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Section 5

Nutrition

Proximal sensing technologies for soils and plants on Eyre Peninsula

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Key messages

- **Proximal sensing reflectance data predicts soil moisture with reasonable accuracy from samples taken at depths (0-10, 10-30, 30-60, 60-100 cm) across 46 Eyre Peninsula locations.**
- **Moderate relationships were found between % organic carbon, pH(water) and soil spectral data.**
- **Reflectance data have been proven useful for predicting the amount of crop macronutrients, including nitrogen, phosphorus, potassium and sulphur.**
- **Further experimental data is required to test the reliability of the existing predictive models of soil absorbance and crop reflectance as a means to predict nutrient content.**

Why do the trial?

This research was done to develop predictive formulas that can be used by growers to estimate in-season soil nutrients from soil samples taken 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 irregular rainfall patterns which are coupled with lower soil fertility. Additionally, calcareous soils with poor structure and low water holding capacity provide additional restrictions 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.

PS 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). PS uses a wide range of wavelengths to predict soil and crop nutritional status in a non-destructive, quick, and inexpensive way. PS technology is mostly limited to laboratory use. The development of small, portable PS devices may allow the use of this technology in farm paddocks in the near future. In this study, we combined different UEP trials to develop predictive models for PS for crop nitrogen, crop nutrient content and soil moisture.

How was it done?

A total of 15 trials were established across 3 seasons (2017-19) in Cummins, Lock, Minnipa, Nunjikompita, Streaky Bay, Cungena and Condada (Table 1). A randomised complete block design with three replicates was used for all trials.

Tissue samples

Biomass cuts were sampled at GS31 (stem elongation) at the 15 trials. The GS31 biomass cuts (1/2 m^2) were dried at 35 degrees in the oven until a constant weight. The dry biomass samples were ground and sent to the laboratory for determination of nitrogen content. The ground tissue samples of GS31 biomass cuts from Nunjikompita, Cungena, Streaky Bay and Condada were tested for macro and micronutrients (nitrogen, phosphorous, potassium, copper, magnesium, iron, manganese, sodium, boron, sulphur and zinc) content at the laboratory.

Table 1. Trial details for the 15 EP trials tested in 2017-19.

Season	Site *Grower* Soil type Plot size	Sowing date	Cultivars	Treatments	Spectral probe used (number of samples)	GSR (mm)
2017	Cummins *Modra* Clay loam 5 m x 1.6 m x 3 reps	21 June	Scepter, Mace, Halberd and Spear	Rainfed, Irrigation (50 mm), non-fertilised and 50 N at stem elongation	FOV* (48), Leaf clip (48)	278
2017	Lock *Burrows* Grey sandy loam 5 m x 1.6 m x 3 reps	6 June	Scepter, Mace, Halberd and Spear	Rainfed, Irrigation (50 mm), non-fertilised and 50 N at stem elongation	FOV* (48), Leaf clip (48)	191
2017	Minnipa *MAC N10* Red sandy clay loam 5 m x 1.6 m x 3 reps	30 May	Scepter, Mace, Halberd and Spear	Rainfed, Irrigation (50 mm), non-fertilised and 50 N at stem elongation	Leaf clip (48)	141
2018	Cummins *Green* Clay loam 5 m x 1.6 m x 3 reps	15 May	Scepter, Mace, Halberd and Spear	Rainfed, Irrigation (50 mm), non-fertilised and 120 N at stem elongation	Leaf clip (48)	288
2018	Lock *Burrows* Grey sandy loam 5 m x 1.6 m x 3 reps	22 May	Scepter, Mace, Halberd and Spear	Extra 20 mm of irrigation at sowing. Rainfed, Irrigation (50 mm), non-fertilised and 120 N at stem elongation	Leaf clip (48)	231
2018	Minnipa *MAC N10* Red sandy clay loam 5 m x 1.6 m x 3 reps	22 May	Scepter, Mace, Halberd and Spear	Extra 20 mm of irrigation at sowing. Rainfed, Irrigation (50 mm), non-fertilised and 120 N at stem elongation	FOV* (48)	178
2018	Nunjikompita *Howard* Red calcareous sandy loam 1.6 m x 10 m x 3 reps	8 May	Scepter	50 kg/ha MAP/DAP with the seed, 50 kg/ha MAP/DAP 3 cm below the seed, normal seeding rate (60 kg/ha) and high seeding rate (80 kg/ha)	Leaf clip (24)	128
				50 kg/ha DAP, 50 kg/ha MAP, 50 kg/ha Urea, 100 kg/ha TSP, 200 kg/ha SSP, 200 kg/ha Complete Nutrient Mix, control at sowing	Leaf clip (36)	
				Fluid Phosphorous (Phosphoric Acid) normal rate (equivalent to 5 kg/ha), high rate (equivalent to 8 kg/ha), Granular phosphorus (Triple P, 50 kg/ha) at sowing	Leaf clip (24)	

