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Dynamic monitoring of NDVI in wheat agronomy and breeding trials using an unmanned aerial vehicle

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ABSTRACT

While new technologies can capture high-resolution normalized difference vegetation index (NDVI), a surrogate for biomass and leaf greenness, it is a challenge to efficiently apply this technology in a large breeding program. Here we validate a high-throughput phenotyping platform to dynamically monitor NDVI during the growing season for the contrasting wheat cultivars and managements. The images were rapidly captured (approximately 1 ha in 10 min) by an unmanned aerial vehicle (UAV) carrying a multi-spectral camera (RedEdge) at low altitude (30–50 m, 2–5 cm^2 pixel size). NDVIs for individual plots were extracted from the reflectance at Red and Near Infrared wavelengths represented in a reconstructed and segmented ortho-mosaic. NDVI measured by UAV and RedEdge camera were strongly correlated with those measured by hand held GreenSeeker ($R^2 = 0.85$) but were offset with UAV readings about 0.2 units higher and more compressed. The high-throughput phenotyping platform captured the variation of NDVI among cultivars and treatments (i.e. irrigation, nitrogen and sowing). During the growing season, the NDVI approached saturation around flowering time (~0.92), then gradually decreased until maturity (~0.35). Strong correlations were found between image NDVI around flowering time and final yield ($R^2 = 0.82$). Given that the image NDVI includes signals from background (soil and senescenced leaves), ground cover from a high resolution hand-held camera was used to adjust the NDVI from UAV. This slightly increased the correlation between adjusted NDVI and yield ($R^2 = 0.87$). The high-throughput phenotyping platform in this study can be used in agronomy, physiology and breeding to explore the complex interaction of genotype, environment and management. Data fusion from ground and aerial sampling improved the accuracy of low resolution data to integrate observations across multiple scales.

1. Introduction

Monitoring the growth of wheat within a season is essential to decision making in both precision farming and in large breeding programs (Magney et al., 2016a; Tester and Langridge, 2010). Low altitude remote sensing provides a practical technology to monitor the crop canopy status at large scales, particularly in agronomic experiments where space, resource and time constraints limit manual sampling. Strong associations have been demonstrated between spectral vegetation indices and attributes of crop growth and development and are being more frequently assessed with the development of new instruments (Brown and de Beurs, 2008; Erdle et al., 2011; Huang et al., 2014; Kyratzis et al., 2015; Cabrera-Bosquet, 2011).

The normalized difference vegetation index (NDVI) which is the differenced ratio of reflectance in the red and near-infrared wavelength (Tucker, 1979), is widely used in both research and commercial agronomy applications (Erdle et al., 2011; Guo et al., 2016; Inman et al., 2008; Lopes and Reynolds, 2012; Marti et al., 2007). The original use of NDVI was prompted by the motivation to indirectly predict grain yield using bands available from space with Landsat satellite data (Aase and Siddoway, 1981; Tucker et al., 1980). The vegetation index NDVI is well correlated with leaf area index (LAI) and is more sensitive to changes in the crop canopy when the LAI is low (i.e. during the early stage), with the signal becoming saturated when the crop canopy closes (Inman et al., 2008; Ma et al., 2001; Marti et al., 2007). Some studies showed that the yield estimated from NDVI had a strong relationship with grain yield in wheat (Magney et al., 2016a; Raun et al., 2001). NDVI also has been used to estimate crop growth status based on the different patterns of reflection of green organs and soil in wheat and other cereals (Lopresti et al., 2015; Mekliche et al., 2015; Morgounov et al., 2014).

Temporal ground-level measurements of NDVI have provided a

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more robust and objective approach to indirectly estimate the stress status of wheat (Lopes and Reynolds, 2012) and in-season requirements for nitrogen fertilisation (Raun et al., 2002). At the same time, NDVI has been calibrated to estimate the nitrogen content, aboveground nitrogen uptake, and nitrogen efficiency of crops (Erdle et al., 2011; Foster et al., 2016; Samborski et al., 2015). The close relationship of NDVI with crop physiological attributes means that NDVI can also explain (or be confounded with) a diversity of other factors, e.g. moisture, nitrogen and growth stage (Edwards et al., 2015; Foster et al., 2016; Marti et al., 2007). NDVI has also been used as a surrogate for visual scoring of spot blotch disease in wheat (Kumar et al., 2016). Hence, when using NDVI, researchers need to be sure of which factors in the experiment are being best represented by the measurement.

The common technology for NDVI acquisition is of two types: 1) tracking seasonal phenology over a wide variety of environments from space using satellite data (Lopresti et al., 2015; Pantazi et al., 2016; Zhang et al., 2016) and 2) field or plot-level estimation to guide the actual production for crops through hand-held sensors (Inman et al., 2008; Lopes and Reynolds, 2012; Magney et al., 2016a). The resolution of NDVI information from satellite data typically ranges from 5 to 30 m pixels and is appropriate for field or regional level monitoring, but is unsuitable in field breeding and agronomy trials given limitations of accuracy and real-time monitoring (Guo et al., 2016; Perry et al., 2014; Tattaris et al., 2016). Ground-level hand-held sensors or cameras have greater accuracy, but are limited in both time and space resolution, with data collection that can suffer from subjective measurement bias and equipment interference (Schirrmann et al., 2016). Specialised ground-based platforms allow collection of finer spatial and temporal resolutions using adjusted NDVI sensors and spectral reflectance sensors (Magney et al., 2016b; Soudani et al., 2012). Given the growing demand for high-throughput phenotyping to support crop breeding, there is greater interest to develop rapid and non-destructive technologies for high-throughput phenotyping (Chapman et al., 2014; Deery et al., 2014; Tattaris et al., 2016).

