mm
2018 GSR: 208 mm
2017 Total: 262 mm
2017 GSR: 141 mm
Yield
Potential yield 2018: 1.6 t/ha (Hancock 2006)
Actual yield 2018: 2.3 t/ha
Potential yield 2017: 1.6 t/ha (Hancock 2006)
Actual yield 2017: 2.3 t/ha
Paddock History
2017: Scepter wheat
2016: Mace wheat
2015: No seeding
Soil Type
Red sandy clay loam
Plot Size
5 m x 1.6 m x 3 reps

Location
Lock - Ian Burrows 2017 & 2018
Rainfall
Av. Annual: 390 mm
Av. GSR: 294 mm
2018 Total: 311 mm
2018 GSR: 231 mm
2017 Annual: 357 mm
2017 GSR: 241 mm
Yield
Potential yield 2017: 2.0 t/ha (W) (Hancock 2006)
Actual yield 2017: 2.4 t/ha
Paddock History
2017: Pasture-vetch-clover
2016: Peas/self regenerating medic pasture
2015: Barley
2014: Wheat
Soil Type
Grey sandy loam
Plot Size
5 m x 1.6 m x 3 reps

Key messages

- **Proximal sensing reflectance data predicts soil moisture with reasonable accuracy at depths (0-10, 10-30, 30-90 cm) on upper Eyre Peninsula in 2018.**
- **Reflectance data may also be useful for predicting the amount of soil nitrogen and crop macronutrients, including but not limited to nitrogen, phosphorus, potassium and sulphur.**
- **Further experimental data is required to use soil and crop reflectance as a means to predict nutrient content because environmental parameters can confound results.**

Why do the trial?

This research has developed predictive formulas that can be used by growers to estimate in-season soil moisture at different depths and crop nutrient content from proximal sensing (PS) data.

The upper Eyre Peninsula (UEP) is a challenging environment for growers, due to the Mediterranean-type of climate, where irregular and infrequent winter rainfall patterns are coupled with low soil fertility. Additionally, poor soil structure, low water holding capacity and limited nutrient availability provide challenging conditions for plant growth, as growers currently use granular fertilisers which require good soil moisture conditions to enable the uptake of nutrients. Topsoils from calcareous soils may dry quickly after rain events, which may explain poor water use and nutrient extraction efficiency.

Proximal sensing technologies have the potential to support grower's nutrient management decisions by monitoring in-season soil and crop water and nutrient content (Allen *et al*. 2017, Arsego *et al*. 2017). Compared to the Green Seeker/normalised difference in vegetation index (NDVI) device, newer PS technology can use a wider range of wavelengths to predict soil and crop nutritional status in a non-destructive, quick and inexpensive way. Until recently, PS technology was limited to laboratory use given the size and robustness of the machinery necessary to perform the analysis. The development of small, portable PS devices has now allowed the use of this technology in the field, allowing for the potential for PS to be utilised by growers in their paddocks in the near future. In this research, two years of UEP trials have been combined to calibrate PS for crop nutrient content, and one year of data has been examined for soil moisture and nutrient content.

How was it done?

A total of eight trials (season 2018) were established, three in Cummins, Lock, and Minnipa, two in Piednippie, and three in Nunjikompita (Table 1). A randomised complete block design with three replicates was used for all trials.

Data from biomass cuts sampled at GS31 (stem elongation) include all eight trials and Lock Cummins and Minnipa replicated trials of 2017. At Lock, Cummins and Minnipa 2017-18, a second biomass cut was performed at GS65 (anthesis). A third biomass sampling was conducted at maturity for grain yield and quality testing at Lock 2017-18, Minnipa 2017-18 and Cummins 2017.

