Society of Precision Agriculture AUSTRALIA

Sydney Institute of Agriculture

Precision Agriculture Laboratory
monitoring | mapping | management

22nd Precision Agriculture Symposium

Monday 9th - Tuesday 10th September 2019

Tramsheds Function Centre
Launceston, Tasmania

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Acknowledgements
This event has been made possible by the generous support of industry. This event is supported by Grains Research & Development Corporation, John Deere, Case IH, Vantage, Topcon Agriculture, Decipher, Data Farming, Ag Leader, Farmers Edge, Echelon, Emmetts, Raven, Ag Logic, Precision Agriculture, Agri Technovation. SPAA wishes to thank these organisations and businesses for their financial assistance in putting this event together. SPAA also acknowledges the contributions from the South Australian Grains Industry Trust (SAGIT) for assisting with the travel arrangements of our grower speakers.

Welcome!

We are in Tasmania for the 22nd Symposium on Precision Agriculture in Australasia, and it is the first time this forum has been held in this 335-island state. A broad range of agricultural activities are undertaken on the main island and the program we have constructed reflects this diversity.

At present there are increasingly complex pressures being brought to bear on farming businesses that must compete on the global stage. Fluidity in trade agreements at the national level, regulatory and climatic issues at the state and local levels, and a plethora of data on production at the farm and field level.

The answer remains…….Precision Agriculture.

The International Society of Precision Agriculture (ISPA) has just completed an extended process of trying to democratically define PA. It has produced a wordy beast:

"Precision Agriculture is a management strategy that gathers, processes and analyses temporal, spatial and individual data and combines it with other information to support management decisions according to estimated variability for improved resource use efficiency, productivity, quality, profitability and sustainability of agricultural production."

It could be argued that a strategy definition doesn't need the inclusion of the tactical data handling detail and that it misses a more overt link to business interactions beyond the farm gate. And it is the issues (and potential data) noted above that are coming from outside the individual farm fences that may well be increasingly important for strategically managing agricultural businesses with precision.

This Symposium will display ideas and technologies that are at the leading edge of developments for the much broader definition of PA that we here in Australasia are all aiming towards. Many people work towards building this event and we trust that you will benefit from the interactions at the domain and personal levels, gain and share insights, and enjoy the southern hospitality at 41.4332° S.

Brett Whelan for The PA Lab and SPAA teams

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Presentation program

MONDAY 9th SEPTEMBER 2019

10.00am	Arrival and Registration
10.30am	SPAA AGM
11.00am	Opening (SPAA President)
11.10am	Mapping soil moisture with an L-Band radiometer on irrigated dairy pastures in Tasmania. *James Hills (TIA)*
11.30am	Field-scale estimation of water use efficiency using historical yields and climate data. *Fiona Evans (Murdoch Univ.)*
11.50am	The Monash-Bosch AgTech LaunchPad. *Christoph Rüdiger (Monash Uni)*
12.10pm	PA and soil management techniques. *Michael Nichols (TAS grower)*
12.30pm	Industry news – John Deere
12.40pm	Lunch
1.30pm	Mapping the spatial extent of soil constraints at the farm-scale. *Edward Jones (PALab USYD)*
1.50pm	Connectivity within an innovation ecosystem: Convergence of data and technology for regional benefit. *Stephen Cahoon (Sense-T)*
2.10pm	Simplot: the journey to PA with Tasmanian potato growers: a story of average blokes battling with nerdy stuff. *Frank Mulcahy (Simplot)*
2.30pm	Site-specific weed management mapping system using an unmanned aerial vehicle (UAV). *Livia Faria Defeo (CAE USQ)*
2.50pm	SwarmFarm robotics: small machines, big technology. *Angus Hogan (SwarmFarm)*
3.10pm	Industry news – Case IH
3.20pm	Afternoon Tea
4.00pm	Industry news – Vantage
4.10pm	Innovation in vegetables: putting PA into practice. *Julie O'Halloran (DAF QLD)*
4.30pm	A vegetable grower's journey with PA. *Andrew Johanson (Mulgowie Farming Company) and Troy Walker (Phantom Farms)*
4.50pm	Using satellite imagery for mapping pasture biomass in real-time. *Iffat Ara (TIA)*
5.10pm	Predicting gastro-intestinal nematodes in sheep using on-animal behaviour sensors. *Jamie Barwick (UNE PARG)*
5.30pm	Industry news – *Echelon (sponsors of PA Connections)*
5.40pm	Close
5.45pm	PA Connections @ Trade Displays
7.00pm	Symposium Dinner @ Tramsheds

TUESDAY 12th SEPTEMBER 2019

8.30am	Welcome
8.40am	Progress in using off-site data for PA. *Mario Fajardo (PALab USYD)*
9.00am	Soil moisture monitoring and prescription irrigation for growing lucerne in sandy soils. *Joe Cook (Keith, SA)*
9.20am	Establishment of a code of practice for agricultural field machine autonomy. *Rohan Rainbow (Grain Producers Australia)*
9.30am	Yield forecasting of root crops with a multispectral satellite sensor in Australia: results from the National Precision Vegetable Project. *Angelica Suarez (UNE PARG)*
9.50am	An approach to sensor-based N decision: updates from the first year of 'Future Farm' field trials. *André Colaço (CSIRO)*
10.10am	Industry news – Farmers Edge
10.20am	Morning tea
10.50am	Industry news – GRDC.
11.00am	SBAS GNSS for horticulture. *Dan Bloomer (Page Bloomer)*
11.20am	Practical data management in the cloud. *Rob Wade/Joe Cook (Sprayer Barn/grower)*
11.40am	Practicing precision: a basis for making precision pay. *Jon Medway (CSU)*
12.00pm	Close and Lunch
12.30pm	Optional PA in Practice tour leaves the Tramsheds
3.30pm	Tour bus @ Launceston Airport
4.00pm	Tour bus @ Tramsheds

Mapping soil moisture with an L-band radiometer on irrigated dairy pastures in Tasmania

Nan Ye[1], Jeff Walker[1], In-Young Yeo[2], Tom Jackson[3], Yann Kerr[4], Ed Kim[5], Andrew McGrath[6] and James Hills[7]

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[2] School of Engineering, University of Newcastle, NSW.
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[4] Centre National d'Etudes Spatiales, 75 039 PARIS CEDEX 01, France.
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Summary

To test the potential of using remote sensing techniques for better optimising irrigation scheduling, a field experiment using both airborne and ground based platforms was conducted over an irrigated pasture site in Cressy, Tasmania during January 2017. A range of instruments were used during this experiment, including airborne L and P-band radiometers and optical and thermal cameras, a buggy-based L-band radiometer, and a hand-held soil moisture sensor.

An aircraft was used to carry the Polarimetric L and P-Band Multibeam Radiometers (PLMR and PPMR respectively), as well as a Canon EOS-1Ds Mark III Digital Single-Lens Reflex (DSLR) camera, a modified Canon 5D Mark III DSLR camera for NDVI, and a FLIR A65 Thermal InfraRed (TIR) camera (Figure 1).

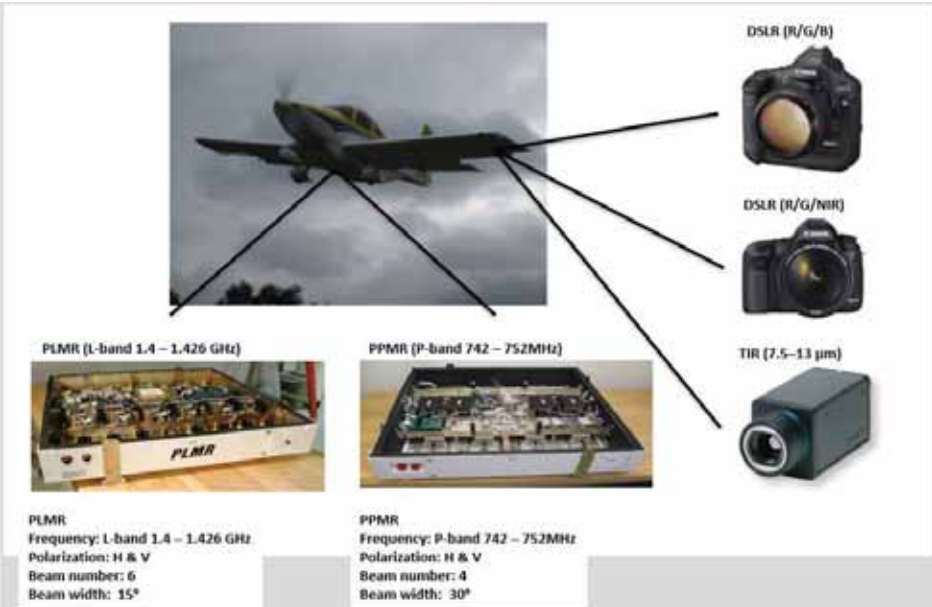

Figure 1. Location of the L and P-band radiometers, digital cameras, and TIR camera on the aircraft.

The PLMR and PPMR mounted on the aircraft provided L-band (1.413GHz) and P-band (752 MHz) dual-polarized (horizontally and vertically) brightness temperature observations at 75m resolution. Similarly, the ETH L-band radiometer (ELBARA), mounted on a small all-terrain farm buggy (Figure 2), provided L-band (1.4GHz) dual-polarized (horizontally and vertically) brightness temperature observations at 25m resolution. A Hydraprobe soil moisture sensor Data Acquisition System (HDAS) (Figure 3) was used as a ground sampling tool for ground validation, providing soil moisture readings on a 75m grid spacing.

Figure 2. Buggy platform, consisting of ELBARA III, multi-spectral sensors (VNIR, SWIR, and TIR), and GNSS-R sensor (LARGO).

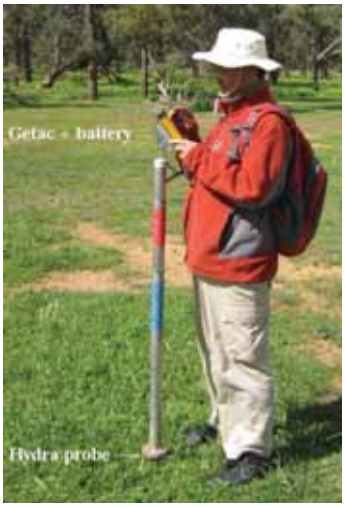

Figure 3. Hydraprobe Data Acquisition System (HDAS).

The preliminary result shows high sensitivity of L-band brightness temperature (TB) to soil moisture (Figure 4), and better spatial retrieval pattern than optical imagery. A fundamental limitation with current L-Band remote sensing technology is that it can only provide moisture information on the top ~ 5 cm layer of soil at most, being one-tenth to one-quarter of the wavelength (21 cm at L-band; 1.4 GHz). To address this limitation an airborne passive microwave sensing capability at P-band (40cm, 750 MHz) is being developed that will provide soil moisture data for the top 15 cm layer of soil.

