‘Digital agriculture’ helping farmers reduce impacts of cropping on the Great Barrier Reef

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Abstract
Nitrogen (N) losses from sugarcane production need to be reduced to help protect the health of the Great Barrier Reef. This challenge comes at a time when digital technologies are becoming more accessible and thus can be harnessed to improve N fertiliser management. We are developing ‘apps’ and advanced analytics to provide farmers with high quality information on: (1) water quality in their local creeks and rivers; (2) the magnitude of risk to production posed by lower N fertiliser rates; and (3) the abatement of N loss associated with those lower N rates, to help farmers potentially access payments from environmental schemes. We are also developing new ways of remotely sensing sugarcane crops so farmers can evaluate better the impacts of changed management on crop performance. This information will facilitate improved agronomic management leading to reduced impacts on the Great Barrier Reef.

Key Words
Sugarcane, Nitrogen fertiliser, Water quality, 1622™, Remote sensing, APSIM.

Introduction

Nitrogen (N) losses to the environment from intensive crop production in wet tropical catchments of north Queensland are a major threat to the health of Great Barrier Reef (GBR) ecosystems (Kroon *et al*. 2016; Waterhouse *et al*. 2017). N losses are directly related to N fertiliser inputs to these crops (Thorburn *et al*. 2013), so considerable effort is being put into optimising N fertiliser management in the region, especially to sugarcane crops that receive more than 90% of N fertiliser applications. These efforts include traditional approaches to improving and extending best practices through agronomic demonstrations, focusing on both conventional and enhanced efficiency fertilisers (*e.g*. http://www.canegrowers.com.au/page/media/latest-news/introducing-EEF60). Despite these activities, there is little evidence of meaningful change in N fertiliser management (Waterhouse *et al*. 2017). This situation begs the questions of why has there been so little change and how could change be accelerated?

There are many barriers to the adoption of new management practices. These include scepticism about the link between N management of their farm and N losses to the environment, uncertainty about the production risk associated with new practices, and difficulties for famers in evaluating the success of the practice (Pannell 2017). These barriers are exacerbated in sugarcane production in north Queensland because of lack of information on the impact of sugarcane production on N losses to catchments (Benn *et al*. 2010), extreme variability in climate and thus production (Thorburn *et al*. 2013), and low precision of satellite-based techniques for monitoring crops at the field scale (Muir *et al*. 2018).

We propose that the provision to farmers of (1) real-time information on water quality in nearby creeks and rivers, (2) risk-based assessments of changed N fertiliser applications and (3) more timely information on crop growth from drone- and satellite-based remote sensing will facilitate faster change in farm management. This paper describes a suite of ‘apps’ developed under the brand ‘1622™’ to deliver these information services to farmers, and thus illustrates how ‘digital agriculture’ can help farmers reduce impacts of cropping on the Great Barrier Reef.

The ‘1622™’ apps

Real time water quality information

In coastal catchments of north Queensland, water quality data are gathered from sensors deployed in both research projects (Davis n.d.; Billing and Rodman 2017) and the Great Barrier Reef Catchment Loads

Monitoring Program (https://www.reefplan.qld.gov.au/measuring-success/paddock-to-reef/catchment-loads/). We are collaborating with these programs to import data streams from high frequency, automatic sensors and display them in a device independent web portal, 1622WQ (Figure 1a). While there are several systems currently available for ingesting and displaying data in a dashboard (*e.g*. https://eagle.io/), the 1622WQ app has been specifically designed to meet farmer needs (based on consultation during user centred design) and has advanced data analytics, not available in other platforms, to mitigate loss and/or corruption of data.