Location
Cummins - Stuart Modra 2017
Rainfall
2017 Av. Annual: 396 mm
2017 Av. GSR: 306 mm
2017 Total: 401 mm
2017 GSR: 278 mm
Yield
Potential yield 2017: 3.3 t/ha (W) (Hancock 2006)
Actual yield 2017: 2.3 t/ha
Paddock History
2016: 44Y89CL canola
2015: Mace wheat
2014: No seeding
Soil Type
Clay loam
Plot Size
5 m x 1.6 m x 3 reps

Location
Cummins - Douglas Green 2018
Rainfall
Av. Annual: 423 mm
Av. GSR: 314 mm
2018 Total: 361 mm
2018 GSR: 288 mm
Yield
Potential: 4.4 t/ha (W)(Hancock 2006)
Actual: 3.3 t/ha
Paddock History
2017: Banker canola
2016: Buloke barley
2015: Wyalkatchem wheat
Soil Type
Clay loam
Plot Size
5 m x 1.6 m x 3 reps
Trial Design
Randomised complete block
Yield Limiting Factors
None

Location
Piednippie - John Montgomerie 2018
Rainfall
Av. Annual: 378 mm
Av. GSR: 225 mm
2018 Total: 233 mm
2018 GSR: 181 mm
Yield
Potential: 3.0 t/ha (W)(Kirkegaard and Hunt 2012)
Actual: 2.0 t/ha
Paddock History
2017: Pasture
2016: Canola
2015: Pasture
Soil Type
Clay calcareous
Plot Size
10 m x 1.6 m x 3 reps
Trial Design
Randomised complete block
Yield Limiting Factors
1% grain loss at each plot, late harvest

Table 1 Trial details for the five EP environments tested in 2018

Trial Details	Lock	Minnipa	Cummins
Varieties	Scepter, Mace, Halberd and Spear wheat		
Sowing date	22 May 2018		15 May 2018
Fertiliser	120 kg/ha Triple Super Phosphate		86 kg/ha Triple Super Phosphate
Herbicide	Boxer gold® 1.5 L/ha, Avadex® 1.5 L/ha, Treflan® 1.7 L/ha, Round up® 2 L/ha, Hammer® 100 ml/ha, Sulphate Ammonia 800 g/ha		
Harvest date	28 November	13 November	16 November

Trial Details	Nunjikompita	Piednippie
Variety	Scepter wheat	
Sowing rate	60 kg/ha (Normal seeding rate) and 80 kg/ha (High seeding rate)	
Sowing date	8 May 2018	6 June 2018
Fertiliser	Different treatments on the trials 50 kg/ha DAP; 50 kg/ha MAP; 50 kg/ha Urea; 100 kg/ha Triple Super (TSP); 200 kg/ha Single Super; 200 kg/ha Complete Nutrient Mix	
Herbicide	Boxer gold @ 1.5 L/ha, Avadex @ 1.5 L/ha, Roundup @ 2 L/ha, Hammer @ 1.6 L/ha, Broadstrike @ 800 ml/ha	
Harvest date	5 December 2018	7 December 2018

The GS31 biomass cuts were dried at 35°C in the oven until a constant weight. Then, dry biomass and grain samples were ground and sent to the laboratory for nitrogen content testing. The ground tissue samples of GS31 biomass cuts from Nunjikompita and Piednippie were also tested for macro and micronutrients (nitrogen, phosphorous, potassium, copper, magnesium, iron, manganese, sodium, boron, sulphur and zinc) content at the laboratory.

A gravimetric method was applied to estimate soil moisture of the samples, which were collected with three samples per replicates at sowing, and one sample per plot at maturity. At Cummins, Lock and Minnipa, soil samples were collected up to 90 cm depth. At Piednippie, the soil sampling depth was limited by limestone at a depth of 30 cm onwards, while a maximum depth of 60 cm was reached at Nunjikompita. Additional soil samples were collected using the same methods described above. However, these soil samples were dried in an oven (35°C until constant weight), sieved and sent to the laboratory for nitrogen content.

Water use was calculated with the following formula: (Soil moisture at sowing + growing season rainfall) - Soil moisture at maturity.

Nitrogen nutrition index (NNI) was calculated by dividing the crop critical N concentration (N% at GS31, 4.7) by the actual N% from the laboratory.

Spectral data was collected for biomass and soil samples using a proximal sensing technology (i.e. a SR-3500 spectroradiometer from Spectral Evolution). When the sky was clear, four biomass spectral readings per plot were collected using a 25° (field of view) bare fibre optic in the field at noon time (10 am - 3 pm). On cloudy days, a leaf clip probe was used to measure four random main leaves per plot.

