Society of Precision Agriculture AUSTRALIA

Precision Agriculture Laboratory

monitoring | mapping | management

# 19th Precision Agriculture Symposium

## Monday 12th - Tuesday 13th September 2016

City Golf Club,
Toowoomba QLD

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## INCREASING THE ADOPTION OF PRECISION AGRICULTURE IN AUSTRALIA

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**Acknowledgements**

This event has been made possible by the generous support of industry. SPAA wishes to thank the following organisations and businesses for their financial and in-kind assistance in putting this event together, and assisting with the travel arrangements of our key note speakers. John Deere, Case IH, Graingrowers Ltd, Manutec, Farmscan AG, Croplands, SST Software, Falcon UAV, Next Instruments, precisionagriculture.com.au, Vanderfield, Precision Cropping Technologies P/L, Precision Terrain Solutions, Farmers Edge, Queensland government, Parkland, Aerial Acquisitions and the South Australian Grains Industry Trust, Grains Research & Development Corporation.

SPAA also thanks the Condamine Alliance for supporting a number of farmers to attend this years' event and the University of Southern Queensland NCEA for welcoming the group to their research facilities.

# Welcome!

The 19th Symposium on Precision Agriculture in Australasia sees the PA community focusing on Queensland. Developments in Queensland have been spectacular within a number of industries for many years and the time is right to expand the reach across multiple industries in the state.

Work across Australasia has also continued to embed the use of PA technologies and techniques within agricultural systems and to push towards more data-driven decisions across operations. And while a number of agricultural industries are beginning to consider the value in coupling information and decisions across the production/supply/consumption sectors to optimise the entire system, the necessary monitoring, integrated feedback and intelligent response to achieve the goal remains poorly developed in nearly all agricultural industries.

This is in major part due to a gap in research and development aimed at combining a technical understanding of the production side of agricultural food and fibre systems with the identification of data requirements at important stages within each sector of the system, the ability to devise technical solutions to data gathering, and the analytical and practical skills to use the data to optimize whole system operations.

This holistic systems view requires the convergence of agricultural science, engineering and agribusiness expertise to gather and effectively utilise digital data. Creating such digital agri-food and fibre systems will drive agriculture towards sustainable production, delivery and consumption. In such systems, data-driven decisions will be whole-system considerate, optimised using intelligently gathered information, and capable of adapting to alterations in operational parameters as well as feedback signals from all sectors.

Developing agriculture through data-driven decisions in this way will also provide new and stimulating pathways to attract a greater number of young, enthusiastic people to engage in the agriculture community. However, to match the practical developments within industry we need to provide new education programs at the secondary and tertiary level that will excite students and deliver skills for this data-driven agriculture. This is now a challenge to all of us, not just current the education community! Resources/support needs to be sector-wide because the benefits will be.

These agricultural systems built on the greater use of data-driven decisions will see us identifying, gathering and using relevant digital data in a more diagnostic way to optimise management and outcomes across all aspects of the breeding and selection (crops and animals), production, processing, distribution, retail and consumption sectors.

As predicted back in 1997 when this Symposium series began, PA will have succeeded when the term PA becomes redundant, the philosophy and attendant technologies and techniques embedded in agriculture. As we move towards data-driven agriculture systems, we can say we are nearly there.

*Brett Whelan*
*for*
The PA Lab and SPAA teams


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| 1.20pm | UAV mapping of rhizoctonia root rot for targeted treatment<br>*Andrea Hills (DAFWA)* |
| 1.40pm | Remote sensing options for predicting rice biomass and nitrogen uptake<br>*Brian Dunn (NSW DPI)* |
| 2.00pm | PA on-farm in the SA Mallee<br>*Wade Nickolls (Pinnaroo SA)* |
| 2.20pm | Industry news – Case IH |
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| 4.40pm | Big data applications for informed decisions.<br>*Lisa Prassack (Prassack Advisors)* |
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| | |
|---|---|
| ***TUESDAY 13th SEPTEMBER 2015*** | |
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| 9.40am | PA in Vegetable cropping - our journey so far<br>*Ed Windley/Ben Moore (Kalbar Growers Group)* |
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| 10.20am | *<u>Morning tea</u>* |
| 10.50am | AgDNA *(Paul Turner)* |
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| 12.10pm | Targeting nitrogen to productivity zones: combining geophysics, yield data and moisture probes to reduce risk and improve profitability<br>*Frank D'Emden (Precision Agronomics)* |
| 12.30pm | PA on Coondarra *St John Kent ('Coondarra')* |
| 12.50pm | Progress on 'Biomass Business- pasture biomass measurement tools<br>*Karl Andersson (UNE PARG)* |
| 1.10 pm | *<u>Close and Lunch</u>* |
| 2.00pm | *NCEA tour* |

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# Does optimum surface landforming offer Precision Agriculture's highest ROI?

**Graeme Cox**

DAVCO OptiSurface, Australia

*Contact: graeme.cox@optisurface.com*

## Summary

Eighty percent of crop yield loss within a field and within years can often be attributed to variable moisture availability, both too little and too much. Excess moisture also plays havoc with machinery operations and farm efficiency. By improving surface drainage and promoting more uniform infiltration, Optimum Surface Landforming has shown to provide a range of profit boosting benefits at a relatively low cost per hectare resulting in a high Return On Investment (ROI).

Optimum Surface Landforming is the process of reshaping the land surface to a specially optimised three dimensional surface using earthmoving equipment fitted with high accuracy GPS machine control technology. It achieves the drainage benefits by eliminating all reverse surface grades that form depressions and smooths the surface to promote more uniform infiltration.

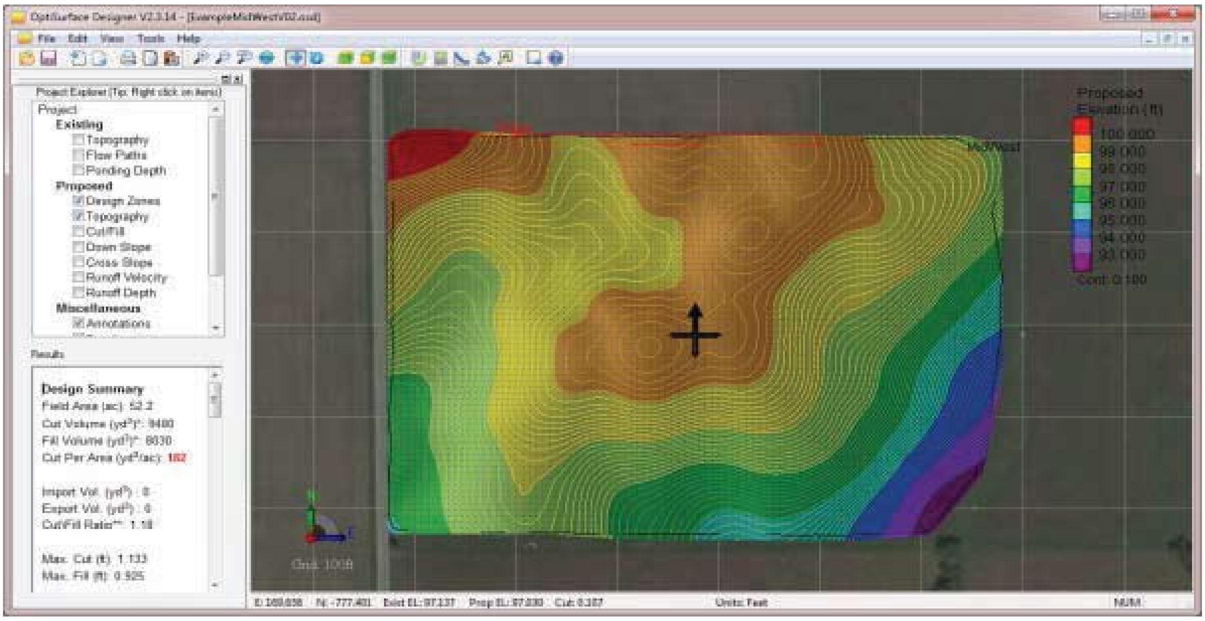


**Figure 1. Optimum Surface landform design for drainage of a 21 ha field.**

Optimum Surface Landforming achieves all the drainage and irrigation benefits of traditional laser grading but with much lower topsoil movement and total earthworks cost. Optimum Surface designs are often 50% to 80% lower in earthworks which make it viable to landform millions of fields previously too expensive to laser landform. It also allows other related benefits like removal of infield ditches and higher machinery efficiencies.

To date, ‘OptiSurface’ landform design software has been used to create designs for over 250,000 hectares around the world. This presentation will present some case studies showing how a high ROI can often be achieved.

**Figure 2. GPS Landforming with an ‘OptiSurface’ design.**

## UAV mapping of rhizoctonia bare patch for targeted treatment

**Andrea Hills[1], Lachlan Beveridge[2], Phil Goulding[3], Daniel Huberli[3] and Geoff Thomas[3]**

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[2]ThinkSpatial; 760 Queensberry Street, North Melbourne, VIC.
[3]Department of Agriculture & Food, WA; 3 Baron-Hay Court, South Perth WA.

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### Summary

Unmanned Aerial Vehicles (UAVs) are becoming more common and as plant pathologists we investigated a novel use for them that grain growers could apply to paddocks affected by the root disease rhizoctonia bare patch. The challenge: can we map the amount of disease in affected paddocks and determine which areas are worth treating by applying fungicide in the following season just to those areas to maximise the economic return from that paddock? How precise can we make the treatment map?

Rhizoctonia bare patch is a root disease of cereals and pulses. When rhizoctonia is severe, the disease reduces plant establishment and stunts growth creating a bare patch, often with rounded edges. Although individual patches are relatively small, commonly ranging in size from 3 - 30 $m^2$, hundreds of unevenly distributed patches can occur and yield losses across a paddock are in direct relation to the total area of crop affected. Yield loss within the patches themselves ranges from moderate (~50% loss) to 100% with seasonal conditions influencing whether surviving plants can access sufficient nutrients and moisture to produce an ear despite their damaged root system.

Growers are generally aware that some sections of a paddock are affected by rhizoctonia more than others but to our knowledge mapping at a paddock scale has not been done since it is a highly laborious task (even for research purposes) due to the relatively small area patches cover and their number, which are into the thousands in badly affected paddocks. Previously, there was no need for mapping as amelioration options such as in-furrow fungicide have only recently become available.

UAVs are an ideal way to map rhizoctonia at a paddock scale as the patches are relatively easy to identify on normal or NDVI images (Figure 1). Other features affecting growth can be distinguished on the basis of size (Figure 2) or the type of edge they have, for instance straight or jagged (Figures 2 & 3) versus rhizoctonia's gradual or rounded edges.

Small areas of patches have been studied and many recur in approximately the same place each year a susceptible crop is grown. However individual patches can appear, disappear, grow, or contract over years. The factors that cause a patch to form or die are unknown, which suggests that paddocks may need to be remapped after several years if a targeted treatment regime is to remain optimal.

Visually rhizoctonia can be distinguished from most other patch causing pathogens such as nematodes or other root rots from the growth habit of the plants within the patch. We have ground-truthed patches in the nine paddocks we studied using root disease assessments and DNA soil tests (PredictaB) and rhizoctonia was the causal pathogen.

(a) (b)

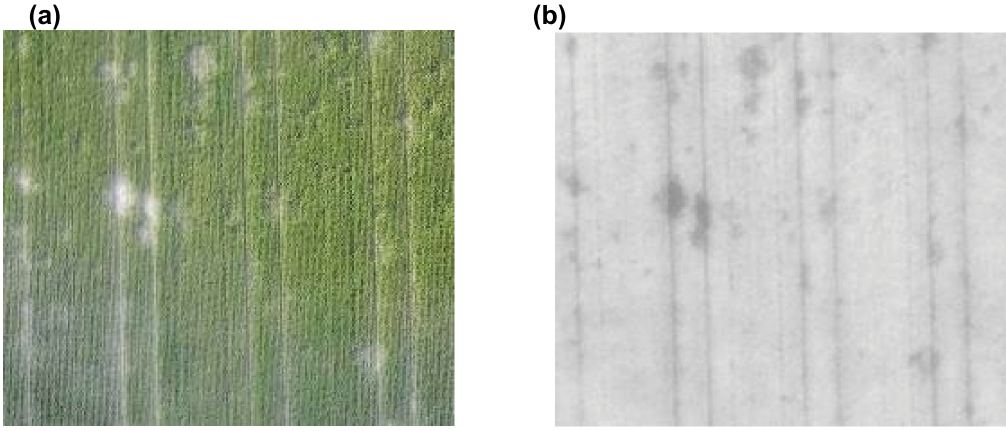

**Figure 1. UAV images (close up) of a cluster of rhizoctonia patches; the large bare patch is 2.4 x 3m in diameter. a) Normal RGB image and b) NDVI image**

(a) (b)

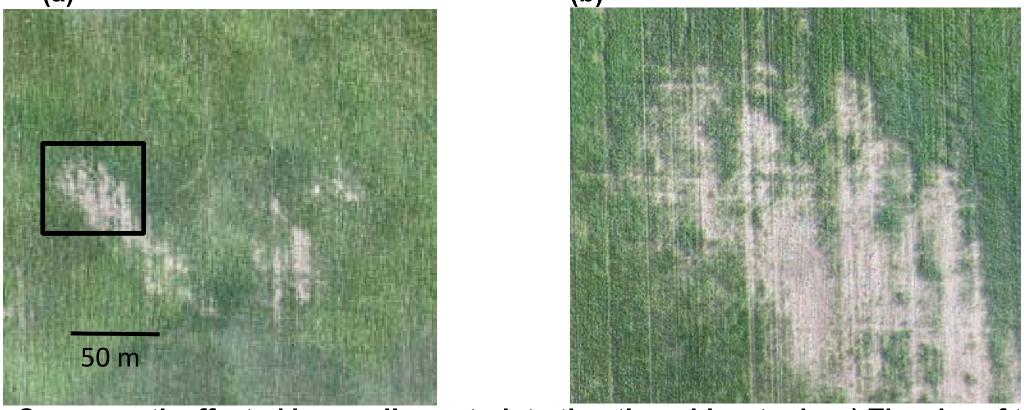


**Figure 2. Crop growth affected by a soil constraint other than rhizoctonia. a) The size of this patch makes it extremely unlikely to be a result of rhizoctonia b) A closer look at the boxed area in a) shows the jagged edge with some normal crop growth within it – both are uncharacteristic of rhizoctonia.**

(a) (b)

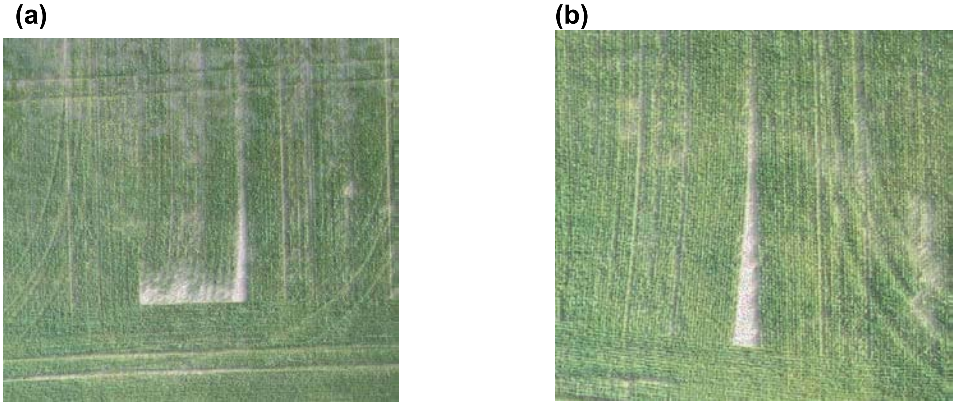

**Figure 3. Non rhizoctonia bare patch: the early turn off for the end of a sowing run can produce jagged or straight edges neither of which is similar to rhizoctonia.**

### *Paddock distribution of patches*

The paddock described in this paper is located near Cascade, 80 km north west of Esperance, WA (UTM 351154; 6286127) (Figure 4) and was chosen for its high

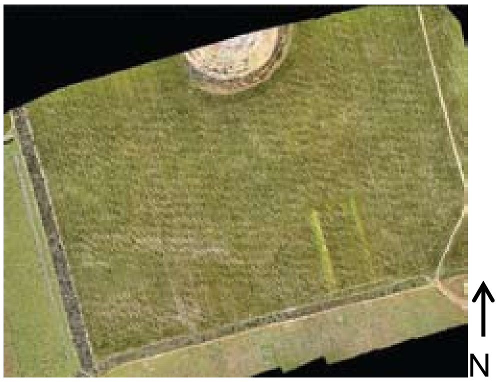


**Figure 4. RGB image of the study paddock (Sept 2015); the western half was used in this study (40ha). A South East Premium Wheat growers Association (SEPWA) broad scale barley variety trial can be seen in the lower south east.**

incidence of rhizoctonia. It is under a crop rotation of canola, wheat, barley, of which the wheat and barley are susceptible to rhizoctonia. The paddock was mapped by UAV to produce RGB and NDVI images in 2014 (wheat) and 2015 (barley).

