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# 1622WQ: A web-based application to increase farmer awareness of the impact of agriculture on water quality

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ABSTRACT

Intensive agricultural practices represent a major threat to aquatic ecosystems because they impair water quality. However, this can be ameliorated by farmers improving crop management provided they are aware of their contribution to declining water quality. Water quality information systems can increase farmer awareness, but most were developed to assess water quality targets set in regulations rather than inform farmers. We developed the 1622WQ application using user-centred design principles to provide farmers with real-time information on nitrate and other contextual variables in their local creeks and rivers. The design process identified barriers to uptake of the application such as: (a) limited internet connection; (b) poor data quality; and (c) operational issues. Once these barriers were addressed, there was substantial uptake. Nevertheless, providing real-time information to farmers is only part of the solution due to legacy issues caused by a digital divide between traditional industries and those that are digitally enabled.

## 1. Introduction

The use of nitrogen fertilisers in agricultural systems has allowed farmers to increase crop production per unit of land, sustaining increasing human populations (Zhang et al., 2015). However, a large fraction of the nitrogen applied in agricultural lands is lost to aquatic ecosystems (Mekonnen and Hoekstra, 2015). Agriculture is responsible for most of the global nitrogen input to freshwater and marine ecosystems (Fowler et al., 2013; Mekonnen and Hoekstra, 2015), which represents a threat to water security via the eutrophication of water bodies (Elser et al., 2007), groundwater degradation (Rosenstock et al., 2014; Thorburn et al., 2003), and increased water-treatment costs (McDonald et al., 2016). Climate change is expected to intensify nitrogen pollution due to increased frequency and intensity of extreme weather events (Jeppesen et al., 2011). To protect aquatic ecosystems from nitrogen and other agricultural pollutants, governments have introduced regulations that define targets for water quality (Kroon et al., 2016; Nainggolan et al., 2018; National Research Council, 2010; Van Grinsven et al., 2012). Achieving these targets requires farmers changing crop management so that nitrogen losses are minimised (Kroon et al., 2016; Nainggolan et al., 2018; Wulff et al., 2014).

Voluntary actions have been shown to lead to long-lasting behavioural change (Ayer, 1997) because of the complexities associated with regulatory approaches (Bohman, 2018). Farmer behaviour can be influenced by a range of factors, such as economic incentives, legal requirements, perceptions, personal factors and beliefs (Gachango et al., 2015; Greiner and Gregg, 2011; Pannell, 2017; Taylor and Eberhard, 2020). For farmers to engage in voluntary actions to improve water quality, they need to be aware of the link between crop management and water quality (Glavan et al., 2019; Macgregor and Warren, 2006). Unfortunately, farmers are often unaware of their contribution to declining water quality (Benn et al., 2010; Glavan et al., 2019; Macgregor and

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Warren, 2006; Okumah et al., 2018) or are sceptical about the impact of agriculture on the environment (Macgregor and Warren, 2006; Pannell, 2017; Stuart et al., 2014). Despite this evidence, many targets for water and land management assume that impacts from farming practices are well understood by farmers (Blackstock et al., 2010). Clearly, for these targets to be reached farmers need to be more aware of the link between farming practices and water quality (Barnes et al., 2009) and there needs to be better dissemination of water quality information to farmers (Gachango et al., 2015).

Several nitrate water quality information systems exist, such as the Land, Air and Water Aotearoa (LAWA NZ, https://www.lawa.org.nz), the Iowa Water Quality Information System (IWQIS, https://iwqis.iowawis.org), the USGS water quality information system (https://www.usgs.gov/products/data-and-tools/real-time-data/water), and the Eyes on the Chesapeake Bay (http://eyesonthebay.dnr.maryland.gov). These systems were primarily developed to assess water quality improvements coming from government programs and report results to governments and the public (Jones et al., 2018) rather than raise awareness among farmers. A different approach is needed to maximise the impact of this information on farmers' awareness (McIntosh et al., 2007). Specifically, to help farmers understand the link between crop management and nitrogen pollution, water quality information systems need to be real-time, high-frequency and provide contextual information that can assist farmers interpret the data (Glavan et al., 2019; Jones et al., 2018). Real-time water quality information systems can facilitate the immediate evaluation of the impact of a recent farming practice (e.g. fertiliser application) on water quality. Moreover, because discharge (i.e. triggered by rainfall) may increase nitrogen loads in running waters over short periods (Jones et al., 2018), high-frequency monitoring systems are needed to demonstrate the link between crop management, river discharge, and nitrogen pollution. In addition, contextual information (e.g. rainfall) can help farmers understand the connection between weather events and nitrogen pollution.

With the aim of increasing awareness of the impact of cropping on water quality, we developed 1622$^{TM}$WQ, a web-based application that provides real-time data on stream water quality. We utilised principles from social science and human-centred design in an effort to maximise the uptake of the application (Jakku and Thorburn, 2010; Rose et al., 2016; Stitzlein and Mooij, 2019). Ultimately, changes resulting from use of the technology and sharing of the lessons with peer networks of farmers is hoped to increase the likelihood of achieving water quality targets (Glavan et al., 2019). Our contribution to knowledge is to describe the pathway of the development process of the application through to descriptions of stakeholder interaction to evaluate the extent to which 1622WQ increased farmer awareness. As such, we report on attempts to mitigate issues of poor internet connectivity, lack of engagement with technologies in general, and poor data quality to emphasise lessons for technology development aiming to achieve impact.