Location
Nunjikompita - Tim Howard 2018
Rainfall
Av. Annual: 299 mm
Av. GSR: 225 mm
2018 Total: 168 mm
2018 GSR: 128 mm
Yield
Potential: 1.9 t/ha (W)(Kirkegaard and Hunt 2012)
Actual: 1.1 t/ha
Paddock History
2017: Medic pasture
2016: Mace wheat
2015: Medic pasture
Soil Type
Red calcareous
Plot Size
10 m x 1.6 m x 3 reps
Trial Design
Randomised complete block
Yield Limiting Factors
Poor germination

Soil spectral data was recorded using a contact probe, measuring four readings per soil sample, for both gravimetric and oven dried soil. Spectral data were pre-treated using standard methodology (Esbensen and Swarbrick, 2018) and analysed using partial least square (PLS) regression in the Unscrambler X (CAMO version 10.5) to calculate (i) the relationship between spectral data and nutrient data and (ii) the relationship between spectral data and soil moisture data. Linear mixed models were fitted using ASReml R version 3. Package software was then used to develop local spectral indices and formulas to predict nutrient content from spectral data (Figure 1).

What happened?

Soil moisture

As a first step, a multi-site PLS of soil moisture versus spectral data analysis was undertaken considering the five locations. The output revealed a strong correlation (R^2=0.86, Figure 2a) between the soil moisture and spectral data.

Six new spectral indices were combined with four reference indices to test a linear relationship with soil moisture for both sowing and maturity sampling dates at each location (Table 2). Cummins showed a completely different trend from all other locations (possibly due to differences in soil texture), therefore was excluded from the analysis. Within each location, most trials exhibited similar results, hence results were reported by location. All indices were significant in the linear analysis for Minnipa and Lock, while Nunjikompita and Piednippie had different indices of significance. Only three spectral indices were significant across all sites (ninson, wisoil and wat3; Table 2), each of these indices represents water vapour peaks of absorbance. The differences in significance within the linear relationship of spectral indices and soil moisture may be related to differences in soil structure across locations.

In order to validate the predictive model (Table 2), a linear model of spectral vs soil moisture was calculated by combining trials sharing similarities in reflectance data (data not shown). As a result, Minnipa and Lock had the highest R^2 for predicting soil moisture, followed by Nunjikompita and Piednippie trials (Figure 3a-c). At Piednippie and Nunjikompita, there was a distinct separation of soil moisture versus spectral predictions according to depth (Figure 3b-c). The greater separation at Piednippie over Nunjikompita may be due to the lower number of soil depths used in comparison with the other trials (Minnipa and Lock 0-90 cm, Nunjikompita 0-60 cm and Piednippie 0-30 cm).

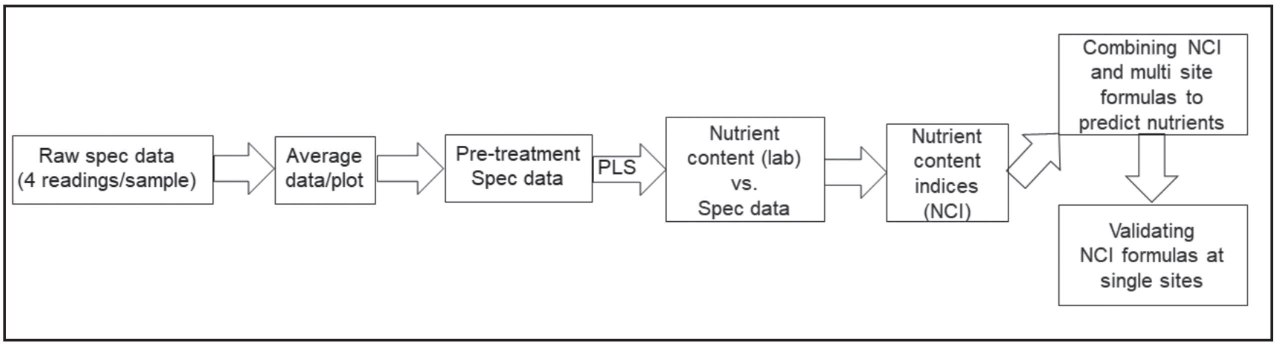

Figure 1 Example flowchart of the spectral (spec) data processing for nutrient data, from collection to the development of spectral equations. PLS=partial least square analysis.