Using an August 2015 NDVI paddock image, rhizoctonia patches were drawn in by hand to show the variable distribution of patches across the study area (Figure 5).

The distribution of rhizoctonia in 2014 and 2015 was similar (Figure 6) – dense areas of rhizoctonia in 2014 produced dense areas of disease in 2015. Almost 30% of the rhizoctonia present in 2014 reappeared in precisely the same location in 2015.

However, the incidence of rhizoctonia (by area) increased substantially in 2015. This is likely to be due to a buildup in soil rhizoctonia levels during the 2014 wheat crop and because barley (the 2015 crop) is more susceptible to rhizoctonia. The short timeframe of this study means that we don't know whether this level of increase is normal. Over time, as more mapping is done, changes in incidence for this rotation and others could be generated with greater precision.

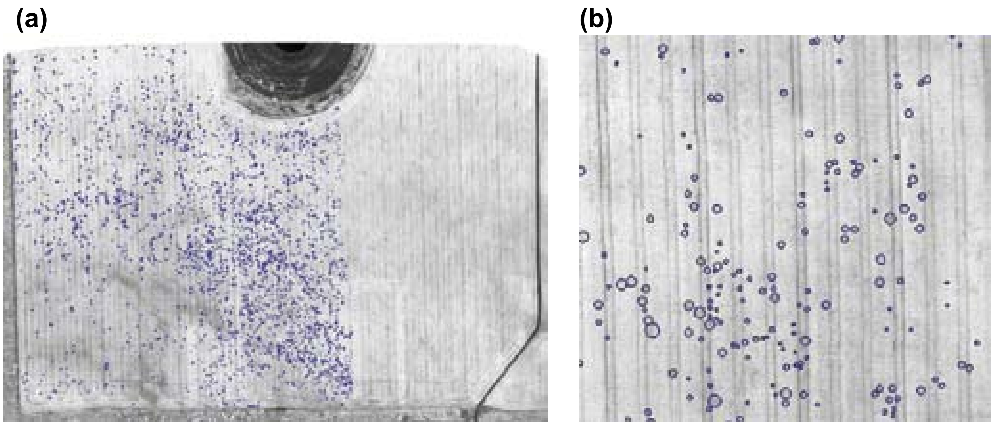


**Figure 5. The variable distribution of rhizoctonia patches in 2015 (shown in blue) can be seen across a) The 40ha study area and b) A 2ha close up. Both are shown against a NDVI background.**

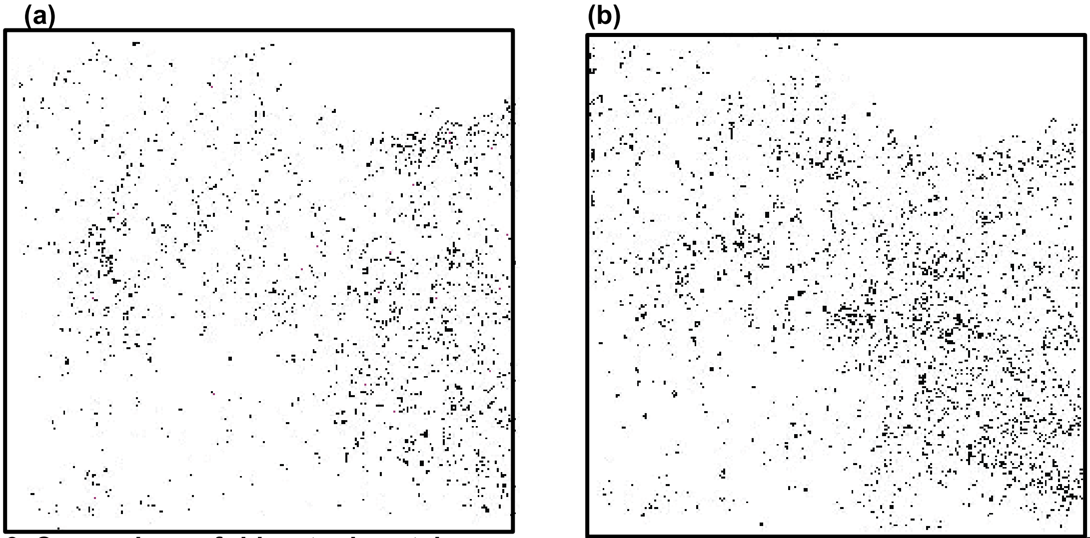


**Figure 6. Comparison of rhizoctonia patches across the study paddock in a) 2014 and b) 2015.**

### *Introducing "RhizoDetector" software*

Marking out rhizoctonia patches by hand on a UAV image using some type of GIS software is time consuming when working at a paddock scale and needs to be automated. With this problem in mind, our project partners at ThinkSpatial, who provide UAV and image expertise, have used rhizoctonia characteristics to create an automated process where the NDVI paddock images are filtered to pick out areas that meet certain criteria. This can be done because each pixel of an NDVI image has a precise value associated with it.

Basically, the program picks out the poor areas of crop regardless of what has caused them before filtering these to select those that are caused by rhizoctonia based on the shape of the poor growth areas - rhizoctonia patches have rounded rather than have sharp edges. This eliminates areas that have poor growth due to factors such as being in a tram line. As rhizoctonia patches are relatively small, a filter that sets a size limit eliminates areas of poor growth that are often soil rather than rhizoctonia related.

A strength of the RhizoDetector is that the area and roundness filters can be changed by the user to determine which patches of low growth are picked out by RhizoDetector as rhizoctonia. The areas selected are shown against the NDVI image, so the user can see the impact of the filter values and decide what best fits their situation (Figure 7). The output is a spatial file that is considerably smaller than the original image file. Our aim is for users to use the file in software such as AgLeader SMS to create a treatment map. RhizoDetector has been developed on Free Open Source Software (FOSS).

While RhizoDetector software is still experimental and requires fine tuning, it will be a key component in the process of generating rhizoctonia treatment maps.

### *From patch map to treatment map*

'Clustering' of patches to produce a treatment map based on the density of rhizoctonia can be done quite precisely for seeding bars with sectional control of liquid system applications.

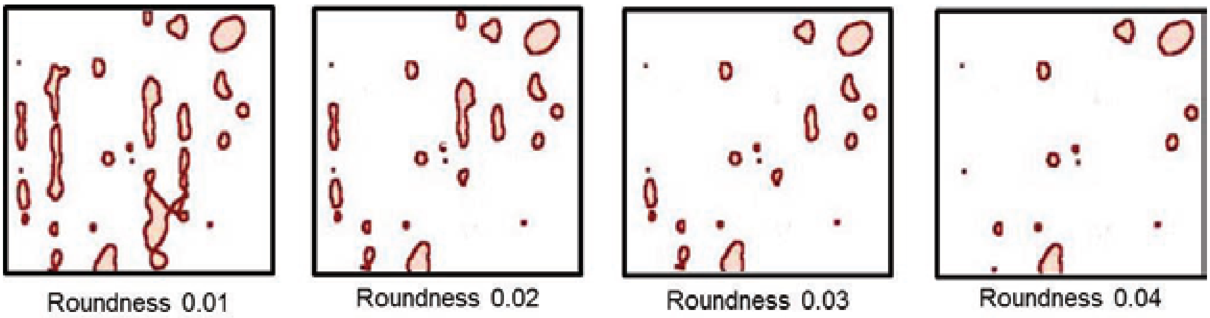


**Figure 7. Close up of a screen output of RhizoDetectector (NDVI image behind has not been copied). The effect of applying an increasing level of roundness from 0.01 to 0.04 (1 is a perfect circle) can be seen as RhizoDetector eliminates less round areas. Here the optimal roundness that selected the majority of rhizoctonia was 0.02.**

This is done by applying a grid system over the rhizoctonia patch map which uses the area of rhizoctonia within it to categorise it as:

1. High - treatment required
2. Medium - treatment recommended but marginal returns, or
3. Low - no treatment required

However a simpler option which provides a larger buffer area to account for potential patch movement especially in barley crops, is to apply a larger grid based on the full width of a sowing run – 12m in this study. The length of the grid (10m) has been selected arbitrarily at this point until we can better quantify the potential patch movement (Figures 8 & 9).

After our study paddock is split into 12 x 10m grids a GIS query categorises these based on the area of rhizoctonia within each grid (Figure 9) using the same three categories. The categories used in the treatment map are based on the level of return growers can expect. This takes into account the yield loss associated with rhizoctonia, the area it occupies, yield recovery when treatment is applied, grain price and treatment cost.

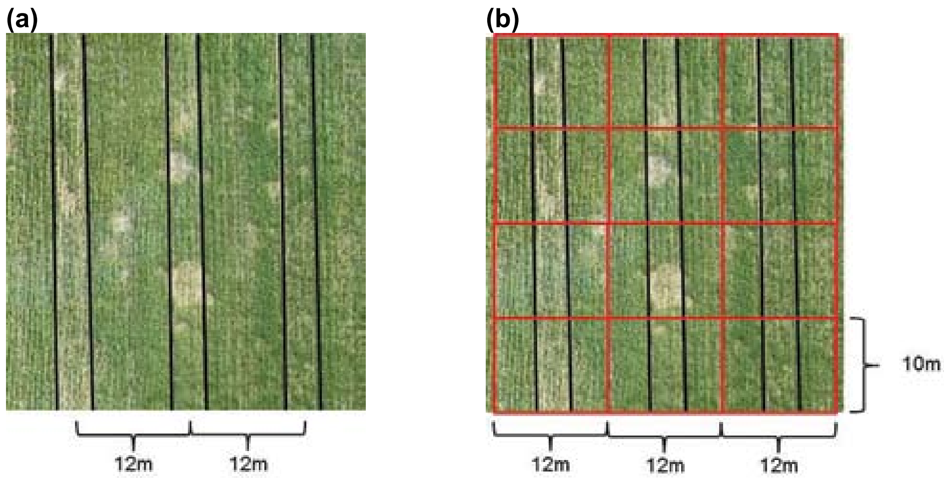


**Figure 8. Gridding of paddocks based on the sowing tramlines; a) Paddock with tramlines 12m apart from centre to centre (shown in black) b) Grids (red) based on sowing tramlines.**

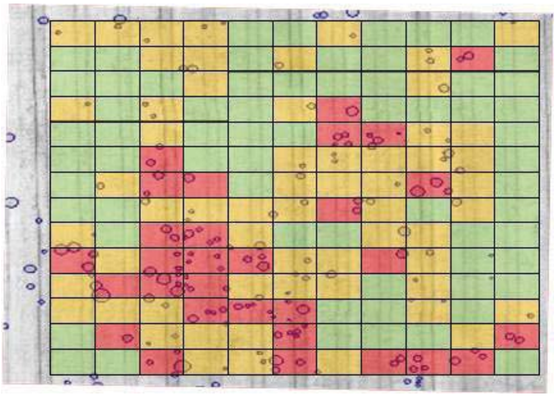

**Figure 9. An example of gridding based on sowing runs to produce a treatment map for use in the following susceptible crop; red – treatment required, orange – recommended to treat (marginal returns), green – no treatment required.**

If rhizoctonia reduces yields in patches by 80%, a treatment area is $120m^2$ (12m seeding bar x 10m length), Uniform in-furrow fungicide recovers 80% of the potential yield loss and costs $25/ha to control rhizoctonia, then 10% of the treatment area ($12m^2$) needs to be affected by rhizoctonia before there is a return on treatment. With a grain price of $230/t there is a return per treatment area of $0.75/t; in the 2ha example in Figure 9, where the average paddock yield of barley was 3.1 t/ha, this would be expected to return at least $35/ha (3.1 t/ha x $0.75 /t x 30 red treatment areas ÷ 2) which could be greater as some areas have more than 10% of the treatment area affected by rhizoctonia.

### *Conclusions*

UAV images, whether RGB or NDVI are a useful way to show the distribution of rhizoctonia bare patch at a paddock scale. Our investigation has shown that rhizoctonia patches do occur at a similar density in particular areas although barley, as expected, has a greater total area affected than wheat. Using these images our experimental “RhizoDetector” software can automatically identify patches caused by rhizoctonia. Clustering of patches to generate treatment maps can be approached in a number of ways but for this disease a less precise approach will still return an economic benefit to growers with paddocks afflicted by rhizoctonia.

### Acknowledgements:

This activity is done as part of the project titled *Improving grower surveillance, management, epidemiology, knowledge and tools to manage crop disease* which is funded by DAFWA and GRDC (DAW00229).


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# Remote sensing options for predicting rice biomass and nitrogen uptake

**Brian Dunn[1], Tina Dunn[1], Iain Hume[1], Remy Dehaan[2], Andrew Robson[3]**

[1] NSW Department of Primary Industries.
[2] Charles Sturt University.
[3] University of New England.

*Contact: brian.dunn@dpi.nsw.gov.au*

**Summary**

Remote sensing has been the buzz word in agriculture for many years and with the relatively recent mass influx of easy to fly drones and lightweight sensors, every second person can now create an NDVI or NDRE map of their field. But what does a map showing lots of pretty colours across your field really tell you? And more importantly, how can it be used to increase your farm's profitability?

In the rice industry there is a potential role for remote sensing that may lead to increased grain yield and profitability. Applying too much nitrogen to rice grown in southern Australia is not only uneconomical but can also increase the risk of low temperature induced pollen sterility, which reduces grain yield. Rice growers have been utilising a tissue test service where they physically collect plant samples from their flooded fields at the panicle initiation growth stage, weigh the fresh weight and send a sub sample into the lab for nitrogen analysis. Based on the measured crop nitrogen uptake levels nitrogen topdressing recommendations are then sent to the rice grower. Only about 30% of growers utilise the free service with many no users saying the requirement to physically sample the crop in the water is a major reason why they do not use the service.

Remote sensing offers a potential opportunity to determine the rice crops nitrogen uptake without collecting physical samples and may also provide information on the variability of nitrogen uptake across the field. A research project funded by NSW DPI and the Rural Industries Research Development Corporation has been investigating the potential of remote sensing options to measure nitrogen uptake of rice at panicle initiation to provide nitrogen topdressing recommendations for rice crops.

To determine how accurately nitrogen uptake of rice at panicle initiation can be predicted using remote sensing, a handheld hyperspectral scanner was mounted on a four wheel motorbike and used for three seasons to scan over 600 plots to measure canopy spectra (Figure 1a). Physical plant samples were collected at the same sites to enable correlations to be developed with the spectra. The correlations are encouraging with panicle initiation nitrogen uptake able to be predicted with an $r^2$ = 0.86 and RMSEP of 16.46 kg N/ha (Figure 1b).

As no commercial hyperspectral sensors are economically viable for scanning rice fields, the four most important wavelengths in the relationship were determined so they can potentially be used in a simple filter instrument. Using only four wavelengths from the hyperspectral relationship, nitrogen uptake was predicted with an R2 of 0.82 and

RMSEP of 18.4 kg N/ha. A filter instrument has not yet been developed for testing in the field.

