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HELPING FARMERS MITIGATE NUTRIENT LOSSES TO THE GREAT BARRIER REEF THROUGH "DIGITAL AGRICULTURE"

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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 better evaluate the impacts of changed management on crop performance. This information will facilitate improved agronomic management leading to reduced impacts on the Great Barrier Reef. We also argue that our experience may have relevance to improving water quality in New Zealand.

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 which receive more than 90% of the N fertiliser applied in these catchments. These efforts include traditional approaches to improving and extending best practices through agronomic demonstrations. Despite these activities however, there is little evidence of meaningful change in N fertiliser management (Waterhouse et al 2017). This situation begs the questions; why has there been so little change and how could change be accelerated?

A common means of improving water quality discharged from agricultural catchments is regulation of use and/or management of farmlands. As has happened in New Zealand (MfE 2017), regulations have been developed to reduce the impact of agricultural activities on the quality of water entering the GBR ecosystems; however, enforcement of the regulations has been inconsistent and governments have mainly relied on voluntary measures (Kroon et al 2016). 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 (Benn et al 2010). Thus, the lack of change in N fertiliser management practices is, perhaps not surprising. We propose that providing farmers with (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 GBR.

The ‘1622™’ apps

Real time water quality information

In coastal catchments of north Queensland, water quality data are gathered from high-frequency sensors deployed in both research projects (Davis n.d.; Billing and Rodman 2017) and the government programs (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 a number of 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 (described below), not available in other platforms, to mitigate loss and/or corruption of data.

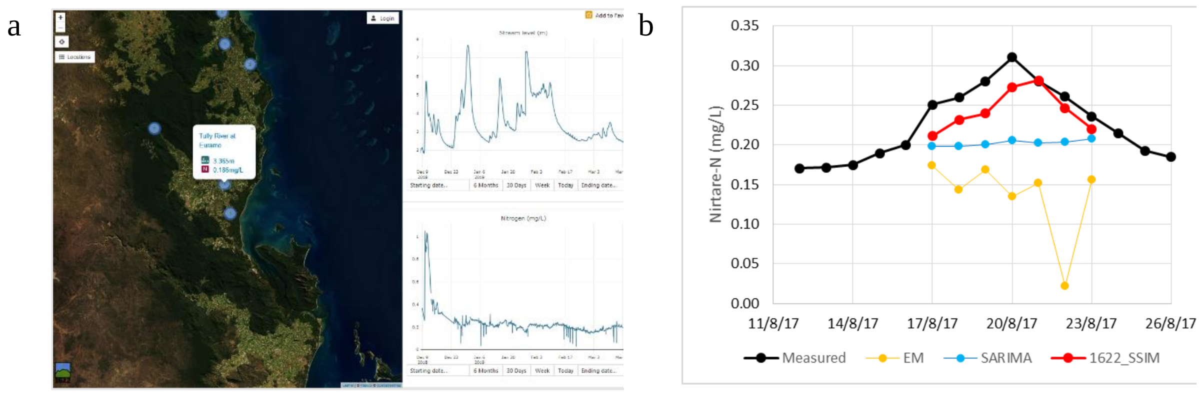

Figure 1. (a) Screen shot of the 1622™WQ app and (b) example data imputation from the SSIM method developed for 1622™ and two traditional imputation methods (EM, Expectation Maximization; SARIMA, Seasonal Autoregressive Integrated Moving Average).

Data corruption can be caused by a range of problems, such as random instrumentation malfunction, out of calibration range values, etc., and impairs 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 of the most recent water quality measurement based on artificial intelligence (Zhang et al 2019a).

Loss of data is inevitable in all automated monitoring systems and reduces 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.

Risk-based approach to optimizing N fertilizer 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 region. As a result, 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 (Keating and Thorburn 2017), 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 rates. Importantly, yield outputs from the app are expressed in terms of likelihood of yield loss (Figure 2), to both 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. In addition to 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 better evaluate the effects of changed N management early in a crop's life. Persistent cloud cover in wet tropical catchments in north Queensland limits image acquisition from traditional satellites (e.g. LANDSAT) and so satellite-based techniques for monitoring crops at the field scale have low precision (Muir et al 2018). 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 fertilizer inputs and maximize yields, while the latter includes "fusing" multispectral and LiDAR data from drones, and using drone-acquired images to better calibrate satellite data.

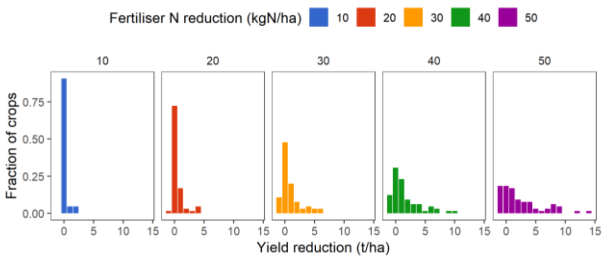

Figure 2. Example prediction of the likelihood of sugarcane yield loss resulting from five reductions in N fertiliser rate (10, … , 50 kg/ha) from a baseline of 130 kg/ha. Data are from early harvested ratoon crops simulated for from 1950 to 2015 for a Coom soil in the southern Tully region.

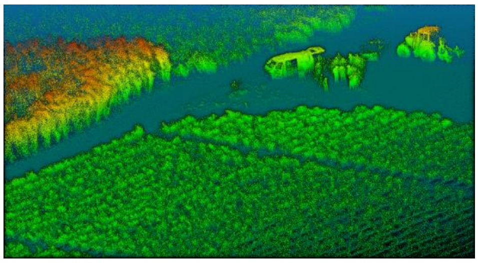

Figure 3. LiDAR scan of sugarcane fields surrounding a group of farmers in Tully, Qld (image by Yuri Shendryk).

Social research and learning

In order for the research and design team to learn as the project progresses, this "digital agriculture" project 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 more appropriately justify 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, whether through voluntary or regulated measures 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. Setting the development and deployment of these tools in a social research and monitoring and evaluation context should increase their impact. If these technologies are used by farmers, "digital agriculture" will have helped them reduce the impacts of cropping on the GBR.

What relevance might the 1622^{TM} tools have to reducing N concentrations in New Zealand's rivers and lakes? The New Zealand government through Regional Councils has implemented many well-developed programs for improving water quality (Duncan 2017). Yet N concentrations have increased in approximately half of New Zealand's lowland rivers (Julian et al 2017) and the National Policy Statement for Freshwater Management was amended in 2017 (MfE 2017) to provide clearer requirements for regional councils to improve water quality. These changes suggest that the *status quo* in water quality improvement may also no longer be tenable in New Zealand. Water quality data in New Zealand is made readily available to the public through Land, Air, Water Aotearoa (LAWA: https://www.lawa.org.nz/); however, at the time of writing the latest information on N was generally from 2017. Perhaps speeding the provision of that information to farmers may help them more deeply engage in water quality improvement activities. There are also characteristics that sugarcane cropping and dairy pasture production share. Both are part of a closely linked, high-value supply chain. Taking a risk-based approach to management of N or other aspects of dairy farming may provide dairy farmers more confidence to change management when the circumstance require it. Thus, our experience with the 1622^{TM} tools may have relevance to New Zealand agriculture.

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