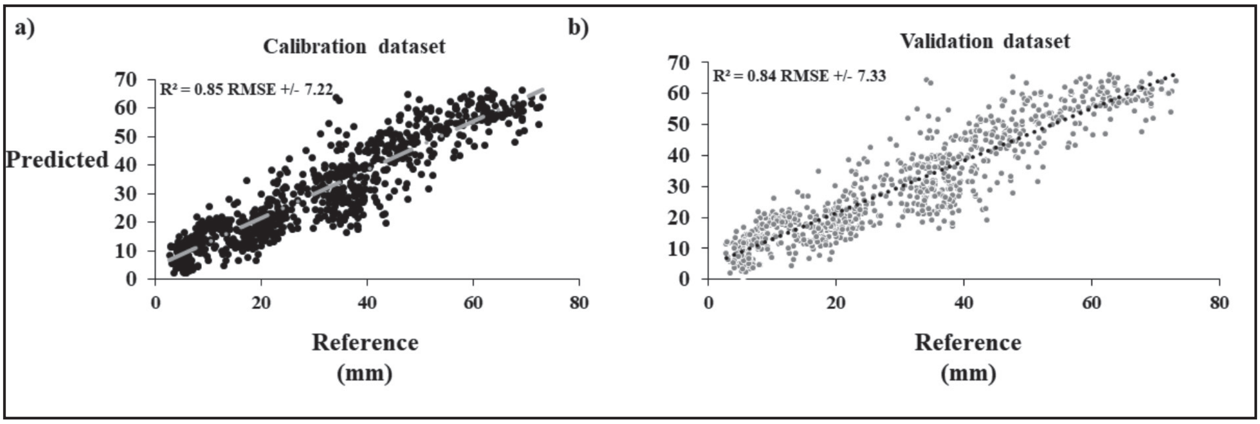

Figure 2a-b Relationship between soil moisture (reference, mm) and the spectral (predicted) data from the five locations on Eyre Peninsula in 2018. RMSE=root mean square error.

Table 2 List of new (wat3-wat9) and published (ninsol, ninson, nmsi, wisoil) spectral indices. The + sign indicates the spectral indices that were significant in the analyses for each location.

Name of spectral indices	Wavelength intervals	Minnipa /Lock	Nunjikompita	Piednippie
ninsol	(2076-2260)	+		
ninson	(2122-2230)	+	+	+
nsmi	(1800-2119)	+	+	
wisoil	(1300-1450)	+	+	+
wat3	(1666-1807)	+	+	+
wat4	(565-606)	+		+
wat5	(1948-2042)	+		
wat6	(350-523)	+		
wat8	(856-1102)	+	+	
wat9	(1290-1500)	+	+	

