Adaptive digital tools for nitrogen management: utilising remote sensing data, modelling and sparse ground truthing

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Abstract
Remote sensing data can be used in conjunction with crop modelling and data analysis tools to estimate the crop canopy nitrogen status and provide up-to-date information to underpin in-season management decisions. In this study cereal tissue samples were calibrated against indices calculated from satellite imagery and used to generate nitrogen mapping models for wheat and barley at tillering (whole plant) and heading (youngest emerged blade) in South Australia.
Crop type was not significant for whole plant samples at tillering ($p>0.99$) but was for youngest emerged blade at heading ($p<0.001$). Biomass dilution (related to NDVI/NDRE) was the main component of variation in tissue N% (91% of variance), and (apart from crop type, 75% of variance) the CCCI was the main remote sensing component related to youngest emerged blade N% at heading (17% of variance).
The nitrogen maps allowed agronomists to test in some fields rather than all and to use a nitrogen map generated using the remote sensing data as a substitute. In conjunction with tools for management zone creation and nutrient prescription, the nitrogen maps were used to target nutrient application in-season with minimal effort on the agronomist's behalf.

Key Words
nitrogen management, remote sensing, drone data, ground-truth, CCCI, NDRE, NDVI

Introduction
Nitrogen status assessment in the canopy of cereal crops poses a challenge to agronomists wishing to recommend an in-season application of nutrients. Reliance on traditional plant sampling approaches alone constrains the insights about the crop nitrogen to several observations in a few locations in the field. To create whole-field nutrient status maps and hence variable rate applications, the information about plant tissue test results needs to be scaled from point to field level.

Fitzgerald et al (2010) developed a relationship between relative crop nitrogen content and multispectral sensing of the crop using 'red edge', red, and near infrared spectral bands. In recent years applying this method in the field has become more feasible with the availability of satellite data in these bands (Sentinel 2), and outfitting drones or fixed-winged aircraft with low-cost multispectral sensors. Translating relative nitrogen content into actual nitrogen content requires biomass, which has been correlated to remote sensing indices such as NDVI in crops with incomplete ground cover (Kalaitzidis et al, 2010). The scaling of a few point-based observations into a spatial layer, which can be used for decision support in nutrient recommendations, is achieved by combining point plant test results, remote sensing data (satellite or drone imagery) and nutrient mapping models.

This study aimed to validate the approach on field crops and highlight areas where further work might be required to achieve reasonable estimates of crop nitrogen content.

Data description
Crops
Data was collected on over twenty fields of wheat and barley near Jamestown in South Australia, in July and October 2018. Fifty-nine tissue samples were collected at the tillering stage (whole plant) and forty-six at head development (youngest emerged blade). Locations for sample collection were chosen to cover the range of NDVI in each field, away from headlands and fencelines, and had support at a similar scale to a Sentinel 2 pixel (10m square). Crops suffered drought from June to August, and frost on October 9th.

Satellite images
The study was originally designed to rely on drone images (in case of cloud), with Sentinel 2 as a backup. Ultimately the head development drone imagery acquisition failed. Fortunately Sentinel 2 images were available close to the sampling dates, correlated well with the drone images at tillering (not shown), and were ultimately used in this study.

Sentinel-2 data (https://earth.esa.int/web/sentinel/technical-guides/sentinel-2-msi/msi-instrument) was recorded for the whole season from May 1 until November 16 2018. The following vegetation indices (VI) were generated: NDVI, NDRE, MSAVI (Qi et al. 1994) and CCCI (Fitzgerald et al. 2010). The MSAVI results were very similar to NDVI and hence not shown.

$$\mathrm{NDVI} = \frac{\mathrm{NIR-Red}}{\mathrm{NIR+Red}} \quad \mathrm{NDRE} = \frac{\mathrm{NIR-RedEdge}}{\mathrm{NIR+RedEdge}} \quad \mathrm{CCCI} = \frac{\mathrm{NDRE-NDRE}_{min}}{\mathrm{NDRE}_{max}+\mathrm{NDRE}_{min}}$$

Results and discussion

Nutrient correlation with Remote Sensing

Nitrogen at both tillering (whole plants) and heading (youngest emerged blade) was strongly related to NDRE and NDVI vegetation indices (Table 1). The NDRE and NDVI were also strongly correlated with each other (around 0.9; not shown). Nitrate was not well related to any multispectral band or index (Table 1). At the head development stage, N% and nitrate were not well correlated with the satellite data. CCCI had the highest correlation with N% (0.35) followed by NDVI (-0.23).

Table 1: Pearson correlation for nitrogen (%) and nitrate (ppm) with remote sensing indices at tillering and heading.

Nutrient/VI	Range	Red Edge	NIR	Red	NDRE	NDVI	CCCI
Tillering:							
N (%)	5.0-8.5	-0.29	-0.42	0.58	-0.62	-0.61	0.11
Nitrate (ppm)	46-3390	0.14	0.15	-0.18	0.21	0.22	0.13
Heading:							
N (%)	2.3-5.5	0.06	-0.17	0.21	-0.12	-0.23	0.35
Nitrate (ppm)	30-423	-0.02	0.25	-0.02	0.09	0.08	0.13

Model development

The Fitzgerald *et al* (2010) scheme for calculating CCCI has the effect of forcing linear bounds on a curvilinear relationship. The variance of CCCI also increases with NDVI, a property which complicates model fitting. In this study log(NDRE) and log(NDVI) were calculated and used to derive a CCCI based on log, rather than linear index values, which also resulted in uniform variance across the range of NDVI and NDRE.