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2019	Condada *Cook* Red sandy loam 12 m x 2 m x 3 reps	6 May	Scepter	Phosphoric acid applied at sowing (water rate of 80 L/ha): 0, 5, 10 and 40 units P; 2. Granular urea applied by stem elongation (units N): 0, 10, 30, 60	FOV* (48)	182
				50-100 kg/ha DAP, 200 kg/ha DAP with high seeding rate (80 kg/ha), 50-100-200 kg/ha MAP balanced with urea, 50 kg/ha DAP with fluid trace elements (Zn Cu, Mn), 50 kg/ha MAP balanced with urea and fluid trace elements (Zn Cu, Mn), normal seeding rate (60 kg/ha), high seeding rate (80 kg/ha), Fluid fertiliser (phosphoric acid) with fluid trace elements (Zn Cu, Mn) applied at sowing	FOV* (39), contact probe (39)	
2019	Streaky Bay *Wheaton* Grey calcareous sandy loam 12 m x 2 m x 3 reps	8 May	Scepter	Phosphoric acid applied at sowing (water rate of 80 L/ha): 0, 5, 10 and 40 units P; 2. Granular urea applied by stem elongation (units N): 0, 10, 30, 60	FOV* (48), contact probe (48)	206
				50-100 kg/ha DAP, 200 kg/ha DAP with high seeding rate (80 kg/ha), 50-100-200 kg/ha MAP balanced with urea, 50 kg/ha DAP with fluid trace elements (Zn Cu, Mn), 50 kg/ha MAP balanced with urea and fluid trace elements (Zn Cu, Mn), normal seeding rate (60 kg/ha), high seeding rate (80 kg/ha), Fluid fertiliser (phosphoric acid) with fluid trace elements (Zn Cu, Mn) applied at sowing	FOV* (39), contact probe (39)	
2019	Cungena *Tomney* Grey calcareous sandy loam 12 m x 2 m x 3 reps	7 May	Scepter	Phosphoric acid applied at sowing (water rate of 80 L/ha): 0, 5, 10 and 40 units P; 2. Granular urea applied by stem elongation (units N): 0, 10, 30, 60	FOV* (48), contact probe (48)	158
				50-100 kg/ha DAP, 200 kg/ha DAP with high seeding rate (80 kg/ha), 50-100-200 kg/ha MAP balanced with urea, 50 kg/ha DAP with fluid trace elements (Zn Cu, Mn), 50 kg/ha MAP balanced with urea and fluid trace elements (Zn Cu, Mn), normal seeding rate (60 kg/ha), high seeding rate (80 kg/ha), Fluid fertiliser (phosphoric acid) with fluid trace elements (Zn Cu, Mn) applied at sowing	FOV* (39), contact probe (39)	

**FOV = field of view/field gun*
DAP = di ammonium phosphate, MAP = mono ammonium phosphate, SSP = single super phosphate, TSP = triple super phosphate

Soil samples

Soil samples were collected from the 15 trials and from 36 additional points in the EP soil moisture probe network paddocks. Soil moisture was calculated by using gravimetric method for all samples, which were collected with three sub-samples per replicates at sowing, and one sample per plot at maturity. In the case of the soil moisture probe network, soil cores up to 100 cm were collected pre-sowing and at harvest. A volumetric estimate was also calculated considering the bulk density information from the nearest APSOIL sites. At Cummins, Lock, Minnipa, Streaky Bay, Condada and Cungena soil samples were collected up to 90-100 cm depth. At Nunjikompita, the soil sampling depth was limited by limestone at a depth of 60 cm onwards. At all sites, additional soil samples were collected using the same methods described above. However, these soil samples were dried in an oven (35 degrees until constant weight), sieved and sent to the laboratory for nutrient content.