## 2. Study site

### 2.1. Regional setting

Our study site comprises some of the river catchments that discharge into the Great Barrier Reef (GBR) World Heritage Listed Site, particularly sugarcane farming in the Russel-Mulgrave, Johnston and Tully catchments of the Wet Tropics (Fig. 1). River flows in these catchments are characterised by high-intensity flood events during the wet season (November–April) which lead to substantial export of nutrients, pesticides and sediments to the GBR (Mitchell et al., 1997). Across all catchments discharging into the GBR ecosystems, agricultural land use is the major source of nutrients, pesticides and sediments (Kroon et al., 2016). Grazing systems occupy >80% of the area and account for most of the sediments loads to the GBR (Waterhouse et al., 2012). Cropping systems (banana, sugarcane) occupy <5% or the area but account for most of the dissolved inorganic nitrogen (DIN, nitrate + nitrite + ammonium) discharged from the catchment (14–940 t year$^{-1}$, Napel et al., 2019). Among cropping systems, sugarcane is the main contributor to DIN load on an annual basis (Thorburn et al., 2013; Thorburn and

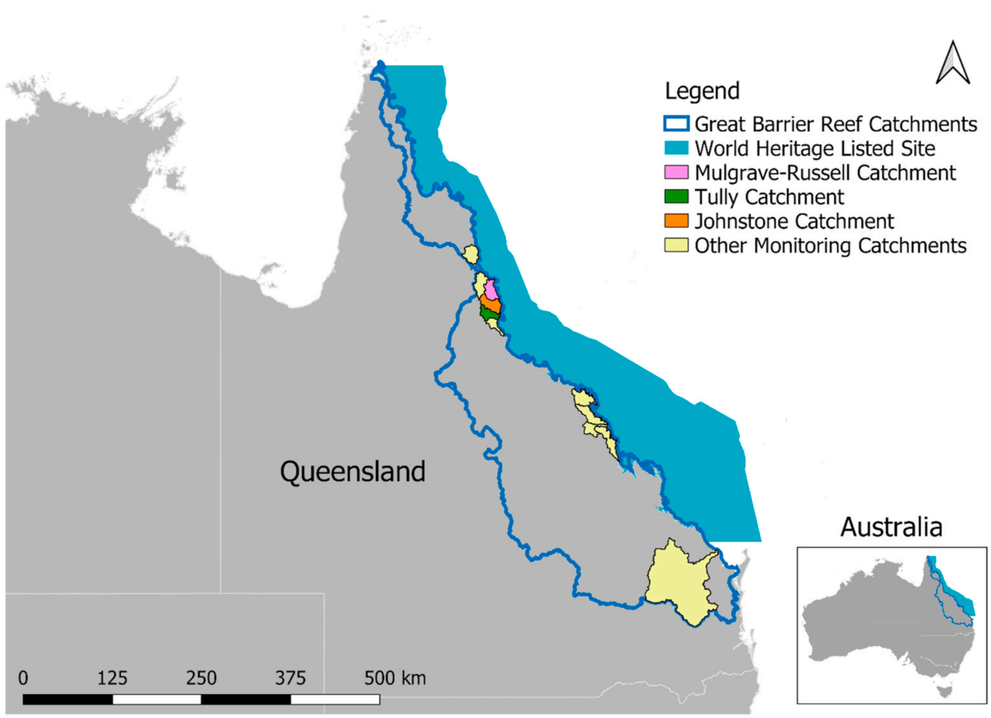


**Fig. 1.** River catchments (blue line) found in areas adjacent to the Great Barrier Reef world heritage listed site (light green). Catchments where real-time sensors have been deployed are shown in yellow and pink. The Russell-Mulgrave, Tully and Johnstone catchments are shown in pink, green and orange, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Wilkinson, 2013; Waterhouse et al., 2012) because it is a widespread crop (~40% of cropping area) grown in areas of high rainfall (1000–4000 mm year$^{-1}$) and it receives large amounts (130–200 kg N ha$^{-1}$) of synthetic nitrogen fertiliser (Thorburn et al., 2013).

High DIN availability in coastal waters promotes outbreaks of the coral-eating crown-of-thorns starfish responsible for much of the decline in coral (De'ath et al., 2012). To protect the GBR, the Australian and Queensland Governments released the Reef 2050 Long-Term Sustainability Plan which sets a target of 60% reduction of anthropogenic end-of catchment DIN loads by 2025 (Commonwealth of Australia, 2018). To achieve this target, farmers in the GBR catchments need to alter crop management so that nitrogen losses to the environment are minimised. These could include reducing N fertiliser application rates or replacing conventional fertilisers with ones that better synchronise N supply with crop uptake (Thorburn et al., 2017).

Despite considerable investment by governments in incentives to promote practice change (Kroon et al., 2016), the adoption of improved practices has been very slow (The Government of Queensland, 2018). Innovative ways of promoting farming practice change have been called for (Great Barrier Reef Water Science Taskforce; Department of Environment and Heritage Protection, 2016).

We recognise that agricultural innovation is not only about adopting new digital technologies, but requires collaboration between scientists and stakeholders throughout the innovation process and through the development of new technologies (Jakku and Thorburn, 2010; Klerkx et al., 2012). As such, the design and development of 1622WQ was guided by interactions with farmers. For practical reasons, we focused on the Russell-Mulgrave catchment (Fig. 1).

### 2.2. Water quality monitoring

Within the study area there are a number of water quality monitoring efforts. The most extensive is the Great Barrier Reef Catchment Loads Monitoring Program (GBRCLMP), a Queensland Government program that collects data across multiple catchments to track long-term trends in water quality entering the Great Barrier Reef lagoon to both validate catchment water quality models and track changes in water quality relative to government water quality targets (https://www.reefplan.qld.gov.au). There are also projects aiming to inform farmers about variation in water quality in specific localities, and how that relates to their farm. The first project established was "Project 25 – Farmers, water quality and on farm decision making" (hereafter referred to as *P25*; Davis, 2019), a farmer-led water quality monitoring program located in the Russell-Mulgrave catchment (Fig. 1). The second, was the "Cane to Creek" (*C2C*) project, an extension officer led project working with farmers to understand water quality in the Figtree Creek sub-catchment of the Mulgrave River catchment (Billing, 2017). The final project is the Wet Tropics Major Integrated Project (*WETMIP*, https://terrain.org.au/projects/wet-tropics-major-integrated-project), measuring water quality at two locations in the Tully River catchment and one location in the Johnstone River catchment (Fig. 1). Prior to collaboration with our developments (described below), water quality data collected in these projects was provided to farmers by project staff at individual or group meetings. The time between collection and these meetings were in the order of months. With the GBRCLMP, data are made publicly available through reports (Napel et al., 2019) and an interactive "Story Map" (http://qgsp.maps.arcgis.com/apps/MapSeries/index.html?appid=9d1aad1e2b444ec6a1890e4032284147); the delay between collection and display is in the order of years.

## 3. 1622WQ application

The 1622WQ application is named after the highest mountain in Queensland (Australia) which is 1622 m in height.