The accuracy of NDVI measurement is largely influenced by the biophysical characteristics of the canopy and growth environment (e.g. vegetation cover, biomass, plant and soil moisture) and effect of the measuring equipment (satellite drift, calibration uncertainties and atmospheric conditions) factors (Gutman, 1999). NDVI trends can also change in response to environmental conditions, e.g. temperature and water regime (Crusiol et al., 2016; Forkel et al., 2013). Sensor view angle, solar angle, radiometric calibration and soil background also influence reflectance from the crop canopy, so the selection of the optimal instruments and measurement conditions for monitoring and predicting crop growth parameters (Mulla, 2013) is crucial. In large breeding programmes, precise non-destructive biomass estimates could be useful in selection, particularly if they are quick, cheap and easy to perform.

Fully or largely automated capabilities have contributed to crop improvement through a combination of modern technologies including genetic engineering, robotics and imaging (Araus and Cairns, 2014; Chapman et al., 2014; Sharma et al., 2015). Biomass estimation for barley has been derived using the crop surface models created from the Unmanned aerial vehicles (UAV) RGB aerial imagery (Bendig et al., 2014), and technological advances such as autonomous mission planning has increased interest in their application in precision agriculture (Khot et al., 2016; Rasmussen et al., 2016; Zhang and Kovacs, 2012). For crop improvement efforts to continue to increase yield potential, the connection of genotypes and phenotypes with high efficiency is needed. An Unmanned Aerial Vehicle with autonomous flight control can be used to undertake remote sensing tasks as quantitative or qualitative information about an object without physical contact (Chapman et al., 2014; Tattaris et al., 2016).

For phenotype analysis at the plot-level based on an UAV image set, a major challenge is to manage and extract plot level data from these massive image datasets. A plot scale automatic segmentation algorithm has been developed for ground cover estimation based on the UAV images (Duan et al., 2017). This method retrieves data from original images, using the orthomosaic and imputed camera positions to identify the plots in each image. These original data have not been blurred or mixed by reconstruction. Another important step is filtering of 'useless pixels' to remove the soil and other background pixels from images (e.g. based on partitioning clustering, Schirrmann et al., 2016). This allows computation of NDVI based on the plant material alone (i.e. removing effects of LAI), and fast efficient filtering is required.

The objectives of this study were to 1) develop a high-throughput phenotyping workflow to estimate the NDVI in the plot–level through an unmanned aerial vehicle and multiple spectral camera, 2) compare the NDVI measured from UAV and a commercial hand held sensor, 3) improve the accuracy of UAV NDVI through merging data from high resolution hand-held camera, 4) characterise NDVI for contrasting cultivars, managements and environments.

2. Materials and methods

This study applied a high-throughput method to monitor dynamic changes of NDVI using a low altitude unmanned aerial vehicle (UAV) platform and a multi-spectral camera in a field experiment with contrasting wheat cultivars and managements. NDVI estimated from UAV was also adjusted by ground coverage obtained from the hand-held camera.

2.1. Field experiments

Wheat experiments were conducted in 2015 at the experimental station of Gatton Campus, the University of Queensland (27.50°S, 153.01°E). Contrasting canopy structures were established by two irrigation treatments (irrigation and rain-fed), two nitrogen treatments (high and low), two sowing dates (normal and late) and eight cultivars. The experimental field was 54 m wide and 161 m long, and split into 4 treatment blocks comprising 621 plots in total, each plot being 2 m (7 rows) wide and 7 m long. The four treatments refer to four irrigation and nitrogen treatments (i.e. RLN for rain-fed and low nitrogen, RHN for rain-fed and high nitrogen, ILN for irrigation and low nitrogen, IHN for irrigation and high nitrogen, Fig. 1). Each treatment was split into two sub-blocks for two sowing treatments. The normal and 'late' sowing dates were 21st May and 22nd June, respectively. Eight cultivars were selected to represent the contrasting traits of canopy structure (i.e. maturity, tiller number, transpiration efficiency, water soluble carbohydrate and protein content) with three replicates in each treatment. The results of three key cultivars are discussed in this study as they were sown at both dates (Suntop, medium-maturity cultivar; Hartog, medium-maturity cultivar; Gregory, late-maturity cultivar). In each sub-block, cultivars were randomized into three replicate blocks in a column-row design by the R package DiGGer (Coombes, 2016). The plant density was 150 plants m^{-2}. Fertiliser was applied at sowing with 205 kg ha^{-1} for high nitrogen and 50 kg ha^{-1} for low nitrogen (Urea, 46% N) after measuring the pre-planting soil nitrogen being ca 32.3 kg ha^{-1} (0–60 cm), averaged for samples across the field about one month prior to sowing. Irrigation was applied to all treatments at sowing and one month after sowing for emergence and development at the early stage (49 mm in total). Additional irrigations were applied only for irrigation treatments when needed with 127 mm applied for normal sowing and 152 mm for late sowing. Seasonal rainfall was 128 mm and 113.6 mm in the normal and late sowing, respectively. Average daily temperatures across the season (June to Oct) were 24.2 °C for maximum and 8.7 °C for minimum. After maturity, the plots were harvested to estimate the yield, with periodic sampling for biomass and plant organ components through the season (not presented here).