Spectral data collection

Spectral data was collected for biomass and soil samples using a PS technology (i.e. a SR-3500 spectroradiometer from Spectral Evolution). Readings with the spectroradiometer were done with clear sky by collecting four spectral readings per plot using a 25^{o} (field of view) bare fibre optic in the field at noon time (10am- 3pm) for the case of biomass. Furthermore, on cloudy days, a leaf clip probe was used to measure four random young leaves per plot. Lastly at Cungena, Streaky Bay and Condada trials, spectral data was only collected on ground tissue samples at GS31 using a contact probe. Soil spectral data was recorded using a contact probe, measuring four readings per soil sample, for both gravimetric and oven dried soil.

Spectral data analysis

Spectral data were pre-treated using standard methodology (Esbensen and Swarbrick 2018). Each spectral dataset was randomly split in two subsets: 1) calibration and 2) validation. The calibration subset represented 75 % of the whole dataset and was used to develop the predictive model. The predictions were calculated 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 nutrient data. The validation subset consisted of 25 % of the dataset and was used to evaluate the predictive power of the PLS model.

What happened?

Spectral readings performed with the contact probe

Soil moisture

As a first step, a multi-site PLS of soil moisture versus spectral data analysis was undertaken considering 46 locations across the EP. The model had a moderate predictive power R^2 = 0.7 with and error of the estimation of 10.4 mm (Figure 1a). This relationship showed higher variability for values over 60 mm. The wider spread may be attributed to: 1) the greater variability of soil types and soil moisture conditions at pre-sowing and post-harvest across the Eyre Peninsula and 2) the lower EP soil types which are characterised by high soil moisture and clay content.

Soil nitrate

A multi-site analysis considering sites from the soil moisture probe network and 2019 trials was performed to test the relationship between soil nitrate and soil spectral data (Figure 2). Similar to soil moisture, a moderate accuracy model (R^2 = 0.7-0.75) was obtained for the relationship between soil nitrate and spectral readings (Figure 2). Further studies should focus on increasing range of variability and further validate the predictive model across different environment conditions, soil types and soil moisture scenarios.

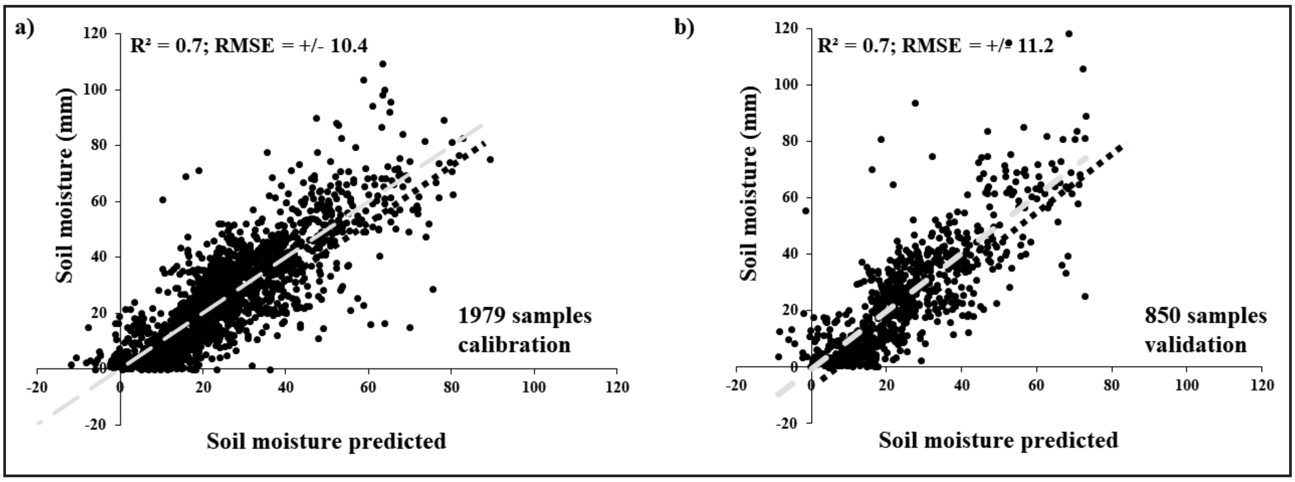

Figure 1a. Relationship between soil moisture (reference, mm) and the spectral (1b predicted) data from the 46 locations on the EP in 2018. RMSE = root mean square error. The black dotted line is the 1:1 line.