(a) (b)

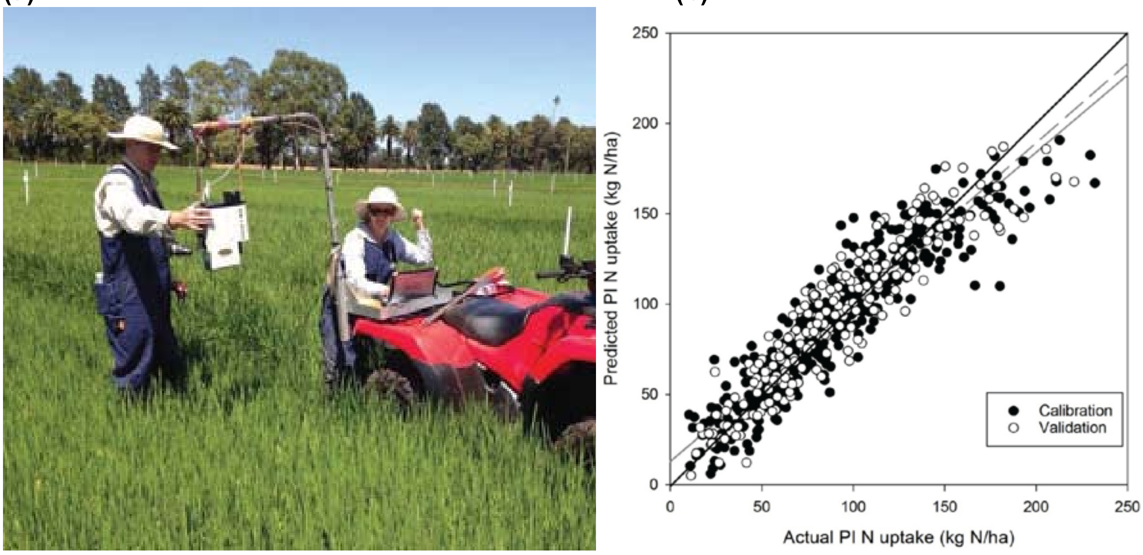


**Figure 1. (a) Scanning the rice canopy with a hyperspectral scanner and (b) the nitrogen uptake relationship developed between the spectra and measured canopy nitrogen uptake.**

The project has also been testing some currently available remote sensing technologies to determine their potential for predicting rice nitrogen uptake.

Two season’s data has been collected using very high resolution satellite imagery (Worldview 3), correlating spectral data with physical rice nitrogen uptake measurements and this has shown considerable potential. A satellite based remote sensing system with automated processing and delivery systems that could generate near real-time management decisions to industry and farmers may be one possible option.

One season’s data has also been collected using the micaSense RedEdge sensor which incorporates bands which include the red edge. This sensor is small and light being specifically designed for small unmanned aircraft systems and provides another option for the rice industry utilising drone technology.

The presentation will include results for rice biomass, plant nitrogen concentration and nitrogen uptake correlations from the Worldview 3 and micaSense sensors for NDVI and indices which include the red edge. The potential benefits and issues of using remote sensing for predicting rice crop nitrogen topdressing requires will also be discussed.

# PA on-farm in the South Australian Mallee

**Wade Nickolls**

Pinnaroo , SA.

*Contact: nickollspartners@internode.on.net*

### Summary

Wade Nickolls farms in a family business at Pinnaroo in the South Australian Mallee. Annual rainfall of around 300 mm is challenging at times with quiet often an early end to the season in spring. Winter crops grown include wheat, barley, lentils, export and domestic hay, canola, lupins and vetch. The Nickolls' PA journey has been evolving slowly over the past 15 years from early guidance to now using a Weedit sprayer and full VR Seeding. Long term no-till, without livestock, has seen some quite poor performing soil types now becoming profitable. Wade believes Precision Agriculture along with no-till has gone a long way to enticing the younger generation back to the land.

# SwarmFarm

**William McCarthy**

SwarmFarm Robotics, Emerald, QLD

*Contact: will@swarmfarm.com*

### Summary

Will joined the SwarmFarm Robotics team in early 2016 as a mechatronics engineer and currently leads the field testing and deployment of the SwarmBot 3 robotic platform (Figure 1). In this presentation, William will discuss the opportunities  and challenges of deploying autonomous weed spraying robots in commercial grain farming operations.

**Figure 1. SwarmBot 3 robotic platform.**

# PPMS: Cattle and pasture production data without the sweat!

**Sally Leigo, David Phelps, Tim Driver**

Precision Pastoral Management Tools Project, Co-operative Research Centre for Remote Economic Participation, Alice Springs NT.

*Contact:* *sally.leigo@nt.gov.au*

## Introduction

The beef industry of Australia continues to search for a reliable and effective technology that can increase production and reduce operating costs. Beef producers in Australia's rangelands manage an average of 7000 head of cattle over 2000 $km^2$ with 6.6 labour units (MLA 2015). To date, collecting and analysing objective data on pasture and cattle performance is done by few beef producers. Hamilton and Banney (2011) reported that 76% of northern Australian beef producers complete no written forage budget. Undertaking regular monitoring of cattle and rangeland pasture is currently expensive, time consuming and requires skills and knowledge that are not readily available in the remote parts of the country. A tool is needed that can provide accurate, objective data on rangeland cattle and pasture production. The Precision Pastoral Management Tools (PPMT) project has spent the past five years developing and testing a cloud-based software system on commercial cattle stations to address these needs. The Precision Pastoral Management System (PPMS), can remotely monitor and analyse cattle and pasture production without any labour or skill inputs from beef producers.

## How does the PPMS work?

The PPMS receives and analyses cattle and pasture production data, produced by remote and automated systems customised to individual cattle stations (see Figure 1.). Beef producers log-in to their customised website to review their cloud-based data at any time. Cattle liveweight data is collected remotely via Precision Pastoral Pty Ltd's Remote Livestock Management System (RLMS) which uses walk-over-weighing technology. Pasture data is provided by satellite as sourced from the company Landgate. Both systems collect data daily and provide a weekly summary.

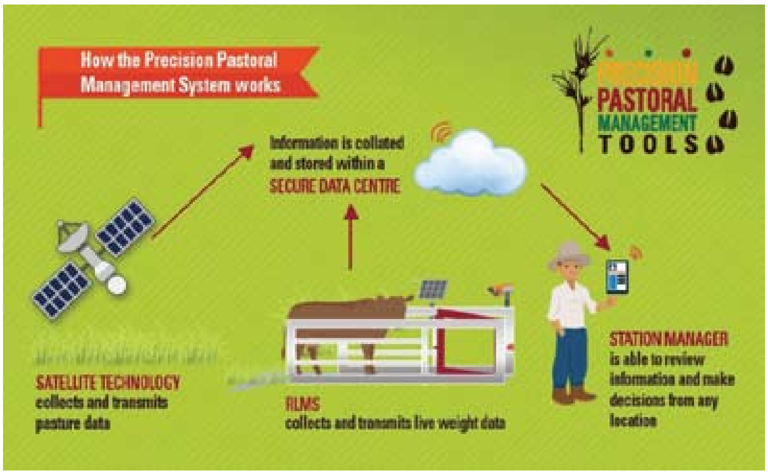


**Figure 1. How the PPMS works.**

Beef producers have been engaged in the development and trialling of the PPMS to maximise adoption. The project has sought to develop a simple, usable delivery of ‘big data’ as an effective decision support tool. Software development has followed an action learning cycle, whereby the PPMS was planned for, a prototype developed, reviewed and adjusted. Key design elements of the PPMS were that: the data needed to be collected and analysed automatically with no need for producer input; and to be intuitive, with no need for training or user guides for the beef producer to use it. The PPMS has been trialled on five cattle stations across northern Australia for three years and a further eleven stations have commenced using the system. Beef producers have used the PPMS to assist with strategic decisions such as the optimal time to sell cattle, adjusting stocking rates, and implementing supplementation programs.

**Benefits for beef producers**

Financial benefits from the PPMS have been demonstrated at Glenflorrie (WA) and Newcastle Waters (NT) stations. At Glenflorrie, the PPMS detected liveweight change 5 weeks earlier than traditional paddock-based monitoring could. The station owner estimated that an early decision to supplement based on the PPMS data could have prevented a loss of 7% saleable liveweight, or a saving of $14,933 across the herd compared with later commencement of supplementation. Similarly, at Newcastle Waters, the PPMS provided the capacity to objectively evaluate their bull supplementation program. Data from the PPMS showed that supplementation could have been started earlier to better meet the target average bull weight of 400kg.

**Figure 2. Bulls at Newcastle Waters Station (NT), using the RLMS.**

Environmental benefits can result from; matching stocking rates with current season feed on offer, wet-season spelling, and evenly spreading grazing pressure. Information from the PPMS allows more informed decision making for these management strategies.  Implementing them generally requires infrastructure development to give the necessary control of grazing. At Undoolya station, the use of the Remote Livestock Management System prompted a 13,300ha paddock to be split and wet season spelling implemented. This improved the pasture yield of the spelled paddock by 60%.

Personal benefits, whilst difficult to quantify, are also accruing from the PPMS. Producers have related how the data from the PPMS has removed anxiety associated with making management decisions such as when to sell, adjust their stocking rates or commence supplementation. As stated by Murray Grey (Glenflorrie station), "*You can't argue with the liveweight data when it starts declining; it was a fact"*. The provision of the liveweight and pasture data has also provided producers with the opportunity to learn more about their production system, as stated by Ben Hayes (Undoolya Station), "*The weight gain and how good they can (grow), I have learnt a lot from that*".

**Conclusion**

The PPMS overcomes previous barriers (scale of operation, labour, time and skill) to undertaking objective measures of cattle and rangeland pasture production. In addition, the use of the PPMS is providing beef producers of remote Australia with financial, environmental and personal benefits. Further, users of the PPMS continue to grow as they become aware of the system and choose to invest in it.

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# Multi-temporal remote sensing for yield prediction in sugarcane crops

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## Abstract

Sugarcane yield prediction is critical for in season crop management and decision making processes such as harvest scheduling, storage and milling, and forward selling. This presentation reports on a recently published method of predicting sugarcane yield in the Bundaberg region (Qld) using time series Landsat data. From the freely available Landsat archive, 98 cloud free (<40%) Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM+) images, acquired between November 15$^{th}$ to July 31$^{st}$ (2001-2015), were sourced for this study. The images were masked using the field boundary layer vector files of each year and the green normalized difference vegetation index (GNDVI), an indicator of crop vigour was calculated. An analysis of average GNDVI values from all sugarcane crops grown within the Bundaberg region over the 15 year period using a quadratic model identified the beginning of April as the peak growth stage and, therefore, the decisive time of image capture for a single satellite image based yield forecasting. The model derived maximum GNDVI was regressed against historical sugarcane yield data obtained from the mill. The coefficient of determination showed a significant relation between the predicted and actual sugarcane yield (t/ha) with $R^2$ = 0.69 and RMSE 4.2 t/ha. Results showed that the model derived maximum GNDVI from Landsat imagery would be a feasible technique to predict sugarcane yield in Bundaberg region. This research, however, warrants further investigation to improve and develop accurate operational sugarcane yield prediction model across other domestic and global growing regions, as the influence of environmental conditions and cropping practices will likely vary the relationship between GNDVI and yield (t/ha).

## Introduction

Accurate and timely prediction of sugarcane (Saccharum spp. L.) crop yield is of vital importance for scheduling crop harvesting, marketing, milling and forward selling strategies of sugarcane industry and to optimize the profitability of this sector. In recent years, remote sensing technologies have been evaluated as a more accurate and cost effective method of sugarcane yield prediction (Robson et al., 2012). Lee-Lovick and Kirchner (1990) first examined the potential benefits of remote sensing for monitoring growth and yield in sugarcane crops and subsequently only a few studies have reported the use of time series observation of satellite imagery for sugarcane yield prediction (Simões et al., 2005; Fernandes et al., 2011; Robson et al., 2012; Mulianga et al., 2013).

The objective of this study was to develop a novel model from time series Landsat TM/ETM+ data to predict sugarcane yield in Bundaberg region. The seasonal growth profiles over a period of 15 growing seasons were developed using time series GNDVI values derived from imagery captured between mid-November to July each year.

## Materials and methods

The study was undertaken over the cane growing region that surrounds the South – eastern Queensland township of Bundaberg, Australia. The area is located between longitudes 151.91°E and 152.49°E, and latitudes 24.51°S and 25.13°S, covering an area of 20,700 ha. The climate of Bundaberg is subtropical with long hot summers and mild winters. The soil type in this area varied enormously due to climate, substance of parent material and topography. The mean annual rainfall of the area was recorded to 964 mm in 2015 (B.O.M.).

In this study, 98 Landsat TM/ETM+ L1T images from 2001 to 2015 with cloud cover less than 40% over Bundaberg region (Path 90 Row 77; Figure) were used. Images acquired between mid-November and July each year were selected as these were identified to encompass the sugarcane growth period in that region. Satellite images were downloaded from the US Geological Survey National Center for Earth Resources Observation and Science via the GLOVIS data portal (http://glovis.usgs.gov/).

Digital image processing software ENVI 5.1 and ArcGIS 10.2 were used for the image processing, analysis, and spatial data integration. In this study, all the Landsat images were geometrically referenced to UTM projection system "WGS 1984 UTM zone 56N" to match with the land cover boundary images. Radiometric normalization was used for the acquired images to reduce reflectance variations between image dates due to atmospheric conditions and surface anisotropy. For the bulk corrections of atmospheric effects simple dark-object subtraction (DOS) method was applied (Chavez, 1988). Notably minor cloud, haze, shadow or bad data pixels were not considered while processing the images.

Sugarcane boundary vector layers for each year were sourced from Bundaberg Sugar Limited. To ensure that the extracted spectral information was specific to sugarcane only, a 10 m internal buffer was applied to each field boundary. All the Landsat images were masked using these boundary layers and the green normalized difference vegetation index (GNDVI) derived, using the following equation (Gitelson et al., 1996).

$$\text{GNDVI} = \frac{R_{NIR} - R_{GREEN}}{R_{NIR} + R_{GREEN}} \quad (1)$$

where, $R_{NIR}$ and $R_{GREEN}$ are the reflectance measured in the near infrared and green spectral bands.

All available average GNDVI data from the 15 year period were plotted against the date of image acquisition and a quadratic model was fitted to visualize the progression of sugarcane crop growth. The model identified when annual maximum crop vigour was achieved, via the peak of the quadratic curve and, therefore, indicated when the optimal timing of image capture to reflect peak growth should occur for the prediction of yield.

The vertex form of the quadratic model as shown in equation (2) was used to shift the vertical axis of the curve according to the acquired GNDVI value in maximum vigour period of a specific year.

$$y = \pm a(x - h)^2 + k \quad (2)$$

Here, "$a$" is a value in the curve that indicates the curvature of the line, the sign (±) on "$a$" tells whether the quadratic opens up or opens down, the sign (+) indicates that the quadratic opens up and the sign (-) indicates the quadratic opens down; h is the horizontal shift of the curve from $x$ = 0, for any standard quadratic equation $y = ax^2 + bx + c$, $h = \left(-\frac{b}{2a}\right)$ and k is the vertical shift of the curve from $x$ = 0, for any standard quadratic equation $y = ax^2 + bx + c$, $k = \left(\frac{4ac - b^2}{4a}\right)$.

Linear regression analysis was performed to evaluate the relationship between the model derived maximum GNDVI value and sugarcane yield. The fifteen yield forecasts from 2001 to 2015 and yield observations at harvest were evaluated and compared using root means square error (RMSE).

$$RMSE = \sqrt{\sum(actual - predicted)^2 / (n-1)} \tag{3}$$

Here, actual means actual yield data (t/ha), predicted means predicted yield data (t/ha) from measured GNDVI values and n is the number of observation.

## Results and discussion

All available GNDVI data calculated from the Landsat images over the 15 year period (2001 to 2015) (n= 98) were plotted against the image acquisition date of year (Figure 1). A quadratic model was best fitted to the data with $R^2$ = 0.72, which represents the annual growth profile of sugarcane crop irrespective of seasonal variation. The vertex form of the model shown in Figure 1 indicates that the GNDVI value reaches to its peak after 145 days of starting date (15th November) and about three months before harvest. This result is consistent with the previous findings of Rudorff and Batista (1990) and (Ueno et al., 2005), where they reported that the best acquisition period of satellite images is about two months prior to the beginning of harvest for the prediction of sugarcane yield. The highest average GNDVI value from the model was 0.58.

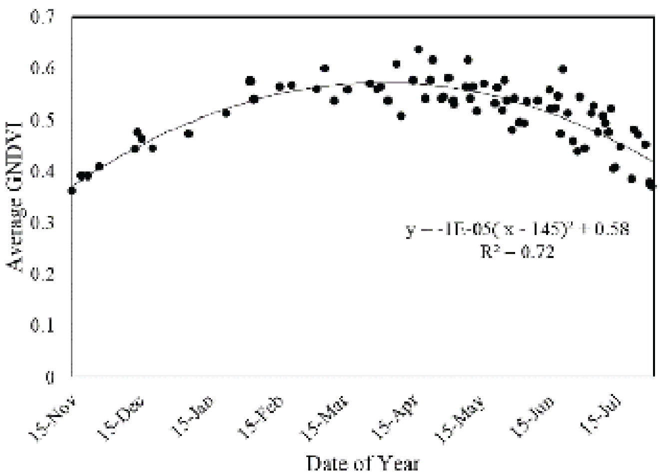


**Figure 1. The average GNDVI values from 2001 to 2015 in the growing period of sugarcane (mid-November to July) against Landsat image acquisition date.**

The model derived GNDVI values were plotted over the calculated GNDVI values from all available Landsat images in each year. The model was shifted vertically in each year to pass through the calculated GNDVI value acquired near or at the maximum vigour period of sugarcane. The highest GNDVI value from the model was regressed against the final average crop yield measured in that year.

