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i-RAT: A discussion support system to rapidly assess economic and environmental impacts of different sugarcane irrigation practices

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ABSTRACT

Water pollution and climate change are among the greatest threats to the iconic Great Barrier Reef (GBR). To improve the GBR's long-term outlook, making improvements on these fronts is required. Owing to the complex interactions between soils, climate, and farm management, a tool is needed to guide agricultural land managers about which management practice changes are more likely to deliver improved water quality and climate resilience outcomes whilst maintaining profitability. Using concepts drawn from social studies of science and technology, a 'discussion' support system (DSS) named Irrigation Rapid Assessment Tool (i-RAT) was developed through participatory processes designed to enhance co-learning from the development of this DSS. i-RAT is a rapid assessment-visualisation tool in an interactive web application (https://i-rat.net) to visualise the impacts of changed irrigation practices for sugarcane farmers and extension staff. Specifically, i-RAT compares these impacts regarding farm economics, water quality, productivity, carbon and nitrogen cycles, and greenhouse gas emission. The core of i-RAT is the sugarcane module from the Agricultural Production Systems sIMulator (APSIM) modelling platform. i-RAT was first developed for the Burdekin sugarcane growing region in Queensland (Australia's largest sugarcane producing region). Various soil types and management scenarios representing farming practices in the Burdekin region were used for simulations (1971–2021) to generate a datacube. In this paper, we describe how fundamental learnings about more (drought) resilient farming systems and more sustainable irrigation practices can be extracted from i-RAT. Details of the participatory approach with research and industry partners that informed the design and function of i-RAT and how APSIM was set up and parameterised are described. A 'what-if' analysis demonstrated the i-RAT features and application.

1. Introduction

The Great Barrier Reef (GBR) is a spectacular ecosystem and one of the most complex natural systems on Earth. A UNESCO World Heritage Area, the GBR is an icon under pressure since 2014, facing severe threats that challenge its resilience. Climate change is the greatest threat to the world heritage status of the GBR, while water quality represents cumulative pressure, further reducing the resilience of the GBR ecosystems to climate change (MacNeil et al. 2019). Land and agricultural activities are the main sources of pollutants from the GBR catchments (Steven et al. 2019). For example, modelled dissolved inorganic nitrogen (DIN) load to the Great Barrier Reef is around 12 kt/yr, mostly delivered by the Wet Tropics (46%) and Burdekin (21%) regions (Bartley et al. 2017). Pollutants originating from agricultural lands cause major damage to coral reefs. Therefore, improvements on two fronts are required to restore the GBR resilience and improve its long-term outlook: (1) effectively improve water quality at a regional scale, and (2) halt and reverse the effects of climate change at a global level (GBRMPA 2019).

Agriculture is the dominant land use in the GBR catchments, with sugarcane being the main crop (Thorburn et al. 2011a). In 2016–17, the gross value of agricultural production in Queensland was $14 billion, of which 22% came from sugarcane production (Australian Bureau of Statistics 2017). In 2019–20, 31.1 million tonnes of sugarcane were produced across Australia, of which approximately 95% was grown in Queensland's coastal regions adjacent to the GBR (Australian Bureau of Statistics 2021).

Sugarcane production systems are usually intensive, with large inputs of fertilisers and water. Irrigation is vital to sugarcane production in many parts of the world, as the crop requires >2000 mm of irrigation water to achieve commercial yields (Thorburn et al. 2013). Irrigation

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increases the chance of N losses (Gheysari et al. 2009; Randall et al. 2015), especially when applied with low application efficiency, which leads to substantial runoff and/or deep drainage. The lower Burdekin region typifies this situation (Thorburn et al. 2011a), where substantial irrigation is applied to crops through furrow irrigation, and N fertiliser applications are the highest among the GBR catchments. Consequently, N has been identified as a chemical of concern to GBR health in the region, as N runoff contributes to algae production, which feeds juvenile Crown-of-Thorns starfish, a marine invertebrate that feeds on coral (Mitchell et al. 2007). Modelling indicates that 21% of nutrient loads to the GBR comes from the Burdekin region (Bartley et al. 2017), largely due to water runoff carrying fertiliser pollutants, predominantly from sugarcane (Waters et al. 2014; Brodie et al. 2015).

Increasing the efficiency of water use and N application in agricultural systems benefits farmers by reducing input costs (Biggs et al. 2021) and must be a part of any strategy to solve water-quality-related issues in the GBR catchments (Mueller et al. 2017; Taylor and Eberhard 2020). Management of nitrogen loads to the GBR to improve water quality has been the focus of major investments by state and federal governments, not-for-profit organisations, and farmers (Waltham et al. 2021; Coggan et al. 2021). The reduction rate of pollutant loads has been slow, reflecting modest improvement in agricultural land management practices (GBRMPA 2019). Future initiatives must deliver timely, best-practice agricultural land management over a wider area to improve water quality. These initiatives must address the issues of over-irrigating (i.e., irrigation losses to runoff and leeching), which costs the farmers more in terms of water use and electricity, and under-irrigating (i.e., higher N losses due to lower yield).

