Proximal sensing technologies on soils and plants in the Eyre Peninsula

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Abstract
Irregular and infrequent winter rainfall patterns coupled with low soil fertility provide a challenging environment for growers in the Upper Eyre Peninsula (UEP). Proximal sensing (PS) technologies have the potential to support growers' nutrient management decisions by monitoring in-season variations in soil water content together with water and nutrient status of the crop. The development of small, portable PS devices has now allowed the use of this technology in the field, enabling PS to be utilised by growers in their paddocks. In this research, two years of UEP nutrition trials have been combined to calibrate PS (SR-3500 spectroradiometer from Spectral Evolution) for crop nutrient content, and one year of data has been examined for soil moisture and nutrient content. PS absorbance data predicted soil moisture and nitrogen with reasonable accuracy (R^2 = 0.6-0.8) at depths (0-10, 10-30, 30-90 cm) on the upper Eyre Peninsula in 2018. In-crop PS reflectance data at stem elongation (Growth Stage 31 = GS31, Zadoks et al., 1974) predicted (R^2 = 0.5-0.8) the amount of crop macronutrients, including but not limited to nitrogen, phosphorus, potassium and sulphur. Further experimental data are required to use soil absorbance and crop reflectance as a means of predicting nutrient content, because some environmental parameters can confound the results.

Key Words
PS (proximal sensing), Upper Eyre Peninsula (UEP), crop and soil nutrients

Introduction
The upper Eyre Peninsula (UEP) is a challenging environment for growers, due to the Mediterranean-type climate, where irregular and infrequent winter rainfall patterns are coupled with low soil fertility. Additionally, poor soil structure and low water holding capacity provide challenging conditions for plant growth, as growers currently use granular fertilisers which require good soil moisture conditions to enable the uptake of nutrients. PS technologies have the potential to support growers' nutrient management decisions by monitoring in-season soil water content together with crop water and nutrient status (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 analyses. The development of small, portable visible near infrared (VIS-NIR) devices has allowed the use of this technology in the field, potentially enabling VIS-NIR to be utilised by UEP growers in their paddocks in the near future. However, the influence of environmental factors on predictions is relatively unknown. 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. This research has developed predictive formulae that can be used by growers to estimate in-season soil moisture at different depths and crop nutrient content from PS data.

Methods
A total of eight nutrition trials (season 2018) were established, one each in Cummins, Lock, and Minnipa, two in Piednippie, and three in Nunjikompita. A randomised complete block design with three replicates was used for all trial designs. Biomass cuts were sampled at GS31 (stem elongation) from all eight 2018 trials and from replicated trials in Lock, Cummins and Minnipa in 2017. The GS31 biomass cuts were dried at 35°C in the oven until a constant weight was achieved. Then, dry biomass and grain samples were ground and sent to the laboratory for nitrogen content testing. Nitrogen nutrition indices (NNI) were calculated by dividing the crop critical N concentration (4.7 N% at GS31) by the actual N% from the laboratory (Hoogmoed et al., 2018). 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. Soil moisture was calculated on 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 to a depth of 30 cm, 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.

Spectral data was collected for biomass and soil samples using a proximal sensor with a wavelength range of 350 to 2500 nm (i.e. a SR-3500 spectroradiometer from Spectral Evolution). When the sky was clear, four biomass spectral readings per plot were collected using a 25º (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 older leaves per plot. In the lab, soil spectral data were recorded using a contact probe, measuring four readings per soil sample, for both gravimetric and oven dried soil. The four spectral replicates were averaged and noisy portions of the spectra (350-400 nm and 2400-2500 nm) were removed. Spectral data were pre-treated using the standard normal variate (SNV, Barney et al., 1989) and Savitzky-Golay derivation (2nd derivative, Savitzky and Golay, 1964, Esbensen and Swarbrick 2018). Crop nutritional content, soil moisture and spectral readings were analysed using partial least square (PLS) regression in 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. Cross-validation was performed applying the leave-one-out (LOO) method with calibration determined on n-1 samples, while validation was established considering the rest of the dataset. Linear mixed models were fitted using ASReml-R V3 (Butler et al., 2009) to develop local spectral indices and formulas to predict nutrient content from spectral data (Figure 1).

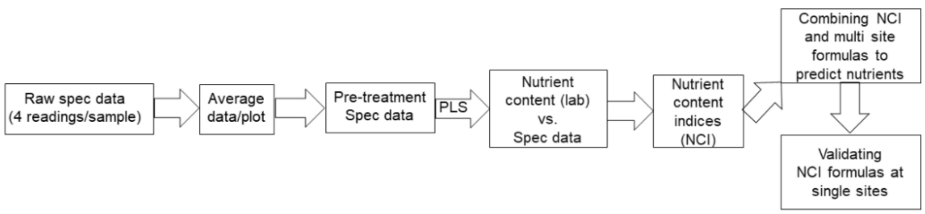

Figure 1. Example flowchart of the spectral (spec) data processing for nutrient data, from collection to the development of spectral equations. PLS = partial least square analysis.