Soil phosphorus buffering index

The relationship between soil phosphorus buffering index (PBI) and soil spectral data was tested using the sites from the soil moisture probe network and 2019 trials (Figure 3). The calibration model was able to explain more than 80% of the variability in the soil phosphorus buffering index (Figure 3a), as expected, a drop of 0.1 R^2 can be observed between the calibration and validation datasets (Figure 3b). It is important to note that the soils that were used for the analysis included both calcareous and non-calcareous soils.

Other soil characteristics

The relationship between spectral data and soil nutrients was further tested, including but not limited to nutrients such as: pH (Figure 4 a-b) and % organic carbon (Figure 4 c-d). The calibration models explained between 70 and 80% of the variability in the soil pH (Figure 4a) and % of organic carbon (Figure 4b). In this case, the R^2 and accuracy were similar between calibration and validation datasets (Figure 4 a-d).

Phosphorus, potassium, sulphur and copper in plant tissue

Potassium and sulphur showed the highest relationship between the laboratory analysis and PS readings (Figure 5a-b and e-f), followed by phosphorus and copper (Figure 5c-d and g-h). Of all the nutrients, copper showed the lowest predictability and the highest difference between the calibration and validation datasets (Figure 5g-h). The use of the contact probe on ground tissue had a higher predictive power for potassium, sulphur, copper and phosphorus compared to the leaf clip predictions at Nunjikompita in 2018 (EPFS Summary 2018 p197), possibly due to better nutrient mobility within the plant.

Spectral readings performed with field gun and leaf clip probes

Nitrogen in plant tissues (N%)

A multi environment partial least square analysis was performed considering 2017-19 trial data from Cummins, Lock, Minnipa, Nunjikompita, Streaky Bay, Cungena and Condada to establish a strong relationship between nitrogen (N%) and spectral data (Figure 6). A total of 349 and 243 samples were used to develop the calibration models for field of view/field gun and leaf clip. Samples were split between tissue samples scanned with the field of view/field gun (Figure 6a) and leaf clip spectral probes (Figure 6b).

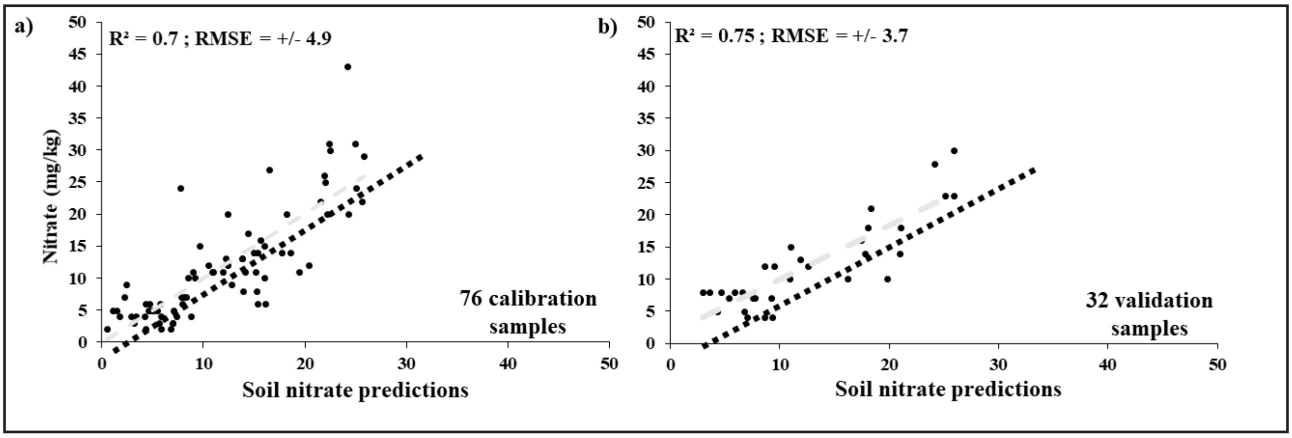

Figure 2a. Relationship between soil nitrate (reference, mg/kg) and the spectral (2b predicted) data from the 46 locations on the EP in 2018. RMSE = root mean square error. The black dotted line is the 1:1 line.