Halting and reversing the effects of climate change requires addressing the issue of atmospheric greenhouse gas (GHG) emissions. Australia's Long-term Emissions Reduction Plan expects a 29–36% reduction in emissions from the agriculture sector. From this perspective, the contribution of sugarcane production to Australia's GHG emissions is an issue of national concern. A study in Brazil (de Figueiredo et al. 2010) estimated that 241 kg of carbon dioxide equivalent were released to the atmosphere per ton of sugar produced. Residue burning (44%) and synthetic fertilisers (20%) were the two major parts of total emissions. In Australia, total CO_2 emissions from residue burning, trash-blanketed, and bare sugarcane fields in the 1994 season were estimated at 7.6 Mt CO_2-C year^{-1}. N_2O emanating from sugarcane soils via denitrification and methane evolution following the burning of the crop were shown to be two other major sources of GHG. On the other hand, the sugarcane crop was also identified as a major sink for C, with uptake by the crop in 1994 estimated at 13.4 Mt CO_2-C/year (Weier 1998). This suggests that management decisions at the paddock level and the productivity of sugarcane lands directly affect the contribution of sugarcane production systems to Australia's total GHG emissions.

Improving water quality and contributing to solutions that mitigate climate change impacts requires a multi-dimensional approach considering the complex interactions between soil, climate, farm management, farm economics, GHG emission, and green finance systems. Hence, a decision support tool is needed to unravel these complex interactions and guide agricultural land managers about which management practices are more likely to succeed in delivering better water quality and climate outcomes whilst maintaining profits at the farmgate. Notwithstanding countless efforts and several policies that have already been formulated to achieve these goals at a regional scale, less emphasis has been put on influencing paddock-scale practices, especially irrigation management, and measuring their effect on the water quality outcome for the GBR. Moreover, there is a need for a new tool that conveniently integrates complex information and measures improvement in sustainability at the paddock scale so that improved management can be better linked to sustainable finance systems. Another tool commonly used in the Burdekin and adjacent regions (i.e., the Paddock-to-Reef Projector) is unsuitable for the paddock-scale investigations. In addition, the new tool must allow farmers to answer, "Is it possible to reduce water and energy consumption without compromising productivity, profitability and sustainability?". However, some challenges must be overcome for such tools to be successfully adopted by the target end-users (see section 2.1).

Therefore, this paper aims to demonstrate, via a practical 'what-if' example, how fundamental learnings about more (drought) resilient farming systems and more sustainable irrigation practices can be extracted from a paddock-scale 'discussion' support system (DSS; Nelson et al. 2002) named Irrigation Rapid Assessment Tool (hereafter referred to as 'i-RAT'). Details of the participatory approach with research and industry partners that informed the design and function of i-RAT and how APSIM was set up and parameterised are discussed.

2. i-RAT development: a co-learning and participatory process

i-RAT was developed as a DSS and rapid assessment-visualisation tool to assess the economic and environmental impacts of different sugarcane irrigation practices. The aim was to make a robust but complex crop model more accessible to farmers and advisors without requiring them to collect data and set up the model for numerous combinations of soil types, weather stations, and management scenarios. i-RAT bridges the gap between better irrigation management and natural capital accounting, with the view to encouraging farmers to consider transitioning to more efficient irrigation practices that will deliver a better economic and environmental outcome. Potential stakeholders and end-users of i-RAT include, but are not limited to, sugarcane farmers, extension officers, agronomic advisors, sustainability financiers, and government agencies.

Burdekin was selected as the pilot area (Fig. 1). With 67,000 ha of the sugarcane-cultivated area producing more than 7 million tonnes per annum, the Burdekin Statistical Area Level 2 (SA2) is the largest sugarcane-producing region in Australia. i-RAT was designed through participatory processes based on the conceptual framework proposed by Jakku and Thorburn (2010). Four 'Focus Groups' were consulted through the design and implementation of i-RAT: (1) the 'Research' focus group: comprising the Paddock-to-Reef (P2R; Australian and Queensland Governments 2022) modelling and adoption teams; (2) the 'Farming' focus group: comprising a selected group of the Burdekin region's sugarcane farmers; (3) the 'Extension' focus group: comprising extension officers from different organisation in the Burdekin. and (4) the 'Finance' focus group: comprising representatives of Queensland Government's Department of Agriculture and Fisheries (DAF), GreenCollar (https://greencollar.com.au), and Queensland Rural and Industry Development Authority (QRIDA; https://www.qrida.qld.gov.au). In this context, i-RAT was considered a 'boundary object' as it created a connection between the participants while remaining sufficiently flexible to be used by different parties for their own purposes (Jakku and Thorburn 2010). This boundary object facilitated the re-framing of assumptions, expectations, and knowledge (i.e., 'technological frames') of participants (including the core team) regarding the problem of efficient irrigation and helped the participants to arrive at a shared understanding of the problem and potential solutions (i.e., 'interpretative flexibility'). While the Research focus group ensured rigour in the scientific modelling processes, the role of other focus groups was to ensure that i-RAT was meaningful and comprehensive yet easy to use with useful and informative outputs.