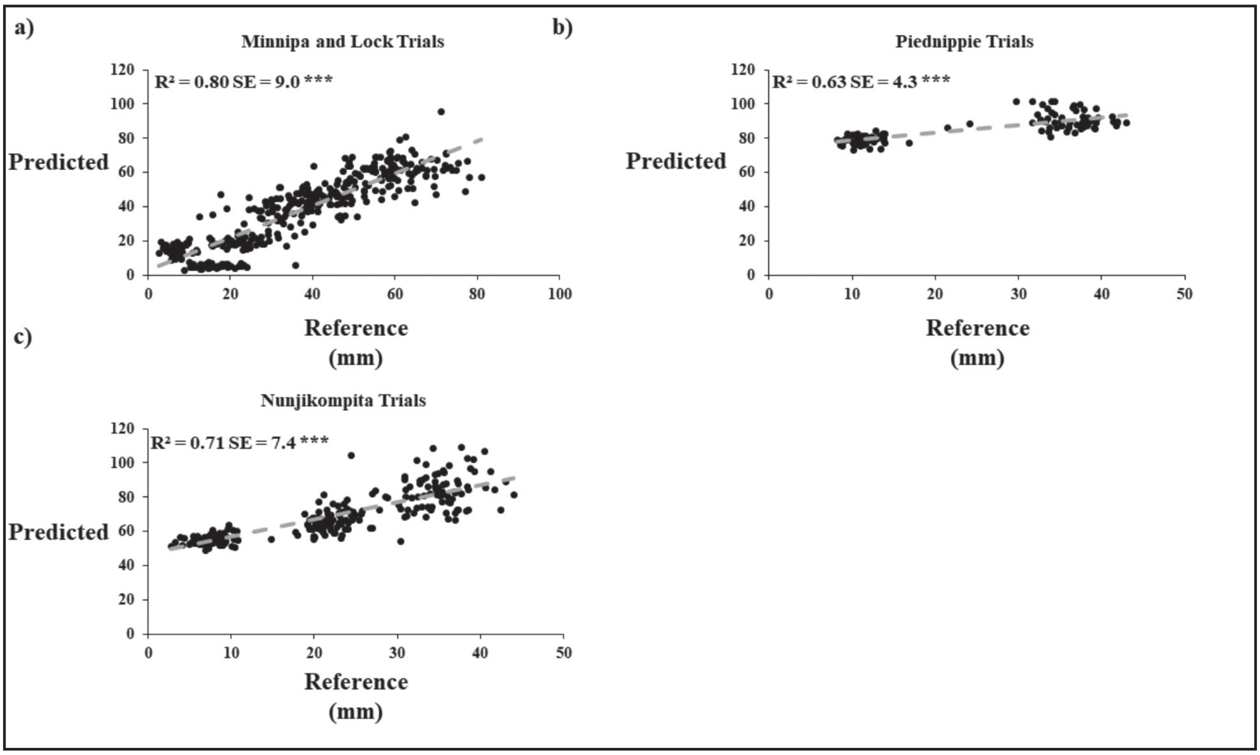

*Figure 3a-c Validation linear models using reference and predicted soil moisture at Minnipa and Lock (a), Piednippie (b) and (c) Nunjikompita trials. SE=Standard error, *** = P<0.001.*

Soil nitrogen

A multi-site analysis considering Lock, Cummins and Minnipa data for 2018 was performed to test the relationship between soil nitrogen and soil spectral data (Figure 4). From the analysis, multiple peaks of regression coefficients were detected with a moderate relationship to soil nitrogen ($R^2=0.56$-0.54, RMSE, Figure 4a-b). Although seven new spectral indices were generated following the same process as in the soil moisture dataset, the variability explained by the data was not sufficient to be used by growers (data not shown). Further studies should examine the potential environmental factors that may affect the relationship between spectral data and soil nitrogen.

Crop nutrient content (nitrogen)

A multi environment partial least square analysis was performed considering 2017-18 trial data from Cummins, Lock, Minnipa and Nunjikompita, and the Piednippie 2018 trial to establish a strong relationship between nitrogen (nitrogen nutrition index) and spectral data (Figure 5a-b).

Crop nutrient content - phosphorus, potassium, sulphur and copper

In the Unscrambler X software, Piednippie and Nunjikompita trials were combined to determine the relationship between GS31 biomass nutrient content measured in the laboratory and biomass nutrient content measured by using spectral data (Figure 6a-c). All micronutrients showed a non-significant relationship between the spectral data and laboratory reference (data not shown). Potassium and phosphorous showed the highest relationship between the laboratory and field reference, followed by sulphur and copper. Particularly, sulphur showed a moderate relationship at the Nunjikompita trial ($R^2=0.6$), while a low relationship ($R^2=0.2$) was detected at Piednippie. Relationships between macronutrients and spectral results would require further testing across multiple seasons and locations in order develop reliable predictive models.

