Sensing technology for measuring crop nitrogen

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Abstract
Quantitative remote sensing has advanced in its ability to measure plant and canopy parameters, with nitrogen being one of the principal components of interest for crop N management. A plethora of sensors and imagers including multispectral, hyperspectral and fluorescence with different characteristics (e.g., passive vs active) have provided researchers and the agricultural industry with choices for measurement. Platforms for mounting sensors range from handheld and tractor mounted to satellites and unmanned aerial vehicles (UAVs). How to quantify canopy N using these hardware tools with spectral indices has been the focus of research for some time. Examples of recent work integrating sensors, platforms and spectral indices will be presented for ground-based proximal fluorescence sensing and passive sensing using ground and aerial platforms.

Key Words
Remote sensing, nitrogen, crops, multispectral, UAV, fluorescence

Introduction
Remote sensing of plants evolved in the 1960s when modern spectrographic methods began being used to measure plant spectral characteristics. Since chlorophyll is such a fundamental plant component, its measurement and characterization has received much attention over the years. Measurement of plant and *in situ* crop nitrogen (N) for the purposes of managing crop production has been on-going using a plethora of sensors, platforms and spectral indices. Various methods of measurement have included multispectral, hyperspectral and fluorescence sensors and imagers. These have in turn been supported by platforms within a range of scales from satellite, plane, tractor, handheld and most recently, Unmanned Aerial Vehicles (UAVs). The selection of sensors and platforms depends on the questions to be answered since there are tradeoffs of scale, extent, frequency, repeat visits, sky conditions, passive vs active sensors, timeliness of data delivery, ease of use, cost and a host of other factors.

Passive remote sensing uses sunlight as its light source, and includes multispectral (discrete, 20-80 nm wide bands) and hyperspectral (contiguous, 1-5 nm wide bands) instruments. Active optical systems utilize separate light sources to allow measurements that are independent of ambient light conditions. Recently, fluorescence measurements with active optical sensors (Agati et al. 2011) have been shown to be useful for measurements of leaf chlorophyll and flavonoids and as an indicator of leaf nitrogen (Agati et al. 2013). In this paper we discuss quantifying crop N using passive and active sensors on various platforms.

Methods
A handheld active light fluorometer (Multiplex 3.6, Force A, Orsay Cedex FRA) with four excitation bands (UV, blue, green, and red) and three detection bands (yellow, red and far red) was used to measure wheat leaf N in both field plots and on cut, stacked fresh leaves to establish calibrations. The fluorometer measurements resulted in a suite of indices from various combinations of the activation and detection wavelengths used (e.g., Gozlen *et al.* 2010). Passive multispectral imagers and hyperspectral proximal sensors (Analytical Spectral Devices, Boulder, CO, USA) were used to develop the Canopy Chlorophyll Content Index (CCCI), used to measure canopy N remotely. The CCCI uses waveband information in the 'red edge' and near infrared portions of the spectrum, which have been shown to be most useful for measuring leaf and canopy N remotely (Cammarano et al., 2014).

Results
One method for assessing canopy N is through active fluorescence sensing. As part of an on-going experiment to measure the impacts of elevated CO_2 on wheat, a handheld active sensor (Fig. 1) was deployed to measure canopy N (Perry and Fitzgerald, 2015). The nitrogen index 'NBI_G' was found to have the highest correlation to leaf and stem %N, with a positive, linear relationship ($R^2 = 0.76$) for leaves harvested at heading (Zadoks 65; Zadoks et al., 1974) (Fig. 2). Figure 3 shows the known reduction in leaf %N due to

elevated CO_2 (Panozzo et al., 2014) across a number of varieties. Figure 4 shows that the NBI_G index was able to capture the reduction of %N in these leaves across a range of wheat varieties.

Figure 1. Pictures of the handheld fluorometer (Multiplex 3.6, Force A, Orsay Cedex FRA).