3. i-RAT modelling framework

The sugarcane module from the Agricultural Production Systems sIMulator (APSIM; Keating et al. 2003; Holzworth et al. 2014) modelling framework generated a data cube containing modelled outputs (1961–2021) from 240,408 simulated scenarios incorporating different weather stations, soil types, and farm management scenarios. These simulated outputs from the crop model were complemented with farm economic calculations as functions of yields, water, labour, and

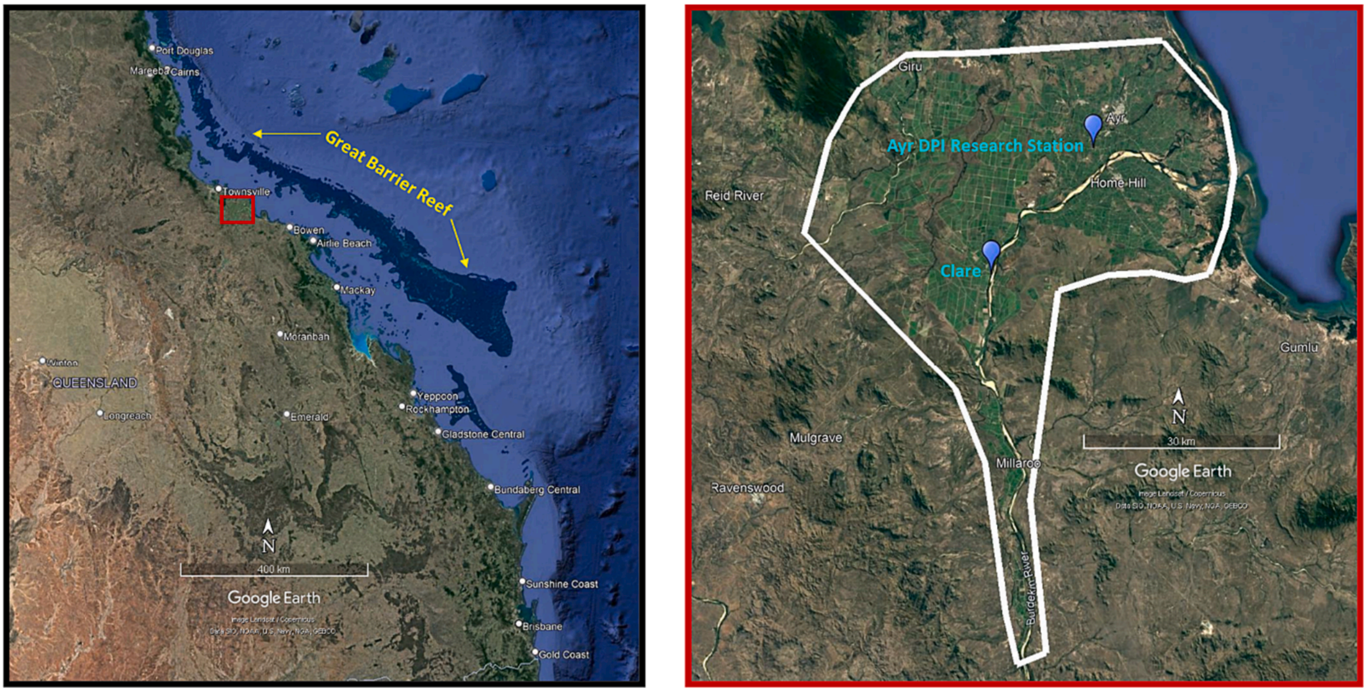


Fig. 1. Map of the Burdekin sugar-producing region in northeastern Australia (left). The white border shows the approximate boundary of the study region (right). Markers are the locations of the two weather stations (Ayr DPI Research Station and Clare).

electricity costs.

The modelling framework was built on the work of the Research focus group and the P2R Projector (https://p2rprojector.net.au; Australian and Queensland Governments 2022). The P2R Projector estimates the water quality improvement of farm-scale agricultural practice change projects. However, due to spatial aggregation and upscaling, the P2R Projector is unsuitable for the paddock scale. This issue was discussed and established in meetings with the members of the Research focus group.

Therefore, an upgraded modelling framework was developed using the framework implemented by the P2R Projector modelling team as the base. All APSIM manager scripts were rewritten in the new type of 'manager scripts' that enables the adoption of the C# programming language. These manager scripts provide more flexibility in implementing complex management scenarios. Regionally representative management scenarios were defined within the new framework in consultation with the Modelling and Extension focus groups. Rigorous testing ensured that the two frameworks would produce reasonably comparable outputs for the same management scenarios.

3.1. APSIM setup

Crop modelling and irrigation scheduling were performed with APSIM, a modelling framework that simulates crop-soil-atmosphere dynamics daily. APSIM requires detailed data on sugarcane physiology and morphology, weather, soil physical and chemical properties, and management (sowing and harvest time, tillage, fertilisation, irrigation, etc.). Various sources of data were used. Fig. 2 shows the data ingestion and modelling framework implemented in APSIM. This structure, implemented in APSIM, has multiple components, each responsible for a part of the data ingestion and modelling process. All these components calculate many intermediary variables that will then be used by other components or in post-processing. Data Manager provides an entry point in APSIM graphical user interface where the user can choose the irrigation scenario, fertilisation scenario, and tillage scenario, among others, and choose parameters related to sugarcane cultivation, e.g., the variety to be sown, sowing depth and sowing density. These data will then be passed on to the other manager components. Run-Off DIN Calculator estimates the volume of N that leaves the paddock via run-off.