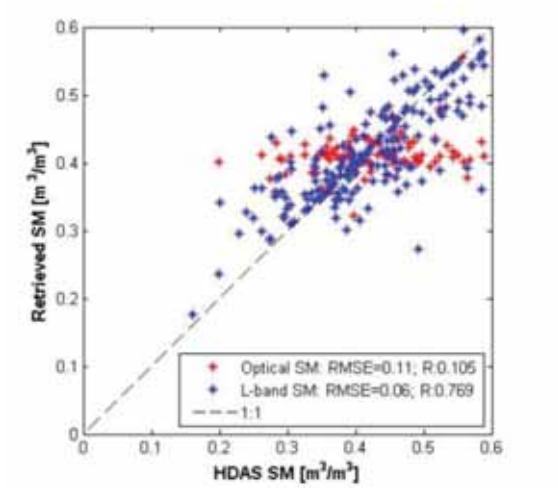

Figure 4. Contrasting sensitivities of PLMR and optical soil moisture predictions based on the thermal and NDVI data.

An example of this PPMR spatial data along with the PLMR and the HDAS soil moisture data is shown in Figure 5. Not only would P-band provide soil moisture information on a soil layer thickness that more closely relates to that affecting crop and pasture growth, but is also expected to produce greater spatial coverage due to the ability to monitor densely vegetated surfaces, and with improved accuracy to that from L-band due to the greater transparency of vegetation and the reduced impact of surface roughness.

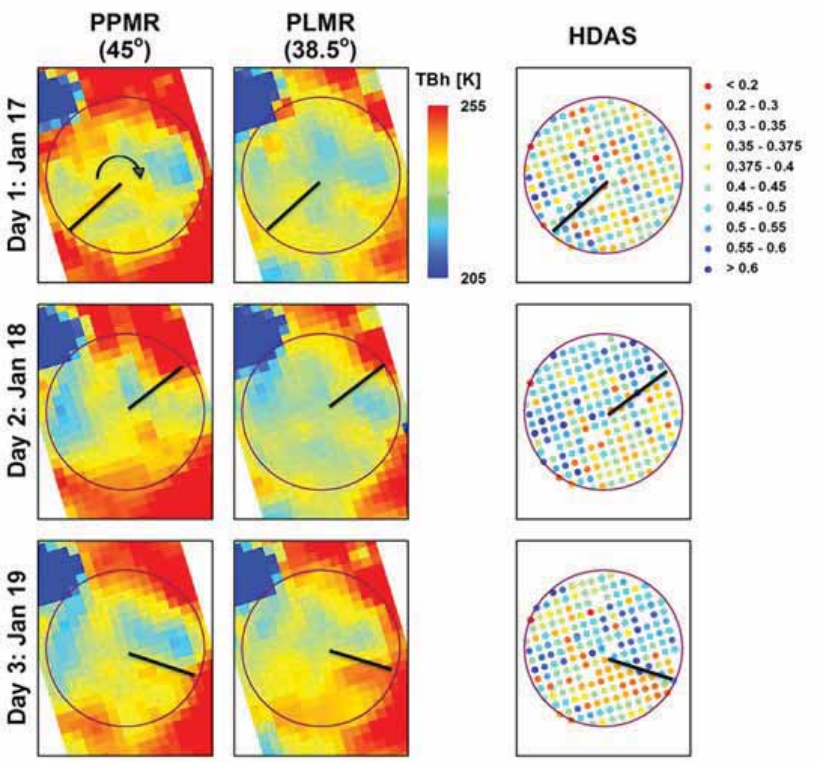

Figure 5. Data collected on 17th, 18th and 19th January 2017: Temporal variation in soil moisture from PPMR and PLMR brightness temperature and HDAS soil moisture data (in cm3/cm3). Also shown here is the location of the irrigation boom (black bars) on each day which moved clockwise.

Field-scale estimation of water use efficiency using historical yields and climate data

Fiona Evans

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Summary

In Australian dryland cropping systems, the largest driver of wheat yield is the amount of water available to the crop during the growing season. The most commonly used estimate of yield potential, the French & Schultz (F&S) model, estimates water-limited potential yield by:

$$Yield = WUE\ (Wavail - evaporation),$$

where $Yield$ is measured in kg/ha, $Wavail$, the water available to the crop, is defined to be one third of summer (November to March) rainfall plus growing season (April to October) rainfall, WUE is an abbreviation for water use efficiency (French and Schultz, 1984). The original definition of the model estimated model parameters $WUE = 20$ and $evaporation = 110$; however common use varies the parameters according to geographic location and rainfall zone.

Because the F&S model does not account for yield variation due to soil type, the 'broken stick' model, is commonly used in Western Australia. It imposes an upper bound to yield potential using a threshold on $Wavail$ that is based on the plant available water capacity (PAWC) of the soil (Oliver et al., 2009). However, PAWC can be expensive to measure, and there can be large variation in PAWC within soil types (Oliver et al., 2006).

This presentation describes a data-driven method that uses a long-term sequence of paddock yield maps to estimate WUE and yield potential across a paddock. The method integrates readily available information measured on and off the farm to provide insight into the spatially variable yield potential of the paddock. Using a nitrogen response model, this approach is shown to have value for site-specific management of fertiliser inputs.

References

Oliver Y. M., Wong, M., Robertson, R. and Wittwer, K. (2006). PAWC determines spatial variability in grain yield and nitrogen requirement by interacting with rainfall on northern WA sandplain. *Proceedings of the 13th Australian Agronomy Conference*, 10-14 September 2006, Perth, Western Australia. Australian Society of Agronomy.

Oliver, Y. M., Robertson, M.J., Stone, P. J. and Whitbread, A. (2009). Improving estimates of water-limited yield of wheat by accounting for soil type and within-season rainfall. *Crop. Pasture Sci.* 60 (12): 1137–1146.

The Monash-Bosch AgTech LaunchPad

Christoph Rüdiger[1], Roslyn Gleadow[2]

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Summary

In order to meet the requirements of future food production, novel technologies to support agricultural practices and supply chains need to be developed and tested. AgTech 4.0 continues to provide opportunities to reshape the agricultural economy as it has the capacity to deliver real time information and improve procurement, transport, manufacturing and quality – while providing the basis for improved transparency and assurance of the food chain.

However, it is often not achievable to undertake extensive field trials with technologies conceived in the laboratory or at the desk. In order to overcome this problem, Monash University and Robert Bosch Australia have joined forces to establish an open and flexible innovation research translation platform where novel technologies can be easily field tested at a smaller scale, before going to the farm-scale. Such a site will allow researchers to validate a proof-of-concept study before full scale farm trials, in close proximity to the lab, allowing for a faster iteration and involvement of a broader range of students and local industries.

The site has been designed and chosen to encourage agile and modular working habits to increase utilisation through interdisciplinary collaboration and industry engagement. In particular, start-ups and scale-ups are welcome to demonstrate their technologies, as the LaunchPad is specifically not reserved for Monash and Bosch, but is an open collaboration platform for industry, other universities, and the government sector.

Current projects include various aspects from a broad background, such as remote sensing of surface hydrology, studying pollination, nitrogen uptake in plants and a technology demonstration by GoTerra, a circular waste management scale-up. Further projects will be established throughout August.

PA and soil management techniques

Michael Nichols

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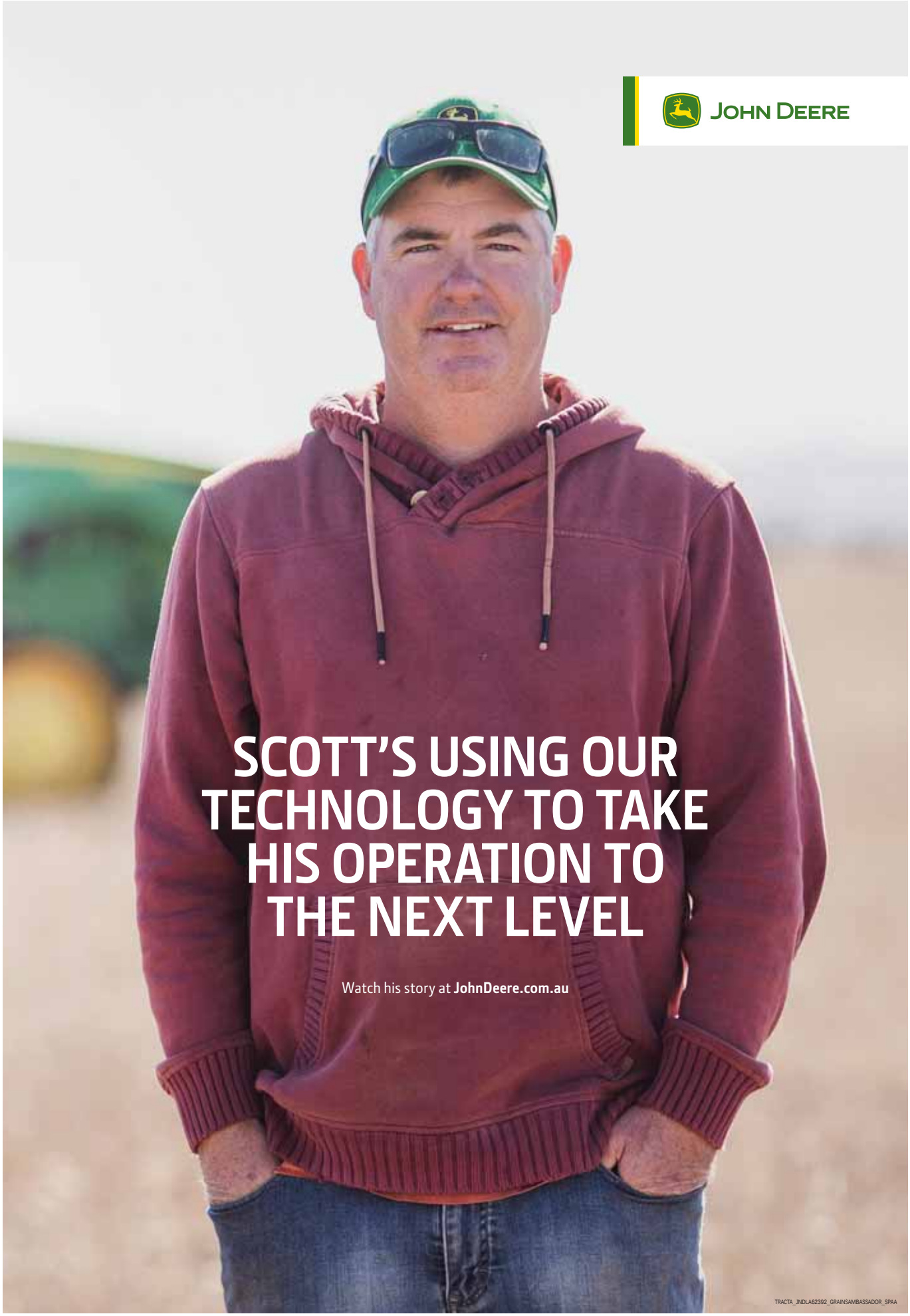
Summary

Michael grows wheat, canola, barley, onions, potatoes, poppies, pyrethrum and yellow mustard seed in red basalt clay loam soils. He also further diversifies with beef cattle and contracting arms to his business.