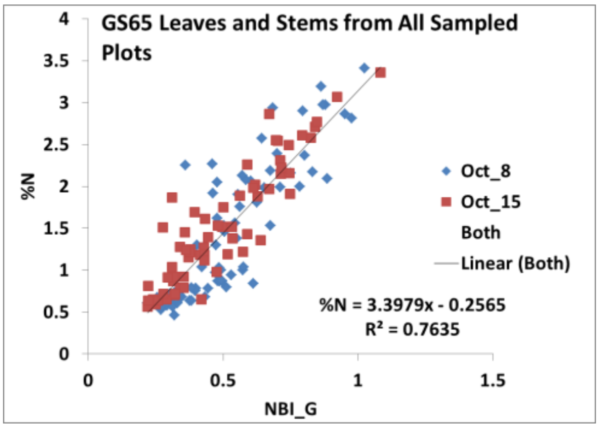

Figure 2. Relationship between the 'NBI_G' fluorescence index at growth stage Zadoks 65 (heading) of wheat.

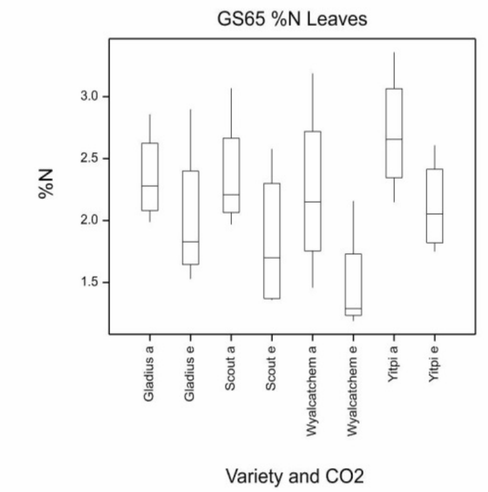

Figure 3. Reduction in %N due to elevated CO_2 across a range of wheat varieties at Z65 (heading), (p<005).

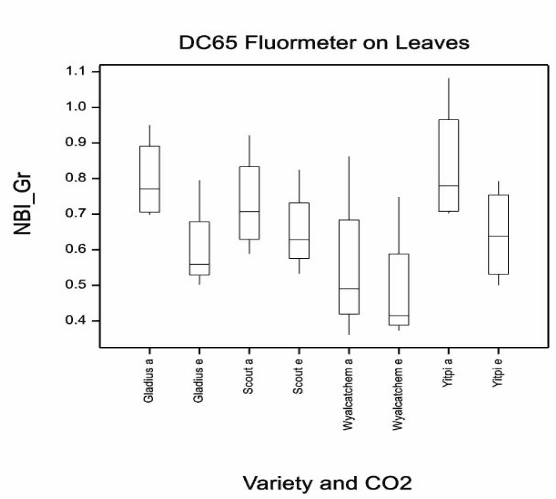

Figure 4. NBI_G index measurement of leaves across the same varieties in Fig. 3 (p<005).

In 2004-06 canopy spectra were measured with a hyperspectral sensor in a wheat crop at Horsham, VIC (Fitzgerald et al., 2010). From this data set, the CCCI was developed to remotely measure aboveground N concentration and content (Figure 5a and b). Comparisons of measured vs predicted results showed that the index could predict plant %N across a wide range of N concentration near stem elongation (Zadoks 31-33) within 0.39 (RMSE) percentage points. The index was better at predicting N in the total aboveground canopy when biomass was included (Fig. 5b).

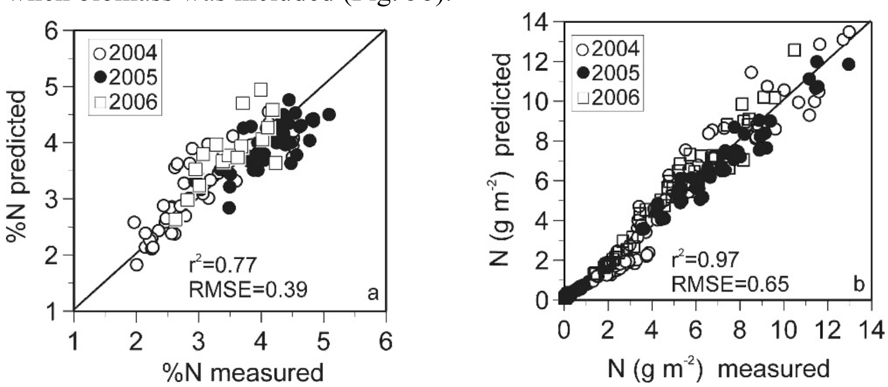

Figure 5. Predicted %N (a) and N content (b) from the Canopy Chlorophyll Content Index (CCCI) for Australian wheat research sites at Horsham.

