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Hyperspectral sensing to detect the impact of herbicide drift on cotton growth and yield

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ABSTRACT

Yield loss in crops is often associated with plant disease or external factors such as environment, water supply and nutrient availability. Improper agricultural practices can also introduce risks into the equation. Herbicide drift can be a combination of improper practices and environmental conditions which can create a potential yield loss. As traditional assessment of plant damage is often imprecise and time consuming, the ability of remote and proximal sensing techniques to monitor various bio-chemical alterations in the plant may offer a faster, non-destructive and reliable approach to predict yield loss caused by herbicide drift. This paper examines the prediction capabilities of partial least squares regression (PLS-R) models for estimating yield. Models were constructed with hyperspectral data of a cotton crop sprayed with three simulated doses of the phenoxy herbicide 2,4-D at three different growth stages. Fibre quality, photosynthesis, conductance, and two main hormones, indole acetic acid (IAA) and abscisic acid (ABA) were also analysed. Except for fibre quality and ABA, Spearman correlations have shown that these variables were highly affected by the chemical. Four PLS-R models for predicting yield were developed according to four timings of data collection: 2, 7, 14 and 28 days after the exposure (DAE). As indicated by the model performance, the analysis revealed that 7 DAE was the best time for data collection purposes (RMSEP = 2.6 and $R^2 = 0.88$), followed by 28 DAE (RMSEP = 3.2 and $R^2 = 0.84$). In summary, the results of this study show that it is possible to accurately predict yield after a simulated herbicide drift of 2,4-D on a cotton crop, through the analysis of hyperspectral data, thereby providing a reliable, effective and non-destructive alternative based on the internal response of the cotton leaves.

1. Introduction

Cotton crops are one of the most highly susceptible crops to phenoxy herbicides, in particular to the herbicide 2,4-D. Even with genetic modifications, it has not been possible to avoid yield loss caused by the off-target movement of the active ingredients (Charles et al., 2007). Although resistance to damage has been demonstrated, it is naive to believe that cotton crops would not be affected by this herbicide when the extent of injury depends upon the climate and proximity to thousands of cereal and fallow fields where 2,4-D is sprayed to control broad-leaved weeds (Bondada, 2011). Significant inconsistencies in the traditional assessment of damage have been proven in several studies (Everitt and Keeling, 2009), however a more precise technique for prediction of cotton yield loss has not been tested. This limitation prevents the farmers to optimise management practices and mitigate losses.

The phenoxy herbicide 2,4-D is a selective synthetic auxin which causes an uncontrolled production of simulated Indole Acetic Acid (IAA) in broadleaf plants (Bondada, 2011). IAA is considered as a master hormone because it influences every aspect of plant growth and development (Grossmann, 2010). When applied as herbicide, synthetic auxins mimic the deformation and growth-inhibiting effects caused by IAA at a very constant concentration until the growth causes plant death. In contrast, the phytohormone Abscisic Acid (ABA) is important in the adjustment to environmental stress, seed development and dormancy (Straub et al., 1994). The biosynthesis of ABA is over-stimulated by herbicide 2,4-D causing growth inhibitors, morphological abnormalities and senescence (Teixeira et al., 2007).

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Remote sensing techniques are widely applied in agriculture due to its capability to provide significant information about the health of the crops. Biophysical and physiological variables are analysed through the visible (VIS)-to-shortwave infrared (SWIR) wavelengths without the need to implement destructive sampling. With high accuracy, the ability to integrate the concept of spatial distribution, environmental conditions and soils has turned remote sensing techniques into a valuable tool for crop assessment (Clevers, 1999; Tian et al., 2005). Hyperspectral sensors are able to detect slight variabilities in the biophysical and physiological aspect of the plants (Rapaport et al., 2015). Through the implementation of partial least squares regression analysis (PLS-R), accurate prediction results (i.e. prediction accuracy = 92%) were obtained when this technique was applied in predicting the grain protein content of wheat (*Triticum aestivum*) (Apan et al., 2006). Hyperspectral sensors have been also used in a variety of applications, such as detection of disease or stress caused by pesticides (Henry et al., 2004), water (Detar et al., 2006), nitrogen (Schlemmer et al., 2013), and other nutrient deficiencies (Chen et al., 2011; Tian et al., 2012). Furthermore, effects on carotenoids, an important pigment of green leaves, were accurately predicted by different statistical approaches applied to hyperspectral data in cotton crops (Yi et al., 2014). These techniques included stepwise multiple linear regression (SMLR), band selection indices, published vegetation indices and partial least squares regression (PLS-R).