A scatter plot of model derived maximum GNDVI against the annual harvested yield in terms of tonnes of cane per hectare (t/ha) from 2001 to 2014 is shown in Figure 2. The data point of 2013 is excluded, due to an extensive flood during 2013 that prevented the harvesting of around 40% of crops. A linear relation with good agreement ($R^2 = 0.69$ and RMSE = 4.2 t/ha) was established between the model derived maximum GNDVI and the annual harvested yield (t/ha). The annual harvested yield of 2015 (87.3 t/ha) is used as a model validation data, which showed an overestimation of predicted yield by only 3.54 t/ha in that year.

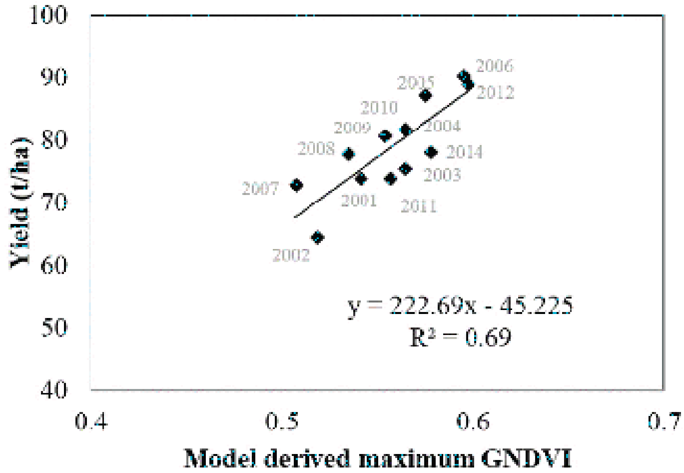


**Figure 2. The scatter plot of model derived GNDVI Vs annual harvested yield (t/ha) from 2001 to 2014. Data from 2013 was excluded as the crops were damaged by flood.**

Previous research by Robson et al. (2016) identified that the time series method can produce a more accurate prediction than a single capture SPOT 5, when GNDVI values derived between February and April were averaged. Therefore, the average GNDVI data from the imagery acquired from February to April for all years were also regressed against the annual harvested yield according to Robson et al. (2016) (Figure 3). Here also the data point of 2013 was not considered due to extensive flooding. The linear correlation was found with $R^2 = 0.48$ and RMSE = 5.46 t/ha. The annual harvested yield of 2015 is over estimated by 5.30 t/ha using the average February to April GNDVI data.

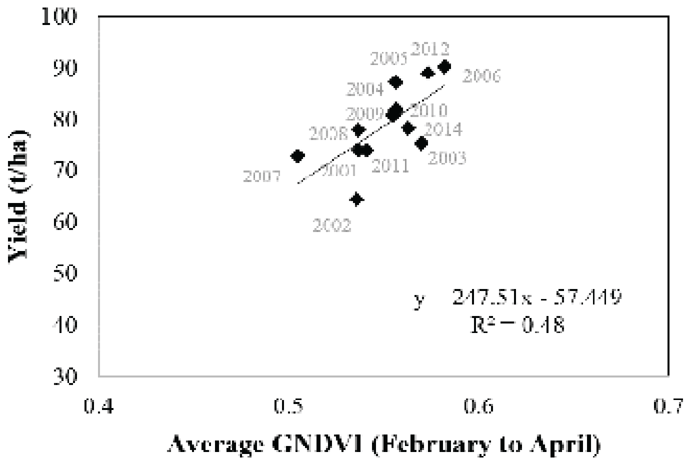


**Figure 3. The scatter plot of average GNDVI (February to April) Vs annual harvested yield (t/ha) from 2001 to 2014. Data from 2013 was excluded as the crops were damaged by flood.**

## Conclusion

This study identified how time series Landsat imagery could be effectively used for monitoring the annual sugarcane crop growth pattern in the Bundaberg region. The historic trends of canopy GNDVI values provide a benchmark for following year's on how annual crop production should progress. The maximum crop vigour or GNDVI value was historically achieved at 145 days from planting i.e. early April. This period is suggested as the optimal growth stage for the acquisition of satellite imagery to be used for regional yield forecasting. The development of a quadratic model that accurately depicts the growth profile of sugarcane has provided the opportunity for the maximum GNDVI to be calculated from imagery captured between November and March. Although results from this study are highly encouraging, additional research is required to model temporal sugarcane growth across other domestic and global growing regions, as the influence of environmental conditions and cropping practices will likely vary the quadratic relationship between GNDVI and yield.

## Acknowledgements

The authors would like to acknowledge the Sugar Research Australia for supporting the Australian yield forecasting project in which this study complimented. The authors gratefully acknowledge the assistance of Gavin Lerch (Bundaberg Sugar Limited) for providing the historical boundary layer map and the yield data.

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# Knowledge management, sensing and control tools for irrigated broadacre cropping

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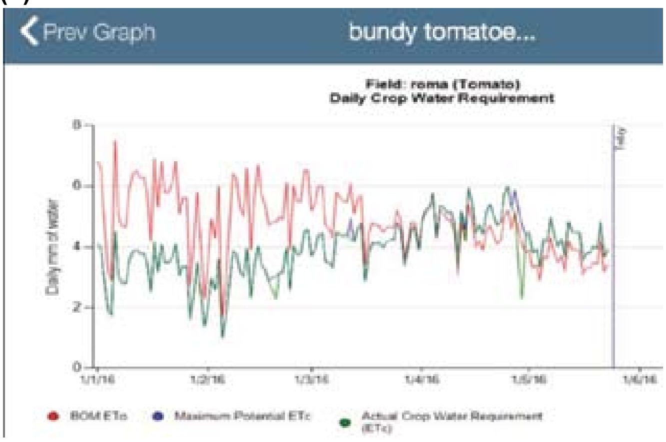
## Summary

The NCEA has developed grower tools for irrigation management to improve productivity and water use efficiency. This presentation will provide an overview of the NCEA's suite of tools as follows:

### Knowledge Management System for Irrigation (KMSI, kmsi.usq.edu.au) for irrigation and energy efficiency assessment, recording and scheduling

KMSI includes a suite of online irrigation, nutrient and energy calculators and database tools suitable for use by both growers and consultants. The two groups of tools are calculators which provide simple input/output interfaces, and databases which are password protect stores of information that can be used for benchmarking. These tools are targeted to growers (which require low detail) and extension/consultant tools (that requiring higher level of skill and some training). Examples include the Irrigation Performance Audit and Reporting Tool (IPART) and the Nutrient Balance and Reporting Tool.

(a)




(b)

**Figure 1. (a) Screen capture of KMSI Scheduling Irrigation Diary (SID) App; and (b) energy assessment being conducted for use in KMSI Irrigation Pump Evaluation and Reporting Tool (IPERT) web tool.**

### Surface Irrigation Simulation, Calibration and Optimisation (SISCO) for optimisation of surface irrigation flow rate and timing

SISCO simulates, calibrates and optimises surface irrigation events. SISCO can simulate temporal variations in inflow rates and spatial variations in soil infiltration, roughness and furrow geometry. Measurements of inflow and advance rate can be entered into the software to estimate characterise soil infiltration parameters and

**Figure 2. Automation of furrows in cotton with small pipe through bank.**

Manning roughness of individual furrows. Surface irrigation cut-off time can then be optimised in the software for individual furrows to optimise uniformity and/or application uniformity. SISCO has been evaluated for cotton, sugarcane and dairy surface irrigation event control and hydraulic optimisation using Rubicon automation irrigation hardware (Figure 2).

### VARIwise for optimisation of site-specific irrigation application for surface and overhead irrigation

VARIwise steps toward autonomous irrigation and nutrient prescription and application by linking infield sensing, closed-loop control strategies and control actuation. 'VARIwise' is a software framework that implements and simulates site-specific control strategies on fields with sub-field-scale variations in all input parameters including nutrients (Figure 3). This enables:

- data input at any spatial resolution;
- incorporation of crop model output for simulated response/prediction of crop response;
- incorporation of hydraulic equations to determine irrigation and fertiliser variability according to sprinkler or surface application hydraulics;
- implementation of image analysis algorithms to extract plant growth and fruiting from cameras on infield vehicles capturing top view images of the crop (irrigation machines and a moped);
- implementation of simple kriging and co-kriging algorithms for assigning measurements to each zone in the field; and
- implementation of control strategies that use a calibrated crop model and/or the
- soil/crop response to predict the application that will produce a desired agronomic response for all sub-field management zones.

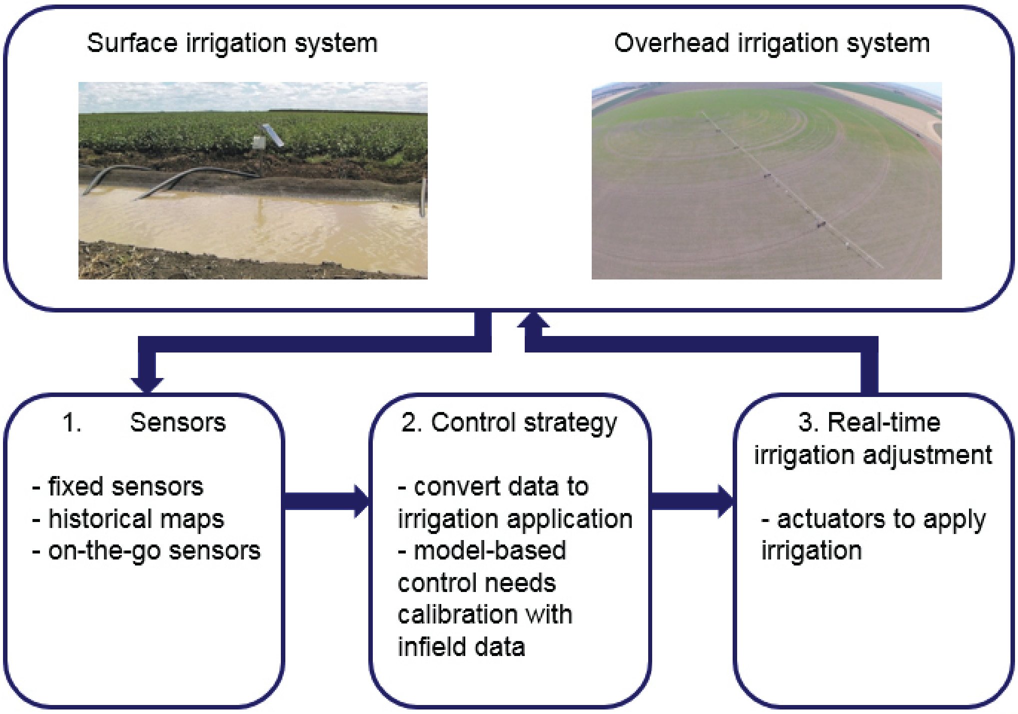



**Figure 3. Generic irrigation control system for surface and overhead irrigation**

VARIwise is being trialled on cotton crops in Jondaryan and Wee Waa, dairy in Tasmania pastures and sugarcane in Ayr. These are being trialled on surface and overhead pressurised irrigation systems with commercial irrigation automation hardware: Rubicon for surface irrigation and Valley or Lindsay Zimmatic variable-rate nozzles for irrigation machines. Low-cost cameras and infield soil moisture sensors collect plant and soil information for the control algorithm.

## Acknowledgements

The authors are grateful to Cotton Research and Development Corporation, Federal Government Rural R&D for Profit program, Dairy Australia, Tasmania Institute of Agriculture, Sugar Research Australia, Queensland Department of Natural Resources and Mines and Queensland Government Accelerate Program for funding.

# Automated analysis of UAV imagery for crop scouting

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### Summary

Crop scouting operations for weeds, pests and diseases are typically limited to parts of a field that can be visually inspected from the ground. UAVs can assist with scouting operations by rapidly imaging whole fields. Automated image analysis is required to fully analyse the contents of UAV imagery. This presentation will outline research to generate a weed map from UAV imagery for the purpose of a prescription weed spraying operation (Figure 1). The UAV imagery enabled quantification of weed populations in the field. This project is funded by the Queensland Government Accelerate program and is in partnership with the University of New England and V-TOL Aerospace.

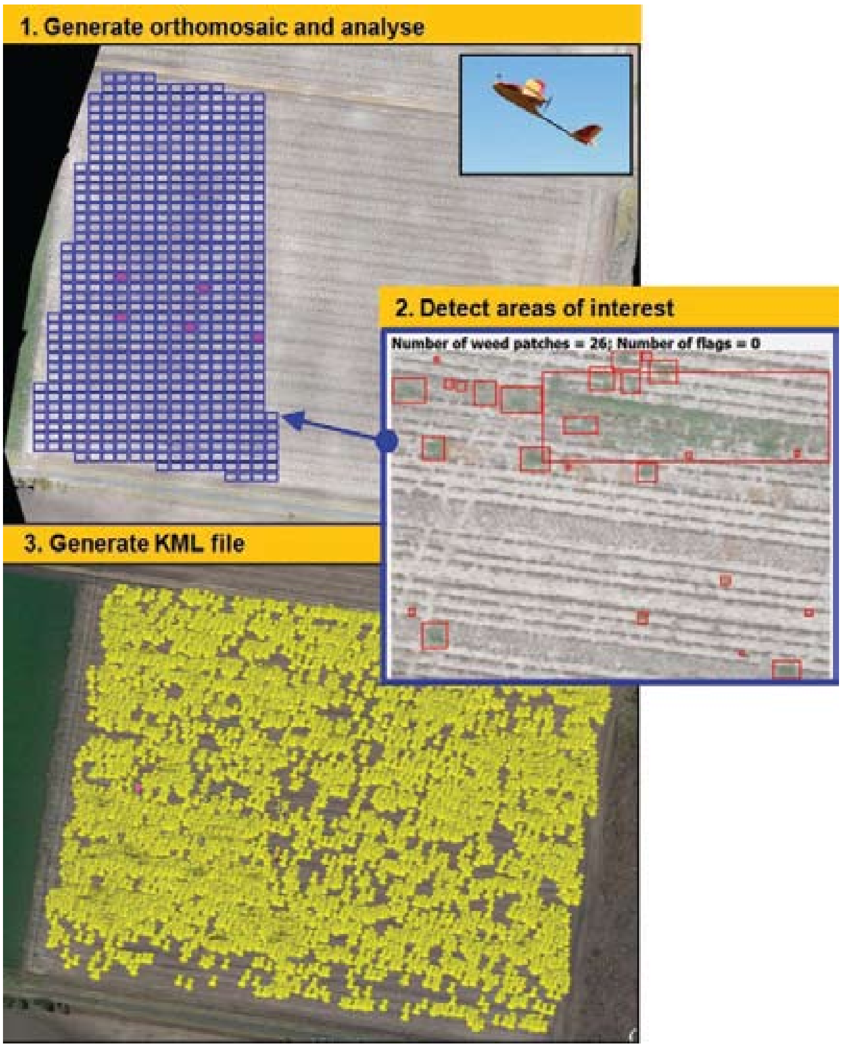


**Figure 1. Image analysis-based weed position sensing from an orthomosaic.**

# Evaluating satellite remote sensing as a method for measuring yield variability in Avocado and Macadamia tree crops

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**Abstract**

Accurate yield forecasting in high value fruit tree crops provides vital management information to growers as well as supporting improved decision making, including post-harvest handling, storage and forward selling. Current research evaluated the 8 spectral band WorldView 3 (WV-3) with a spatial resolution of 1.2 m, as a tool for exploring the relationship between individual tree canopy reflectance and a number of tree growth parameters, including yield. WV-3 imagery was captured on the 7th of April, 2016, over two Macadamia (Macadamia integrifolia) and three Avocado (Persea americana) orchards growing near the Queensland township of Bundaberg, Australia. Using the extent of each block, the WV-3 imagery was sub-setted and classified into 8 Normalised Difference Vegetation index (NDVI) classes. From these classes 6 replicate trees were selected to represent high, medium and low NDVI regions (n=18) and subsequently ground truthed for a number of yield parameters during April and May, 2016. The measured parameters were then correlated against 20 structural and pigment based vegetation indices derived from the 8 band spectral information corresponding to each individual tree canopy (12.6 m2). The results identified a positive relationship between derived vegetation indices (VI) and fruit weight (kg/tree) R2 > 0.69 for Macadamia and R2 > 0.68 for Avocado; and fruit number R2 > 0.6 for Macadamia and R2 > 0.61 for Avocado. The algorithm derived between the optimum VI and yield for each block was then applied across the entire block to derive a yield map. The results show that remote sensing of tree canopy condition can be used to measure yield parameters in Macadamia and Avocado grown in the Bundaberg region.