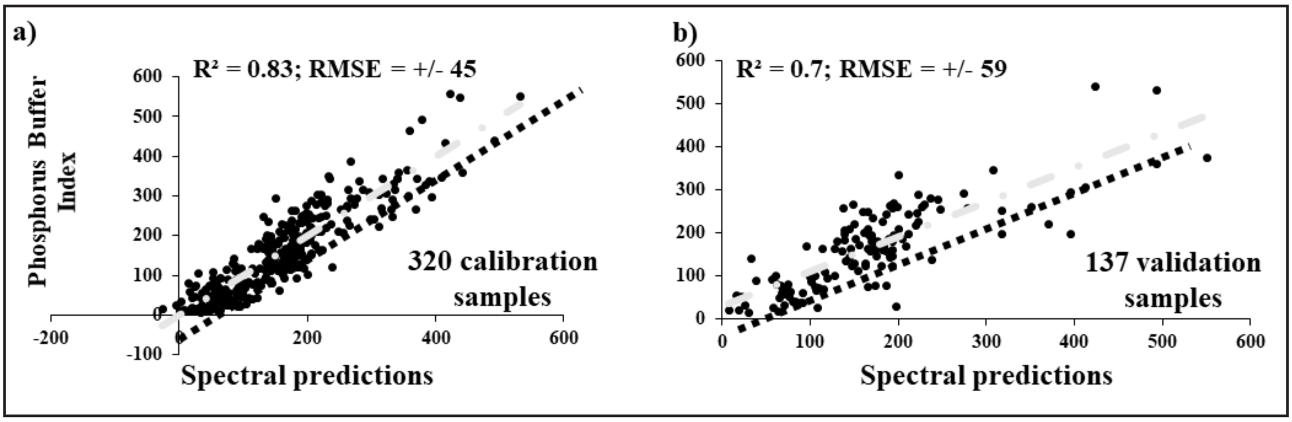

Figure 3a. Relationship of soil phosphorus buffering index and the spectral (3b predicted) data from the soil moisture probe network sites and 2019 trials. RMSE = root mean square error. The black dotted line is the 1:1 line.