High rainfall (~1200mm) coupled with fertile red basalt clay and loam soils make high yields achievable, but it is a case of getting out what is put in previously. Michael uses a full-analysis soil test on all paddocks each season to make sure they are not depleting nutrient reserves. This information is used to make custom blends of fertiliser for each field and crop which are then applied through accurately timed variable-rate inputs and a stringent disease management program. During January 2018, Michael's attention to detail saw him harvest an Australian crop record for wheat, with an average yield of 13 tonnes per hectare off 16.6ha, with a net return of $1777/ha.

The use of detailed soil mapping and in-season NDVI monitoring (drone technology) allows Michael to develop his own prescription fertiliser maps, which drives variable rate application of fertiliser inputs throughout the growing season. This variable-rate approach not only evens out the crop in terms of performance in Michaels's case, but also drives significant savings on input costs.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Mapping the spatial extent of soil constraints at the farm-scale

Edward Jones[1], Pat Hulme[2], Brendan Malone[1], Alex McBratney[1]

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Summary

This research presents a case study of applying digital soil mapping techniques to delineate the spatial extent of soil constraints on a large cotton farm in Queensland, Australia. A proximal sensing survey was conducted to collect electromagnetic induction, gamma radiometric and elevation data over an area covering ~2,000 ha. A cut and fill map and a bare soil redness index from the Landsat 5 satellite were combined with the data from the proximal sensing survey to create a covariate database. This data was used to direct the sampling of 70 soil cores at four depths (0-30, 30-60, 60-100, 100-140 cm) which were analysed in the laboratory for pH(1:5 $CaCl_2$), exchangeable cations, EC and texture (sand, silt, clay). Relationships between the laboratory measured properties and the covariate dataset were investigated and used to create surfaces of each property at the four depths across the study area. Correlations between modelled soil properties and cotton lint yield for the 2016-'17 growing season and satellite borne vegetation indices for five years in total were investigated. Modelled soil properties were found to have greater correlations with cotton yield and vegetation indices than proximal sensed data alone. A multivariate yield model was constructed on a per paddock basis and used to deconvolute potential negative effects on yield from individual soil properties. This approach identified discrete locations across the study area where depth to an exchangeable sodium percentage (ESP) of 10%, depth to an electrical conductivity (ECe) of 10 dS m^{-1}, and areas of reverse grade in elevation were likely to be responsible for reduced cotton yield. Delineation of yield constraints in this way provided insight into management options to ameliorate these constraints.

Connectivity within an innovation ecosystem: convergence of people, data and technology for regional benefit

Stephen Cahoon

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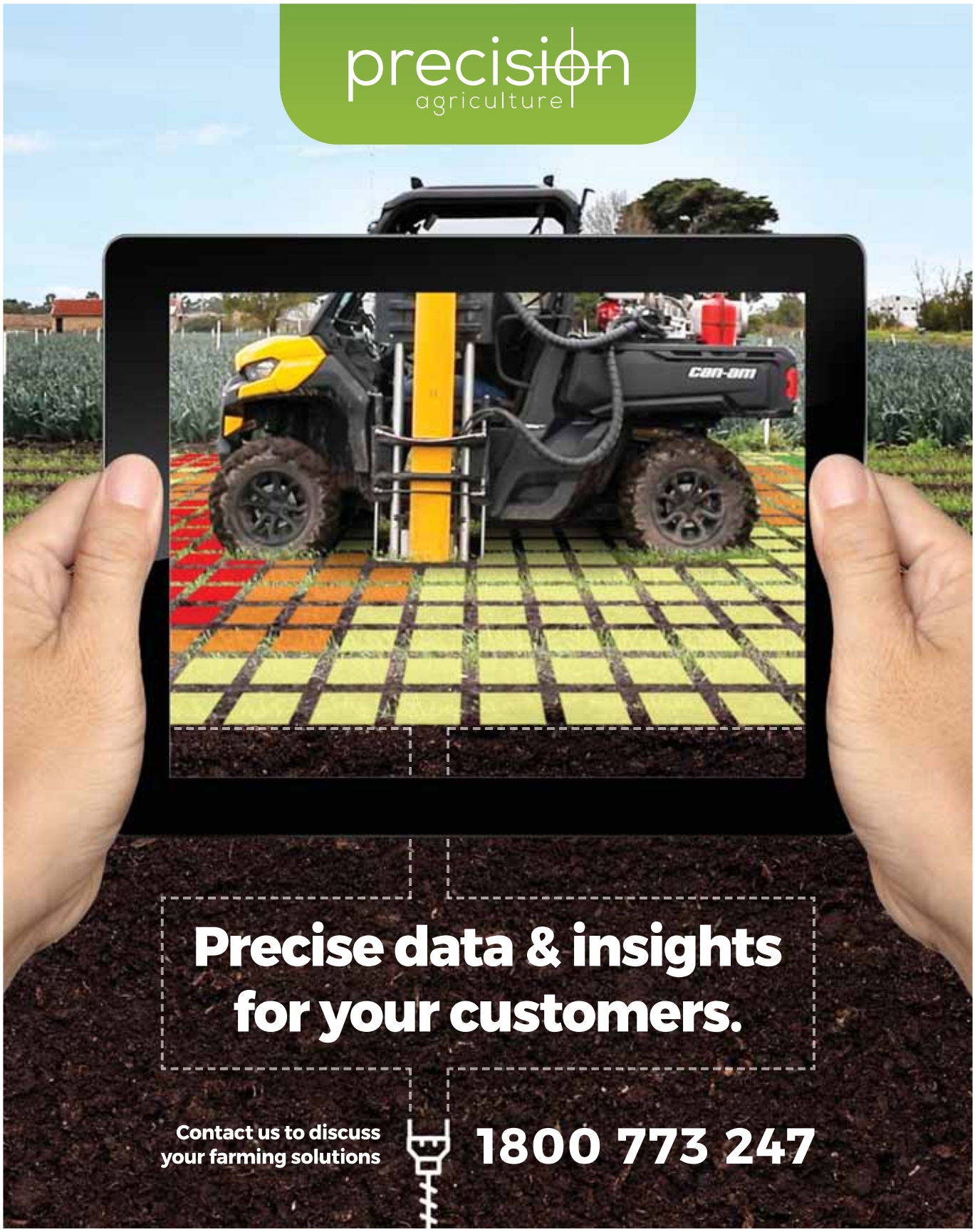
Summary

Too often, the introduction of new technologies prompts discussion directly related to the technologies such as sensors; instead of the focus being on the value and benefits users can gain from adopting the technologies. In particular, the value and benefits can be gained from new insights, verifying rules of thumb currently used in industry, and indeed gaining evidence from data that rethinks urban myths and their influence on current practices. The opportunity that awaits is the converging of people, data and technology and undertaking this within an innovation ecosystem.

The integrated innovation ecosystem developed by Sense-T is one approach that has provided a foundation on which to develop strong collaborations in a people-centric manner beginning with a co-understanding of the issues facing industry from the small to medium to large businesses that leads to co-designing workable and realistic solutions within the constraints that may be faced by the organisation. Assessing the data currently collected and/or available and then determining other data that may be required to assist decision-making is core to the design and development of the solutions, potentially in the use of sensors, and often in remote locations.

Thus, connectivity becomes the means of achieving workable solutions, that is, connectivity between people, connectivity between sensors and data platforms via cost-effective telemetry options, and connectivity between data from various sources in a federated manner. Through the Sense-T projects funded by industry and government over a period of over seven years, the integrated innovation ecosystem has been tested and refined, and represents an end-to-end data value chain approach to creating solutions via people, data and technology. Connectivity examples provided in the presentation explain how LoRa networks (low power, long range) have been used with success in rural, semi-rural and urban environments.

The Sense-T innovation ecosystem is now undertaking a new iteration into regional and national contexts, some of which involve the development of decision supports systems to provide data across complete interstate supply chains from farm to retail markets. However, the core of the innovation ecosystem remains - the convergence of people, data and technology and importantly the need for a meaningful collaborative approach between business, government and researchers.



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FARM PERFORMANCE

APPLIED RESEARCH

Simplot: the journey to PA with Tasmanian potato growers: a story of average blokes battling with nerdy stuff

Frank Mulcahy

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Summary

Eleven years of cumulative work has created better understanding of variations in crop performance, the linkages to inhibiting soil conditions such as drainage, depth to clay and pathogen populations.

From 2008

EM38 soil conductivity mapping was used to understand field variations, quickly followed by aerial NDVI imagery and eventually yield mapping capability on potato harvesters. Computerised crop modelling was an emphasis for several years only to be benched due to inaccuracy.

Working closely with Neil Meadows of Terrapix we evolved into the PA space relatively quickly with Neil imaging potato crops through the floor of a Cessna aircraft. Neil's work at the time was globally leading with 100 potato crops being imaged and formatted within 24 hours. "Fly today, provide the image to the customer tomorrow". Locally, Michael Coote, an innovative farmer from Scottsdale had developed a variable rate centre pivot irrigator. In 2014 the learnings were bolstered by Sydney University in a joint project led by Prof. Brett Whelan with funding from HIA (Project PT 13000). So, the potential for a complete set of maps for any crop site was researched and provides a foundation for growers. Through our work we seeded the market but the foundation is yet to be built upon.

Predicta PT®, pathogen DNA analysis provided by SARDI, has been employed since its commercial inception in 2009 and good understanding of pathogens is ever growing. Current work includes strategic mapping of GPS'd locations within potato crops where regular sampling of soil is helping determine the timing of disease proliferation and the potential for more strategic disease management.

NDVI imagery shows the relationship with yield and soil-borne disease. A negative correlation with the nematodes Pratylenchus penetrans and Pratylenchus crenatus suggests a tendency for the present loads to be negatively impacting yield. Positive correlations with Pratylenchus neglectus, Meloidogyne hapla and Powdery Scab may indicate that where yield is highest, pathogen loads are beginning to build but are not yet at damaging levels.

NDVI imagery has shown:

- Substantial within-field and between field variation in soil physical and chemical properties, elevation and crop yield.

- Differences in both plant N and plant P, the two major elements applied in fertilizer management regimes, are significantly influencing NDVI

- Early season NDVI surveys are responding significantly to differences in soil properties and disease pathogen load.

- Soil Nitrogen and Potassium show a significant positive relationship with yield and the results suggest that when the exchangeable cations Al, Ca and Mg increase as a portion of CEC then yield can be negatively impacted.

- Manganese concentrations in the plant tissue show a positive relationship with yield which may indicate an important potential for deficiency in the regions.

- Significant correlation to soil physical variability when gathered early in the season

- Significant variation in plant physical and chemical properties, as well as important soil nutrient properties and crop yield when gathered from week 14 onwards.

- Greater than 3-fold variation in potato yield within fields (mean 64.3 t/ha, S.D. 17 t/ha) warrants continued, and more detailed investigation into improvements in the allocation of inputs to the potato production system.

- Accurate, easy to gather yield data will be essential for the development of site-specific management in potato production. Improvements to existing retrofit systems should continue and harvester manufacturers encouraged by industry to develop factory-fitted systems.