## Introduction

Accurate pre-harvest yield prediction in high value fruit tree crops is essential to improve decision making process from the grower through to the industry level. Currently, yield estimation in Macadamia (Macadamia integrifolia) and Avocado (*Persea americana*) orchards is undertaken by visual count of a small number of trees. However, this method is labour intensive, provides a limited sample size and the accuracy is often poor. Satellite based remote sensing techniques have the ability to provide regular, synoptic, multispectral and multi-temporal information on spectral behaviour of tree crops over large areas at a high level of detail. This technology potentially offers a non-destructive, time efficient and cost beneficial alternative to replace the current manual system of pre-harvest yield estimation (Gao et al., 2014).

The objective of this study was to identify if Avocado and Macadamia yield could be determined by the spectral characteristics of individual tree canopies and whether the relationship could be extrapolated across the entire block to develop a yield map.

## Materials and methods

The study was conducted during the 2016 harvest season on two commercial Macadamia (*Macadamia integrifolia*) (cv. 741) and three Avocado (*Persea americana*) (cv. Haas) blocks located near the township of Bundaberg, Queensland, Australia (Figure 1). The area is located between longitudes 152.12°E and 152.38°E, and latitudes 25.11°S and 25.23°S.


**Figure 1. Location of the 5 field sites, Bundaberg, Queensland, Australia.**

Multispectral WorldView-2 imagery was captured over the selected macadamia and avocado field sites on the 2 September 2015 (2 m resolution). To identify 'zonal' variability in tree vigour across each block a Normalised Difference Vegetation Index (NDVI) was applied to the imagery, followed by an unsupervised classification (Figure 2). Individual trees representing high, medium and low NDVI zones (6 replicates of each - a total of 18 trees), were selected from the 5 blocks and later ground truthed.

Field sampling of all blocks coincided with their respective commercial harvest. For the two macadamia blocks this occurred between the 11th- 17th April 2016, whilst for the avocado blocks this was during the last week of May, 2016.

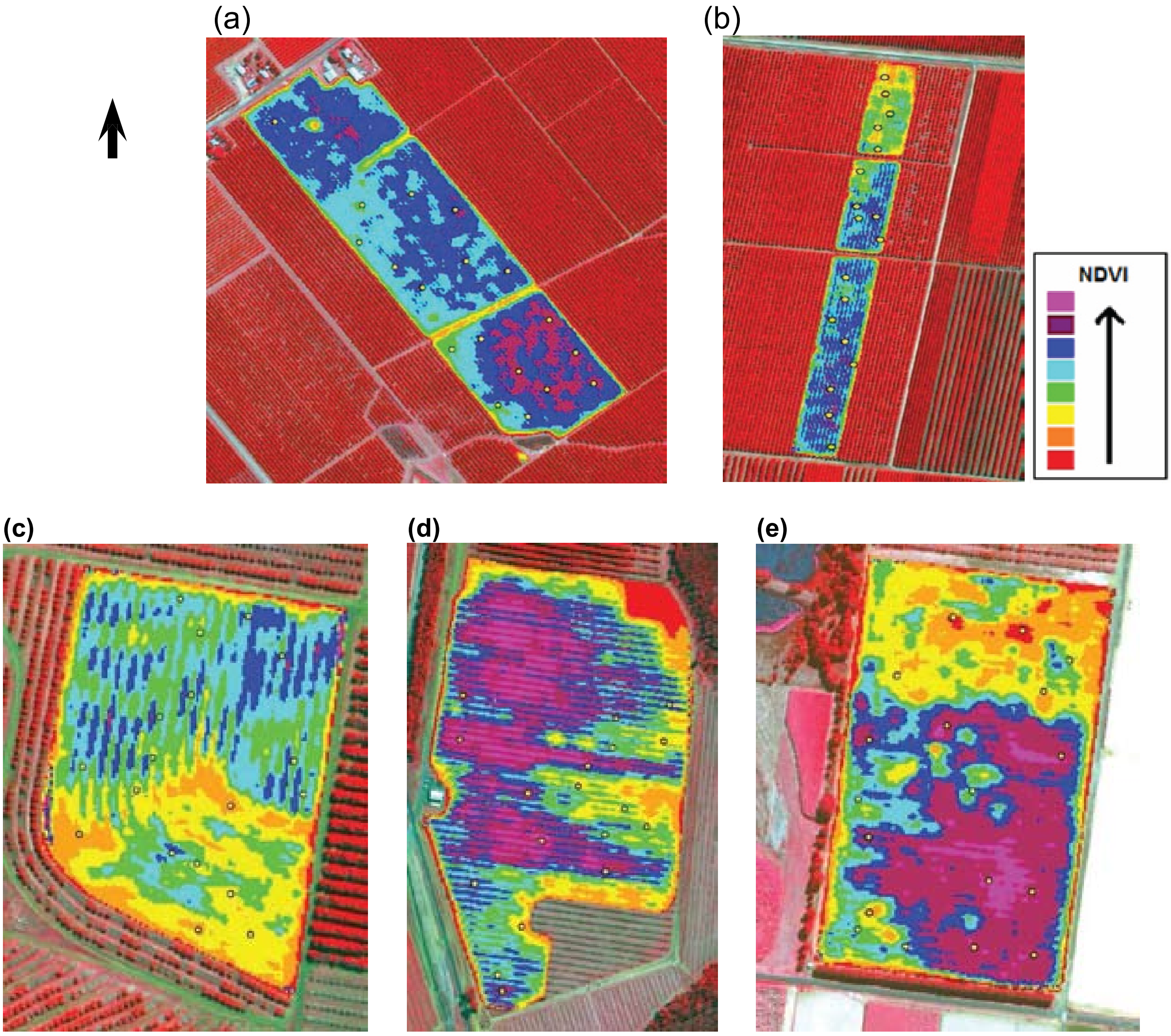


**Figure 2. Classified NDVI images derived from WV-2 image captured 2 September 2015 of two Macadamia blocks: 19.4 ha (a) and 5.5 ha (b) and the three Avocado blocks: 14.4 ha (c), 6.8 ha (d) and 11.3 ha (e). The yellow markers indicate thelocations of the individual trees sampled for yield parameters.**

All harvesting was undertaken manually, with all fruit/nuts from each tree counted and weighed on site. For avocado, this provided a direct measure of total yield and fruit number per tree. For macadamia, harvest samples from each tree were de-husked and weighed, with a 100 nut sample retained for drying and then re-weighing to calculate moisture content, then yield and nut number per tree. The geographical position of each tree centre was recorded using a hand-held Trimble DGPS (Trimble, Sunnyvale, CA, USA).

To determine if the yield parameters measured in the field could be related to the spectral characteristics of the corresponding tree canopies, an additional WV-3 image was acquired on the 7th of April 2016 (1.2m resolution). The image acquisition was timed after final fruit set in late January and before harvesting in late April/May. To extract the canopy spectra of each sampled tree, the differential GPS locations were overlayed onto the WV-3 image using ArcGIS 10.2 (Environmental Systems Research Institute. Redlands, CA). Following the methodology developed by Robson et al., (2014), a 2 m radius buffer area was applied around each GPS reference point creating a 12.6m2 area of interest (AOI). This AOI was applied over each individual sampled tree to extract the 8 band WV-3 spectral information for each canopy using the open source software Starspan GUI (Rueda et al., 2005). Twenty structural and pigment based vegetation indices, detailed by Apan et al., (2003), were derived from the extracted spectral information and regressed against total fruit weight (Kg/tree) and fruit number for each block. For each block, the VI with the highest regression coefficient to the measured parameter was identified.

In order to predict total block yield and derive a yield map, the canopy specific reflectance data for each block was sub-setted using a mask derived from a 2-D histogram scatter of red versus near infrared reflectance pixel values. The algorithm developed from the regression between VIs and total fruit weight and fruit number per tree was then applied to the sub-setted images to convert the reflectance value of each pixel into the measured parameter. A density slice was then applied to provide a parameter specific scaled colour ramp for each block. An example of this process, applied to Avocado Block 3 is provided in Figure 3.

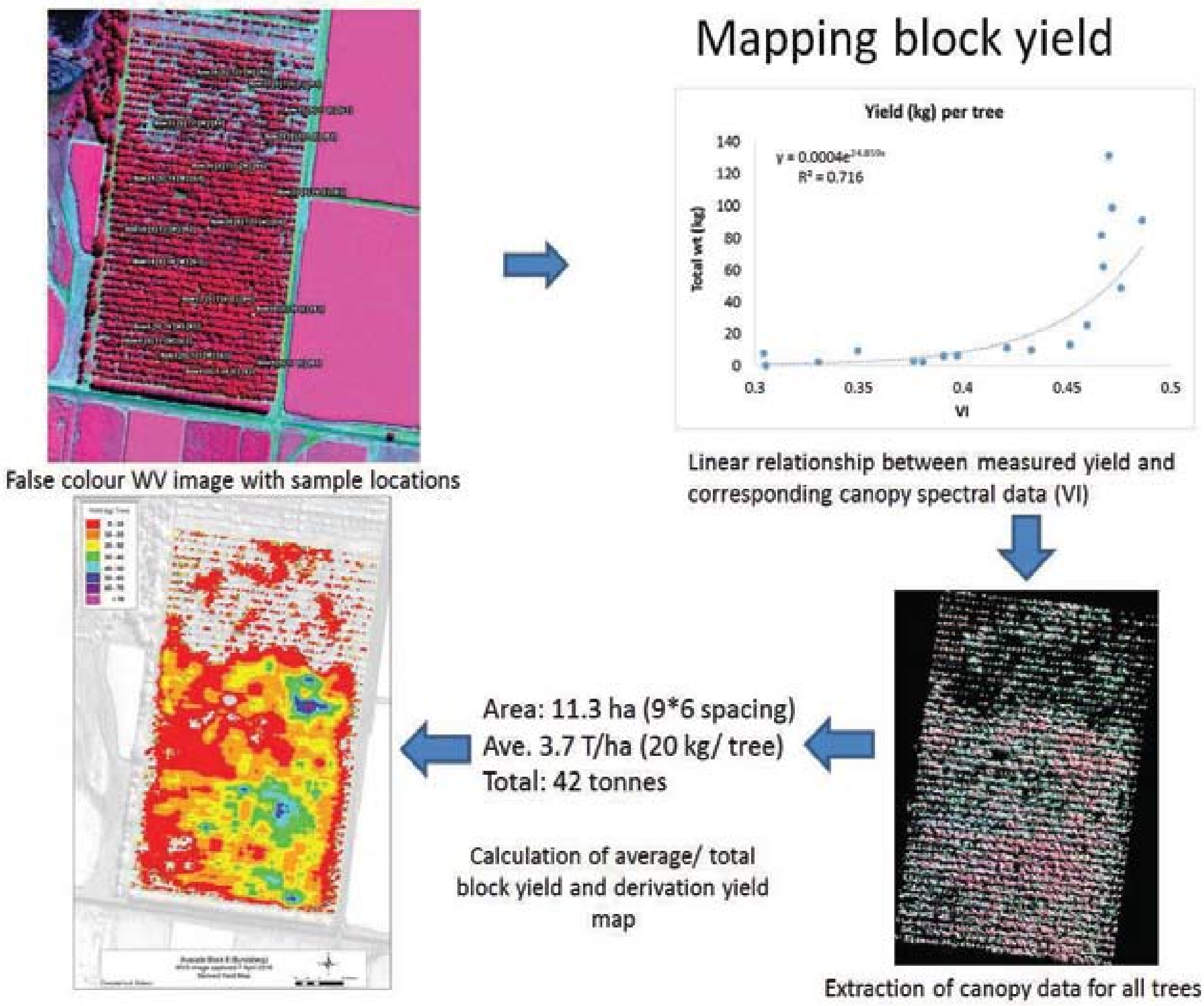


**Figure 3. The analysis process used for the prediction of total fruit yield and for the derivation of a yield map from a WV-3 image and targeted ground sampling. Results and discussion**

## Results and discussion

The strong correlations identified between the varying VI's and measured yield parameters in Figure 4 are hypothesised to be the result of the relationship between tree vigour (health and size) and fruit filling/retention (Avocado), and macadamia nut retention capacity.

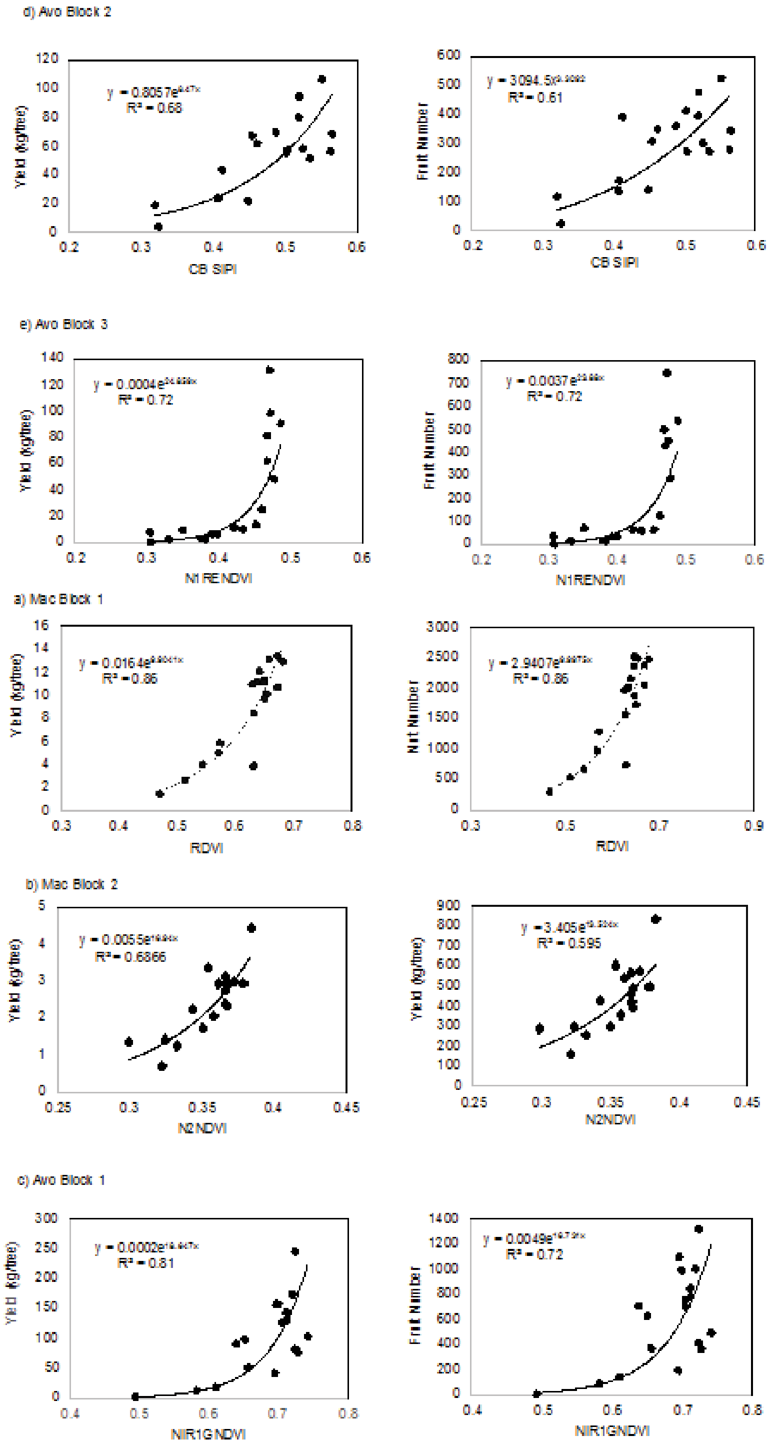


**Figure 4. Scatter plots derived between the measured yield parameters (yield and fruit/ nut number) and the highest correlating vegetation index derived from canopy reflectance for 2 macadamia and 3 avocado orchards.**

For Macadamia Block 1 RDVI (Renormalised Difference Vegetation Index) produced the highest regression coefficient to both total nut weight (Kg/ tree), and total nut number per tree ($R2 = 0.86$), whist for macadamia Block 2 N2NDVI (Mid NIR Normalized Difference Vegetation Index) was optimal ($R2 = 0.69$ and $R2 = 0.6$) respectively. For Avocado Block 1, N1GNDVI (Green Normalized Difference Vegetation Index) produced the strongest regression coefficient for total fruit number (Kg/tree) and number of fruit per tree ($R2 = 0.81$ and $R2 = 0.72$). CB SIPI (Coastal Blue Structure Insensitive Pigment Index) was optimal for Avocado Block 2 ($R2 = 0.68$ and $R2 = 0.61$) and N1RENDVI (Red-edge Normalized Difference Vegetation Index) for Block 3 ($R2 = 0.72$).