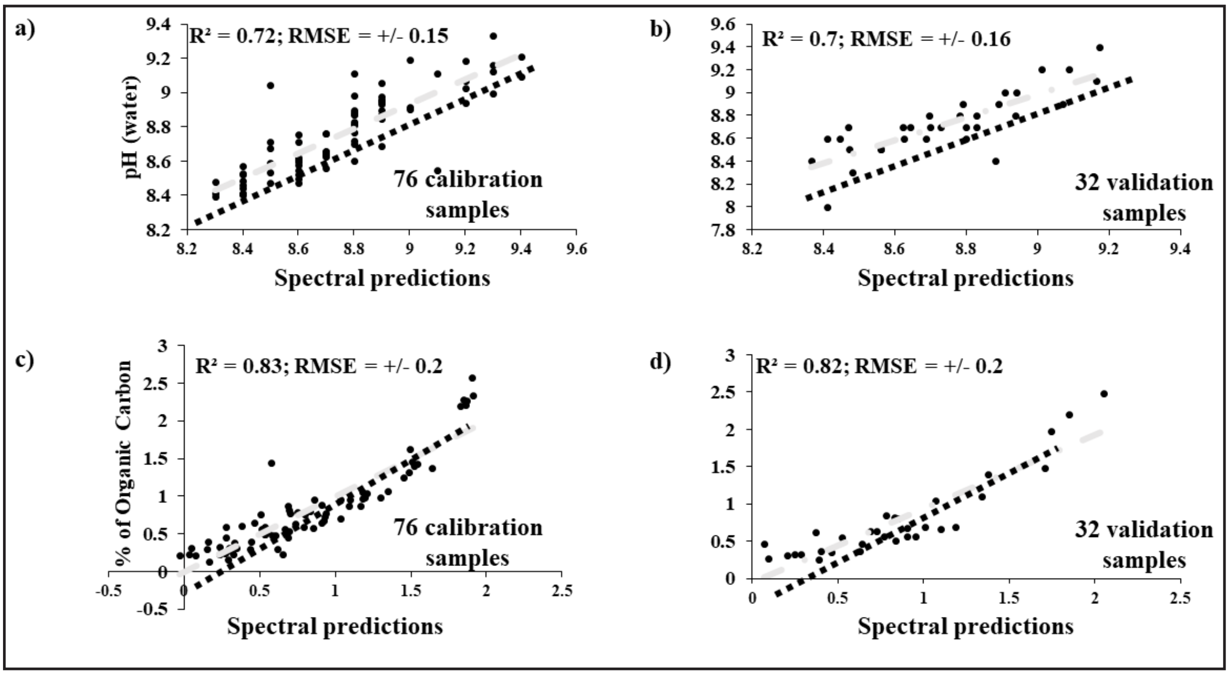

Figure 4. The relationship of lab measurements of soil pH (a-b) and organic carbon % (c-d) and the spectral (predicted) data from the soil moisture probe network sites and 2019 trials. RMSE = root mean square error. The black dotted line is the 1:1 line.