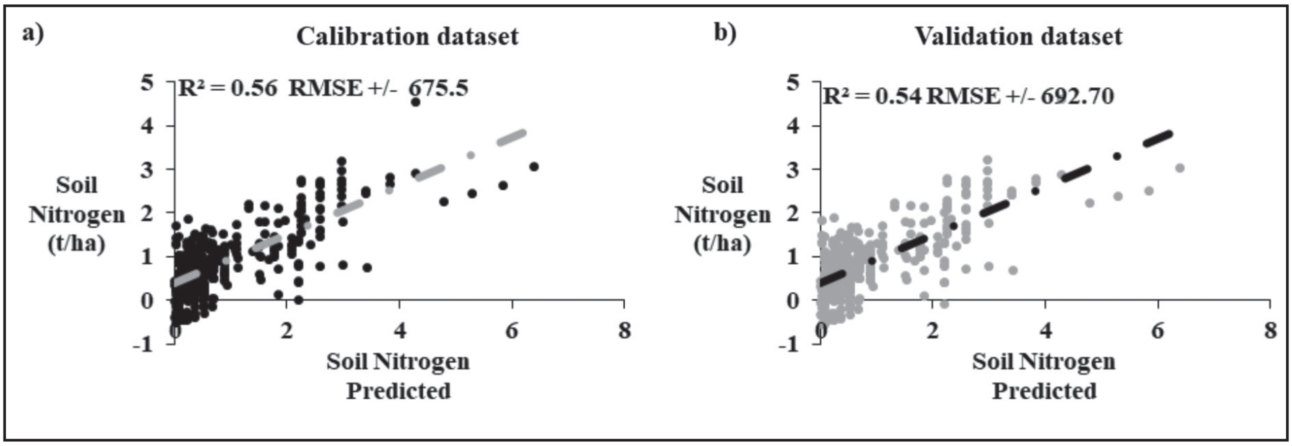

Figure 4a-b Output of the partial least square regression analysis in the Unscrambler software X between the soil nitrogen (kg/ha, reference) and the spectral (predicted) data from Cummins, Minnipa and Lock trials. In (a) linear relationship between reference and prediction, in (b) weighted regression coefficients across the 350-2500 nm spectra. RMSE=root mean square error

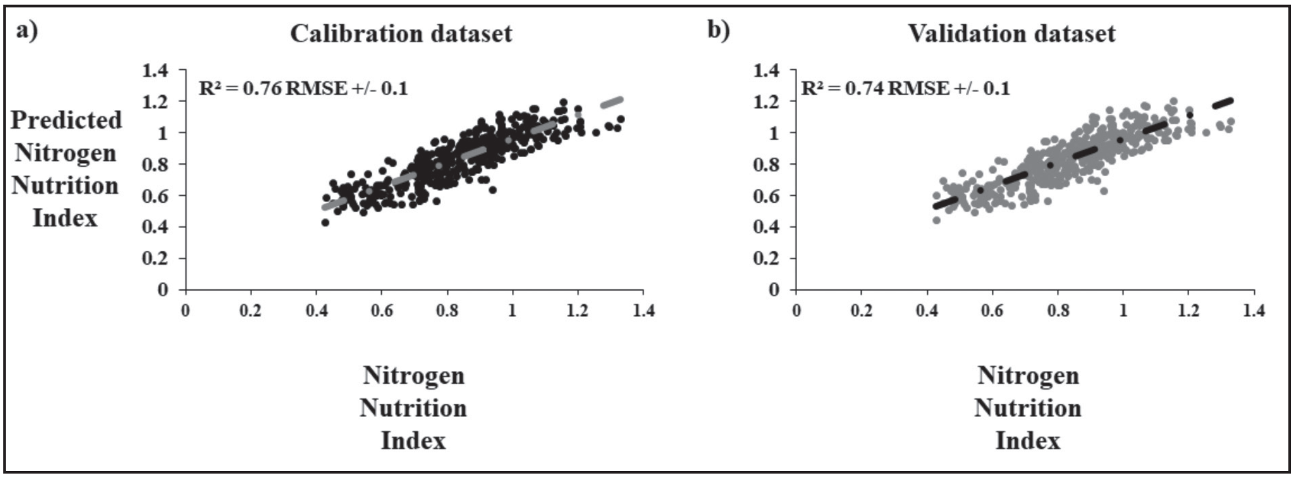

Figure 5a-b The relationship of crop nitrogen (reference) and the spectral (predicted) data from Cummins, Minnipa, Lock 2017-18 and Nunjikompita, Piednippie 2018 trials. RMSE=root mean square error.