### 3.1. Data sources and storage

High-frequency nitrate concentrations ($NO_3$-N, mg N L$^{-1}$) were obtained from OPUS and NICO sensors (TriOS, https://www.trios.de/en/sensors.html, accuracy: 5% + 0.1 mg L$^{-1}$ $NO_3$-N) in deployed in tidal and non-tidal waters, respectively, in the water quality monitoring programs and projects described above. Other parameters are also monitored in these programs, river or creek height (m) being of particular relevance here. To date, the GBRCLMP program monitors 10 of the 35 river catchments draining into the GBR through 11 real-time stations measuring water level and/or water quality variables including nitrate. The water sampling intervals range from 10 to 60 min. Data from the program are stored in a cloud-based platform named Eagle.io (https://eagle.io) where water flow (m$^3$ s$^{-1}$) and N loads (t d$^{-1}$) are calculated for the two locations that have reliable rating curves (Tully River at Euramo and Tully Gorge National Park), as well as water level and nitrate concentration data. All data from this program are referred to as "Queensland Government" in the app. P25 has, to date, deployed four monitoring stations collecting nitrate concentrations every 60 min. In the C2C project, nitrate concentration is collected every 60 min at one monitoring station. In the WETMIP project, nitrate concentrations are recorded every 30 min at two locations in the Tully River catchment and one location in the Johnstone River catchment. Data from these projects are also stored in cloud-based platforms, including Eagle.io. They are identified in the app by their project names.

Our early user research (described below in section 4.3.2) highlighted that farmers in GBR catchments saw rainfall as an important factor in both their farm performance and management and the driver of nitrogen losses from their farm. Thus, rainfall data is also integrated into the 1622WQ application to enable farmers to establish the link between rainfall, fertiliser application and nitrogen pollution. Rainfall data are obtained from the Australian Bureau of Meteorology (http://www.bom.gov.au) which collects rainfall data every 60 min on the GBR catchments. In addition, 10 rainfall gauges were deployed by the project team in the Russell-Mulgrave catchment collecting data every 10 min. All data streams are stored in Eagle.io.

### 3.2. Prototype

Different versions of the 1622WQ prototype were developed using the Shiny framework (https://shiny.rstudio.com), an open source R package that provides a web framework for building web applications using R (https://cran.r-project.org). Shiny facilitates turning analyses into interactive web applications without requiring HTML, CSS, or JavaScript knowledge (Beeley, 2013). Prototypes were deployed on the shinyapps.io platform (https://www.shinyapps.io) and access was restricted by user identification, preventing anonymous visitors from accessing the application. The user interface consisted of three tabs (see Supplementary Material Figures A1-3): (1) a "Locn" tab that displays a list of all locations and allows users to filter and select locations, (2) a "Map" tab that allows users to select a location, and (3) a "Data" tab that displays data streams for the selected location. The prototype obtained data from CSV files and did not leverage any form of caching which caused latencies in data loading times.

As described in section 4.3, social science and user experience research identified that the latencies in data loading times and the need for a two-step user registration discouraged farmers from using the application. These barriers for technological uptake were exacerbated by poor internet connectivity. The additional complexity needed for addressing these issues meant that it was more effective to transition from Shiny to a single-page application (SPA).

### 3.3. Application

#### 3.3.1. Description

The application, accessible through https://wq.1622.farm, was designed as an online mobile-first Single Page Application (SPA) with no installations required on desktop or mobile, allowing us to partially address internet connectivity issues by keeping network requests to a minimum. Internet connectivity issues were also alleviated by allowing for local caching of data streams and locations. As previously indicated, the complexity of registration and logging-in acted as a barrier to uptake. Thus, the web-based application was designed so that publicly available data streams are accessible without the need for registration. Registration and login systems were continued to access private data streams, which are password-protected.

When opening the application, the user is presented with an annotated map displaying the locations where data streams are available (Fig. 2). When a location is selected some key figures (i.e. latest nitrate concentration/load) are displayed. The user can browse and search specific locations by clicking on the "Locations" button located in the top navigation area (Fig. 2). Locations can be bookmarked by clicking on the "Favourite" button, allowing for quick data access in future interactions (Fig. 3).

When selecting a location, charts displaying data streams for that location are shown. On desktop, both the charts and the map are visible to facilitate navigation (Fig. 3). On mobile, an "exit" button was implemented to return to the map (see Supplementary Material Figure A4). The charts are easy to navigate (i.e. scrolling on desktop or pinching on mobile readjusts the time span). To facilitate the interpretation of the data, contextual information such as yearly and monthly average values are also displayed (Fig. 3).

### 3.3.2. Architecture

The 1622WQ application was developed as a React SPA with a Django microservice-based backend (https://www.djangoproject.com) and a PostgreSQL database (https://www.postgresql.org). These were implemented for speed and utilize all open source frameworks and libraries (Fig. 4). The Django microservices expose authorized access to the Data Index stored in a PostgreSQL database. The backend consists of: (a) a Data Service that acts as an intermediary between the frontend, the database and Eagle.io; (b) a Discovery Service that retrieves a list of data streams from Eagle.io; and (c) an Access Service that manages access to the data streams. The data service checks that the user has permission to access the data and requests data from Eagle.io by searching for the details stored in the Data Index. A management system allows administrators to manage Data Index permissions (through the 1622WQ Management interface) as well as import new data sources into the Index (through the Discovery Service interface). The Discovery Service crawls Eagle.io for new data sources and displays them through an interface where administrators can select the new data sources to be added to the Data Index. Once data sources are added, the Access Service can be used to restrict access to users or groups of users. Data filtering and infilling is conducted in Amazon Web Service (AWS) Lambda (see section 4.1 and 4.2). The web-based interface was written in Typescript utilising the React JavaScript library (https://reactjs.org) and Redux framework (https://redux.js.org) for state management, allowing for fast page loading times. The map was managed through the Leaflet library (https://leafletjs.com) and the imagery obtained from Mapbox (https://www.mapbox.com). The interactive charting library ECharts (https://www.echartsjs.com) was used for displaying time series of the data streams.