Results

Soil moisture

As a first step, a multi-site PLS of soil moisture versus spectral data analysis was undertaken using all of the five site locations. The output revealed a strong correlation (R^2 = 0.84 - 0.85, Figure 2a-b) between the soil moisture and spectral data.

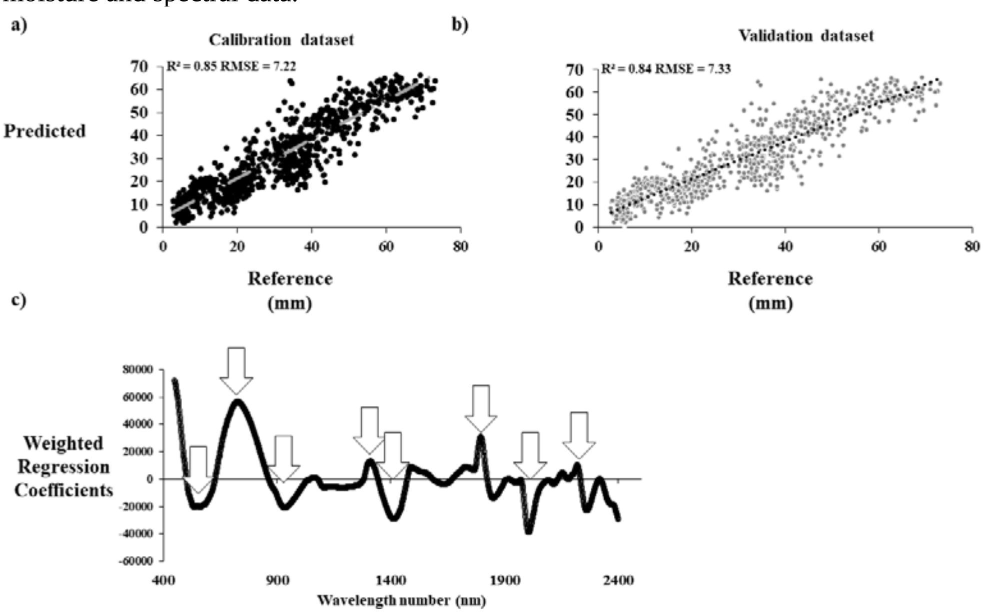

Figure 2a-c. Output of the partial least square regression analysis in the Uscrambler software X between the soil moisture (reference, mm) and the spectral (predicted) data from the five locations showing (a-b) the linear relationship between reference and prediction at both calibration and validation datasets (leave-one-out approach). In c), weighted regression coefficients are plotted across the 400-2400 nm spectra. Arrows point to high and low peaks of absorbance. RMSE = Root Mean Square Error.

Six new spectral indices (400-523 nm, 565-606 nm, 856-1102 nm, 1290-1500 nm, 1666-1807 nm and 1948-2042 nm) were combined with four reference indices to test a linear relationship with soil moisture for both sowing and maturity sampling dates at each location. Cummins showed a completely different trend from all other locations (possibly due to differences in soil texture), and that site 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), 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, a linear model of the spectral indices 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 (R^2 = 0.8, SE = 9), followed by Nunjikompita (R^2 = 0.7, SE = 7) and Piednippie trials (R^2 = 0.6, SE = 4). At Piednippie and Nunjikompita, there was a distinct separation of soil moisture versus spectral predictions according to depth. 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).

Crop nutrient content (nitrogen)

A multi environment partial least square analysis was performed considering 2017-18 Cummins, Lock, Minnipa and Nunjikompita, and Piednippie 2018 trials to establish a relationship between nitrogen and spectral data (Fig. 3a-b). The weighted regression coefficient plot was used to design new spectral indices (Fig. 3c), which are currently in the process of being developed and validated at single sites.