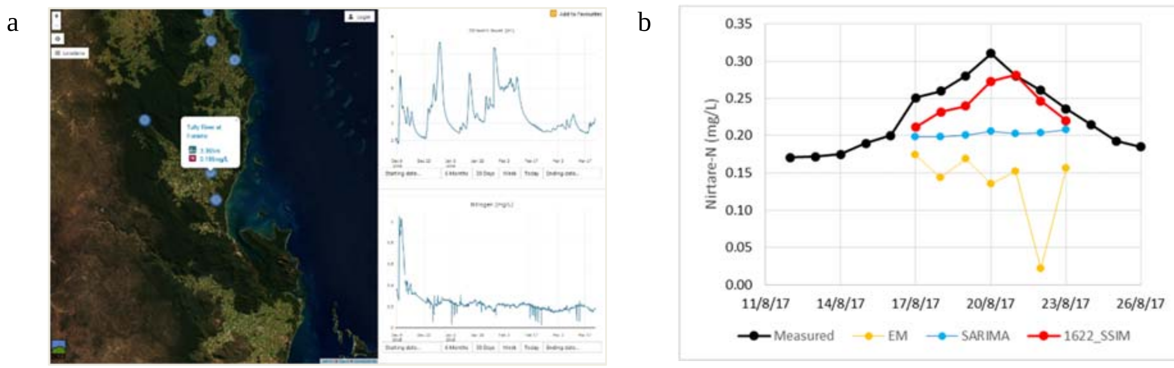

Figure 1. (a) Screen shot of the 1622^{TM}WQ app and (b) example data imputation from the SSIM method developed for 1622^{TM} and two traditional imputation methods (EM, Expectation Maximization; SARIMA, Seasonal Autoregressive Integrated Moving Average).

Loss and/or corruption of data is inevitable in all automated monitoring systems and these problems reduce the value of data to all end users. To reduce the impact of data loss, we have developed a model (SSIM; Zhang *et al*. 2019b), based on state-of-the-art sequence-to-sequence deep learning architecture, to 'infill' missing data with estimated values. The SSIM model provides superior performance to traditional 'infilling' methods (*e.g*. Figure 1b), reducing a range of error metrics (root mean square error, mean absolute error, mean absolute percentage error and symmetric mean absolute percentage error) by 70 to 98 % compared with six established data 'infilling' techniques.

Data corruption can be caused by a range of problems, such as random instrumentation malfunction, out of calibration range values, and impair visualisation and/or user interpretation of the data (*e.g*. 'random' spikes in Figure 1a). We are developing and deploying a range of filters (not applied to the data shown in Figure 1a) to identify and, in some cases, remove these anomalous data prior to end user display. We are also looking at new ways to predict water quality in the days or weeks ahead based on artificial intelligence (Zhang *et al*. 2019a).

Risk-based approach to optimizing N fertiliser management

The Australian sugarcane industry has well developed recommendations for N fertiliser management that have been evaluated in ~30 experiments or demonstration trials in the wet tropics (Schroeder *et al*. 2014). While this appears to be substantial evaluation, especially given the relatively small area (~136,000 ha) of sugarcane crops in the region, the wet tropics is a very heterogeneous region with a wide diversity of soils and climates. Thus the evaluation effort is not relevant to many farms. In the Tully region for example, recommendations have been developed/tested in three main experiments. The soils on which these experiments were located cover only 26 % of the region. Further, there are two distinct sub-climates in the region and all experiments were located in the northern one. So these experiments represent conditions of a small fraction of the region. The other factor is the limited time (several years), and therefore annual climate variations over which the experiments were conducted.

Employing cropping systems modelling is a way to extrapolate limited empirical experience to different soils, climates and across years, and we have developed the 1622WhatIf app to give farmers site- and time-specific information on the effects of N fertiliser rate on crop performance. The data displayed come from soil- and climate-specific simulations of sugarcane yield and N losses at a range of N. Importantly, yield outputs from the app are expressed in terms of likelihood of yield loss (Figure 2), both to convey the uncertainty inherent in predicting the future behaviour of cropping systems and allow farmers to integrate crop performance predictions into their own risk management preferences. As well as yield, outputs include predictions of N losses to the environment through different pathways. This information will allow farmers to participate in emerging markets for abating both greenhouse gas (*i.e*. nitrous oxide emissions from soils) and water-borne nitrogen discharges (https://www.reefcredit.org/) from these catchments.