- The use of mid-season aerial imagery should be encouraged for the early detection of within field deficiencies in the major macronutrients (N,P,K). Reflectance measurements other than NDVI (e.g. red edge NDVI, thermal) should be explored.

- The use of early-season aerial imagery to detect build-up of soil-borne pathogen load should be further investigated.

- Variable-rate irrigation should be explored based on the changes in soil type identified using soil ECa surveys or early-season aerial imagery. Results here suggest there may still be a significant negative impact on yield from temporary waterlogging caused by within-field variation in soil water holding capacity.

So, in 2019?

The Precision Ag work has identified the blockages, mostly engineering issues, which need refinement to be broadly adopted by growers. The historic pathogen DNA mapping project is identifying the ebb and flow of pathogens and the probable best fit of other crops within the whole rotation.

Simplot within its own farming operation has strong back up by Rueben Wells providing elevation maps and drainage plans. The mantra of “plants don’t eat, plants drink, plants drink but they don’t swim” emphasises the importance of water use in crops. Drainage is critical and total elimination of potentially wet areas from being planted mitigates risk. One is far better to plant and harvest 70% of an area rather than plant 100% of the area with the risk of losing 30%.

We don’t use the yield monitors on potato harvesters at this time. This is an engineering and timing issue. An accurate map cannot be generated until the crop is fully harvested and it requires a technician to generate the map. Going forward, yield maps will need to be live so a farmer can truth points of variance within a crop at the time of harvest.

We currently yield map our annual harvest of 3,500 hectares of processing peas, with processing beans and sweet corn to be included.

Some of the progressive famers who have invested in precision aids feel somewhat frustrated at the lack of after sales service. There are many solutions being marketed but they don’t always address the problem.

Site-specific weed management mapping system using an unmanned aerial vehicle (UAV)

Livia Faria Defeo, Bruen Smith, Troy Jensen

Centre for Agricultural Engineering, The University of Southern Queensland, QLD.

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Summary

There is currently a need to optimize herbicide application, in order to minimize its use and resistance. Precision agriculture is used by many farmers to optimize their operations and reduce various inputs. However, current herbicide spray systems do not yet fully utilize boom section control to deliver targeted herbicide application. Although there are many platforms available in the market to create variable rate prescription maps, these systems are not suited to detailed broad acre herbicide application. As a result, farmers often choose to conduct blanket herbicide applications, which leads to a negative environmental impact and promotes herbicide resistance.

With recent advances in Unmanned Aerial Vehicle (UAV) systems, it is now possible to image large fields (> 40 hectares) with relatively high resolution (< 2.5cm) and observe weed infestations in detail. However, there exists a gap in the current technology to create workable prescription weed spray maps from this imagery. Therefore, the University of Southern Queensland has developed a mapping system, which automatically generates herbicide prescription maps using UAV imagery and machine vision techniques, in order to provide an alternative to current herbicide application systems and as a market entry into precision spot spraying.

SwarmFarm robotics: small machines, big technology

Angus Hogan

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SwarmFarm Robotics has had their machines contracted out and operating on beta tests for various users, and now the company has released a commercial agriculture robot 'Indigo' based on its SwarmFarm 5 platform. The company has numerous plans for developing uses for the SwarmFarm 5 platform which will be discussed

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Innovation in vegetables: putting PA into practice

Julie O'Halloran[1], Celia van Sprang[1], Gayathri Rajagopal[1], Ian Layden[2]

[1] Queensland Department of Agriculture and Fisheries, Gatton, QLD.
[2] Queensland Department of Agriculture, Nambour, QLD.

Summary

Adoption of precision agriculture (PA) in the Australian vegetable sector, although still in its infancy, is increasing. The aim of the project, "VG16009: Adoption of precision systems technology in vegetable production" has been to demonstrate commercially accessible PA technologies to increase adoption within the industry. Several case studies have been documented throughout the project that include the use of technologies, such as drones, soil mapping sensors (EM38, Veris® and SIS), specialised application of machinery (e.g. yield monitors, TerraCutta® software for precision landplaning and variable rate applications) in a range of vegetable crops and across Australia.

These case studies focused on why the technology was implemented, what was done and how the results/information from these technologies are being used and resulting management outcomes. Where possible, cost-benefit information was also incorporated into the case study. From these case studies, project staff have identified increased adoption across various applications of PA technologies. This includes the use of drones in vegetable systems, precision drainage technologies, and soil sensing to better manage in field variability.

A key component in these case studies was the involvement of relevant PA service providers. This has facilitated a broader network for both growers, agronomists and PA service providers. One of the key outcomes of this project has been the next steps in PA identified by case study participants, highlighting their continued PA journey into the future.

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A vegetable grower's journey with PA

Andrew Johanson[1], Troy Walker[2]

[1] Mulgowie Farming Company, Mulgowie, QLD.
[2] Phantom Produce, Bowen, QLD.

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Mulgowie Farming Company

Andrew Johanson is the Sustainable Farming Practices Manager for the Mulgowie Farming Company, which is the largest producer of fresh sweet corn and green beans in Australia. They are also significant producers of broccoli and pumpkin.

Starting as a small family farming venture in the Lockyer Valley over 75 years ago, Mulgowie Farming Company has grown to over 5000 hectares of production across Queensland, New South Wales and Victoria and has earned a reputation for being an industry leader in the growing, packing, distribution and marketing of Australian fresh vegetables.

The company embraces advances in soil science, alluvial geomorphology, precision agriculture and agronomy in the management of the farms, soil and crops.

Phantom Produce

Troy Walker and family own Phantom Produce, which runs a capsicum, cucumber and tomato growing operation in Bowen for both domestic and export markets.

The region has had a number of weather-related challenges in the recent past that have impacted production. On top of these, the business works at staying sustainable and profitable, keeping up with new industry regulations as well as maintaining sound biosecurity practices.

Phantom Produce have introduced larger tractors, GPS auto-steer for controlled traffic farming and variable-rate fertiliser application and moved to trickle irrigation to help tackle some of these challenges.

Using satellite imagery for monitoring pasture biomass and real-time

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Summary

For effective pasture utilisation, livestock grazing systems require real time pasture monitoring and measurement. Manual techniques are laborious and have limited large-scale application due to the area of the paddocks required to be monitored. The recent inception of large, freely available daily volumes of data from earth observation sources have potential to aid real time management of pastures remotely, saving livestock managers both time and money.

The aim of the present research is to use daily high resolution multi-spectral (RGB and NIR) images from Planet Labs to determine whether such imagery can be used in real-time for monitoring to aid grazing management decisions for a wool producing enterprise. The study area located in Okehampton, approximately 10km north of Triabunna on Tasmania's east coast, with Merino sheep rotationally grazing paddocks over almost 1000 ha. We used machine learning to estimate pasture biomass within each of the 32 paddocks. Destructive Field samples of pasture biomass were undertaken with samples collated and used to validate the model. This is a work in progress. If the validation is satisfactory, we will assess the capability of Planet Labs imagery to be used to determine how often sheep should be moved from one paddock to another based on a minimum pasture biomass threshold.

Predicting gastro-intestinal nematodes in sheep using on-animal behaviour sensors

Jamie Barwick[1], Glen Charlton[2], Jane Lamb[3], Derek Schneider[1]

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Introduction

As the push for greater production from a smaller resource base continues, Australian graziers are being forced to look for ways to sustainably increase outputs. The cost of roundworms to the sheep and wool industry is in excess of $430 million annually (Lane et al. 2015), which is the highest animal health cost the industry faces. This is a rise from the earlier estimates of $369 million (Sackett et al. 2006) with approximately 80% of these costs associated with lost production. Not only can roundworms significantly reduce productivity, they can potentially result in compromised animal welfare at the individual and/or flock level.

Given the rise in anthelmintic resistance along with the stable lamb market and increasing wool prices, there is a need to investigate ways of lowering these annual economic losses. Innovative solutions are required to meet this challenge, particularly through the early identification of infected individuals. If graziers were able to identify worm infections before clinical symptoms become apparent (i.e. high FECs), there is potential to substantially reduce the associated high levels of lost productivity.

This project investigated the potential to develop a behaviour prediction model capable of monitoring gastro-intestinal nematode infections in sheep based on activity measurements derived from accelerometers. Behavioural algorithms may help livestock producer's decision making via the detection of individual animals displaying abnormal behavioural patterns associated with worm infection, potentially leading to earlier detection and intervention before clinical disease becomes apparent.

Methods

The project consisted of 30 Merino hoggets, randomly separated on weight into three treatment groups with 10 animals per group: 10 animals artificially infected with 4000 L3 *Haemonchus contortus* larvae, 10 animals artificially infected with 6000 L3 *Trichostrongylus colubriformis* larvae and 10 control animals (uninfected). The trial ran for 38 days with control animals being drenched on a weekly basis from day 21 onwards. Weekly faecal egg counts (FECs) and packed cell volume (PCV) measurements were taken to assess for level of internal parasite infection and host wellbeing. A threshold level of 1000 eggs per gram (epg) was set with all animals exceeding this threshold being treated with Zolvix (anthelmintic drench). On days 21 and 28, 6 and 3 animals respectively from the *H. contortus* group exceeded this threshold. Accelerometers and GNSS tracking collars were deployed on animals within each group to monitor animal behaviour and location. From the accelerometer signatures, a behaviour prediction model was developed from which variations in activity durations between groups was investigated. GNSS collars provided the average daily distances travelled per animal, allowing weekly comparisons between treatment groups to be analysed.

Results

A behaviour prediction algorithm was developed from the ear attached accelerometer sensor. To develop an accurate prediction model, a number of different machine learning algorithms were tested for accuracy and sensitivity. The dataset used for model development had the following distribution of behaviours: grazing (46%), standing (28%), walking (12%) and lying (14%) and was obtained from 5 individual sheep across 37 hours of observation. As shown in Figure 1, the Random Forest (RF) produced the highest overall prediction accuracy. Therefore, this model was used to segregate the entire 38 days of accelerometer data into active (34%) or inactive (66%) behaviour categories.

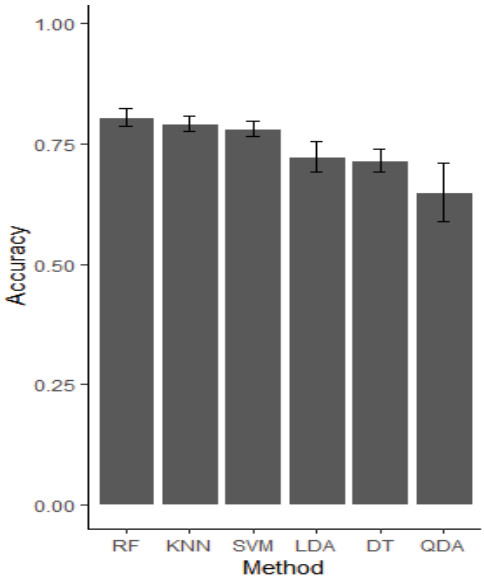

Figure 1. Accuracy of each method for predicting sheep behaviour: linear discriminant analysis (LDA), quadratic discriminant analysis (QDA), decision tree, support vector machine (SVM), k-Nearest neighbour (KNN), and Random Forest (RF).