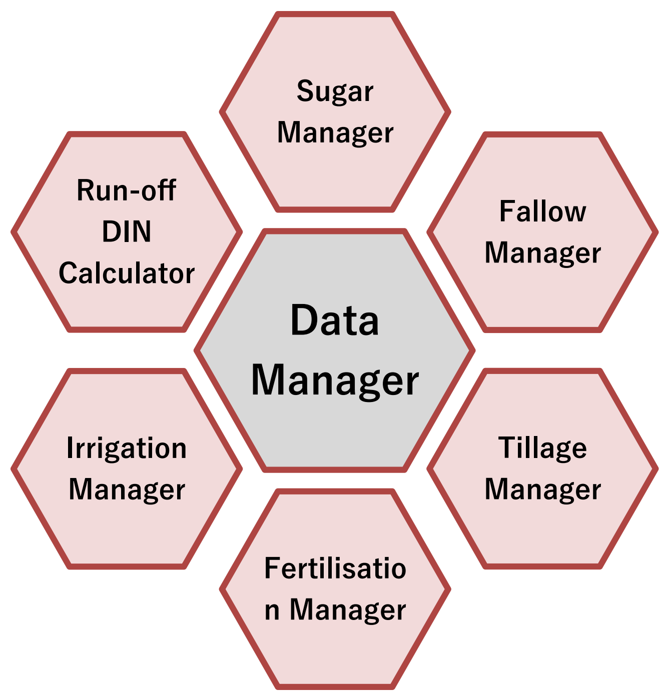


Fig. 2. Data ingestion and modelling framework implemented in APSIM.

3.2. Simulation scenarios

To generate a data cube that covers a wide range of representative paddock management scenarios, many simulations needed to be run. Each simulation represented a combination of scenarios for soil (six soil classes), planting (six scenarios), tillage (seven scenarios), irrigation

Table 1
Number of irrigations during the crop establishment phase for different irrigation scenarios. The values in parentheses show the last day of the crop establishment phase. SWD: soil water deficit.

Scenario	Plant	Ratoon 1	Ratoon 2	Ratoon 3+
SWD-Based	Drip irrigation: SWD > 15% of PAW over the top 600 mm of soil Furrow irrigation: SWD > 40% of PAW over the top 900 mm of soil			
Low-Frequency	3 irrigations (91 days)	4 irrigations (87 days)	4 irrigations (80 days)	4 irrigations (66 days)
Medium-Frequency	4 irrigations (91 days)	5 irrigations (87 days)	5 irrigations (73 days)	5 irrigations (65 days)
High-Frequency	5 irrigations (91 days)	6 irrigations (87 days)	6 irrigations (72 days)	5 irrigations (62 days)

frequency (four scenarios), irrigation rate (13 scenarios), dry-off period (three scenarios), and N fertilisation rate (three scenarios) and timing (one scenario). The scenarios previously investigated by the P2R Projector modelling team were reviewed, and amendments and/or modifications were applied, if necessary, to create more realistic and representative scenarios. In total, 240,408 scenarios (all combinations of scenarios × two weather stations) were simulated continuously (i.e., without resetting the initial water/N conditions at the beginning of each crop) using six simulation starting years (to simulate plant crop, all ratoons, and bare fallow in every year) over the 60-year period of 1961–2020 (>86 million crops) and analysed. Crop model simulations and post-processing of the outputs were executed using the JCU High-Performance Computing platform ('Zodiac').

3.2.1. *Soil and weather data*

Six soil profiles were selected (two from the APSoil database, v3.37, and four from Donnollan 1991; Attard et al. 2009; Hesp et al. 2011) that represent the dominant soil types in the Burdekin region. These soil profiles represented six different soil classes regarding plant-available water (PAW; Low, Medium, and Very High) and water infiltration (Very Low, Low, Medium, and Very High). Currently, we are using data from the SILO patch point dataset (Jeffrey et al. 2001) for two weather stations (Ayr DPI Research Station and Clare; Fig. 1).

3.2.2. *Crop/fallow cycles*

Six scenarios were defined with planting times ranging from March 15 to August 15 with a plant crop, four ratoons, and bare fallow. Sugarcane planting was simulated for the cultivar 'Q117′ considering 10 plants/m^2 and a planting depth of 15 cm. Plant crops were harvested 12–15 months after planting, while ratoons were harvested 7–13 months after the harvest of the previous crop, depending on the selected scenario.

3.2.3. *Tillage*

Five tillage scenarios were defined, representing conservation-tillage to intensive-tillage regimes. The first tillage, if any, was performed one day after this period. In APSIM, tillage operations can have two effects: (1) reduction in the soil curve number (CN) value (i.e., reducing run-off), and (2) incorporation of plant residuals in the soil. Each operation can cause one or both effects. Tillage depth, CN reduction, a fraction of residue incorporated, and cumulative rain required to reset the value of CN to its original value were determined for a wide range of tillage operations and were implemented in relevant APSIM input files.

Any operation in the model, including planting and tillage, was subject to soil workability, i.e., an operation was plausible if available moisture in the first soil layer was less than the Drained Upper Limit (DUL) of the layer. If this criterion was not met, the operation would be postponed and skipped if postponed for more than ten days.

3.2.4. *Residue burning*

The user can choose whether crop residue is burnt before a harvest. In APSIM-Sugarcane, a fraction of leaf (live and senesced) and cabbage can be 'burnt' at harvest, with the remaining material becoming surface residue in the APSIM-SurfaceOM module. Here, 85% of the leaf and cabbage was assumed to be 'burnt'. Choosing to keep crop residue instead of burning it was only possible if zonal tillage scenarios were selected.

3.2.5. *Irrigation*

Five irrigation frequency (i.e., timing) scenarios were defined (Table 1), including low, medium, and high-frequency regimes along with two soil water deficit (SWD)-based irrigation scenarios (scenarios 'SWD-Based-Drip' and 'SWD-Based').