Whilst the results do indicate a strong relationship between the spectral characteristics of the tree canopies and the measured yield parameters for each block, the identification of differing optimal VI's does indicate a locational or abiotic/biotic influence. For example Macadamia block 2 suffered severe nut losses during a hail storm that occurred during September 2015. Whilst this is not ideal for regional forecasting, that being the application of one 'generic' algorithm over each tree species, it does indicate that through the targeted sampling of a small number of trees an accurate yield map can be derived.Yield maps were derived from the algorithms identified in Figure 4 (Figure 5). These classified maps offer a number of commercial benefits including early detection of tree stress, assisting in management decisions within an orchard block and harvest segregation by indicating the high and low growing regions in a block. From the derived productivity zone maps, total predicted yield (fruit weight (t/ha converted from kg/tree and fruit number per tree) was counted for each block of Macadamia and Avocado crops.

## Conclusion

High spatial resolution WV3 imagery provides an alternative to the time consuming and labour intensive estimation techniques, currently used to predict yield for Macadamia and Avocado crops. The results illustrated a good correlation between different VIs and total fruit weight and fruit number, which could provide the growers with a reliable estimation of their production. By extending this study to other Macadamia and Avocado blocks in the Bundaberg region and other horticultural growing regions in Australia, it will allow a better understanding of the relationship between VIs and tree yield to be developed. Further investigation is also warranted to determine if the inclusion of site specific conditions such as: soil type, nutrient concentrations, or rainfall may allow for a regional yield prediction algorithm to be developed.

## Acknowledgements

The authors of this paper would like to acknowledge the Rural Research and Development For Profit Scheme, Horticulture Innovation Australia Ltd, Australian Macadamia Society and Avocado Australia Ltd and for providing funding and support to undertake this research. Also Simpson Farms, Clayton Mattiazzi, Ray Norris, Andrew Wallis, Tom Redfern and David Depaoli for allowing the field work to occur on their properties. Lastly Sushil Pandey, Brooke McAlister and Oliver Robson for their assistance with field sampling.

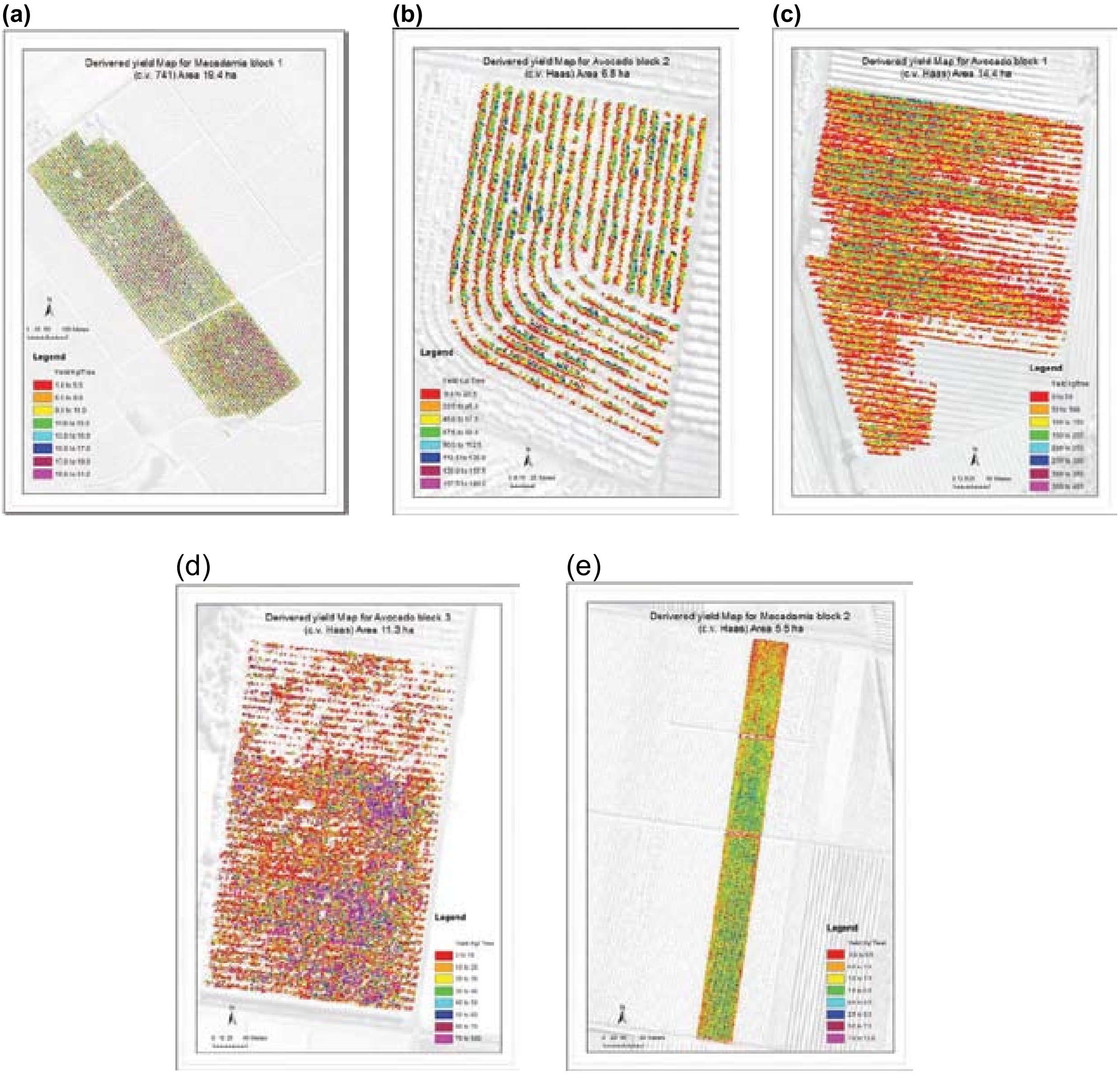

**Figure 5. Classified yield maps derived from the best fit model of the relationship between VIs and total fruit weight (kg/tree) for the two Macadamia and three Avocado blocks.**

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# 101 ways to make Precision Agriculture work in Qld Vegetables

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**Abstract**

The project '*Adoption of variable rate technology in Queensland's intensive vegetable production systems'* implemented and optimised a range of precision technologies across Queensland's major vegetable growing regions. A variety of precision agriculture tools were used to map and ground truth spatial and temporal variability including: satellite imagery, proximal crop sensors, electro-magnetic induction (EMI) soil mapping, strategic soil sampling and spatial yield mapping through retrofitting yield monitors to existing harvesters (potato, sweet potato and carrots).

Crop sensing imagery effectively identified variability in crop biomass, with proximal sensing tools proving the most applicable in vegetable production systems. The features of precision vegetable systems differed across farms and growers: groundtruthing spatial variability could be as simple and low cost as hand held grid pH sampling of a field to intensive, costly zonal and grid nutrient analysis. Reported outcomes from variable rate (VR) lime applications have varied from similar total lime inputs (but targeted to spatial variation in pH) to significant lime savings (40%) when compared with traditional lime applications; crop responses following VR applications range from 25% increase in yield in lower performing areas to anecdotal accounts of improved uniformity.

Yield monitoring and mapping is critical to support some quantification of the costs of underperforming areas and evaluation of potential management options. Yield data was used to classify what percentage of field areas were performing at different yield levels. Multiple data layers (crop sensing, EMI soil mapping, yield mapping and groundtruthing data) facilitated greater understanding of field variability and the underlying causes. Significant relationships were identified between crop sensing imagery and yield monitoring data, similarly for EMI soil mapping and yield monitoring data. These indicated that early season spatial variability in crop biomass remained evident in final spatial yield results. In one example, EMI soil mapping explaining 27% of the yield variability.

Vegetable growers and agronomists involved in the project have demonstrated an increase in their knowledge of spatial variability and have access to tools to detect and reduce within block variability.

# Variable rate technology in vegetables – a collective approach

**Ben Moore[1] and Ed Windley[2]**

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**Summary**

Ben Moore and Ed Windley have small family mixed cropping (vegetables, grains and fodder) operations situated in the Fassifern Valley, approximately 90km south west of Brisbane, Queensland. Both are members of a small local vegetable grower group that has been working towards the implementation of precision technologies, in particular variable rate technology for the past 2 years.

This group has been involved in a larger project exploring the value that precision agriculture technologies provide to vegetable systems. The group has been able to purchase a range of technologies that are shared by group members. This includes crop biomass sensors, yield monitors and variable-rate equipment. Through the application of these technologies DJM Farming and Kengoon Farming have gained more detailed understanding of the variability within their farming operation.

The range of precision technologies they now have access to has provided them with multiple data layers to assess spatial variability, develop strategies to manage it and obtain cost benefit data to assess the value of any intervention. The presentation will provide some background on the groups' members and their journey to implement precision and variable rate technologies.

# Maximising efficacy with WEEDit spot spraying technology

**Steve Norton**

Croplands Equipment

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### Summary

WEEDit Spot Spraying Technology is the latest development in controlling weeds in fallow. For years we have looked at summer spraying simply as stopping the weed from going to seed and spreading. Current day thinking is that we are managing our summer weeds to eliminate seed set, maximize water use efficiency and maintain nutrition.

The WEEDit technology should be viewed as an important tool in delaying the onset of herbicide resistance. Commonly only spraying 10% of the paddocks allows the efficient use of high water volumes, robust chemical rates and allow the use of more expensive herbicides that otherwise could not be afforded in a blanket application. Combining this technology with dual tanks and dual spray lines creates the ultimate flexibility when applying non compatible or expensive products.

WEEDit's near infrared beam detects the active chlorophyll in the plant and the sensors read the fluorescence created to activate the correct number of nozzles relevant to the plant size. Nozzles mounted 200mm apart apply chemical from a number of angles to ensure penetration and coverage. Close nozzle spacing minimizes the impact of shading from standing stubbles such as sorghum and wheat.

Conventional sprayers using flat fan nozzles (Figure 1), apply chemical well to one side of the plant in the direction of travel. To use contact herbicides in a herbicide resistance strategy, coverage is imperative for weed control.


**Figure 1: 40 degree flat fan nozzle**

Croplands have developed a ceramic full cone nozzle which penetrates both forwards and backwards creating good coverage to the backside of the plant. These wide angled 60 and 80 degree full cone nozzles (Figure 2) are very effective on elongated plants, such as fleabane and skeleton weed. These nozzles maintain their pattern and are very effective under 18km/ hour, which is ideal for WEEDit and best practice application.

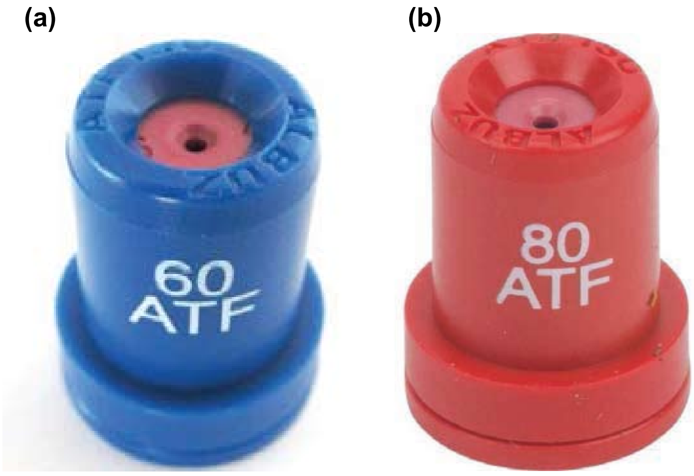


**Figure 2. (a) 60 degree ceramic full cone nozzle and (b) 80 degree ceramic full cone nozzle.**

The WEEDit sensor (Figure 3) is mounted very high at 1100mm above the ground. This allows the five sensor channels to read every 200mm across the boom and activate the required number of nozzles. The effect of this on application rate is a substantial increase of both water and chemical effectively dosing larger plants, compared to much smaller plants only receiving a dose from one single nozzle. The speed of the WEEDit engaging the target largely comes down to the performance of a fast acting PWM (Pulse Width Modulating) valve. These valves can activate on and off up to ten times per second, which is responsible for the accurate targeting of chemical to weed. As the sprayer travels across the paddock all sensors take a reading every 1mm of forward travel allowing for detection of very small targets. This sensor has a unique automatic calibration function which allows for use in both day and night - even correcting itself as clouds cast shadows across a paddock or working around fence lines under trees with only part of the sprayer operating in the shade.

**Figure 3. WEEDit Sensor**

The WEEDit system is the best sensor on the market and delivers chemical accurately to the target with a droplet spectrum and nozzle angling to ensure penetration and coverage is maximized. Coverage is king with contact chemicals, enforcing the importance of appropriate nozzle selection to target.


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# AgDNA – Maximising field level profitability using spatial data analytics

**Paul Turner**

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### The emerging internet-of-things

The recent explosion in availability of low cost sensors, cloud computing and wireless connectivity has given rise to the Internet-of-Things (IoT). IoT is a term used to describe the connectivity of previously "dumb" devices to the Internet. Once a device is connected online the underlying data can be analysed to improve performance, therefore turning it into a "smart" device and increasing its value to the user.

Agriculture is undergoing its own IoT revolution with every major Original Equipment Manufacturer (OEM) and aftermarket hardware provider enabling their products for Internet connectivity. The resulting online data stream is typically hosted by the manufacturer on a cloud server and made available (with the grower's permission) to third party data analytics companies such as AgDNA for further value added services. Examples of data being hosted online include weather, soil moisture, as applied seeding / fertilizer / chemical / irrigation, yield, imagery, commodity prices etc.

### Ongoing challenge of Precision Agriculture implementation

Optimising crop yield relies on a wide range of inputs and is highly variable given agriculture's dependency on weather, management practices and local growing conditions. Therefore access to precise real-time data presents a significant opportunity to improve on farm decision-making, yield and overall farm profitability.

Precision Agriculture (PA) has long been regarded as the holy grail of sustainable farming using the principals of optimising crop inputs ie right place, rate, timing and method. However, the practicality of managing vast volumes of unstructured data from multiple sources and interpreting their meaning has been a significant barrier to entry for many farmers. Even if PA is implemented within the farming operation, calculating its return on investment (ROI) has resulted in its own challenges due to the lack of tools available to accurately quantify the financial returns.

### How IoT is being used to maximise farm profitability

Now that the major OEM's and hardware manufacturers have enabled their products for IoT connectivity the question becomes "what do I do with all this data?" Individual data sets on their own only tell part of the story, it's like viewing a historical yield map from a drought year and concluding that additional nitrogen would have increased yield. Instead multiple data sets taken at the right time and location throughout the season are needed to provide context and turn data into valuable information capable of supporting critical farming decisions.

