Potential for machine vision of grain crop features for nitrogen assessment

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Abstract
Existing approaches for determining nitrogen (N) requirements typically involve measuring biomass and sensing near-infrared-based crop reflectance indices. There is potential for automated assessments of tiller counts, plant size and colour using machine vision to help indicate plant N status. Existing demonstrations of machine vision systems are typically for a single field rather than multiple fields. A barley and wheat field study has been conducted to identify robustness of machine vision across multiple sites for assessing biomass, and plant N status and concentration. Three N trial sites were established in Western Australia and South Australia during the 2020 season with low and rich-N strips. Each strip and the paddock were sampled in five to seven locations for plant N uptake, plant N concentration, and plant response using crop dry biomass and machine vision cameras. Machine vision algorithms were implemented on oblique images to extract indicators of vigour (colour) and physical size (line length and density that represent tillers and branches). Linear regression analysis identified that a normalised green red difference index from the colour machine vision system was strongly correlated with biomass and could add value to biomass and plant N assessment. Further work is to incorporate machine vision parameters into a data-driven N decision making method.

Keywords
Image analysis, biomass, automation, variable-rate, Future Farm project

Introduction
Nitrogen (N) represents 30-40% of input costs for cereal grain crops and this cost is continually increasing. Automated crop sensors can help assess biomass to guide site-specific plant N status assessment. These crop response measurements are typically determined from colour indices in near-infrared wavelengths using proximal sensors (Poley & McDermid 2020) and satellite imagery (Revill et al. 2019) and linked with machine learning models (Chlingaryan et al. 2018), N dilution curves (Wang et al. 2017) and/or biophysical models (Lawes et al. 2019) to assess N requirements. Reflectance sensing (e.g. the normalized difference vegetation index; NDVI) can have inconsistent correlations with N status across different stages and seasons (Porter 2010). For example, Colaço and Bramley (2020) report the highest coefficient of determination (R^2) of 0.65 for the normalized difference red edge index (NDRE) vs mid-season N uptake univariate models. Biomass is also commonly assessed using height measurements from a LiDAR scanner (e.g. Colaço et al. 2021*a* with R^2=0.62 for a single field).

An alternative approach to assess colour indices is with a colour machine vision system which is potentially lower cost (<$600) than proximal crop reflectance sensing (~$10 000) and can be linked with N decision making. Colour indices have been demonstrated to be correlated with biomass with R^2=0.59-0.78 from UAVs (Jibo et al. 2019), and plant N concentration in a single field from a normalised green red difference index (NGRDI) in the RGB colour space with R^2=0.75 (Jiang et al. 2019). Existing research focusses on a single site, and the ability for machine vision to assess biomass and plant N status is required across multiple sites. There is also potential to investigate the use of other colour spaces, including HSV (hue, saturation, value) and L*a*b* that may more accurately assess colour as they separate the lighting and colour information. Machine vision algorithms can also assess physical size features including fractional canopy cover using a plant segmentation algorithm

(Ashapure et al. 2019) and leaf/branch counts (density) and geometry (area, height, width) using a line detection algorithm (Boyle et al. 2015).

This paper reports a field study to identify how machine vision could complement other sensing technologies in an automated biomass and N sensing system for wheat and barley across multiple sites. This was achieved by establishing N application trials and collecting machine vision, biomass and plant N status data at growth stage 31 (GS31) when in-season N may be applied. Data analysis is presented to identify the machine vision inputs most strongly correlated with biomass and plant N status and, in further work, could link with a N application sensing system.

Methods

Field sites and data collection

Three field trial sites were established in SA and WA with low and rich-N strips as detailed in Table 1. Table 2 outlines the data collected at each site at GS31. An action camera Sony FDR-X3000 action camera (1920 x 1080 pixels, $550) was selected with image stabilisation to compensate for camera shake and robustness to low light. The machine vision camera was installed to capture oblique images of the crop. Biomass and plant N concentration were measured from dry matter cuts during plant sensor data collection in each sampling location. Plant N uptake was determined by multiplying the plant N (%) and biomass.

Table 1. Field trial sites for sensor data collection with different N treatments.

Site	WA-Dandaragan	SA-Tarlee	SA-Tumby Bay
Crop	Wheat	Barley	Wheat
Number of sampling locations in each strip	5	7	5
N applied in low, mid, and rich strips until GS31 (kg N/ha)	30.0, 72.0, 114.0	9.9, 46.7, 92.7	16.2, 29.2, 108.2
Closest BOM weather station	Badgingarra Research Station (39.4 km)	Roseworthy (34.1 km)	North Shields (Port Lincoln) (19.1 km)
Accumulated rainfall until GS31 (mm)	84.7	59.6	76.6

Table 2. Data collected in each sampling location at GS31 at each field trial site.

Data	Category	Data types
Inputs	Machine vision – Sony X3000 action camera	Machine vision parameters: cover (%); colour channels in RGB, HSV and L*a*b* colour spaces; colour indices using R, G, B; physical size parameters cover, line geometry (pixels)
Outputs	Dry biomass	Biomass (kg/ha)
	Plant N status	Plant N uptake (kg/ha) calculated from biomass over area, plant N concentration (%)

Data processing and analysis

After data collection at GS31, the plant sensor data and images corresponding to each sampling location were extracted. Fractional canopy cover was measured using a plant segmentation algorithm (Kumar & Miklavcic 2018), and the average colour index across the segmented plant pixels in each image were calculated after extracting the individual red (R), green (G) and blue (B) channels from the RGB images; hue/colour, saturation/shade and intensity/lighting channels from the HSV images; and L*, a* and b* from the L*a*b* images (Ashapure et al. 2019). Line detection algorithms were implemented to count the leaves and branches per unit area and their areas, widths and lengths (Boyle et al. 2015). Linear regression analysis was applied between the machine vision parameters and biomass and plant N status. These are represented as Pearson's correlations (r) and coefficients of determination (R^2).