For the low, medium, and high-frequency scenarios, irrigation scheduling was done separately for two parts of the growing season. Three to six irrigation events were simulated between the beginning of crop establishment and a maximum of 91 days later (Table 1). The irrigation frequency increases after establishment (Table 1) as demand for water increases before slowing as demand slows prior to dry-off (i.e., the period prior to harvest during which irrigation is stopped). During the peak-demand phase, irrigation was performed regularly (every 7, 10 and 14 days, respectively). Moreover, three scenarios (5, 8 and 11 weeks) were defined for the dry-off period.

In the soil water deficit (SWD)-based irrigation scenarios, irrigation was triggered when SWD within the top 600 mm was larger than 15% of plant available water (PAW). In the 'SWD-Based-Drip' scenario, which represented a fully automated high-frequency, high-efficiency (90%) irrigation regime (e.g., subsurface drip), irrigation water was applied as much as it was needed to fill the soil profile over the maximum of the rooting depth and 600 mm. In the 'SWD-Based' scenario, however, irrigation water was applied as much as the amount set by the irrigation amount scenario. In these two water-deficit-based scenarios, an irrigation event was triggered only if at least two days had passed from the last irrigation event.

Thirteen irrigation amount scenarios (50, 65, 80, 95, 110, 125, 140, 155, 170, 185, 200, 250, and 350 mm) were simulated. Irrigation events were postponed based on the following rules: (1) two days delay for a 20-mm 3-day rainfall, six days for a 50-mm rainfall, and ten days for a 100-mm rainfall, while 3-day rainfall was capped at 7 mm × (irrigation cycle + 2) to account for the soil water holding capacity, assuming a maximum evapotranspiration rate of 7 mm d^{-1}; (2) one day delay for every 7-mm daily rainfall (capped at 7 mm × irrigation cycle); (3) taking the maximum value obtained by the two rules; and (4) capping the delay to the number of days passed from the previous irrigation event, to account for lesser effect of rainfalls closer to the previous irrigation. The postponement rule did not apply to the SW-based scenarios.

3.2.6. *N fertilisation rate*

Three scenarios were simulated for the 'base' N application rate: 180, 200 and 220 kg ha^{-1}. For plant sugarcane, 25% of N fertiliser was applied on planting day, and the rest 90 days after planting. For ratoons, all N was applied the day after harvest of the previous plant/ratoon. Under SWD-Based irrigation scenarios, one irrigation event was triggered one day after N was applied.

3.3. *Run-off DIN modules*

The Paddock-to-Reef Modelling Team (Vilas et al. 2022) calibrated and validated a model with more than ten years of data from two of the main Australian sugarcane regions, a high (Wet Tropics) and moderate

(Mackay Whitsundays) rainfall area. This model was used to estimate DIN in run-off. The model predicts DIN losses in runoff from both inorganic and organic fertilisers (RMSE = 0.37 and 2.0 kg N ha^{-1} for the Wet Tropics and Mackay Whitsunday regions, respectively) as a function of the concentration of nitrate and ammonium in the first layer of the soil profile (0–10 cm) and the amount of predicted runoff.

3.4. Greenhouse gas emission

Multiple sources of greenhouse gas (GHG) emission were considered: (1) CO_2 emission during the decomposition of soil organic material, (2) nitrous oxide (N_2O) emission during nitrification and denitrification, (3) emission due to pumping of water, and (4) N_2O and CH_4 (methane) emission due to residue burning. The APSIM SoilN module estimated the first two sources. CO_2 emission was defined as efficiency coefficients representing the proportion of carbon retained in the system. APSIM assumes, by default, that 60% of decomposed carbon (C) is lost to the atmosphere. N_2O emission during nitrification is calculated as a proportion of nitrified N (Li et al. 2007). N_2O emission during denitrification is calculated by combining predictions of denitrification with the ratio of N_2 to N_2O emitted during denitrification (Grosso et al. 2000). The amount of GHG emission due to pumping depends on the fuel used and energy required to pump a unit of water. CO_2 emission factors for combustion were extracted from IPCC (2006a).

According to IPCC (2006b), for estimating GHG emissions due to plant residue burning in agricultural areas, only CH_4 and N_2O emissions should be considered because the crop growth in a 1-year period would compensate for the CO_2 emissions. This hypothesis was also applied to carbon monoxide (CO) as it is quickly converted to CO_2 in the atmosphere. NO_x emissions were also not considered in our estimations because their global warming potential is uncertain.

The IPCC (2006b) methodology was applied to estimate GHG emissions from burning. The emission factors adopted were 2.7 and 0.07 for CH_4 and N_2O (g kg^{-1} of burned dry matter), respectively (Andreae and Merlet 2001). At this stage, GHG emission resulting from the combustion of fuel is not considered.