The effect of internal parasites on activity levels

The filtered time series data was analysed to generate a dataset that contained the duration and start time (hour of the day) for every activity bout for each animal within the study. This was then used in a survival analysis. This was undertaken to determine if there is any difference in activity levels as animals begin to show signs of increased internal parasite burden. Survival analysis is typically used to analyse time periods related to failures and events, such as the death of organisms in response to treatment and disease or failures in equipment under differing stress levels or situations. Simply, it allows us to analyse the expected duration of behavioural events occurring. The Kaplan-Meier (KM) method (Kleinbaum, 2005) was applied to estimate survival functions for the *Haemonchus*, *Trichostrongylus* and *Control* group activity durations. The survival curved based on the probability of each length of active behaviour period (grazing and walking) were developed for each group and the statistical significance of the difference of each curve analysed. In order to remove mixed behaviours, activity bouts where only 10 successive epochs produced the same active/inactive status were used. Comparison between all groups (*Control*, *Haemonchus* and *Trichostrongylus*) across each week and comparison between weeks within each group was performed.

For Haemonchus group animals showing an epg > 1000 at day 21, there was no significant difference between weeks 1 and 2. There was significant difference between weeks 2 and 3 and a significant difference between weeks 1 and 3. This indicates animals with a high worm burden in week 3, had a lower probability of having longer periods of active behaviour. On

day 23, these animals were drenched. After drenching animals appeared to resume similar levels of activity as displayed in week 1, with pre and post drenching activity lengths being significantly different.

For Trichostrongylus group aniamls, no animals reached the drenching threshold and were therefore not drenched until trial completion (Figure 2). Activity period lengths declined from weeks 1 to 3, with activity lengths being significantly different between weeks 2 and 3 and 1 and 3. Control aniamls maintained a zero or low epg count throughput the trial period. There was little variation in the length of activity between weeks 1 to 3 with no significant difference.

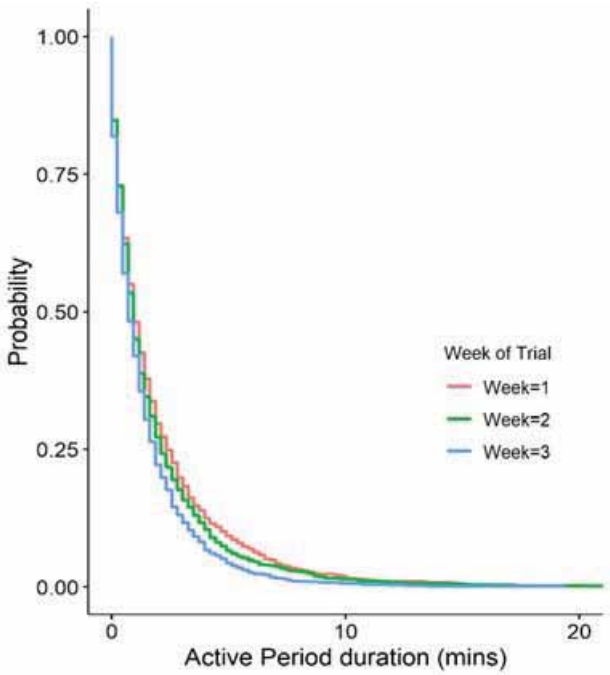

Figure 2. Kaplan-Meier estimates for the survival analysis based on the active period duration for the Trichostrongylus group animals across weeks 1, 2 and 3.

Conclusion

The potential benefits that a remote behaviour alert system could provide to industry are enormous. This project has identified activity levels of sheep differ with internal parasite burden, confirming the possibility that a real-time monitoring system, where producers can be alerted if their animals are showing abnormal activity patterns (i.e. an increase/decrease in grazing activity length) may become a reality. Similar modelling principles could also be applied to the identification of other diseases such as flystrike.

Acknowledgements

This project was funded by the Australian Government Department of Agriculture and Water Resources and Australian Wool Innovation Limited.

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Landmark Echelon

Variable Rate Potash

Case Study

Echelon is Landmark's Precision Agriculture Service. We offer a range of services and software to help meet agronomic needs. The following case study demonstrates how we work with clients to effectively manage problems in a precise way.

Problem

A historical lack of K inputs has resulted in highly potassium depleted sand across a paddock of mixed soil types. Due to logistical constraints at sowing K is being underapplied.

Solution

Together the grower and agronomist decided to spread Muriate of Potash as a capital top up in a variable rate application.

Grower Practice

The grower operation is 5,500ha over 70km, all cropped with an average wheat yield of 2.2t/ha and a wheat-wheat-barley-canola rotation. Fertiliser at sowing is commonly 55kg x MAP/MOP 70/30 + 50L UAN banded.

kg/ha	N	P	K
Applied at sowing	25	8.8	**8.1**
Approx. removal over rotation		7	**11**

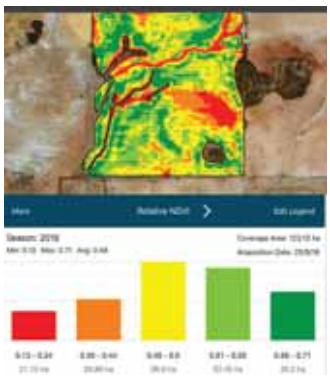
Financial Summary:

With the VR application, the saving to grower was 32kg/ha below the planned blanket application of 100kg.ha. This equates to a $18.50/ha saving.

Process:

There were five key steps to this PA process;

1. Does NDVI imagery at peak biomass match the agronomist and grower's knowledge of soil types? **No.**



2. Do colour images show soil type variation, eg Google Earth? **Yes.** Are there any soil tests? **Yes. But they don't cover the range of soil types. Agronomist wants to improve site selection for future sampling.**

3. Match the image with grower and agronomist knowledge and physical inspection to zone the paddock.

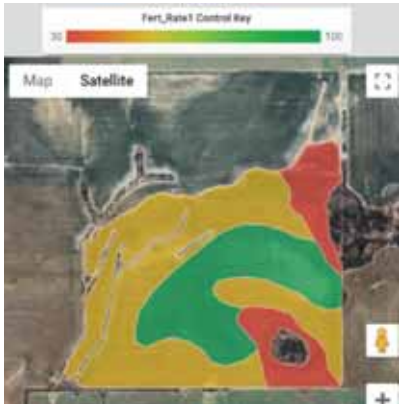
4. Decide on MoP application rates over a big range of soil types.

100kg MoP: Sand (beach sand) and yellow 'wodgil' (naturally acidic).

50kg MoP: Loamy sands and some light grey clay.

30kg MoP: Heavy red loam and 'Lake Loam' (Salmon gum vegetation)

5. Create VR map in Echelon, transfer to I4M online and execute application.



Progress in using off-site data for PA

Mario Fajardo

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Introduction

Precision agriculture practices and related instrumentation (i.e. grain yield and photosynthetic activity sensors, satellite imagery), provide an ever-increasing amount of data that can be effectively used as a support for decision making. While the adoption is gradually increasing, only some farmers are systematically collecting this information and only a few of them are making use of its full potential. A first study presented this year at the European Conference of Precision Agriculture (Fajardo et al., 2019), used a set of 47 contiguous paddocks located in Western Australia to test the possibility of forecasting yield potential at 5m resolution using no more than 6 covariate layers (NDVI imagery, modelled soil attributes and on-farm proximal sensing data) using state-of-the-art modelling i.e., Convolutional Neural Networks (CNN). First results showed that off-site data presents great potential for on-site decision making with external data. The objective of this new study was to forecast wheat yield at 5m resolution using the same methodology but with a bigger set of covariates (36 layers including several layers of satellite imagery, elevation data and modelled soil attributes). Preliminary results show a great improvement of the predictions with R2 values ranging from 0.4 to 0.71 with a mean of 0.35 and RMSE values from 7 to 18% of the total yield production.

Material and Methods

Study area

The study was conducted on a large aggregation of private farms (with 11 fields or paddocks used in this study and 47 in total) located in the southern agricultural region of Western Australia. The soils of the area are typically sandy with notable amounts of gravel, with Sodosols (Isbell, 2002) dominating.

Data layers

Thirty six layers where used including Sentinel-2 Bands 2,3,4,5,6,7,8,8A,11,12 and GNDVI, NDVI, MCARI , EVI,SATVI and SAVI indices for the clearest images of Autumn and Winter respectively (32 layers in total) plus elevation and slope from a Hydrologically Enforced 10m DEM (Geosciences Australia), and finally surface total nitrogen and clay derived from the Soil and Landscape Grid of Australia.

Model specifications

Intuitively, CNNs take most of the concepts of an Artificial Neural Network (ANN) (LeCun et al., 1990) which are an attempt to use concepts from neurobiology, where many neurons (or nodes) are linked by synapses (or weights) between them. A typical neural network design will involve an input layer with n nodes, and one or

more hidden layers that will carry and modify information from the input layer to a final output layer, which results in a function of the multiple weights of each of the hidden layers.

If, in the different neurons, a tensor (n-dimensional array) with at least 2 dimensions is used instead of a one dimensional vector (as in the case of any other pixel-wise modelling for example) then, information from the surroundings of a value (e.g., pixel sample) can be considered. Our approach followed the scheme presented in Figure 1.

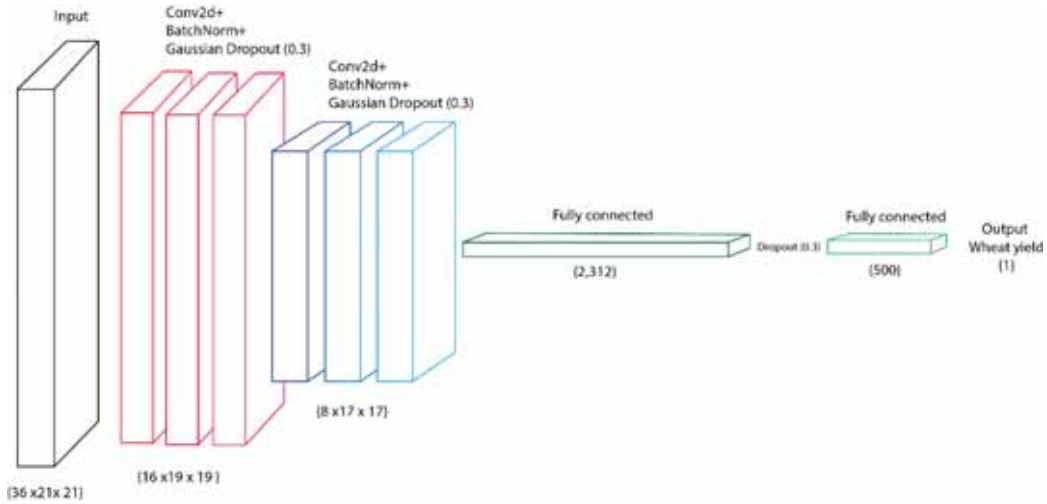

Figure 1. CNN architecture used for wheat yield prediction (AKA Mario-Net-B), curly brackets represent dimensions of each array.