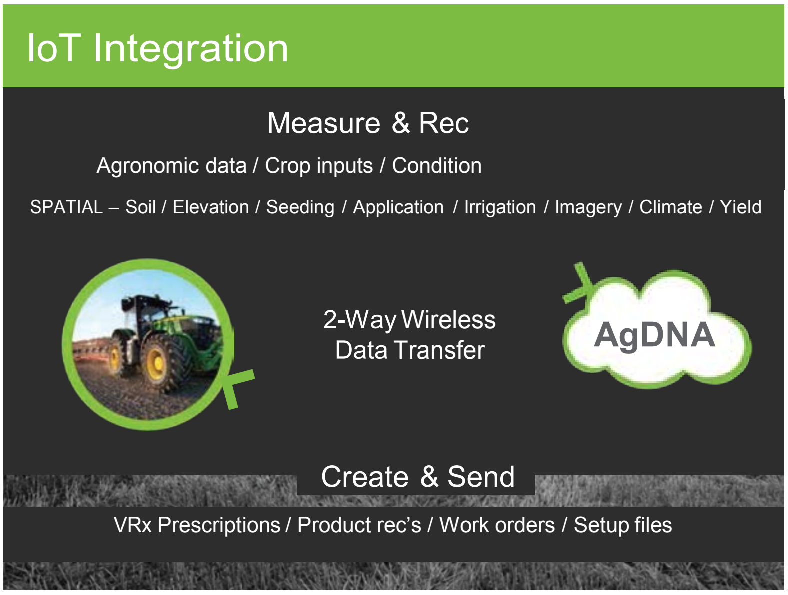


**Figure 1. Automated data inputs and outputs**

AgDNA has developed a world leading[1] enterprise level precision farming platform that integrates and automates IoT technologies for crop production. The company has data licensing agreements with the major OEM's (eg John Deere, Case IH, New Holland, AGCO) and utilizes the real-time data from the in-field machinery and other online sources to provide a comprehensive picture of the entire farming operation. Not only is the data gathered and processed in near real-time, it is recorded and analysed spatially to provide geo-referenced insights for every hectare across the farm. Examples of the various data inputs and outputs can be seen in Figure 1.

The automated sensor data streaming from the tractor, sprayer or combine is supplemented with additional financial information specific to the grower's operation. For example each purchase of seed, chemical or fertilizer can be recorded using the product inventory module to determine average purchasing cost of each input. These costs are then calculated for every litre of chemical, ton of fertilizer or bag of seed as it is applied throughout the field.

Other costs that are automatically calculated for each in field activity include diesel consumption, labour rates, equipment costs etc. An example of field activity costs and their variability can be seen in Figure 2 whereby uniform seeding application cost differs from one part of the field to another due to the soil variability and higher equipment operating costs in heavier soil conditions.

### Pixel Profit – an automated P&L of every hectare

By geo-referencing costs spatially throughout the field, the next logical step is to determine income and ultimately the net profit. AgDNA captures the yield data along with the contract sale price to produce an income map. This is then analysed against the corresponding expenses to produce the net profit spatially across the field.

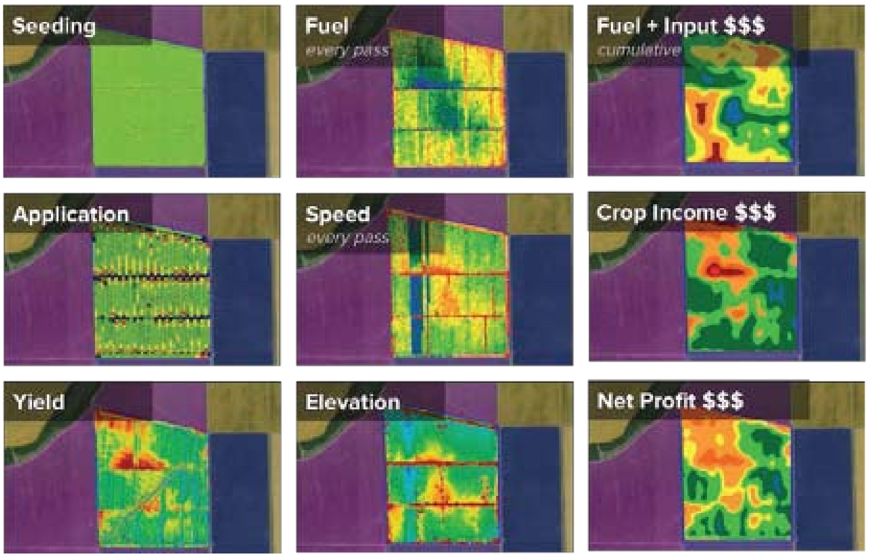


**Figure 2. Pixel Profit (field level) income, expenses and net profit**

The system then categorizes net profit in terms of poor, average and high and assigns a colour-coded legend of red, green and blue respectively (see Figure 3). The user can then point and click on any part of the field to get a breakdown of costs and ultimately an overview of profit limiting factors and what remedial actions might be available to address the issue and optimise profitability for that part of the field.

It is important to note that they system is designed to optimise profitability which is different to maximising yield alone. For example there may be a yield-limiting factor such as slope and aspect, which results in water runoff and growing limitations that are difficult to overcome with nutrient management alone. Therefore the optimal course of action may be to plant with a drought tolerant hybrid for that section or reduce the nitrogen applied due to the limited water holding capacity of that field region ie optimised seed variety (increase yield) or reduced N inputs (lower costs).

**Figure 3. Pixel Profit (farm level) profitability zones poor, average and high**

### Next steps - from data analysis to predictive insights

Using IoT and cloud computing to determine intra-field profitability is just the beginning for this emerging technology. This is one of many use cases within the AgDNA platform that includes other real-time farm management tools such as:

- Job scheduling and logistics
- Equipment optimisation
- Inventory management
- Agronomic reporting

The greater value to be unlocked is predictive analytics whereby real-time spatial data is collated, benchmarked and analysed to provide agronomic insights about upcoming decisions such as probability of a certain disease forming, forecasting spray windows, recommended nitrogen application etc.

The goal is not to become a black box agronomic advisor, but instead to become a highly accurate decision support tool to help make timely and informed decisions. A tool that is capable of considering all possible variables to help increase yield, lower operating costs and maximize profitability with minimal user input.

The presentation will include a complete overview of the data sources, analysis process and resulting output to identify per hectare field profitability and possible improvement scenarios.

Note: [1]AgDNA listed by Lux Research in their "Top 10 most innovative companies for 2015" http://farmindustrynews.com/blog/agdna-among-top-10-innovative-companies?utm_content=34770992&utm_medium=social&utm_source=twitter

# A methodology to assess the accuracy and reliability of yield monitor data in sugar

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## Summary

Being able to accrue the full benefits as a result of adopting Precision Agriculture Technologies is dependent on having complete confidence in the layers on which the decisions are based. The research that has been conducted as part of the Sugar Research Australia (SRA) funded project CSE022 has shown the yield data, from a range of sensors, can reliably show the spatial patterns commensurate with other data layers. Depending on how the original sensor data is filtered, manipulated and attributed to the block from which it was cut, can have considerable bearing on the accuracy and reliability of the resultant yield maps. However, performance of the sensors and resulting data, is compromised by consignment errors, and also sensor 'noise' derived from the vagaries of harvest, especially at row ends.

Having confidence in the sensor values, and hence the yield maps produced using this data, is the major output of the current project. This will be achieved by producing a program/app/package that will evaluate, clean and prepare the data as input to the mapping protocol for rigorous map generation. The yield mapping protocol (Bramley 2012) combined with the new 'evaluation tool' will provide a much better understanding of the sensing options to determine when the data and believable and when it is not. This paper will report on the progress and development of this research, along with other activities at the NCEA.

# Changing with time

**Denis Pozzebon**

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**Summary**

Denis farms approx 130 hectares of sugarcane at Airville in the Burdekin District using minimum tillage and fallow cropping techniques. Denis has been pioneering the use of GPS-equipped vehicles, precision technologies and techniques in the cane industry. He bought his first GPS in 2007 after borrowing a friend's GPS-equipped tractor to plant fallow season legumes as a green manure crop. At the same time, Denis began working with independent agronomists Tony Crowley and Peter McDonald to have his farm EMI mapped.

These maps and associated georeferenced soil tests provide the foundation for Denis's farming system. Denis uses Farm Works to keep electronic records, import maps and a store/produce a range of farm management data. He has records dating back to 2007 for land preparation, nutrition and weed management as well as a range of EM and yield maps.

In 2010 Denis purchased a variable-rate controller for his fertiliser box to apply variable-rate management across the different zones identified through the EM mapping process. He has been able to use the accumulated data over the years to refine his nutrient management to three management zones, based on clay, silt and sandy soils, and now also uses the information to apply ameliorants, such as gypsum, at variable rates.

He now has developed a system to manage these 3 zones differently for fertiliser, irrigation and harvesting. Fertiliser rates are different for each zone, and on the sandy soil the application is split. Soil moisture probes in each soil type are used to guide the irrigation management and the sandy soils are harvested green. Soil testing is still undertaken in the fallow times and the EM maps are used to guide the sample locations.

More recently Denis has acquired variable-rate controllers for his chemical application gear. He has controllers on a boom spray and his shielded sprayer. Denis says that the technology has made farming easier and the combination of data and precision technology allows him to invest his money and time where it is most required.

# New innovations and tools for airborne pest and disease surveillance for agriculture

**Rohan Kimber[1], Jenny Davidson[1], Les Zeller[2], Paul Kamel[2], Greg Baker[1], Helen De Graaf[1]**

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**Summary**

New technology applied to agriculture is developing rapidly creating new opportunities for surveillance of exotic airborne pests and diseases threatening broadacre grain crops. Subsequently, the Grains Research and Development Corporation (GRDC) initiated a recent project lead by the South Australian Research and Development Institute (SARDI) to undertake CRC Plant Biosecurity Project 2014 ‘New tools for field grains surveillance and diagnostics of high priority exotic pests’.

The objectives of this project have resulted in development and evaluation of new ‘Smart’ Spore and Insect Trapping systems which collect samples referenced to parameters such as GPS and climate data (temp, wind direction, RH) and include wireless data transmission of digital images or improved design for downstream diagnostics of pest targets such as molecular assays. These approaches aim to demonstrate the benefits when science is in partnership with engineering to include automation and innovation into trapping systems for smart capabilities with high sampling frequencies, which are suited to both monitoring for endemic pests or rare influxes of exotic spores or pests. Prototypes currently under evaluation at SARDI include the Mobile Jet Spore Sampler, Sensor Moth Trap and Insect Suction Trap and the result of collaboration with engineers at the University of Southern Queensland as well as strong linkages to Burkard Manufacturing Co. (Stuart Wili) and Rothamsted Research (Prof Jon West) in the United Kingdom.

To fully realise the benefits of this emerging technologies, area-wide (network) applications of these devices are required to fully appreciate their role in coordinated reporting for point of origin and dispersal dynamics of targets within fields or growing regions. This applies not just to exotic targets in the grains industry, but also endemic threats, and equally applicable to horticulture and viticulture pests. For effective pest and disease surveillance innovation must merge with robust sampling protocols, rapid detection and data interpretation for accurate interrogation of spatial data generated from a network of samplers. This is particularly important given the size and scale of Australia’s agricultural industries to achieve a reduction in the economic impact and overall improvement in the time for an industry to respond to incursions of airborne pests and plant pathogens or the information flow for improved management decisions by the end-user.

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# Targeting nitrogen to productivity zones in the WA wheatbelt

**Frank D'Emden**

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## Summary

This study observed wheat and barley yield responses to varying post-emergent nitrogen rates across different soil types in a dryland cropping system over the 2014 and 2015 seasons in the Western Australian wheatbelt. An electromagnetic survey was used to segregate the trial paddock into two dominant productivity zones as determined by soil type and historical yield maps. Potential economic gains from targeting post-emergent nitrogen rates to soil productivity zones varied between $8/ha and $29/ha.

## Methods

A 195ha paddock north of Ravensthorpe (-33.2800; 120.1713) was surveyed using a DualEM 1S with data points logged at 1 second intervals at a ground-speed of 20km/hr and swaths spaced at 30m. The EM data was ground-truthed by analysing soil cores to depths of 30-60cm for a range of analytes including EC, pH, organic carbon, NO3, NH4, P, K, S, exchangeable cations and particle size.

Figure 1 shows the 50cm EM map which was used to formulate the soil zone boundaries. Soils with >50mS/m apparent electroconductivity (ECa) were considered to be calcareous loams, while those <50mS/m ECa were considered to vary between sandy gravel duplexes and shallow sandy duplexes. This classification was confirmed through ground-truthing observations of changes in surface texture across the ECa gradient. The interpreted soil distributions comprised 45% calcareous loams and 55% sandy gravel duplexes across the trial paddock.

Table 1 shows the difference in particle size analysis between the contrasting soil types from soil cores taken when soil moisture probes were installed (see Figure 1). These differences are typical of the high and low production zones represented by the respective calcareous loam and sandy gravel duplex soils, and are consistent with previous observations from across the surrounding 1800ha property.

**Table 1 Particle size analysis results (mid-infrared method) for the two dominant soil types across the study paddock.**

| | Particle size analysis (%) | | | | | |
|---|---|---|---|---|---|---|
| Depth (cm) | Sandy gravel duplex | | | Calcareous loam | | |
| | Sand | Silt | Clay | Sand | Silt | Clay |
| **0 - 10** | 90 | 4 | 7 | 80 | 1 | 19 |
| **10 - 20** | 91 | 2 | 7 | 71 | 4 | 26 |
| **20 - 30** | 83 | 1 | 16 | 62 | 3 | 36 |
| **30 - 50** | 60 | 7 | 33 | 65 | 6 | 29 |
| **50 - 70** | 65 | 2 | 33 | 62 | 4 | 34 |

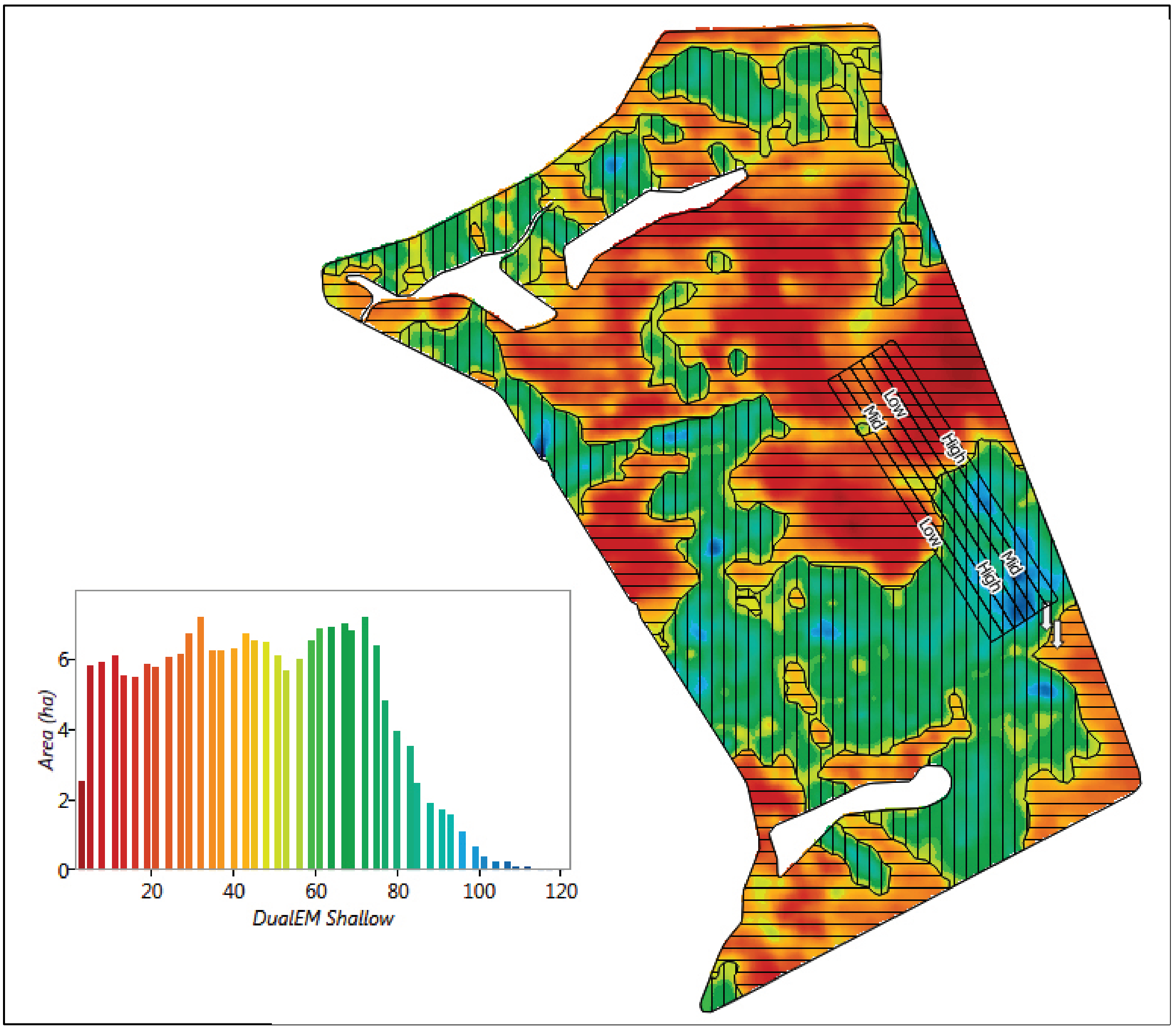


**Figure 1 Map showing variation 0-50cm electromagnetic induction (mS/m ECa), interpreted zones (horizontal lines = low productivity (55%), vertical lines = high productivity (45%)) across the trial paddock, with relative N treatments labelled. Soil moisture probe locations indicated by arrows.**

In-season N treatment rates for the high and low productivity zones were arrived at through discussions with the host grower and historical yield variations. Soil moisture probe data and Yield Prophet simulations were also used as points of comparison.