Novel remote sensing of crops
Developing novel techniques for monitoring crop performance, from satellite- and drone-based sensors, is critical to allow farmers to evaluate better the effects of changed N management early in a crop's life. Persistent cloud cover in wet tropical catchments limits image acquisition from traditional satellites (*e.g*. LANDSAT). We are examining more modern satellites (*e.g*. Sentinel-1 and -2) and developing new analytics to enhance the quality of images from them (Shendryk *et al*. 2019). We are also developing drone-based collection of multispectral and LiDAR scans (*e.g*. Figure 3), both as stand-alone and combined approaches. The former includes using LiDAR and multispectral sensors mounted on small rotorcraft drone to observe fine-scale variations in sugarcane and improve the efficiency of fertiliser inputs and maximise yields, while the latter includes 'fusing' multispectral and LiDAR data from drones, and using drone-acquired images to better calibrate satellite data.

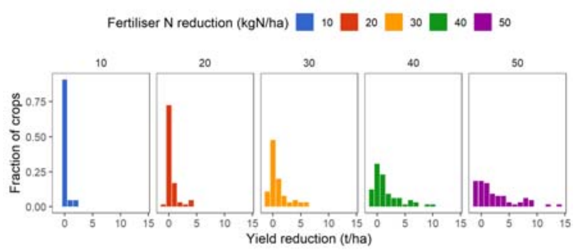

Figure 2. Example prediction of the likelihood of sugarcane yield loss resulting from five reductions in N fertiliser rate (10,…, 50 kg/ha) from a baseline of 130 kg/ha. Data are from early harvested ratoon crops simulated for from 1950 to 2015 for a Coom soil in the southern Tully region.

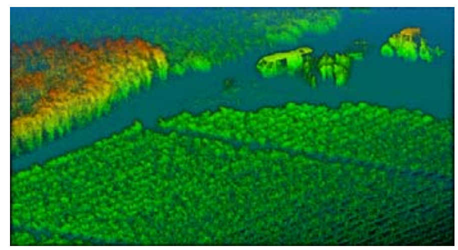

Figure 3. LiDAR scan of sugarcane fields surrounding a group of farmers in Tully, Qld (image by Yuri Shendryk).

Social research and learning
In order for the research and design team to learn as the project progresses, this project in 'digital agriculture' includes iterative cycles of product development alongside co-learning regarding socio-technical considerations (Jakku *et al*. 2019). The addition of a social research component to monitor, evaluate and learn with the project team provides the opportunity for real-time feedback in order to justify more appropriately shifts in priorities and wider agricultural system engagement. This learning process allows for increased project efficiency based on foresight of structural social limitations, *i.e*. low levels of digital literacy or existing stakeholder conflict, in order to capitalise on this opportunity for rural innovation (King *et al*. 2019).

Discussion
The imperative to reduce N losses from sugarcane farming in the wet tropics means that the status quo in N fertiliser management is no longer tenable (Kroon *et al*. 2016). Thus, N fertiliser management needs to be 'disrupted'. This need comes at a time when 'digital agriculture' is developing rapidly, and harnessing these developments is a valuable opportunity to chart the future course of optimising N management. The Australian sugarcane industry has a well-developed capability in water quality monitoring (mentioned above) and agronomic modelling (Thorburn *et al.* 2017) so using digital technologies to provide more relevant information to farmers from these data sources will enhance their N management decisions. Developing more timely and precise ways to monitor crops is an important component that needs to be developed to enhance farmers' ability to track the impact of their management on their crops. If these technologies can be successfully developed and used, 'digital agriculture' will have helped farmers reduce the impacts of cropping on the Great Barrier Reef.

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