Results

Table 3 compares the correlations and coefficients of determination between the machine vision parameters and biomass and plant N status. The machine vision parameter that had the strongest correlation with biomass and plant N status was NGRDI ($r=0.841$, $R^2=0.71$ and $r=0.722$, $R^2=0.52$, respectively). This is comparable with machine vision systems reported in the literature using machine vision systems from UAVs (up to $R^2=0.78$) and LiDAR ($R^2=0.62$) at a single site. This demonstrated the robustness of the machine vision system across multiple sites and indicates potential to incorporate machine vision into data-driven biomass and plant N assessment models for N decision making methods (e.g. Colaço et al. 2021*a*).

From Table 3, the machine vision parameters were better correlated with biomass than plant N status which may indicate a need for other site-specific information. This may be achieved by combining multiple machine vision parameters, e.g. colour and physical size, to estimate biomass and plant N status.

Table 3. Linear regression analysis between machine vision parameters and biomass and plant N status where * indicates statistical significance ($p<0.05$).

Machine vision parameter		Biomass (kg/ha)		Plant N uptake (kg N/ha)	
Colour space	Feature	r	R^2	r	R^2
RGB	R	0.030	0.001	0.024	0.001
	G	0.458*	0.210	0.389*	0.151
	B	0.388	0.151	0.356	0.126
	NRBDI	0.425*	0.181	0.417*	0.174
	NGRDI	0.841*	0.708	0.722*	0.522
	Cover	0.566*	0.320	0.480*	0.231
	Line density	0.605*	0.366	0.495*	0.245
	Line area	0.475*	0.225	0.380	0.144
	Line height	0.422*	0.178	0.337	0.113
	Line width	0.416*	0.173	0.350	0.123
HSV	H	0.664*	0.441	0.587*	0.345
	S	0.242	0.059	0.174	0.030
	V	0.289	0.083	0.247	0.061
L*a*b*	L*	0.262	0.069	0.225	0.050
	a*	0.265	0.070	0.234	0.055
	b*	0.261	0.068	0.225	0.051

Conclusion

Trials were conducted to identify the potential for machine vision to indicate biomass and plant N status for wheat and barley at GS31. From linear regression analysis across three sites, the machine vision parameter best correlated with biomass and plant N uptake was a colour index incorporating greenness and redness in the RGB colour space (NGRDI). This suggests that machine vision can complement other sensors for estimating biomass and plant N status and further work will be conducted to implement a multivariate modelling approach assessing biomass and plant N status for N decision making.

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References

Ashapure A, Jung J, Chang A, Oh S, Maeda M and Landivar J (2019). A comparative study of RGB and multispectral sensor-based cotton canopy cover modelling using multi-temporal UAS data. Remote Sensing 11(23):2757.

Boyle RD, Corke FMK and Doonan JH (2015). Automated estimation of tiller number in wheat by ribbon detection. Machine Vision and Applications 27:637–646.

Chlingaryan A, Sukkarieh S and Whelan B (2018). Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review. Computers and Electronics in Agriculture 151:61-69.

Colaço AF and Bramley RGV (2020). Future farm - towards an improved sensor-based approach to nitrogen management. GRDC Research Update.

Colaço AF, Richetti J, Bramley RGV and Lawes RA (2021*a*). How will the next-generation of sensor-based decision systems look in the context of intelligent agriculture? A case-study. Field Crops Research. 270(June):108-205.

Colaço, AF, Schaefer, M and Bramley, RGV (2021*b*). Broadacre Mapping of Wheat Biomass Using Ground-Based LiDAR Technology. Remote Sensing 13(16):3218.

Jiang, J, Cai, W, Zheng, H, Cheng, T, Tian, Y, Zhu, Y, Ehsani, R, Hu, Y, Niu, Q, Gui, L and Yao, X (2019). Using Digital Cameras on an Unmanned Aerial Vehicle to Derive Optimum Color Vegetation Indices for Leaf Nitrogen Concentration Monitoring in Winter Wheat. Remote Sensing 11(22):2667.

Jibo, Y, Guijun, Y, Tian, Q, Feng, H, Xu, K and Zhou, C (2019). Estimate of winter-wheat above-ground biomass based on UAV ultrahigh- ground-resolution image textures and vegetation indices. ISPRS Journal of Photogrammetry and Remote Sensing 150:226-244.

Kumar P and Miklavcic S (2018). Analytical Study of Colour Spaces for Plant Pixel Detection, Journal of Imaging, 4(42).

Lawes RA, Oliver YM and Huth NI (2019). Optimal nitrogen rate can be predicted using average yield and estimates of soil water and leaf nitrogen with infield experimentation, Biometry, Modelling, and Statistics 111:1155-1164.

McCarthy AC and Baillie CP (2020). Future farming: Machine vision for nitrogen assessment in grain crops. GRDC Research Update. 10 September.

Poley LG and McDermid GJ (2020). A systematic review of the factors influencing the estimation of vegetation aboveground biomass using unmanned aerial systems. Remote Sensing 12(7):1052.

Porter W (2010). Sensor Based Nitrogen Management for Cotton Production in Coastal Plain Soils, Master of Science Thesis, Clemson University.

Revill A, Florence A, MacArthur A, Hoad S, Rees B and Williams M (2019). The value of sentinel-2 spectral bands for the assessment of winter wheat growth and development. Remote Sensing 11L2050.

Wang X, Ye T, Ata-Ul-Karim ST, Zhu Y, Liu L, Cao W and Tang L (2017). Development of a critical nitrogen dilution curve based on leaf area duration in wheat. Frontiers in plant science 8:1517.