As shown, the input layer corresponds to the extracted values from each of the 36 raster layers (Sentinel2, clay, etc.) from a 21 x 21 window (Figure 2).

Figure 2. An example of eight sampling locations (top). Detail of four of those locations with central pixel highlighted in white (middle) and detail of two sample locations with a 21 x 21 pixel contextual sample (lower).

As the model involves many sequential layers its “depth” becomes bigger, this is the reason why this kind of modelling is classified as “Deep Learning”. Deep networks have shown to produce better results when using convolutional processes as demonstrated by Krizhevsky et al. (2012).

Sampling design and modelling approaches

In order to optimize the number of samples and the observed yield variability a Conditioned Latin Hyper-cube sampling (Minasny and McBratney, 2006; Roudier, 2011) design was employed to select the sampling locations. Within each field, a fixed percentage (2%) of the total number of pixels (5m resolution) was sampled, hence using this design each field will have a balanced contribution to the model, in terms of within-paddock variability.

All the analyses were made using both Python (for the raster extraction using Google Earth Engine) and R for the sampling design and modelling. CNN modelling was implemented using R package “Keras” with a “TensorFlow” Python back-end (Chollet and Allaire, 2018).

Model performance

Modelling performance was measured using three metrics, these were the well-known, coefficient of determination (R^2), root mean squared error (RMSE) and Linn’s concordance correlation coefficient (LCCC). All yield information was scaled between 0 to 1 for privacy reasons.

Results

Performance in terms of R^2 ranged from 0.4 to 0.71 with a mean of 0.35, and these results were much higher compared with those observed in the first tests with only 6 layers (Fajardo et al., 2019) where the best model using CNN’s had an R^2 of around 0.5. RMSE values fluctuated around 7 to 18% of the total yield production, which were similar to the previous work. LCCC values observed a range from 0 to 0.75 with a mean centred in 0.35.

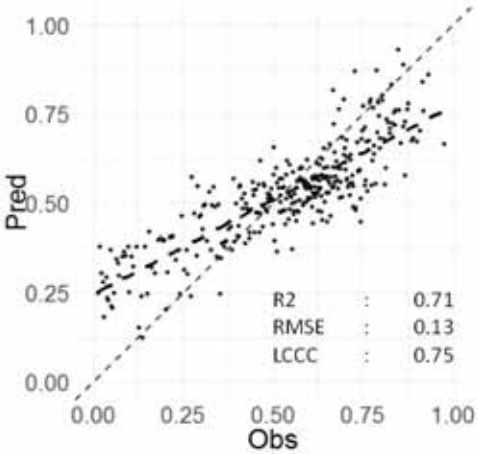

Figure 3. Performance plot of the paddock with the best yield prediction.

Interestingly, the site with the best predictions was not the one that had the highest amount of surrounding paddocks, suggesting that those variables that carried valuable information are not necessarily geographically correlated (Figure 4).

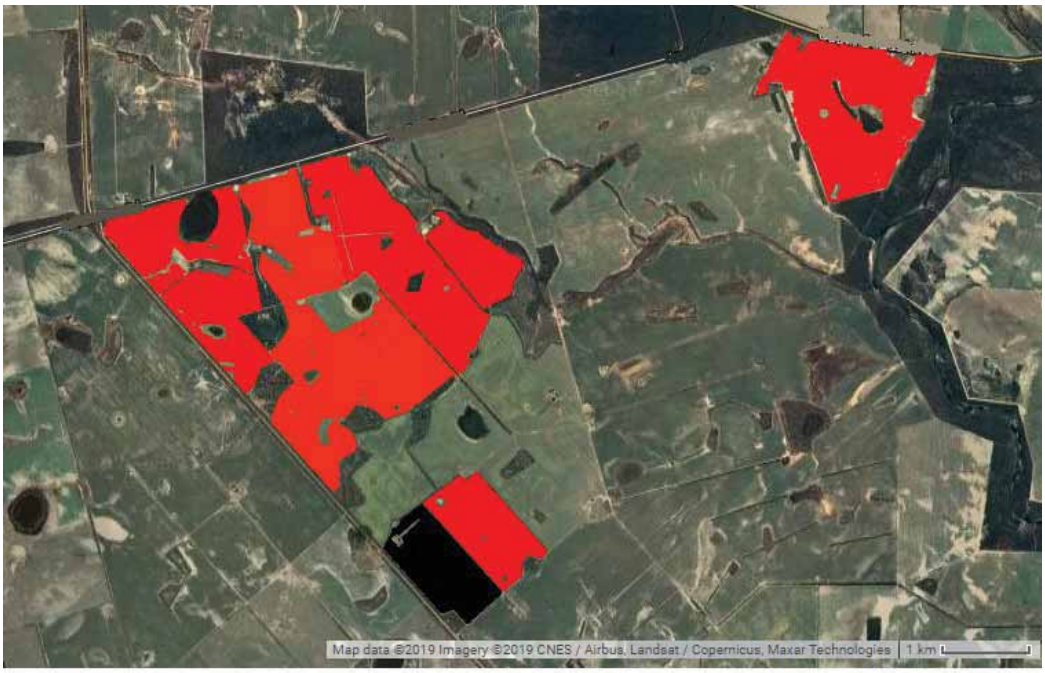

Figure 4. Predicted paddock (in black) using information from surrounding paddocks (in red).

Figure 5 shows a spatial prediction of the best model (blacked out paddock in the lower left of Figure 4), where the main patterns are well forecast. An interesting fact is the smoothness of predictions when using convolutional layers. Basically, 2D convolutions work as sliding windows, which provide a smoothing effect similar to kriging. This makes sense if we consider that a set of points (in this case a 21 x 21 window) is used to predict the values at a single point, exactly how kriging methods operate.

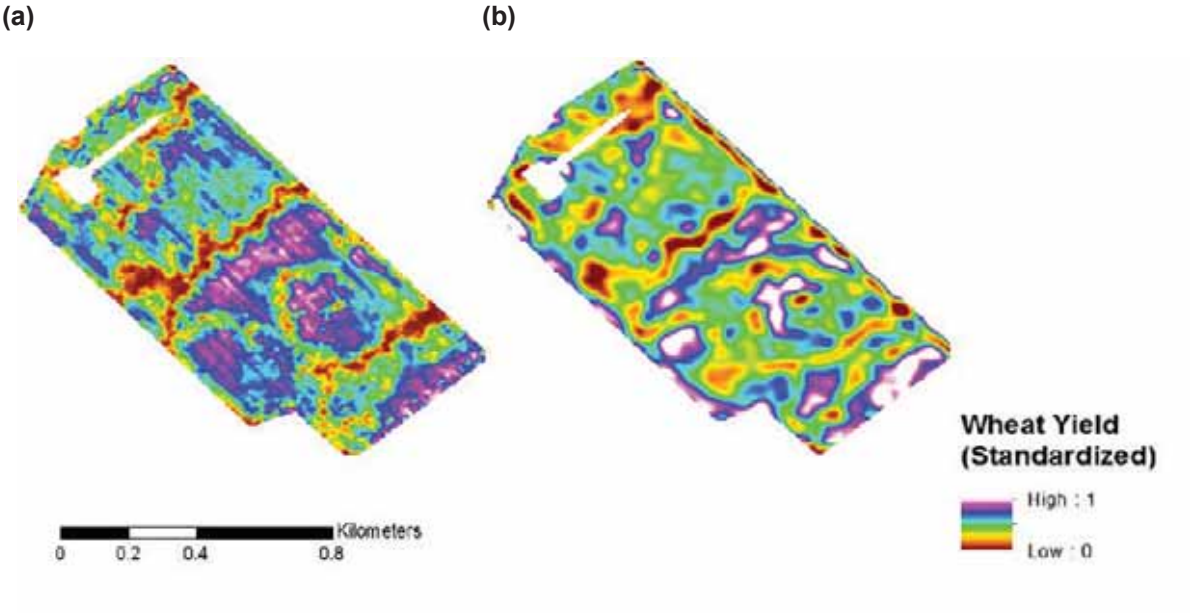

Figure 5. Spatial prediction for the selected paddock. Observed yield (a) and predicted yield (b).

It is important to understand that this modelling approach uses in-season information (satellite imagery) and soil and terrain information but no prior yield information from the field where yield is to be predicted. Future work will focus on selecting an appropriate set of covariates and compare this type of modelling with predictions using on-site information. Wheat yield forecasting using CNN modelling still lacks uncertainty measurements, and future modelling will attempt to rectify this by exploring the use of Gaussian processes or similar methodologies.

Conclusions

This study presented an enhanced version of a previous attempt of using Convolutional Neural Networks in order to forecast wheat yield only using information from outside the target paddock. The results showed an improvement when more layers of information (satellite imagery in this case) was used. Spatial predictions reflected the main patterns appropriately.

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Soil moisture monitoring and prescription irrigation for growing lucerne in sandy soils.

Joe Cook

Keith, SA

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Summary

Joe Cook and his family run a business with irrigated and dryland lucerne as the main pillar, including 300ha of seed production, which is around 50 per cent of the business. They also grow about 400ha of wheat, barley, lentils, canola and oaten hay and run 1450 Merino ewes joined to Poll Dorset rams to produce crossbred lambs.

The farm sits in a 450mm rainfall zone with soil that is generally sandy over a limestone and clay base.

Joe chooses to use a consulting group to help him manage his water, the soil moisture monitoring technology and the data. Joe will be giving us a first-hand look at why PA works for him, and why he chooses to out-source some of the work.

Establishment of a code of practice for agricultural field machine autonomy

Rohan Rainbow

Consultant to Grain Producers Australia

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Advanced technologies have revolutionised many industries but have also created a need for social adjustment, had an impact on regional communities and required changes in national skills requirements and training needs.

The introduction of autonomous machinery will have a significant impact. Already we have witnessed mining and manufacturing industries become increasingly automated due to global competition, labour costs and the need to improve productivity and efficiency. A recent study of the potential benefits of Digital Agriculture, including agricultural machine automation, highlighted potential returns of $878 million for the grains industry from reduced labour costs. An additional $91 million return would come from reduced chemical use through improved targeted application using sensing and automation. However, for these benefits to be

realised, commercial pathways to adoption and industry confidence in the use of autonomy technologies is required.

For agriculture to actualise the productivity benefits from agricultural machine autonomy, there is a need for Australian agriculture to build confidence in the ability for commercial tractor and machinery manufacturers to commercialise these technologies in Australia. An options paper was recently developed by Grain Producers Australia (GPA), which detailed key components required to deliver both commercial investment confidence and improved social confidence in their use.

GPA consultant Dr Rohan Rainbow has held detailed discussions with all the manufacturers who have autonomous tractors in commercial incubation. There is unanimous concern regarding the uncertainty of future regulation in the agricultural machine autonomy space. Manufacturers have indicated support for a producer and industry-led development of a Code of Practice. Such a document would build government and regulator confidence in the ability for agriculture to successfully integrate the introduction of autonomous tractors and other agricultural machinery. While there has been considerable government interest regarding the need for and opportunities to come for agriculture, government do not wish to lead the pursuit of these opportunities.