3.5. APSIM parameterisation

The default values of radiation use efficiency (RUE) for plant and ratoons were set at 1.8 and 1.65, respectively (Robertson et al. 1996). While it is usually assumed that potential photosynthesis (i.e., RUE) is reduced by 80% when the fraction of crop roots exposed to water logging reaches 100% (Meier and Thorburn 2016), these parameters were deemed to cause too severe water-logging impact for the Burdekin region (personal communications with the P2R Projector Tool modelling team). Therefore, to account for the erratic and local nature of water-logging across a paddock, it was assumed that RUE was affected when the fraction of water-logged roots exceeded 70% and was reduced by 30% when it reached 100%. While in some of the previous studies and projects (including early versions of P2R Projector), the impact of lodging was simulated when daily rainfall exceeded 20 mm when plant biomass was above 20 t ha^{-1} (Thorburn et al. 2011a; Biggs et al. 2013; Meier and Thorburn 2016), the impact was not considered here due to its erratic and unpredictable spatial pattern in a single paddock and for lack of reliable field data. Transpiration efficiency coefficient (TEC) was increased from 8.7 (Inman-Bamber and McGlinchey 2003) to 12.4 g kPa kg^{-1} (Jackson et al. 2014) when the water stress factor (i.e., water supply/demand ratio) reduced from 1.0 to 0.31 (Inman-Bamber et al. 2016). The effect of atmospheric [CO_2] on transpiration efficiency coefficient (TEC) and RUE was simulated with the model proposed by Webster et al. (2009). Daily atmospheric [CO_2] was estimated using a 3rd-degree polynomial fitted ($R^2 = 0.999$) on the monthly data obtained from the Cape Grim station (Ziehn et al. 2016).

4. i-RAT review process

Following several internal meetings, the i-RAT project team met with the focus groups multiple times between March 2021 and September 2022. A beta version of i-RAT (v1.0) was developed via a step-by-step process in close consultation with the Research, Extension, and Finance focus groups. These groups were first surveyed about the ‘problem’ i-RAT was intended to address and how to formulate the potential solutions. The survey results were collated and discussed by groups, and the path forward was agreed upon. The boundaries of the analyses (i.e., soil, irrigation, planting, and tillage parameters, etc.) were also negotiated, and a trade-off was achieved between maintaining the simplicity of the tool whilst still providing sufficient details desirable to the focus groups, all constrained by data availability and computational resources to conduct simulations and analyses.

Multiple sub-versions of the user interface were developed and tested, each incorporating new/improved features. Finally, the alpha version was presented to six members of the Farming focus group in May 2022 via a series of one-on-one demonstrations by an extension officer. Expectations, experiences, and learnings were documented and combined with the feedback received from other focus groups and incorporated into the design of i-RAT.

The beta version was developed using Shiny, an open-source R package that provides an elegant and powerful web framework for building web applications using R. Before releasing the alpha version of i-RAT (v2.0), the interface was rebuilt using ReactJS, a highly used open-source JavaScript library, to improve the loading speed and eliminate the need for a costly server to host/run the application. The alpha version was released in August 2022 and presented to the Farming focus group in September-October 2022. The final review of i-RAT was conducted in two meetings in September 2022, wherein it was presented to the other focus groups.

5. i-RAT user interface

To ensure gradual exposure and learning, two different user interfaces were designed. The ‘basic’ user interface was used through the development phase and was presented to the farmers and extension officers. The ‘premium’ user interface, described in the following sections, was presented to the Research, Extension, and Finance focus groups. This version of the user interface provides more options and enables more comprehensive analyses of water balance, N/C balance, and GHG emission.

5.1. Inputs

- **Paddock settings** (Fig. 3A, Fig. 4): the user can define the paddock settings to explore the data cube by changing options via the drop-down lists. Current options include region (currently only Burdekin), weather station (currently Ayr DPI Research Station and Clare), soil (six soil types), planting scenario (six scenarios), display results (averaged across all crops, plant only, or individual ratoons), tillage scenario (seven scenarios classified in four groups), residue burning, dry-off period, N fertiliser, fallow (currently only bare fallow), and paddock size. A help button is provided for each menu which leads to a relevant section in the i-RAT documentation. In addition, the user can change water cost, energy used for pumping (for surface and drip irrigation), energy cost and other parameters to reflect the reality of the paddock. These parameters are used to estimate water and energy savings due to changes in irrigation management.
- **Irrigation settings** (Fig. 3B): in this section, the user can compare two irrigation scenarios. Each scenario is defined by irrigation frequency (during the establishment phase and the peak-demand period) and irrigation amount.