A follow-up study (Cammarano et al., 2011) validated this index using data from Australian and Italian wheat research sites (Fig. 6). Perry et al. (2012) used the CCCI to estimate paddock scale %N in barley from RadidEye satellite imagery using the APSIM crop simulation modelling package to estimate biomass as an input (Fig. 7).

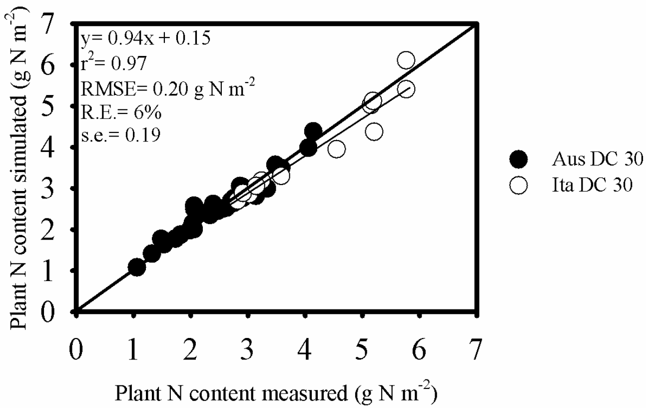

Figure 6. Prediction and validation of wheat aboveground N content using the CCCI.

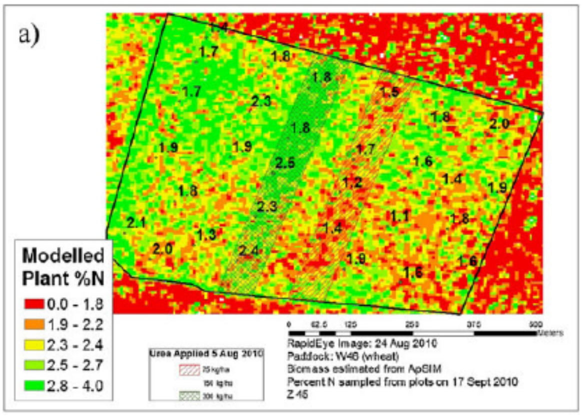

Figure 7. CCCI derived from RapidEye satellite imagery for a barley paddock. Plant %N derived from the CCCI shown in color while the actual %N contents of collected samples are shown as values.

The CCCI has also been used to map a macadamia orchard from a UAV (Fig. 8, Felderhof and Gillieson, 2011). Higher values of CCCI related to higher yields of macadamia. The CCCI is also being used to map canopy N in on-going research using a multi-rotor platform with a custom-built multispectral imager (Fig. 9). The UAV can image very fine detail, at individual crop row scale (Fig. 10), making it useful for research, including sensor-based field phenotyping.

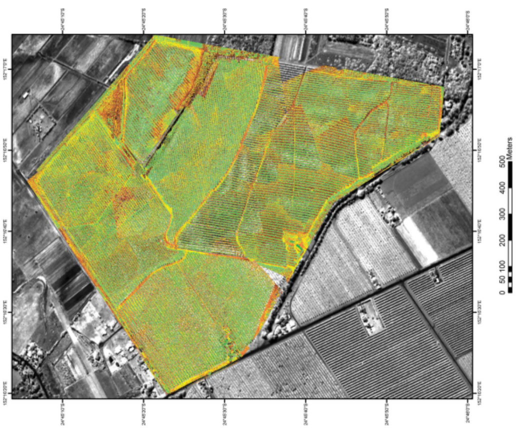

Figure 8. CCCI image from a macadamia orchard collected from a Unmanned Aerial Vehicle.