The mining industry successfully took a proactive approach to develop a mining industry Code of Practice. This document is now a legally recognised standard and was ultimately endorsed by the WA government and is now being considered by others state governments as a cost effective and pragmatic approach to machine autonomy. The mining industry Code of Practice was also influential in improving social confidence for increasing machine autonomy in mining.

GPA believes agriculture must take a similar approach to developing the world first Code of Practice for agriculture field machine autonomy. With widespread agricultural machine autonomy imminent in Australia, it is essential that a proactive approach is led by producers to ensure social and regulatory confidence in successful, risk managed adoption is maintained.

The prospectus for the Code of Practice has been prepared by GPA to encourage stakeholder collaboration and investment. The Code of Practice can be further customised throughout the development process to address future political and community confidence risks. GPA will lead the development of a Code of Practice for agricultural field machine autonomy to meet the needs of the Australian grains industry. There is an open invitation for other field-based plant industries to participate with the aim that this also meets their needs.

This process to develop the Code of Practice will be co-funded by GPA, producer and industry organisations with manufacturer co-investment. The aim is to deliver an agreed Code of Practice by 1 March 2020 for presentation to government and wider industry stakeholders. GPA proposes that other field-based plant industries, agricultural chemical and machine manufacturers invest into and participate in this process. GPA invites comment, feedback and written commitment to participate in the establishment of an Industry Code of Practice for Agricultural Field Machine Autonomy by 30 September 2019.

Yield forecasting of root crops with a multispectral satellite sensor in Australia: results from the National Precision Vegetable Project

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Summary

In precision agriculture, the assessment of satellite multispectral sensors in vegetable crops is limited. Through the industry funded project VG16009 'Adoption of precision systems technology in vegetable production', AARSC-UNE with the support of the QLD Department of Agriculture and Fisheries (DAF) has been assessing RS technologies for yield forecasting across multiple growing regions and commercial vegetable farms. This presentation covers the approach and results obtained from the use of high-resolution multispectral satellite sensors for the prediction of carrot yield across three growing regions (Western Australia, Queensland and Tasmania). The relationship between carrot canopy and reflectance data was assessed using 20 different vegetation indices. Correlation analysis was performed to identify the best vegetation index for yield forecasting. Yield maps were generated and compared with commercial harvested yield reported by the growers. Furthermore, yield variability maps were developed to easily identify underperforming areas. Calibration of the prediction model as well as selecting the optimal vegetation index were critical for accurate results. High accuracies (up to 95%) have been obtained across different growing seasons, crop management and soil conditions. The results demonstrated the application of RS data in the prediction of yield and yield variability in vegetable crops.


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Updates from 'Future Farm': a new approach to sensor-based nitrogen research

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Summary

The adoption of sensor-based site-specific nitrogen management in Australian grains production has been low despite sensors such as the N-sensor®, GreenSeeker®, and Crop Circle™ being commercially available for at least a couple of decades (Bramley and Ouzman, 2019). A recent review of the different sensors and algorithms available concluded that, even after decades of research and development, there is little robust evidence supporting their beneficial use (Colaço and Bramley, 2018). One of the possible reasons for such an outcome is the fact that current sensor-based N strategies usually rely solely on the crop sensor input to generate variable rate N recommendations (Colaço and Bramley, 2018); that is, models are univariate and so do not account for other potentially useful input to an N decision such as soil moisture status. Furthermore, recent evidence indicates that univariate sensor calibrations (those between vegetation indices (VIs) derived from crop sensors and input variables to N decisions; e.g. yield potential or crop response to N) are site and year-specific (Colaço and Bramley, 2019), which means that extrapolating such calibrations to a range of environments can result in large prediction errors, unless site-year covariates are also used in the models.

A new approach to sensor-based nitrogen decision making for the Australian grains industry is being developed and tested in the Future Farm Program, a multiparty initiative co-funded by the Grains Research and Development Corporation (GRDC). In contrast to the univariate, plot-based, mechanistic algorithms which characterize most sensor-based N research, this approach features three main scientific/experimental novelties:

- Data sources: A multivariate approach combining digital information from crop and soil sensors, historical spatial data, publicly available datasets (e.g. satellite imagery and weather data) and crop models is being used to predict the optimum N decision or variables that can be used for an N decision.
- Experimentation: On farm trials in Future Farm are paddock-scale, spatially distributed and implemented and monitored using precision/digital agriculture tools (e.g. variable rate applicators and yield monitors).
- Analysis: Two approaches to the use of digital data for the N decision are being evaluated: The first uses sensors to predict variables which can inform a mechanistic N decision model; that is, sensors are calibrated to predict N uptake or yield potential and inform a mid-season N decision based on a nutrient budget approach. The second uses multiple sources of information combined to directly predict an optimum N decision using a non-mechanistic algorithm.

In the following sections, we briefly describe the on-farm spatially distributed experimental design being used along with preliminary data and intended analysis.

Experimental design and collected data

The winter grain season of 2018 was the first year of a five-year program, with trials conducted in WA, SA and Vic. The on-farm trials feature N-rich and N-minus strips and target calibration points where plant and soil samples are collected (e.g. Figure 1). The experiments were designed with three specific objectives in mind: to provide a range of crop and soil conditions for collection of sensor calibration data; to provide on-farm information of crop response to N application and an optimum N decision to which a multivariate sensor-based model can be calibrated; and to allow investigation of the value of zone-specific reference areas (N-rich and N-minus strips) for the in-season N decision .

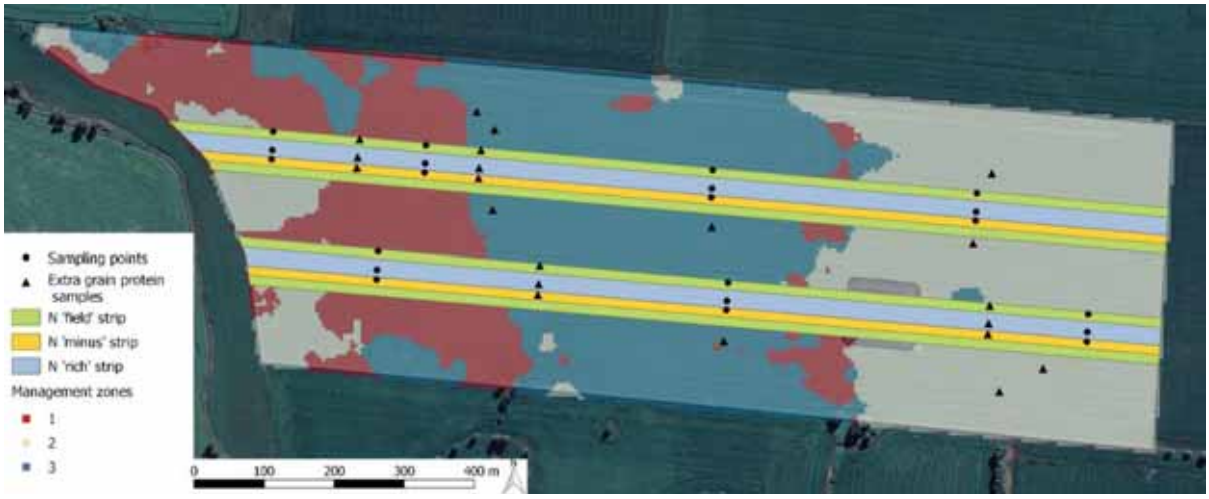

Figure 1: Field trial design at Tarlee, South Australia.

In 2018, at the South Australian site (Figure 1), N-rich and N-minus strips were applied across the paddock area after emergence of the wheat crop using a liquid fertiliser sprayer. For this paddock, one third of the farmer's 39 m boom sprayer (13 m) was turned off for the N-minus strip whilst the rest of the boom (26 m) applied almost double the N rate used in the rest of the field. In Figure 1, the N 'field' strips represent an adjacent strip area that received the same amount of N as the rest of the paddock. Strips crossed the different management zones in the paddock, which were previously defined based on a cluster analysis of historical yield and soil electrical conductivity maps. Sensor readings and biomass cuts were collected at the beginning of crop jointing (gs 31) at 21 target locations across strips and zones to calibrate the sensor VIs to variables that are relevant to the N decision (biomass, N uptake or grain yield). Soil samples were collected pre-sowing, at gs 31 and at the end of the season. During the crop development, the strips were monitored with proximal and remote sensing. The trial was then harvested using a header fitted with a yield monitor and on-board protein sensor. More details on the data being collected is available in Table 1.

Table 1: Information being collected at the 'core' on-farm trials of Future Farm.

Variables	Source	Spatial Resolution	Crop stage
Vegetation indices	Proximal and remote sensing	Across paddock	Tillering to jointing
Visible and near-infrared crop reflectance	Hyperspectral sensing	Target points	Jointing
Grain yield and protein	Yield and protein monitors	Across paddock	Harvest
Crop height and biomass	Light detection and ranging	Across paddock	Tillering to jointing
Biomass, plant N concentration, and other plant nutrition status	Plant sampling	Target points	Jointing and harvest
Soil N and other fertility status	Soil sampling	Target points	Pre-sowing, jointing and harvest
Soil moisture	Soil moisture probe	For each zone	Daily across season
Soil texture, drained lower and upper limits, bulk density	Soil profile characterization	For each zone	-
Soil electrical conductivity, soil gamma radiation, historical yield, etc.	Historical data base	Across paddock	-

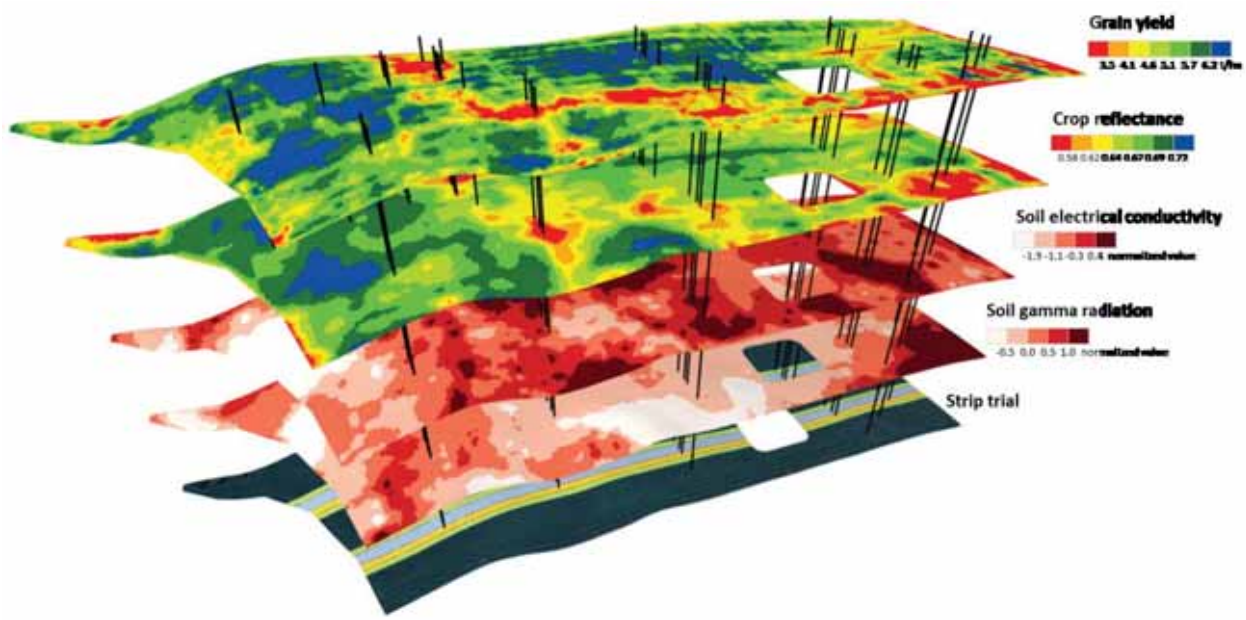

Figure 2: An example of stacked spatial data collected in Future Farm trials, crossed with target calibration points and overlayed with the N strip trial.