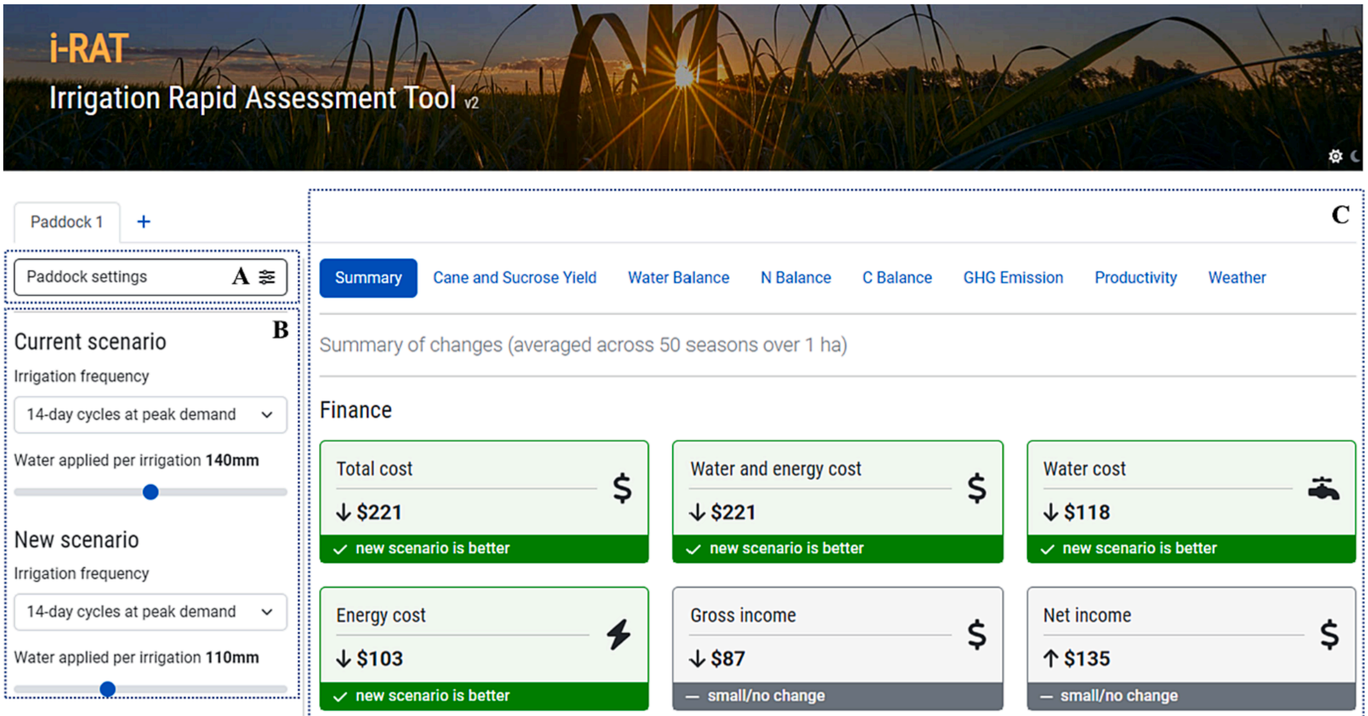


Fig. 3. The premium version of the graphical user interface of i-RAT (v2.0; https://i-rat.net). See Fig. 4 for available options in section **A** (Paddock settings). Section **B** is where the user can define two (Current vs New) irrigation scenarios. Section **C** (Outputs) is not shown in its entirety (see Fig. 5 for all available sections, including Finance, Water Quality, Water and Energy, Productivity, and Greenhouse Gas Emission).

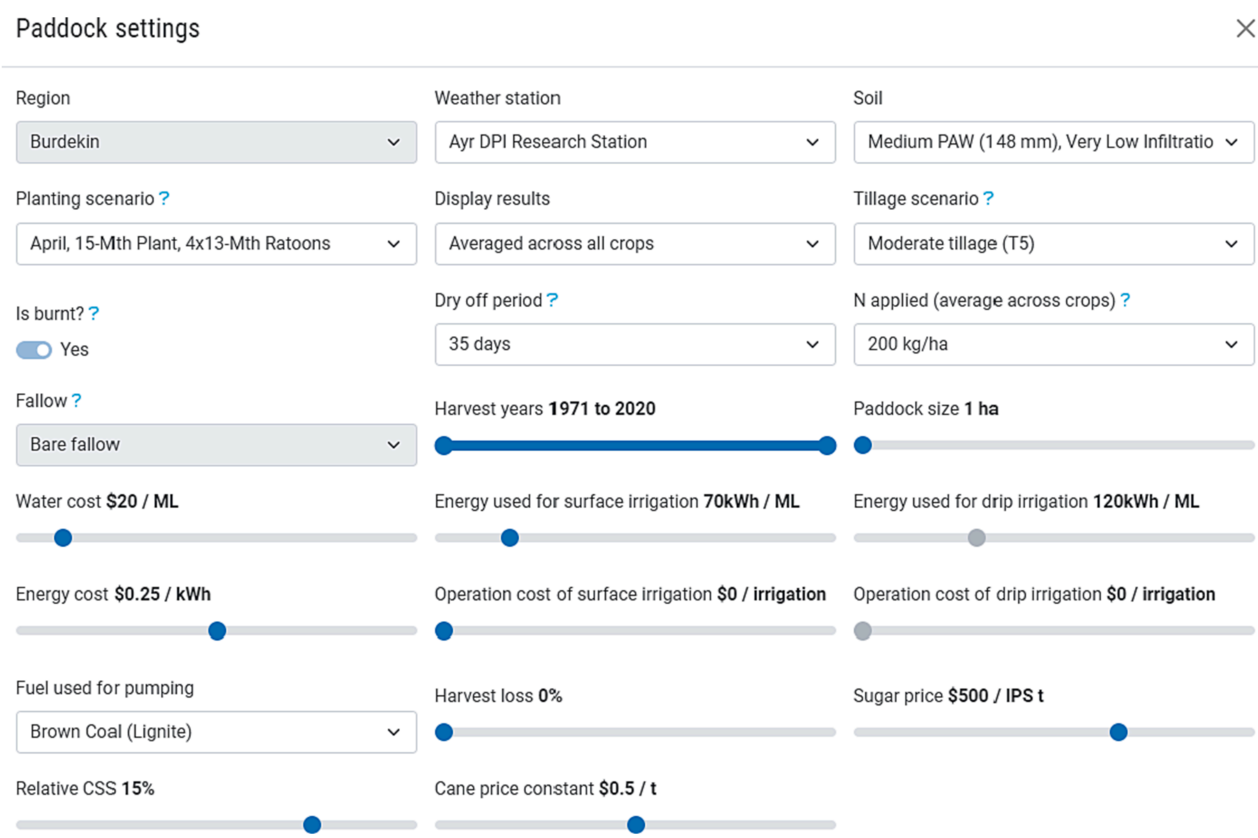


Fig. 4. Options Available under ‘Paddock settings’ section in the premium version of the user interface (see Fig. 3).