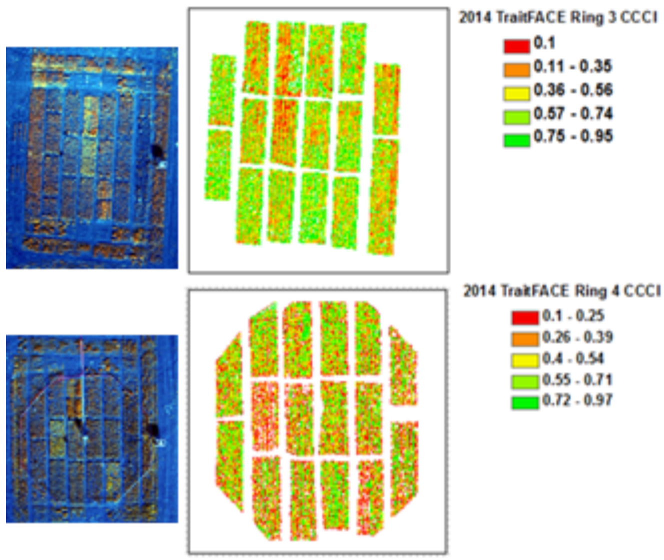

Figure 9. Multi-rotor platform used to mount a custom multispectral imager for derivation of the CCCI.

Figure 10. CCCI values from an experiment in wheat across several varieties and irrigations. Green shows higher CCCI. values relating to higher plant N contents.

Future remote and proximal platforms will likely add different sensors such as LiDAR, which is an active system that can quantify canopy morphology. And, as imagers and batteries become lighter and UAVs become more powerful, deployment of multiple sensors will become more common to measure many biophysical plant and soil characteristics simultaneously, e.g., hyperspectral, thermal, LiDAR, fluorescence, active optical. The challenge will be data integration, interpretation and usefulness to the end-user.

Conclusion

Much progress has been made since the early days of remote sensing research to be able to quantify the amount of N in crop canopies. The choice of platform and desired scale of measurement determines the exact configuration required to map the canopy. The recent rapid availability of UAV platforms will likely accelerate the use of sensor systems but the wavebands that measure the desired characteristics need to be incorporated into the sensor packages. The choice of spectral index and algorithms such as used in the Canopy Chlorophyll Content Index (CCCI) demonstrated here are required in order to make the technology useful for research and farming applications.

References

Agati GZ, Cerovic G, et al. (2011). Light-induced accumulation of ortho-dihydroxylated flavonoids as non-destructively monitored by chlorophyll fluorescence excitation techniques. Environmental and Experimental Botany 73(0), 3-9.

Agati GL, Foschi L, et al. (2013). Fluorescence-based versus reflectance proximal sensing of nitrogen content in Paspalum vaginatum and Zoysia matrella turfgrasses. European Journal of Agronomy 45, 39-51.

Cammarano D, Fitzgerald G, O'Leary G, Chen D, Basso B, Grace P. (2011) Use of the Canopy Chlorophyll Content Index (CCCI) for remote estimation of wheat nitrogen content in rainfed environments. Agronomy Journal 103(6), 1597-1603.

Cammarano D, Fitzgerald GJ, Casa R, Basso B (2014). Assessing the Robustness of Vegetation Indices to Estimate Wheat N in Mediterranean Environments. Remote Sens. 6, 2827-2844.

Felderhof L and Gillieson D (2011) Near-infrared imagery from unmanned aerial systems and satellites can be used to specify fertilizer application rates in tree crops. Can. J. Remote Sensing, 37(4), 376-386.

Fitzgerald, GJ, Rodriguez D, O'Leary G. (2010). Measuring and predicting canopy nitrogen nutrition in wheat using a spectral index – the canopy chlorophyll content Index (CCCI). Field Crops Research 116, 318-324.

Ghozlen NB, Cerovic ZG, et al. (2010). Non-Destructive Optical Monitoring of Grape Maturation by Proximal Sensing. Sensors 10(11), 10040-10068.

Panozzo J F, Walker, CK, et al. (2014). Elevated carbon dioxide changes grain protein concentration and composition and compromises baking quality. A FACE study. Journal of Cereal Science 60(3), 461-470.

Perry EM, Fitzgerald GJ, Nuttall J, O'Leary G, Schulthess U, Whitlock A. (2012) Rapid Estimation of Canopy Nitrogen of Cereal Crops at Paddock Scale Using a Canopy Chlorophyll Content Index. Field Crops Research, 134, 158-164.

Perry, EM and Fitzgerald, GJ. Reflectance and fluorescence measurements for wheat traits under elevated CO2. Proceedings of the 17th Australian Agronomy Conference 2015, Hobart, Tas, 21 – 24 September 2015.

Zadoks JC, Chang TT, Konzak CF (1974). A decimal code for the growth stage of cereals. Weed Research, 14, 415–421.