## 4. Testing and evaluation

### 4.1. Erroneous data

Errors and anomalies are commonly found in real-time water quality data (Zhang et al., 2019). Erroneous measurements are a result of sensor malfunction, lack of sensor maintenance, physical interference with the sensors, communication failures, among others. This is a particularly acute problem for water quality monitoring in GBR catchments. The sensors accessed for 1622WQ are commonly deployed amongst vegetation on river or creek banks, in remote locations (e.g. up to 1000 km from a water quality technician). In these settings, debris from vegetation often causes physical interference with the sensors, which can take some time to repair a malfunctioning sensor. Erroneous measurements (described below) make it difficult to interpret the data and can also lead to lack of confidence by stakeholders in the measurements. To tackle these issues, we introduced a process to filter out obviously erroneous data.

The most common problems with nitrate data that we encountered

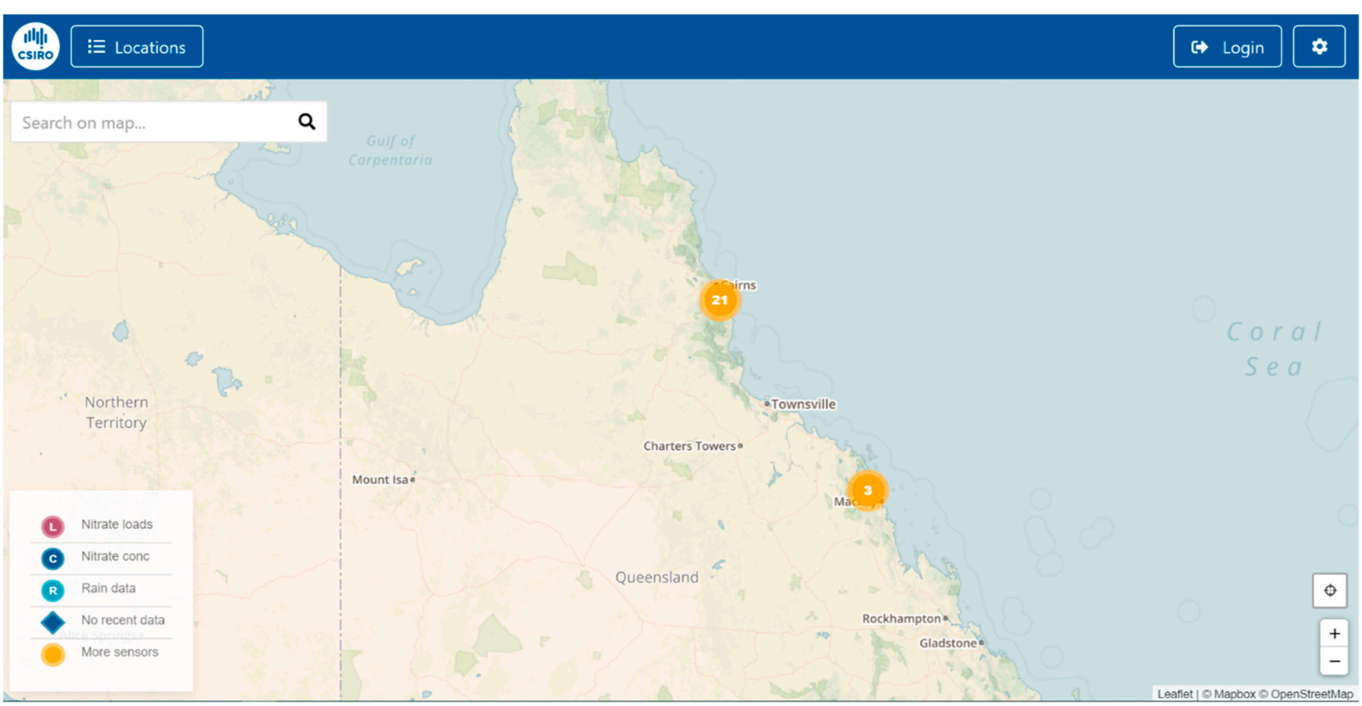


**Fig. 2.** Main page as shown on a desktop computer screen.

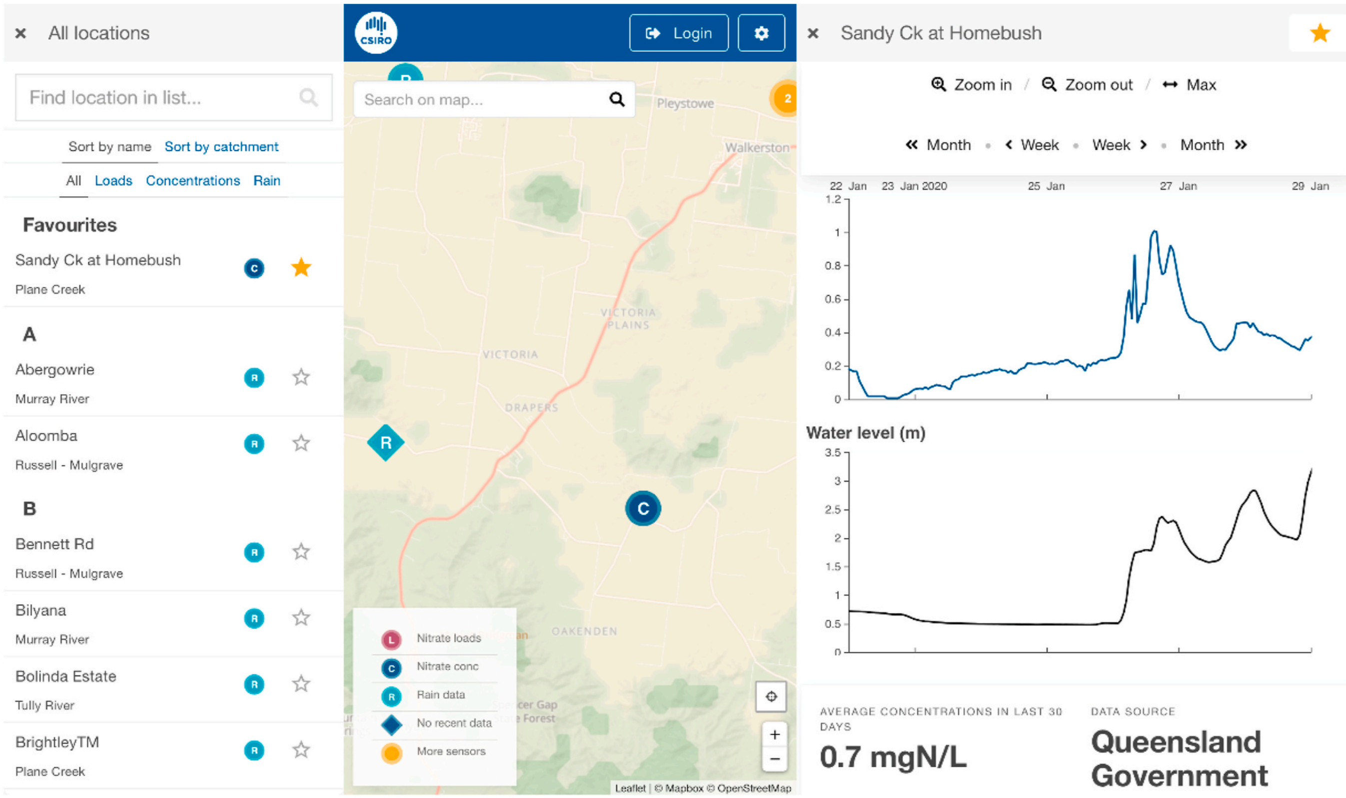


**Fig. 3.** Application showing the locations list (left) and charts (right) as shown on a desktop computer screen.

were (1) the presence of negative values, and (2) unrealistically rapid change in nitrate concentrations. Negative values were removed by the data filter. Changes in nitrate concentrations that exceeded the 98% quantile for a specific location were also considered unrealistic for the environments being monitored and removed (Helsel and Hirsch, 2002). In addition to data issues, we identified problems with the sensors related to the need for inspection and maintenance of the sensors. These problems can be recognized through reference variables (related to light intensity), which are implemented by the sensor manufacturers and indicate that the quality of the measurement is compromised (TriOS optical sensors, 2019a, 2019b). In our data set, we removed nitrate values when the sensor reference variables were below or above the thresholds defined by the sensor manufacturers. We also removed data that had been labelled as erroneous data by the water quality program/project managers.

The filtering system is implemented in AWS using the architecture shown in Fig. 5. Firstly, individual data streams are retrieved from Eagle.io using the HTTP API and cache into AWS. Then, the three filtering modules are applied sequentially using the AWS Lambda service. Finally, the filtered data streams are written back to Eagle.io. Filtering removes values from the data stream. Small gaps (less than 5 data points missing) created by the filtering algorithms are filled by linear interpolation, which is implemented in the filtering module. However, linear interpolation is not appropriate when multiple data points are missing and a more sophisticated infilling method (described below) is used.