Initial model exploration showed a Random Forest regression model (based on data reduced using Principal Components Analysis – PCA) produced good results fitting variation in N%. These results were not reproducible with a least-squares approach using the same set of input data without PCA. The PCA reduces the data to three dimensions: a major one (1) positively correlated with both NDRE and NDVI, a minor one (2) negatively correlated mostly with CCCI, and a third small component (3) describing variation perpendicular to the main NDRE-NDVI direction (Table 2). The loadings were similar at both measurement times.

Table 2: Principal Components loadings on remote sensing indices across all sampling dates, and for tillering and heading samples separately.

Timing	All samples			Tillering			Heading		
Component/ variate	PC1	PC2	PC3	PC1	PC2	PC3	PC1	PC2	PC3
St. Dev.	1.577	0.716	0.012	1.414	1.001	0.008	1.519	0.833	0.019
Log(NDVI)	+0.606	+0.413	+0.680	+0.702	+0.123	+0.701	+0.612	+0.442	+0.656
Log(NDRE)	+0.620	+0.291	-0.729	+0.707	-0.006	-0.707	+0.650	+0.191	-0.736
CCCI(logs)	+0.498	-0.863	+0.080	+0.083	-0.992	+0.091	+0.450	-0.876	+0.171

In attempts to predict crop N% using only remote sensing data, NDVI/NDRE becomes a proxy for biomass in the relationship between crop N% and biomass.

Models of tissue N

Models of N% at tillering and heading are potentially quite different. When fitted using principal components calculated on remote sensing data from all samples, the main NDVI/NDRE component (1) was highly significant at tillering ($p<0.001$), with a small weakly significant effect related to the orthogonal NDVI/NDRE component (3, $p=0.083$), and no significant effect of crop ($p>0.99$, Table 3). At heading, the crop effect was highly significant ($p<0.001$), along with a significant positive effect related to the CCCI (component 2, $p=0.029$). The results were slightly changed with components calculated on the individual sets of sample data (ie tillering and heading in Table 2). No improvement could be made with components calculated on individual crop data with this sample set for the heading samples, nor were there significant interactions at heading between crop type and the principal component 2 effect ($p=0.25$).

Table 3: Sources of variance (% sum of squares) in linear models of N% fitted to crop type (barley/wheat) and principal components calculated across sample times or separately for tillering and heading samples. *** p<0.001, * p<0.05, + p<0.1.

Timing	All samples		Separate	
Source	Tillering	Heading	Tillering	Heading
Crop	0.0	75.2***	0.0	75.2***
PC1	91.2***	5.5	89.7***	1.7
PC2	1.3	17.0*	2.8	20.7*
PC3	7.4+	2.3	7.4+	2.3
Adj R2	47.9	42.0	47.9	42.0
RMSE	0.55	0.51	0.55	0.51

The final models fitted were at tillering:
$N\% = 5.71 (\pm 0.18) - 0.72 (\pm 0.12) \times PC1 - 13.47 (\pm 8.31) \times PC3$
And at heading:
$N\% = 3.41 (\pm 0.12) - 0.12 (\pm 0.12) \times PC2$ for barley, with the additional constant
$+0.61 (\pm 0.17)$ for wheat

The tillering model represents a negative effect of NDVI/NDRE increase; effectively the dilution of nitrogen with biomass, and a positive effect with NDRE increase and NDVI decrease. This latter effect can be thought of as the positive effect of NDRE related to crop nitrogen content, not captured between CCCI and NDVI. The CCCI is an estimate of the NDRE effect with NDVI held constant. This effect is orthogonal to that; in physiological terms (ie Fitzgerald *et al.*) at constant Canopy Nitrogen Index, NDRE will be increasing as NDVI increases with biomass.

The heading model is a more conventional model, where CCCI is positively related to tissue N%. There is no clear effect of biomass dilution (which would be evidenced by a relationship with NDVI, NDRE or both). That is consistent with the youngest emerged blade sampling method used on that sampling, which should be less affected than whole plant samplings and more directly related to Canopy Nitrogen Index.

The difference between crops at heading could feasibly relate to the morphological differences between wheat and barley and their effect on the remote sensing ‘signal’. At heading the differences would be more pronounced. Equally, it is also possible that the generally lower barley N% reflects later development stage or some other confounded difference between wheat and barley in this study.

Conclusion

A method for development of a regional crop-type-specific nitrogen model was tested, which could be applied on the field-scale to monitor a crops nitrogen concentration with minimal need for plant tissue testing. Log transformation of NDVI and NDRE, and calculation of CCCI accordingly was suggested to improve numerical consistency, and the use of Principal Components Analysis to derive the truly orthogonal elements of NDVI, NDRE and CCCI. For whole-plant samples at tillering, where biomass dilution was a factor, tissue N% was estimated mostly from the biomass dilution effect related to NDVI and NDRE, but also partly by the NDRE effect not captured in the main CCCI effect. For youngest emerged blade samples at heading, the main CCCI effect was better related and biomass dilution less a factor. There were significant crop type effects at heading which need to be understood further before models are applied at that stage.

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