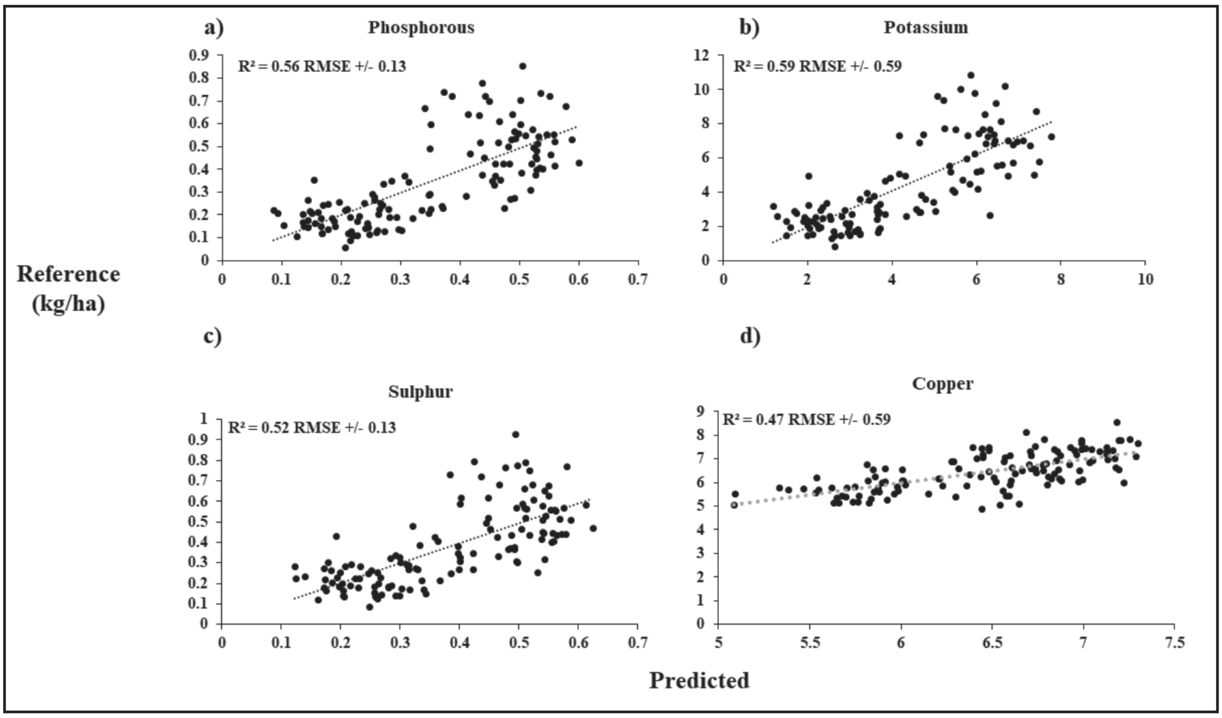

Figure 6a-d The relationship between crop nutrients (kg/ha, lab reference) and spectral data (predicted) data from Nunjikompita and Piednippie in 2018 trials. RMSE=root mean square error.

What does this mean?

PS technology could provide a useful method for estimating soil and crop nutrient content as it is a quicker and cheaper method than traditional laboratory results. Spectral predictions of soil moisture and depths appear to be reliable and stable across different soil types and depths. Spectral predictions of crop nitrogen have shown a strong relationship across six EP locations. In calcareous soils, a moderately stable relationship was also found between spectral indices and nutrients other than nitrogen, especially sulphur. However, in order for growers to use PS technology on soil and crop nutrient content in the field, further research and studies are needed to determine the environmental conditions that allow specific arrays of spectral indices to have a significant relationship with nutrients.

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Bibliography

Allen, D. J., Ware, A, & Porker, K (2018) New technologies for wheat crop monitoring on the Eyre Peninsula Eyre Peninsula Farming Systems Summary 2017, p. 120-126.

Arsego, F., Ware, A., C. Mariano & V. O. Sadras (2018) Estimating water and N co-limitation levels of wheat using remote sensing technologies across upper Eyre Peninsula Eyre Peninsula Farming Systems Summary 2017, p. 127-130.

Hancock, J., Water Use Efficiency of Crops and Pasture (2007). Eyre Peninsula Farming Systems Summary 2006, p. 87-90.

Hunt, J. R., and J. A. Kirkegaard. (2012). A guide to consistent and meaningful benchmarking of yield and reporting of water-use efficiency.

Monjardino, M., et al. Are farmers in low-rainfall cropping regions under-fertilising with nitrogen? A risk analysis (2013). Agricultural Systems 116: 37-51.

Sadras, V. O., & Roget, D. K. (2004). Production and environmental aspects of cropping intensification in a semiarid environment of southeastern Australia. Agronomy Journal, 96(1), 236-246.

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