### 4.2. Missing data

Large gaps (more than 5 data points) in data streams can be produced during the filtering, e.g. as a result of sensor malfunction or due to network communication outage. Multiple approaches have been developed to infill gaps in the data (Box et al., 2013; Pankratz, 1983). However, they usually give poor estimates when applied to large data gaps. Thus, to infill large gaps we implemented a new sequence-to-sequence imputation model (SSIM) based on a deep neural network (Zhang et al., 2019). The SSIM uses the state-of-the-art sequence-to-sequence deep learning architecture, and the long short-term memory network (LSTM) to utilize information that varies over time. The model provides superior performance in recovering missing data sequences, reducing a range of error metrics (root mean square error, mean absolute error, mean absolute percentage error and symmetric mean absolute percentage error) by 70–98% compared with six established data infilling techniques (ARIMA, seasonal ARIMA, matrix factorization, multivariate imputation by chained equations, and expectation-maximization; Zhang et al., 2019). The SSIM model has been implemented for water level streams in the three locations where it was tested: Russel River, Mulgrave River at Deeral and Johnstone River. We did not implement the infilling algorithm on nitrate data streams as there are challenges associated with infilling data streams with large gaps. We intend to expand the functionality to other sensors and data streams as more data becomes available and deep learning models are better developed.

### 4.3. Social science and user experience

For the research and design team to learn as the project progressed, we considered the socio-technical aspects of the 1622WQ application (Jakku and Thorburn, 2010; Rose et al., 2016; Stitzlein and Mooij, 2019). The addition of a social research component allowed us to more appropriately justify shifts in priorities during the development of the application and identify structural and functional limitations, i.e. the initial low levels of digital literacy and potential existing stakeholder conflict as they respond to different incentives (Jakku et al., 2018; Shepherd et al., 2018). Most importantly, our social research and participatory design process provided grounds to recognise such issues and respond to them, so enhancing impact by balancing the priorities of the different stakeholders involved in the application (King et al., 2019).