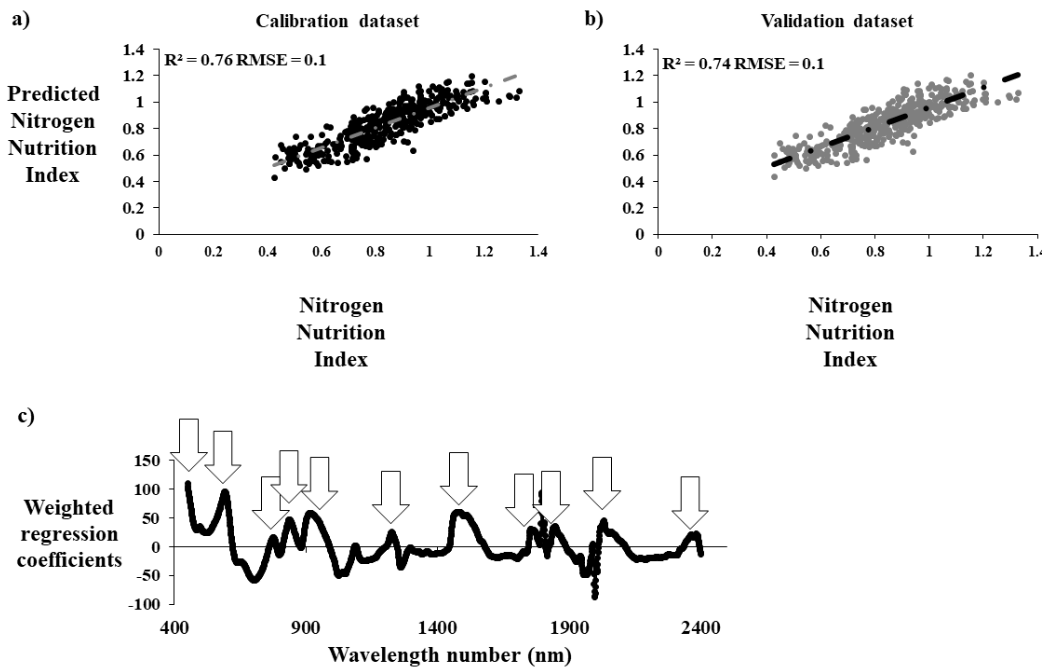

Figure 3a-c. Output of the partial least square regression analysis in the Uscrambler software X between the crop nitrogen (Nitrogen Nutrition Index, reference) and the spectral (predicted) data from Cummins, Minnipa, Lock 2017-18 and Nunjikompita, Piednippie 2018 trials. In (a-b), a linear relationship is evident between reference and prediction using calibration and validation datasets (Leave-one-out approach). I). In (c), weighted regression coefficients are plotted across the 400-2400 nm spectra, and arrows point to high peaks of reflectance. Saturation peaks at 1760 and 2000 nm were caused by atmosphere effect on field of view lens. RMSE = Root Mean Square Error.

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 4a-c). Potassium and phosphorous showed the highest relationship between the laboratory and field reference, followed by sulphur and copper. When the nutrient content indices were validated at single sites, sulphur showed a moderate relationship at the Nunjikompita trial (R^2 = 0.6, data not shown), while a low relationship (R^2 = 0.2, data not shown) 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.

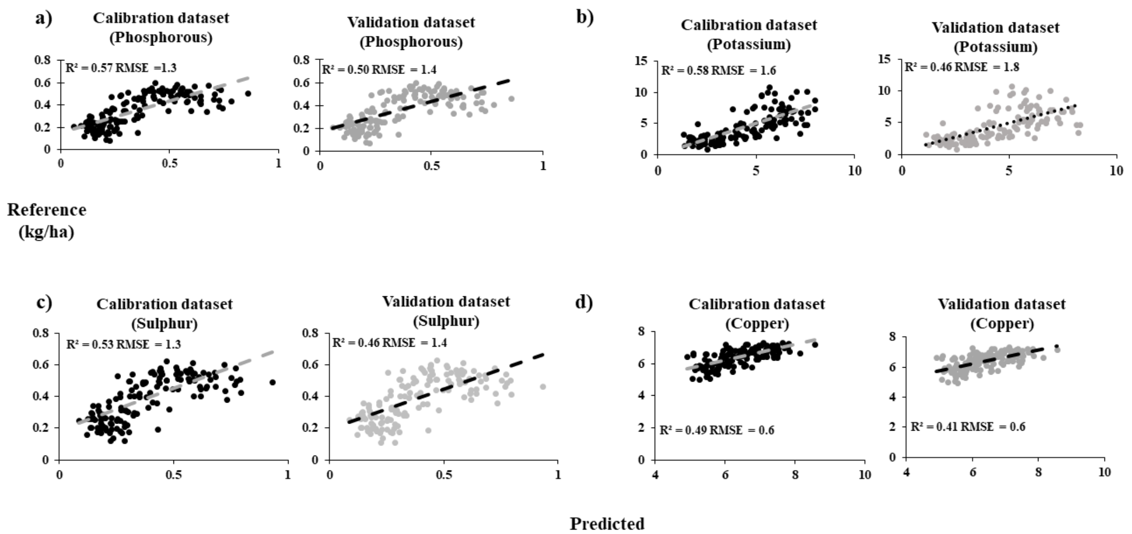

Figure 4a-d. The relationship between crop nutrients (kg/ha, lab reference) and spectral data (predicted) data from Nunjikompita and Piednippie in 2018 trials. In (a-d), a linear relationship is plotted between reference and prediction using calibration and validation datasets (Leave-one-out approach. RMSE = root mean square error.

Conclusion

Vis-NIR technology could provide a useful method for estimating soil and crop nutrient content as it is a rapid 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 phosphorous. 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 environment conditions that allow specific arrays of spectral indices to have a significant relationship with nutrients.

Acknowledgements

The present project is part of the strategic partnership investment initiative between SARDI and GRDC (scope study DAS00165). Special thanks to Douglas Green, Stuart Modra, Ian Burrows, John Montgomerie, Tim Howard, Jake Hull and families for providing the location of field trials. Thank you to Andrew Ware, Brenton Spriggs, Sue Budarick and Katerina for their collaboration with field activities.

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