Remote sensing data has been also used to discriminate species (Ghosh et al., 2014), canopy variables and structures (Lefsky et al., 2002; Marshall and Thenkabail, 2015; Rama Rao, 2008). With the objective of examining the healthiness of vegetation, this technology has been further applied to estimate different biophysical and physiological variables and pigment contents of vegetation over a large number of crops (Barnes et al., 2000; Li et al., 2001; Pinter et al., 2003). Other remote sensing studies have analysed the relationship between cotton reflectance and lint yield (Li et al., 2001). Yield was found to be highly correlated with conductance and transpiration rate as they are positively correlated with flower production (Detar et al., 2006). Studies on the effects of 2,4-D on cotton crops demonstrated that photosynthesis was highly affected by this herbicide leading to ineffective photosynthesis process affecting cotton boll production and development (Perumal et al., 2006; Sullivan et al., 2007). Spectral bands in the green, red and NIR regions have been identified as good predictors of yield and they are also associated with the health condition of the plants (Plant et al., 2000; Zhao et al., 2005). Photosynthesis has a strong relationship with the spectral bands around 700 nm which is also related to physiological stress (Merton et al., 2004; Zhao et al., 2007b). As the visible and NIR bands respond to different conditions of the crop, it may be possible to determine yield based on those responses (Pinter et al., 2003; Thulin et al., 2012; Zarco-Tejada et al., 2005). In other studies at different scales, reflectance datasets were successfully used to monitor crop growth and yield. Low altitude digital imagery provided accurate information for classifying and quantifying different variables of crop growth and development at high spatial resolution (Oberthür et al., 2007). On the other hand, at a national and international scale, daily reflectance provided by AVHRR and MODIS data (coarse spatial resolution) were analysed to monitor global cereal yield during the last three decades (Zhang and Zhang, 2016).

In order to minimise the influence of soil (Yu et al., 2015), pigments, moisture, and the general variability of external factors on leaf and canopy reflectance (Cyr et al., 1995; Zhao et al., 2007a), several narrow and broadband vegetation indices have been developed. However, their applicability may be limited by the pigments' variability per unit leaf area and the potential saturation at low leaf area index (LAI) which is related to spatial and temporal situations (Blackburn, 2007; Carter, 1998; Zarco-Tejada et al., 2005). On the other hand, hyperspectral sensors may allow the detection of very small changes within the plant due to reflectance changes on the electromagnetic spectrum which often consist of hundreds of highly correlated wavelengths. These sensors rely on the efficiency of the processing and analysis techniques to isolate one single response variable with a sample size greatly smaller than the number of predictors (Rapaport et al., 2015; Wold et al., 2001).

Using an algorithm that deals with hundreds of highly correlated variables, partial least squares regression (PLS-R) analysis is commonly used and considered a powerful tool in spectroscopy (Indahl and Næs, 2004). Furthermore, PLS-R optimises the resulting model by reducing the dimensionality of the electromagnetic spectrum (Mevik and Wehrens, 2007; Wold et al., 2001). While various statistical methods are available for quantitative studies, such as neural networks (de Castro et al., 2012; Goel et al., 2003), PLS-R has proven to be optimal as a first-step approach for supervised classifications (Indahl et al., 2009) and it is also one of the most effective methods for quantitative predictions (Mevik and Wehrens, 2007). To date, despite successful yield predictions studies and discrimination of healthy from unhealthy plants damaged by herbicide drifts, a research gap still exists to accurately model of yield loss caused by 2,4-D herbicide drift in cotton crops using hyperspectral data.

The primary aim of this study was to estimate damages caused by 2,4-D herbicide drift on cotton crops through the analysis of the following: (i) influence of dose in the amount and quality of yield, photosynthesis, conductivity and two hormones - IAA and ABA; (ii) prediction of yield at four different time periods after the exposure to herbicide; and (iii) identification of the influence of the time periods after the exposure in the performance of yield prediction models.

2. Materials and methods

2.1. Experimental design and treatments

Four replications composed of nine treatments were established in a commercial cotton field (151°32′40.0″E, 27°25′47.5″S) near Jondaryan with dose and timing of exposure as factors. Jondaryan is a rural town in the Darling Downs region, about 140 km west of Brisbane and midway of Toowoomba and Dalby (Queensland, Australia). The general location the study area, treatments, buffer zones and replications are shown in Fig. 1.

In this study, three doses were investigated: Nil, 5% and 50% of the recommended label rate of 2,4-D (*Amicide Advance 700*®; 700 g/L 2,4-D) at three different timings of exposure: 4–5 nodes (S1), 7–8 nodes (S2) and 11–12 nodes (S3) (see Table 1). Each treatment plot was composed of 5 rows with one meter row spacing and 5 m long (Fig. 2). A buffer zone of 5 m × 5 m was established to reduce any risk of drift from the treatments. The herbicide was applied when plants reached the stage of growth defined as factors under optimal environmental conditions between 9 and 10 am local time. Plants were treated only once and directly sprayed in two rows of the 5 rows available. A CO_2 Research Sprayer provided by The Queensland Department of Agriculture and Fisheries (DAF) at Toowoomba was used, with walking speed of 1 m/s for all treatments (Fig. 2). The pressure was 2 bar, the nozzle size TTI110015, and the water volume was set to constant rate at 143 L/ha. Within each treatment, five randomly selected plants were sampled to collect data. When destructive sampling was necessary (i.e., for IAA and ABA analysis) the plants were marked to be excluded for future analysis. Standard management practices were applied to all treatments before and after the spray activity. In two replications, some treatments required to be moved as some rows looked slightly affected by drift from an herbicide spray in a neighbouring field.