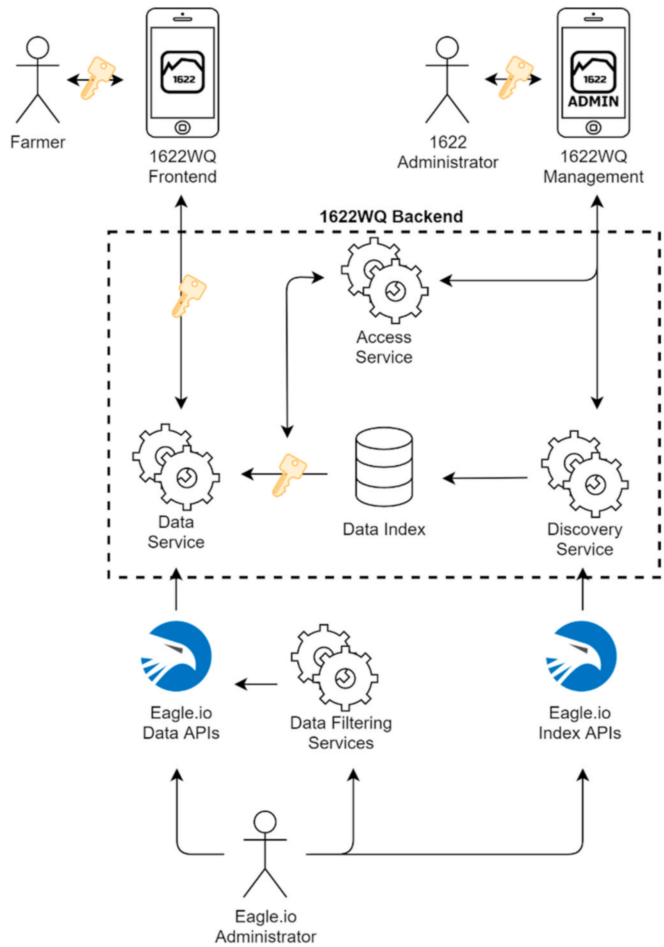


**Figure 4.** 1622WQ application architecture. Keys mean that authentication may be required.

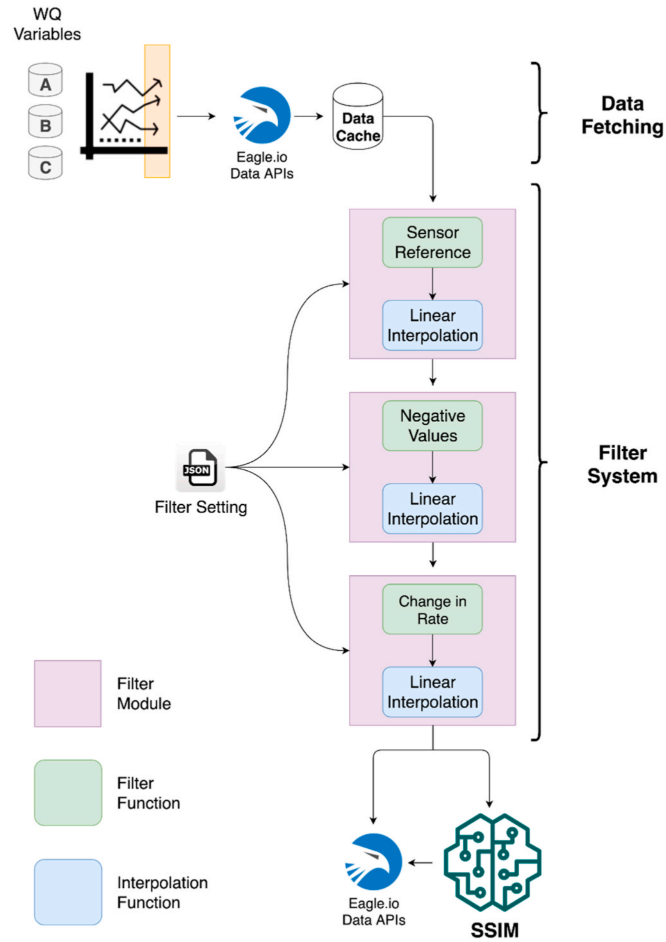


**Fig. 5.** Structure of the filtering system implemented in AWS lambda. SSIM: sequence-to-sequence imputation model (see section 4.2).

*4.3.1. Social science considerations of the 'farmer' and need for a monitoring framework*

Due to existing knowledge of the context within which regional agricultural stakeholders operate, what has been termed the digital divide in terms of lack of access to, use and understanding of digital technologies (Rotz et al., 2019; Shepherd et al., 2018), a co-development approach was encouraged by social researchers advising the project team. A combination of social research and human-centred design (and more specifically user experience) were involved from the early stages of the project in an attempt to operationalise learning from existing research on agricultural technology development (Ditzler et al., 2018; Glover et al., 2019) (see Fig. 6).

The challenge of innovation evaluation in such an impact-focused project was addressed by embedded social research and development of a novel conceptual framework to capture changes in stakeholders perceptions of technology overtime, the digi-MAST framework (Fielke et al., 2020). This framework was built on the notion of "digi-grasping" and the different engagements that stakeholders have with specific technologies at given points in time (Dufva and Dufva, 2019). Digi-MAST characterises the level of people's understanding of a digital technology through four modes:

- *mystery* (M), no knowledge of the relevant digital technology or dismissive if aware, not interested in engaging further due to various factors;
- *aware* (A), have heard of the technology but are still unsure of the implications and how it might influence their behaviour;
- *spark* (S), see the potential value of the technology and wants to understand how it contributes in the specific social and physical context; and
- *transform* (T), using the digital technology confidently and sharing it with others to change the way stakeholders do things.

Following innovation system research protocol, the social researcher conducted semi-structured interviews with 12 farmers from the Russell-Mulgrave catchment during Okumah et al., 2018 (Fig. 6), of whom had been interviewed prior to the development of 1622WQ and had previously interacted with the prototype (see section 4.3.2 and Fig. 6). We also interviewed farm management advisors (n = 3) and researchers (n = 5) working in this region or scientific area to get a better understanding of the system into which the technology was to be deployed. We undertook a total of 20 formal interviews; this number is not unusual for highly qualitative methods (Fielke and Wilson, 2017; King et al., 2019; Thorburn et al., 2011; Turner et al., 2020). Based on the interview responses, we assessed the mode of digi-MAST in which the interviewees were operating in relation to 1622WQ. Most farmers were in one of the first two modes of digi-MAST (*mystery* and *aware*) with little evidence of them being in the *spark* or *transform* modes at that time. On the other hand, advisors and researcher responses fell in the *spark* and *transform* modes at the same point in time. These results were in part due to pre-existing barriers to uptake and the 'flow' of the technology transfer approach. Specifically, there were farmers that either did not have (or want) access to a smart phone or had limited internet service. There were other barriers to uptake of the application related to data quality and design issues that were addressed in version 2.1. Subsequently,

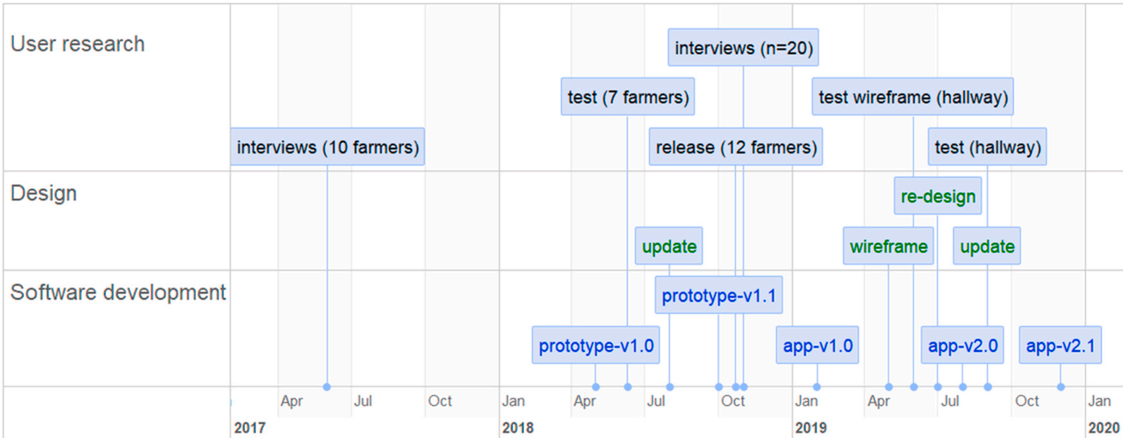


**Fig. 6.** Timeline of user research, design and software development interactions for the 1622WQ application.

semi-structured interviews using this version were held with 3 leading farmers and there was evidence of transition to the *spark* or *transform* modes confirming the benefits of our human-centred design approach. In addition, the transition to the *spark* or *transform* modes was further supported by a project collaborator who indicated:

"*Since its recent launch, I am regularly contacted and queried by influential growers in my study catchment as to particular water quality events occurring in their local waterways (often before I am even aware of them myself). This development demonstrates a major paradigm shift in how farmers can engage with water quality monitoring in their local environments, and one that cannot be understated.*"

*4.3.2. Participatory 'user experience' design process and plan to evaluate impact*

The 1622WQ application development process followed a user experience design approach (Stitzlein and Mooij, 2019) to maximise the likely use of the application (Rose et al., 2018, 2016). Social scientists and human-computer interaction experts in the project team conducted both formal and informal user experience workshops and "hallway" testing (testing by random individuals) over a 20-month period (Fig. 6). The design process started in 2017, when a context assessment was undertaken through structured interviews with 10 farmers from the Russell-Mulgrave catchment to identify their desires and needs regarding water quality information. These interviews confirmed their desire for readily accessible information and revealed the basic features the farmers wanted in the application, such as the format of data display (e.g. line graphs), the ability to compare data across time and/or locations, and the preferences about information displayed on the main page. These interviews also revealed that farmers were interested in rainfall data so that they could track farm performance and adjust management. Version 1.0 of the prototype (prototype-v1.0) was developed based on this feedback, with a major development being that rainfall data was added as bar charts.

Prototype-v1.0 was then tested with a group of 7 farmers. In this interaction, we identified the need for a list of sensor locations to be presented to users, as well as a map interface to facilitate the selection of the sensors. Prototype-v1.1 incorporated these features and was released to a group of 12 farmers, through one-on-one interactions, in October 2018. Google Analytics use data and subsequent informal interviews 3 months later revealed that most of the 12 farmers had not accessed the prototype-v1.1, and those that had, did so rarely. When asked for specific feedback on the prototype, these farmers indicated that the two-step registration/activation process, which involved contacting the app manager to register and then logging-in to activate the account, was a substantial barrier to its use. They also specified the need for contextual information to help them interpret the data (e.g. mean nitrate concentrations). In addition, latency when loading data and data errors (e.g. negative nitrate values) further diminished their interest in visualising the data.

Version 1.0 of the application (app-v1.0) was developed in February 2019 (Fig. 6) considering the feedback provided on the prototypes. Specifically, app-v1.0 was developed so that data could be visualised rapidly (facilitated by the caching and architecture of the application) and the need for the two-step registration/activation process was removed overcoming significant barriers that were present earlier. Also, the filtering and infilling techniques described above were implemented in this version. The app-v1.0 also included the mean nitrate concentration for the past 30 days to help farmers interpret the data. This information was provided below the charts rather than within the charts to avoid the addition of a legend that would make the visualisation of the data in mobile platforms less neat. Wireframes (model) for the next development of the application were designed then tested with a limited number of stakeholders (~10, "hallway" testing). The application was re-designed based on this feedback (app-v2.0). Additional hallway testing was undertaken and app-v2.0 was updated to app-v2.1 to improve the interaction with the map interface. Also, at this time the 10 rainfall gauges were deployed in the catchment and data from these were include in the app-v2.1 as requested by the farmers. Version 2.1 was completed in December 2019.

The application was publicly released in January 2020 with coverage of the launch in print and television media in GBR catchments. Google Analytics data showed there were >1100 users in the 5 months after the public launch (compared with ~1400 sugarcane farms in the region; Australian Bureau of Statistics (ABS), 2010) with a "bounce rate" of 24–29%. These use statistics starkly contrast the experience following the release of prototype-v1.1, highlighting the benefit of the process leading to the design changes to overcome the barriers to uptake of the earlier versions.

## 5. Discussion

Improving water quality in agricultural catchments is a global priority (Mekonnen and Hoekstra, 2015; Zhang et al., 2015). It is crucial for farmers to be aware of water quality near their farms and understanding the influence of their farm management on water quality in order for them to willingly change their management practices (Glavan et al., 2019; Macgregor and Warren, 2006). Further, providing this information to farmers in **real time** will better show the link between farm management and water quality (Glavan et al., 2019) and facilitate changed management (Okumah et al., 2018). These are important objectives in our study area, as improving farm management in catchments adjacent to the GBR is a critical action to protect this world heritage listed area (De'ath et al., 2012; Kroon et al., 2016). Yet, as described in Section 2.2, in water quality monitoring programs in the study region, even in those specifically aiming to influence farmer behaviour, there was a delay (months to years) between measurement and availability to farmers of water quality results. Sometimes the feedback to farmers was facilitated by project staff (P25, C2C and WTMIP projects, Section 2.2), other times information was published on a website of the GBRCLMP that farmers could view, if they both knew of its existence and were motivated. The situation in our study region is not unusual. Current information systems for water quality in agricultural catchments mainly focus on evaluating progress towards water quality targets (Jones et al., 2018) or on evaluating nutrient mitigation scenarios (Strömbäck et al., 2019). They are not real-time and/or tailored to being accessed by farmers, and thus are likely to be ineffective in increasing awareness of water quality among farmers. There are few exceptions, one being the "Nitrate App" developed by Deltares (https://www.deltares.nl/en/software/nitrate-app/) that presents results from nitrate test strips collected by farmers to encourage them to adopt best management practices. However, the reliance on nitrate test strips restricts the use of this system to (1) places where nitrate concentrations high enough to be within the detection limits of test strips, and (2) locations where manual, and thus infrequent sampling yields useful information. Neither of these pre-conditions are met in our study area, and thus water quality monitoring is done with sensors that have low detection limits and measure at high frequency (e.g. hourly). We have overcome the data access barriers with the 1622WQ™ app, which shows nitrate concentrations and other relevant information from high frequency measurement campaigns in real time. The use statistics (Section 4.3.2) also show a clear demand for this information. Our evaluations (Section 4.3.1) further show that exposure to 16222WQ and the data it displayed "moved" stakeholders along the digi-MAST framework (Fielke et al., 2020), from *Mystery* about the technology and data displayed to *Transform*(-ation), where they shared it with others to change their actions. Thus, the 16222WQ app clearly fulfills a necessary condition, awareness of water quality, for reducing farmers' barriers to change practice to improve water quality. After 1622WQ has been in operation for longer periods, its impact on farmers' attitudes and their farm management will become clearer through information reported by the Queensland Government's *Paddock to Reef Integrated Monitoring, Modelling and Reporting Program* (The Government of Queensland, 2018).