Intended analysis

Prediction of an optimum N decision

The design implemented allows the data to be analysed using a few different approaches. Figure 3 illustrates the data from yield and protein monitoring at harvest and the difference in grain N removal between the N-minus and N-rich strips along the length of the strips. The results of a moving window t-test (Lawes and Bramley, 2012) assessing the differences between strips are also shown. The difference between the N-minus and N-rich strips can be used to calculate an N recommendation (in this case, the N rate which will maximize grain N removal) along

the length of the paddock based on a given fertilisation efficiency factor (N rate = N removal difference between strips / fertiliser efficiency factor). Other options for N rate calculations include an N budget approach based on soil data collected around each of the target points and crop modelling. Grain and fertilizer prices can also be added for the estimation of economically optimum N rates. Figure 3 also illustrates the NDRE (normalized difference red-edge index) collected at mid-season from the Sentinel satellite.

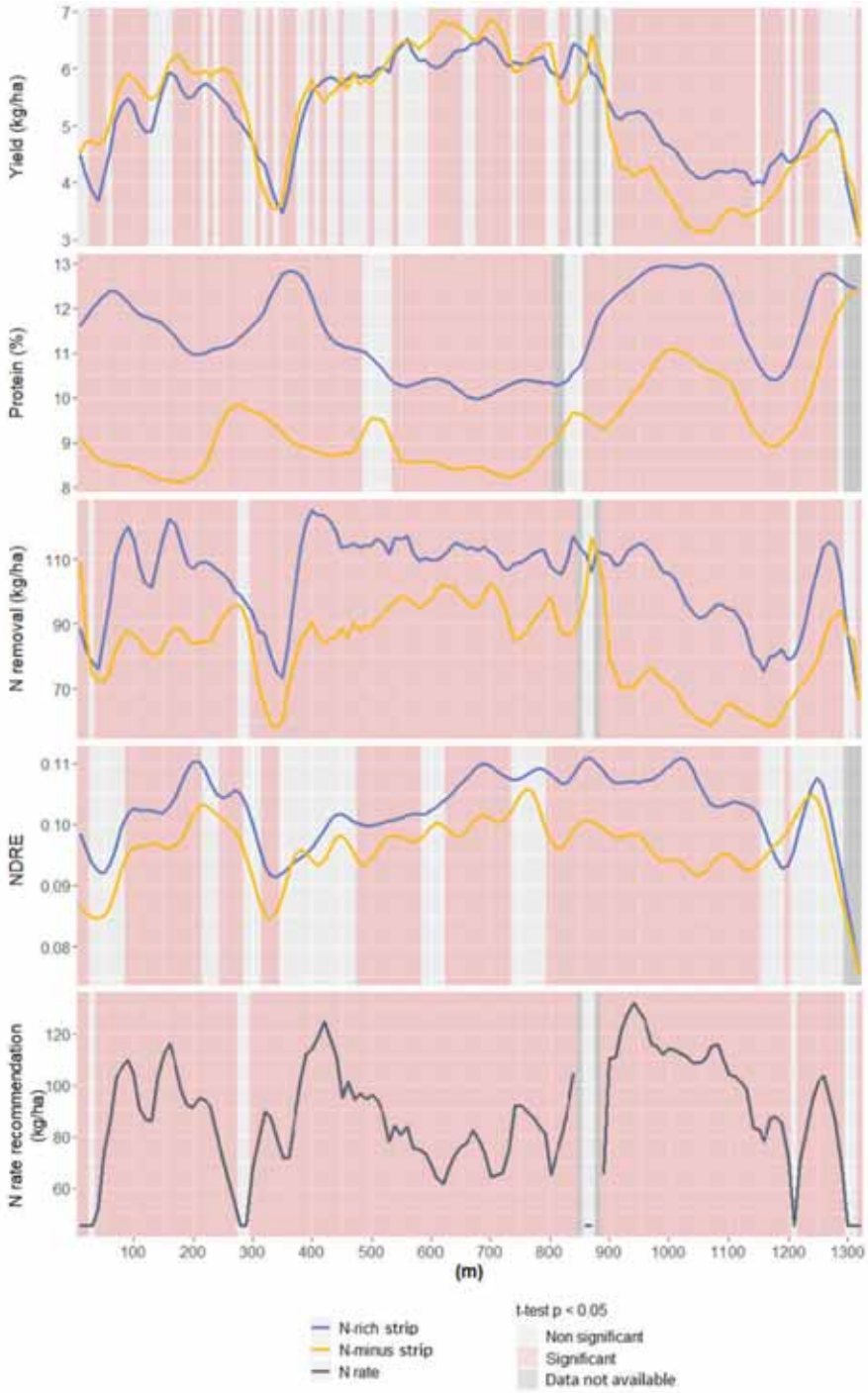

Figure 3: Grain yield, grain protein, grain N removal and mid-season crop NDRE across the length of N-rich and N-minus strips (top four graphs) (results of strip comparison based on moving window t-test shown in different background colours) and N rate recommendation (bottom graph) along the length of the strips.

Response indices (ratios between adjacent N-rich, N-minus and N-field strips) can be calculated and used, along with other data sources (Table 1), as predictors of optimum N rates using machine learning techniques. Such analysis will allow the assessment of which combination of variables can best predict an optimum N decision and where they should be measured (within reference areas (e.g. N-rich, N-minus), under normal field conditions or both).

Sensor calibrations

Starting in 2019, the 'core' experimental sites such as the one described above are being complemented with multiple 'satellite' sites across the southern region. Such trials are based on simpler and less monitored experimentation. In most cases, these are N strip trials initiated by the collaborating farmers to help inform their mid-season N management. Crop reflectance data from hyperspectral and multiband sensors, along with soil and plant samples are being collected in each trial. The goal is to generate calibrations for crop sensors to predict variables that can be used in N decision models; e.g. plant N uptake and yield potential. By using local covariates such as soil and weather characteristics, we expect to achieve global calibrations which can be used across a range of environments and seasons.

Final considerations

We believe the experimental approach being implemented in Future Farm (based on multivariate data sources and spatially distributed on-farm experimentation) may offer benefits over traditional sensor-based N research. Multiple variables for modelling and validation can be measured across a range of conditions within the same field. Of course, such trials should also be spread across sites and years to maximize the variability in the data. The approach for data analysis will also allow the comparison between traditional sensor-based N decision tools which are underpinned by sensor calibration and mechanistic knowledge and a novel non-mechanistic sensor-based algorithm, which could open new possibilities for a range of applications in digital agricultural research, experimentation and crop management.

References

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SBAS GPS for Horticulture

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Summary

This project investigated potential improvements in GNSS positioning accuracy using satellite-based augmentation (SBAS) in various farming environments in NZ. Put simply, SBAS is a system with a network of known land-based control points that provides correction via satellite signals to GPS units. The US equivalent is WAAS, the European equivalent is EGNOS.

The project tested the SBAS technology, comparing it with commercial systems currently available. Through insights gained from growers, the economic benefit SBAS could bring were assessed for incorporation into a full economic analysis and business case.

Vegetable growers view RTK-GPS as the Gold Standard and use it where precise positioning has value. Uncorrected signals are suitable for some applications, but sub-metre is preferred. Handheld devices are often tried and generally rejected after disappointment, losing potential benefits of better management if better location data were available.

Apple growers appear slower to adopt GPS technologies because they identify a gap between very expensive and unwarranted RTK-GPS and cheap inadequate alternatives. The SBAS technology offers fit-for-purpose guidance and logging that could change the way growers use positioning technologies to enhance management and profitability.

Static location is beneficial for recording points of interest such as diseased plants, weeds and harvest bin location. Kinematic guidance allows growers to find correct rows and track operations such as spraying, ensuring no misses or double ups.

The project was completed by Page Bloomer Associates with support from GPS Control Systems and Hectre Group and funded under a joint Australia/New Zealand government initiative through Frontier SI and LINZ.

Practical data management in the Cloud

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Summary

Joe Cook

Tasmanian farming contractor and manager Joe Cook grows broccoli and cauliflower for leading Australian food manufacturer Simplot. As one of the company's Farming Partners in the vegetable growing heartland of the state's north west, his operations produce seven thousand tonnes of vegetables, grown on multiple sites spread over a 200 km radius, with extra land leased from local owners in addition to his own.

Rob Wade

Rob Wade is the manager of SprayerBarn in Latrobe, and works with growers to incorporate PA technology into farm and crop management.

They will discuss the benefits of moving to a fully integrated cloud-based data management system. Having contracted in the region's vegetable industry for thirty years and been a Farming Partner with Simplot for ten, Joe sees a cloud-based system as extremely useful for the control of data, farm and operational planning and data analysis.

Practicing precision: A basis for making precision pay

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Summary

PIP (Precision in Practice) is an innovative new approach to identify and treat in field management zones. It is a two-phase process that requires stepping back from detailed site investigations to firstly develop of an understanding of the context of localised areas within the broader landscape and its influence on crop and pasture growth.

PIP Phase 1 (PIP 1) begins with collation of existing spatial and farm data to develop an accurate set of farm maps, including total area, arable area and elevation. Onto this base, historic satellite imagery (NDVI) and conductivity, elevation and yield data (when available) are spatially analysed to identify areas of difference (zones). These are verified by soil profile investigations to determine fundamental soil characteristics as they relate to the broader landscape and subsequent farmer feedback. PIP 1 enables the accurate and cost-effective identification of production zones within paddocks or management units that are statistically different.

PIP Phase 2 (PIP 2) examines the agronomic and farm system implications of the information derived from PIP 1 to aid decision making and determine the optimal allocation of resources in the production system, so that both the soil resource and farm profit improve.

Using the zone and landscape information developed by PIP 1, in conjunction with the experience of the land manager and their agronomist, PIP 2 supports the development of strategic management plans for individual paddocks and subsequent targeted zone-based soil sampling as required.

Initial projects have resulted in estimated input savings of up to $110.09/ha through adjustment of lime, manure and phosphorous application within the first year for individual paddocks. In other instances, the detailed zone sampling has highlighted the significant pH stratification between the 0-5cm/5-10cm/10-15cm/15-20cm layers as a major potential constraint and opportunity/challenge for differential management

Notes

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