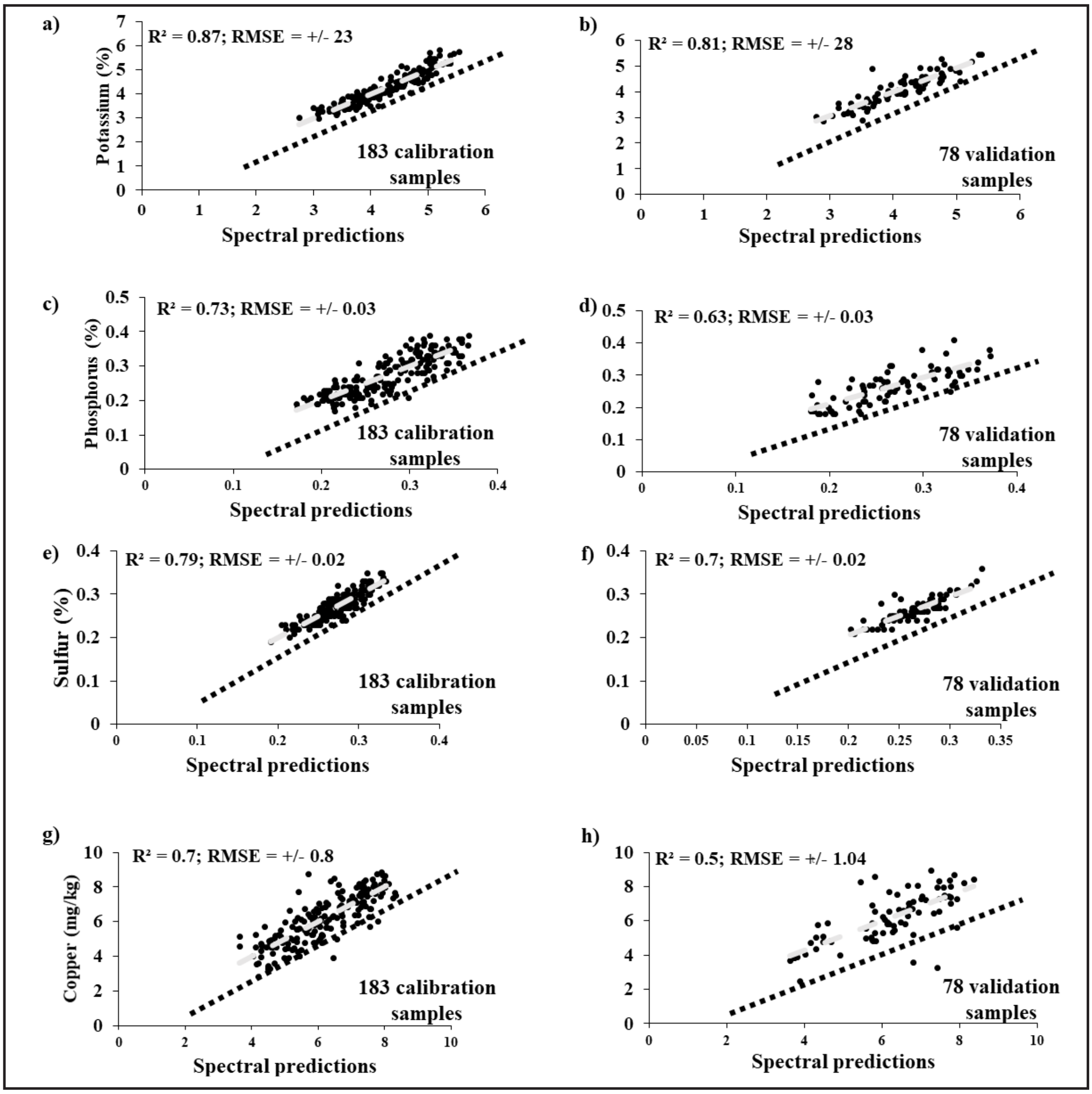

Figure 5a-h. The relationship between crop nutrients (lab reference) and spectral data (predicted) data from Streaky Bay, Cungena and Condada in 2019 trials. RMSE = root mean square error. The black dotted line is the 1:1 line.

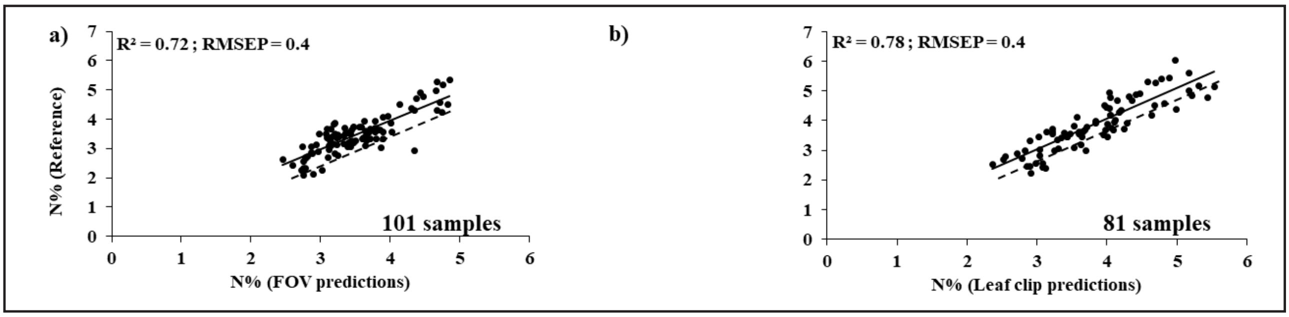

Figure 6a-b. Predictions of crop nitrogen (reference) from spectral (predicted) data using field of view (FOV, a) and leaf clip (b). RMSE = root mean square error. The black dotted line is the 1:1 line.

What does this mean?

This research indicates that PS technology could provide a useful method for estimating different soil characteristics of agronomic interest and crop nutrient content in a fast, cheap and reliable method. Given the number of samples and different locations used in the analysis, spectral predictions of soil moisture appear to be reliable and stable across EP. Special attention should be taken when working with wet soil conditions, especially with above 60 mm of soil moisture due to higher variability. Soil nutrients have shown a moderate relationship between lab and spectral estimates, especially phosphorus buffering index. Nutrients such as % organic carbon and pH, were also analysed and a calibration model is feasible for a wide variety of soils of the EP.

PS of crop nitrogen levels have shown a strong relationship across EP locations as previously observed in the literature (Ecarnot *et al*., 2013, Silva-Perez *et al.*, 2018). In calcareous soils, a moderately stable relationship was also found between PS data and nutrients other than nitrogen, especially potassium and sulphur.

Further research and studies are needed to test the reliability of the predictive models which have been developed on soil and crop nutrient content over further seasons.

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