Three N management strategies (high, paddock average and low) were replicated twice across a soil type/management zone boundary within the paddock, resulting in 12 treatment plots. Nitrogen treatments were applied as liquid urea ammonium nitrate (UAN) via boomspray with streaming nozzles. Plots were 30m wide to accommodate one sprayer width. Paddock average N rates were applied across the remainder of the paddock.

Yield data was collected via John Deere yield monitor with a 12m front, ensuring at least 1 full harvester swath width per N treatment. Grain quality samples were collected from the harvester grain tank mid-way through each plot, with grain samples analysed for protein and screenings.

Table 2 describes the treatment dates and mid-season N rates applied in the 2014 and 2015 growing seasons. Nitrogen fertiliser was deep-banded at flat rates of 7 and 8kg/ha across each trial during sowing in 2014-15 respectively.

Standard agronomic practices for weed, pest and disease control were applied uniformly across trial plots throughout the growing season according to recommendations provided by the growers' agronomist.

**Table 2 Mid-season nitrogen treatment application dates and rates**

| | 2014 | 2015 |
|---|---|---|
| **Crop type** | Wheat | Barley |
| **Sowing date** | 22nd May | 29th April |
| **N treatment application** | 18th July | 7th July |
| **Post-emergent N treatment rates (kg/ha)** | 16, 23, 32 | 13, 26, 42 |
| **Growing Season[1] Rainfall (mm)** | 252 | 215 |

## Results

Grain yield was higher across the calcareous loam compared to the sandy gravel duplex soils across both years, with average yield differences across all treatment of 1.4t/ha and 0.5t/ha in 2014 and 2015 respectively (Table 3). Despite a higher growing season rainfall, yields in 2014 were lower due to a hot, dry spring finish.

When compared to the paddock average N rate, there was no yield penalty from applying 7kg/ha less N on the sandy gravel duplex in 2014, while the higher yield potential in 2015 led to a 100kg/ha (3%) yield decline from a 13kg/ha reduction in N on this soil type.

Yields on the calcareous loam responded by 200kg/ha (5%) to an additional 9kg/ha and 16kg/ha of N in 2014 and 2015 respectively compared to the paddock average.
There was a tendency towards higher protein and lower screenings on the sandy gravel duplex, however these differences were not high enough to result in any potential grain quality segregation. There were no protein nor screenings responses to N rate on either soil type.

**Table 3 Wheat and barley yield differences by soil type and mid-season nitrogen treatment in 2014 and 2015, with target N rates for each soil type shown in bold.**

| Season | Nitrogen rate (kg N/ha) | Calcareous Loam | Sandy Gravel Duplex |
|---|---|---|---|
| 2014 (Wheat) | 16 | 3.7 | **2.5** |
| | 23 | 3.8 | 2.5 |
| | 32 | **4.0** | 2.4 |
| 2015 (Barley) | 13 | 3.9 | **3.6** |
| | 26 | 4.1 | 3.7 |
| | 42 | **4.3** | 3.6 |

[1] April 1st to October 30th.

### *Economic implications*

The value of targeting N rates to soil type was determined by multiplying the yield differences between targeted zone rates and flat N rates by grain price, net of nitrogen cost differences then weighted according to the estimated soil type distributions. Grain prices were assumed to be $275/t and N costs assumed at $1.60/kg ($675/t for UAN = 51c/L) for both years.

Table 4 summarises the resulting analysis, showing that, among other factors, the benefit of varying N rates by productivity zone was influenced by the difference in yield between zones.

**Table 4 Economic value of allocating lower N rates to sandy gravel duplex and higher N rates to calcareous loamy soils based on grain prices of $275/t, costs of $1.6/kg N, and soil type distributions of 45% loam and 55% duplex.**

| | 2014 | | 2015 | |
|---|---|---|---|---|
| | **Calcareous Loam** | **Sandy Gravel Duplex** | **Calcareous Loam** | **Sandy Gravel Duplex** |
| **Yield difference (t/ha)** | 0.19 | 0.04 | 0.22 | -0.12 |
| **Gross income difference ($/ha)** | 52 | 11 | 60 | -34 |
| **N cost difference ($/ha)** | -14 | 11 | -26 | 21 |
| **Net of N cost ($/ha)** | 38 | 22 | 34 | -13 |
| **Zone weighted benefit ($/ha)** | 17 | 12 | 15 | -7 |
| **Total difference ($/ha)** | 29 | | 8 | |

## Discussion

In a review of case studies across the Australian wheatbelt, Robertson et al. (2008) found the high level of variability in the benefits of VRT could be attributable to fertiliser management practices and the degree of within paddock yield variation. Wong and Asseng (2006) found similar yield variability in relation to ECa and plant-available water capacity in the WA Wheatbelt.

However, Llewellyn et al. (2016) observed that the interaction between seasonal rainfall distribution and evaporation rates has a stronger influence on yields than ECa zones in the low rainfall mallee region of south-east Australia.

This study provides a practical demonstration of the benefits of targeting N to productivity zones as determined by the EM zones, however these benefits are expected to be limited to regions with predominant winter rainfall and where EM is strongly correlated with plant-available water capacity.

Recommendations for further study include assessing the benefit of including radiometrics and wetness index in the development of productivity zone boundaries, and the variation in observed benefits to targeted N according to seasonal rainfall distribution probabilities.

**Acknowledgements**

This project was made possible through funding from the Australian Government's Action on the Ground program and the generosity of the host growers, Bevan and Karyn Tuckett.

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# PA on 'Coondarra'

**St John Kent**

'Coondarra', Jimbour, QLD

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**Summary**

St John Kent, farms over 1000 ha at Jimbour, north of Dalby growing sorghum and chickpeas mainly, with a barley, faba beans, a little wheat and opportunity cotton. St John has held a long-term commitment to conservation farming to maximise water infiltration and water use efficiency.

St John's objective is profitable and environmentally viable farming using stubble retention and, where practical, continuous cropping using precision agriculture and controlled traffic operations. St John has been pioneer in practically, and agronomically successfully, applying these technologies in Queensland. This presentation will describe his approach and the journey.

# Estimating pasture biomass with active optical sensors

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## Summary

Accurate and reliable assessment of pasture biomass remains a key challenge for grazing industries. Livestock managers require accurate estimates of pasture biomass over their farm for optimal stocking rate decisions. This paper reports on our investigations into estimating pasture biomass in Tall Fescue (Festuca arundinacea), perennial ryegrass (Lolium perenne) and Phalaris (Phalaris aquatica) pastures in Tasmania, and three regions in Victoria and in the Northern Tablelands of NSW. We used the Trimble® GreenSeeker® Handheld to measure normalised difference vegetation index (NDVI), and measured height using a rising plate meter. The optimal model to estimate biomass across regions, seasons and species during two years was a combination of NDVI and height. The combined height and NDVI index was significantly correlated with pasture biomass for grasses for each region in the winter and spring collection periods ($r2 = 0.62 – 0.77$, $P < 0.001$). Data collected in a third year will be used to test the accuracy of the models. Remaining challenges in estimating the pasture biomass include the effect on NDVI of mixed swards, senescent material, and the background soil, and developing a means to easily obtaining a measure of height.

## Introduction

Accurate and objective measurement of pasture biomass is a key requirement for producers for improving grazing system productivity by allowing graziers to better meet the feed requirements of their livestock. Accurate, real-time biomass estimates also enables producers to meet residual pasture targets resulting in improved sustainability, increased grazing utilisation and subsequent increases in pasture growth rates; all of which increase red meat production (MLA, 2004; Westwood, 2008). It is estimated that improving pasture estimates has the potential to increase farm profitability by approximately 10% in Australian beef and sheep enterprises (Henry et al. 2013).

Current technologies available for real-time pasture biomass estimation include rulers, light sensors, rising plates, capacitance probes, or vertical height and texture sensors. However, most commercially-available tools have been targeted at the dairy industry with relatively homogenous pastures. Their application to the generally more variable red meat pastures is limited due to cost, mode of deployment, inability to delineate the green fraction (Trotter et al., 2010). Active Optical Sensors (AOS) are a relatively new class of sensor that use their own light source to measure optical reflectance of the target canopy unaffected by ambient light conditions. Sensors that use red and near-infrared light can provide the normalised difference vegetation index (NDVI) which correlates to the photosynthetically active biomass of the canopy. To date AOS have been developed for use in the cropping industry (e.g. to infer crop nitrogen levels), however recent research has demonstrated the potential for applying the same technology to estimate the green fraction of pastures (Flynn et al., 2008; Trotter et al., 2010; Trotter et al., 2012). These sensors are the most accurate up to 3 000 kg green dry matter (GDM) per hectare (Trotter et al., 2010) which provides a potentially ideal tool for pasture managers seeking to monitor biomass between the optimal production range of 1 000 to 2 500 kg GDM/ha (MLA, 2004).

Here we assess the potential of a relatively low-cost active optical sensor (Trimble® GreenSeeker® Handheld, GS, approximately \$700AUD) to estimate pasture biomass on grass-based pastures in northern NSW, Victoria and Tasmania. We are evaluating the reliability of the GS combined with height data across a range of monocultures and mixed swards, across different seasons, regions and pasture growth stages.

**Methods**

We took calibration cuts over 2014-2015 from five locations in the Northern Tablelands, ten locations throughout Victoria, and four locations in Tasmania. Measurements were made in winter and spring in Victoria, also in autumn in Tasmania, and year-round in the Northern Tablelands. The sites are grass-based pastures with variable amounts of clovers. We measured between 8 and 15 samples per site to obtain a range in biomass. Before cutting the pasture, we measured the height using a falling plate and recorded the NDVI measured from 1 m. We cut pasture in a 70 cm x 30 cm quadrat, designed to fit the footprint of the GS. The samples were weighed, subsampled (at least 50 g) into green and senescent material, then oven dried for 48 hours at $70^{o}$C and weighed again. The GDM and total dry matter (TDM) per hectare were then calculated. Post-cut NDVI was recorded, and photos were taken before and after cutting for verification purposes. Data analysis and modelling was performed in MS Excel and R (version 3.2.5, R Development Core Team, 2014). Green dry biomass was fitted against NDVI, height, a combined NDVI x height index, and a log transformed height x NDVI. In each of the presented groups, the NDVI x height index model represented the best fits. Sampling continues in 2016 at the same sites and new sites, and will be used to test the validity of the models.

**Results and Discussion**

Green dry matter ranged from less than 100 kg/ha (ryegrass and phalaris pastures in autumn and early winter in Tasmania, Victoria and the Northern Tablelands) to 10 700 kg/ha (ryegrass in spring on the northern Tablelands), with 80% of the GDM between 370 and 3 800 kg/ha.

In many instances, the NDVI 'saturated' near 0.8 (e.g. Figure 1a) as the scanned canopy prevented detection of the biomass below (Liu et al., 2012). This saturation necessitates the inclusion of height in the calibration models (Figure 1b). In some instances, height alone provided the better model, though this was uncommon, and occurred when only a restricted NDVI range was sampled (Figure 1c).

The calibrations of GDM for measurements made in winter and spring in each region were moderately well correlated with the NDVI x height index (r2 = 0.62 to 0.77, Table 1). The winter-spring period is of key importance for southern producers, and the strength of the combined data provides a confidence that regional calibrations can be deployed to provide objective estimates of GDM.

(a) (b) (c)

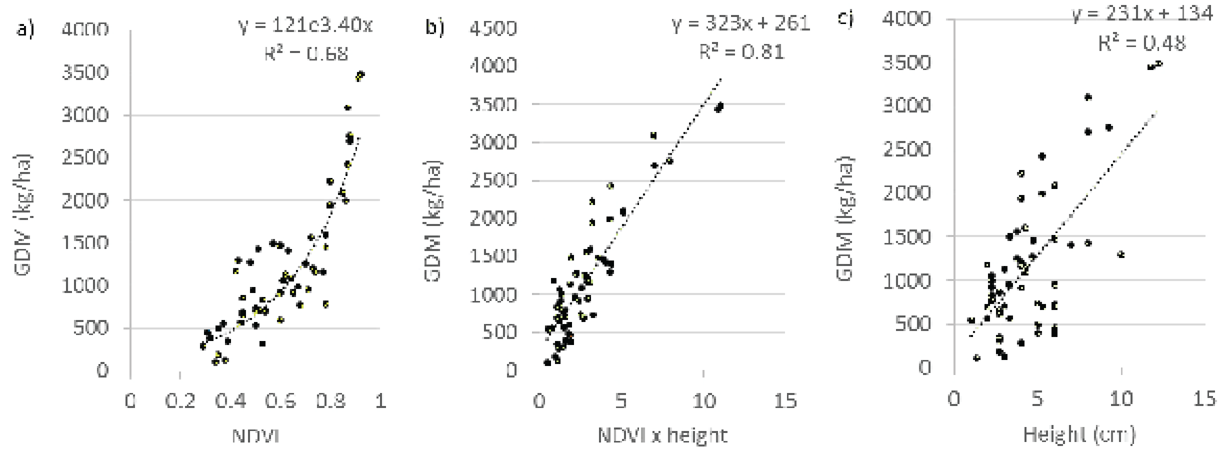


**Figure 1. Example of GDM against a) NDVI, b) NDVI x height, and c) height.**

The relatively large error (RMSE) associated with the models indicates the constraints when combining datasets, and further investigation into the pasture and environmental conditions (e.g. seasonal conditions, soil moisture, clover content) leading up to sampling are warranted. Further refinement needs to consider the effects of bare soil and of senescent material in the pasture canopy that influence the NDVI measurement.

The effect of varying conditions on the calibrations is shown by the decreased reliability of the model when including the autumn and the summer cuts in the Northern Tablelands (Table 1). The majority of the additional cuts in the Northern Tablelands were taken on pure swards. The differences that emerged may reflect the different phenological responses of the species measured, differences that may not be so distinct in more mixed swards. In contrast, some individual sets of cuts taken at each site yielded better results (r2 up to 0.97). Such high individual correlations provide the scope for producers to tailor calibrations to their conditions.

The results showed the potential benefits of using AOS to estimate pasture biomass. As the aim of developing the GS calibrations is to enable farmers to rapidly and objectively estimate biomass, a ready estimate of height is also required. To address this requirement, we are trialling a lidar to collect height data (Trotter et al. 2016, Schaefer and Lamb 2016). In addition, we and developing a mobile phone app to calculate biomass in real-time using the calibrations. These systems also provide the potential to locally calibrate satellite remote sensing systems, thereby expanding the area and frequency of pasture biomass assessments for livestock producers. Ideally, the development of combined units measuring height, NDVI and providing real-time biomass estimates will provide a package that can be easily used by producers.


## Acknowledgements

This work was funded by the CRC for Spatial Information (CRCSI), established and supported under the Australian Government's Cooperative Research Centre's Program, and Meat and Livestock Australia (MLA).

**Table 1. Calibrations for grass-based pastures in NSW, Victoria and Tasmania.**

| Region | | Combined Winter+Spring | All cuts |
|---|---|---|---|
| Northern Tablelands | $r^2$ | 0.70 | 0.45 |
| | n | 289 | 545 |
| | Mean | 2191 | 2616 |
| | RMSE | 982 | 1312 |
| Central Victoria | $r^2$ | 0.77 | |
| | n | 66 | |
| | Mean | 1373 | |
| | RMSE | 541 | |
| Southern Victoria | $r^2$ | 0.62 | |
| | n | 82 | |
| | Mean | 1743 | |
| | RMSE | 375 | |
| Western Victoria | $r^2$ | 0.77 | |
| | n | 326 | |
| | Mean | 1206 | |
| | RMSE | 469 | |
| Tasmania | $r^2$ | 0.66 | 0.68 |
| | n | 82 | 153 |
| | Mean | 1189 | 1120 |
| | RMSE | 403 | 380 |

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## Notes

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