In developing the 16222WQ app we instituted a deliberate design methodology to maximise the impact of the software. To maximise the benefit from research investment, new technologies need to be developed in concert with stakeholders, rather than through purely top-down technology transfer approaches where the social and design aspects are left unaccounted for (Glavan et al., 2019; McIntosh et al., 2007). We developed 1622WQ, a web-based application that delivers real-time, high-frequency data on stream nitrate to farmers, as well as contextual information that facilitates the interpretation of the data. These characteristics are needed to increase farmer awareness of the impacts of crop management on nitrogen pollution (Glavan et al., 2019; Jones et al., 2018). However, through stakeholder engagement we identified that there were barriers to farmers accessing the app that needed to be overcome before 1622WQ could have meaningful impact. The first barrier was related to the quality of the data. Data quality issues are common in sensor networks (Zhang et al., 2019) and can occur because of breakdowns, lack of sensor maintenance, or a range of other reasons. This issue is particularly important in our case study because the sensors are in remote areas (e.g. up to 1000 km from a water quality technician), so timely maintenance is not always feasible. The second barrier was related to the design of the application. The prototype required user registration and logging-in to access the data, which discouraged farmers from using the prototype. Farmers were also discouraged by the latencies in data loading times. The last and most problematic barrier was the unease some farmers had in interfacing with digital technology. While limited internet connection and/or lack of the appropriate technology to support web-applications (e.g. smart phone) may be part of the underlying problem, we are also concerned about the possibility of a 'digital divide' between urbanised and technology proficient locations and more regional or remote areas where traditional industries dominate (Rotz et al., 2019).

While the pre-existing barriers to technological uptake (e.g. lack of appropriate technology) were not possible to address in this study, data quality and design issues were. There were various errors in the data output from the water quality sensors and correcting these data prior to end-user presentation is important to build trust in the tools (Eastwood et al., 2019) and thereby influence farmers' behaviour, especially if the new behaviour (e.g. reducing fertiliser application rate) carries a level of risk (Musvoto et al., 2015; Pannell, 2017). To address data quality issues, we created filtering algorithms that remove erroneous data and data imputation models (Zhang et al., 2019) that fill data gaps. These imputation algorithms were only implemented on a few water level data streams because many sensors in the application area had only been recently installed and did not have enough data to train the imputation models. Additionally, only data gaps shorter than ~1 day were infilled in 1622WQ as imputation accuracy is strongly affected by the size of the data gaps (Cao et al., 2018; Tang et al., 2019). Our informal interactions with farmers lead us to believe that filtering and imputation will be accepted provided imputed data are clearly marked, as farmers accept there can be problems with monitoring and appreciate transparency about data management. Future interactions will more formally evaluate farmers attitudes towards the pre-processing of data.

Design issues that limited the use of the prototype were also addressed. Specifically, we designed the application so that no registration or logging-in is required and keeping network requests to a minimum. While we tested these changes on a small group of farmers, the number of users since the launch of 1622WQ (>1000 in four months) suggest these changes have facilitated scaling up of the technology. Future work will continue to ensure the application is accessible by and relevant to all farmers in the relevant locations, not just the digital literate (Rotz et al., 2019), to enhance the extent to which 1622WQ can change farmer behaviour utilising a novel social impact framework in digi-MAST (Fielke et al., 2020; Rose and Chilvers, 2018).

During the development of the application, it became clear that the different water quality programs/projects used different protocols to calibrate and maintain sensors, and different protocols for assigning quality codes to data, thus limiting comparison of results between programs/projects. These differences were revealed by bringing these data streams into the single platform provided by 1622WQ. To achieve a common data delivery platform for these disparate programs/projects, a community of practice was established for real-time nitrate monitoring. The main objective of this community was to develop agreed protocols and standards for sensor maintenance, calibration and data quality coding that would enable the comparison of nitrate measurements across different projects. Thus, the development of 1622WQ was instrumental in ensuring consistency and promoting collaboration across the different programs.

The broader contribution of this technological case study (1622WQ) lies in clearly demonstrating the value of transdisciplinary research and in reducing the 'digital divide' that creates diverging and unequal relationships between stakeholders and digital technologies (Salemink et al., 2017). Although this divide is widely recognized (Billon et al., 2010; Pant and Hambly Odame, 2017; Roberts et al., 2017), examples like our work - with close interaction between technological development, social science and user experience - highlight empirical methods that will help overcome at least some of the barriers discussed. As such, this paper supports the role of science openly combined in various innovative forms to increase impact in the form of individual practice change and ultimately the environmental sustainability of agriculture via digital technological development.

## 6. Conclusion

This study describes the development of a web-based application in which we used human-centred design to identify the way in which farmers engage with and use technologies. The human-centred design, as well as the social science component of the project, enabled us to identify barriers to uptake and co-develop the application with target end-users. We showed that failure to consider the systemic context within which new technologies are developed and adapted will prevent widespread use of technologies (adoption) and therefore decrease the likelihood of achieving water quality targets (impact). We also showed how the application, through providing a common data delivery platform, created a community or practice across disparate water quality programs and projects. Our work highlights the importance of integrating different disciplinary expertise over time and the potential for longer term added value created through collaborative approaches to technology development that are not possible in traditional technology transfer efforts.

### Software availability

The 1622WQ application is freely available through https://wq.1622.farm/.

### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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### Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envsoft.2020.104816.

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