5.2. Outputs

- **Summary** (Fig. 3C): provides a colour-coded summary of (simulated) changes achievable by going from Current to New irrigation scenario. It consists of a few sections with information on the impact of change in irrigation scenario on water and energy cost, water quality (N and soil loss), total amount of irrigation water applied, number of irrigations, energy used, cane and sucrose yields, Gross Production Water Use Index (GPWUI = cane yield / (gross water applied + effective rainfall), Nitrogen Use Efficiency (NUE), and GHG emissions.
- **Cane and Sucrose Yield** (Fig. 3C): provides visualisations for cane and sucrose yield changes due to changes in the irrigation scenario from Current to New irrigation scenario. 'History chart' lets the user visually inspect and 'count' the number of seasons (out of 50 simulated seasons) where the target variable increased/decreased or did not change substantially (shown in grey). 'Count plot' and 'Count table' show the number of seasons in which the change in target variable would have been in a pre-defined range (e.g., ±5-10%). 'Probability plot' shows the same data that 'Count plot' shows, except in the form of probability. 'Pie chart' shows the probabilities of improvement and worsening of the target variable. 'Box plot' shows the variation (10, 25, 50, 75, and 90th quantiles) of the target variable under each irrigation scenario.
- **Water Balance** (Fig. 3C): provides visualisations for various components of water balance, including irrigation water applied, runoff, deep drainage, evapotranspiration, crop transpiration, soil evaporation, number of irrigations, and in-season rainfall.
- **N Balance** (Fig. 3C): provides visualisations for N balance, including plant N uptake, N loss via run-off and leaching, denitrification, surface residue N burnt, soil inorganic N at harvest, harvested cane N content, soil organic N at harvest, N2O emission from soil, and N2O emission from burnt biomass.
- **C Balance** (Fig. 3C): provides visualisations for carbon (C) balance, including soil C at harvest, surface residue C burnt, and surface residue dry matter burnt.
- **GHG Emission** (Fig. 3C): provides visualisations for GHG emission, including total GHG emission, CO2 emission from the soil, N2O emission from the soil, N2O emission from burnt biomass, CH4 emission from burnt biomass, and GHG emission from pumping.
- **Productivity** (Fig. 3C): provides visualisations for GPWUI and NUE.
- **Weather** (Fig. 3C): provides visualisations for long-term averages and annual time-series of weather data (minimum and maximum temperature, rainfall, evaporation, and radiation).

The new scenario is considered better (displayed in green) or worse (displayed in red) than the current scenario only if the impact of the change in the irrigation scenario on the target variable is greater than ± 5%. Otherwise, the change is shown in grey.

6. Extract learning from i-RAT: A 'what-if' analysis

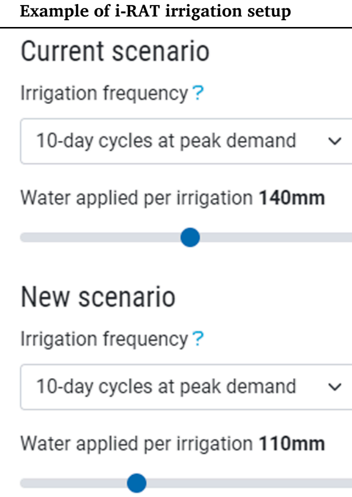
6.1. Context

Suppose that a farm manager is considering improving their irrigation practice to enhance the farm's financial status. The farm is in the Burdekin region and has several blocks where soil with 'Medium PAW & Very Low Infiltration' is dominant. Currently, irrigation is applied every ten days during the peak-demand period and during each irrigation event, 140 mm of water is applied via a furrow irrigation system (Table 2). The sugarcane crop is planted on April 15 and harvested after 15 months, followed by four 13-month ratoons. A moderate tillage scenario (up to 10 operations) is applied before planting and after harvest. Crop residue is burnt before each harvest. The dry-off period is 35 days, and 200 kg ha^{-1} of N fertiliser is applied to each crop. The electricity to operate the pump is provided via a local company and is generated at a power plant that burns brown coal. Other management decisions and financial variables are depicted in Fig. 4.

The farm manager sought consultation from an extension officer. They decided to use i-RAT to perform a series of 'what-if' analyses to explore a few relatively simple options which might improve water and energy use efficiency. The options included reducing the irrigation amount from 140 mm per irrigation to 110 mm, 80 mm, and 50 mm (see the last column of Table 2). They created three 1-ha paddocks, which only differed regarding New Scenario. Then, they went through the Summary Tab first to quickly grasp the outcome of such a change on farm finance, water quality, water/energy use, productivity, and GHG emission (Fig. 5). They also used the visualisation tabs to explore the implications for multiple aspects of the production system. Along with the impact of this change on the farm's water-energy productivity, they wanted to know if this change might improve their farming practices regarding water quality and GHG emissions.

In the next section, we present i-RAT outcomes in detail for one selected scenario (reducing irrigation amount from 140 mm to 110 mm per irrigation event; hereafter the '140-110′ scenario). At the end, we provide a summary of their findings for all three scenarios/paddocks and how they performed a multi-criteria analysis to answer their questions.

Table 2
Irrigation scenarios for the example 'What-If' analyses. For other paddock parameters, see Fig. 4. Operation cost and harvest loss are not considered in these analyses.

Soil type	Irrigation frequency	Irrigation rate	Example of i-RAT irrigation setup
Medium PAW Very Low Infiltration	10-day cycles at peak demand	140 mm	

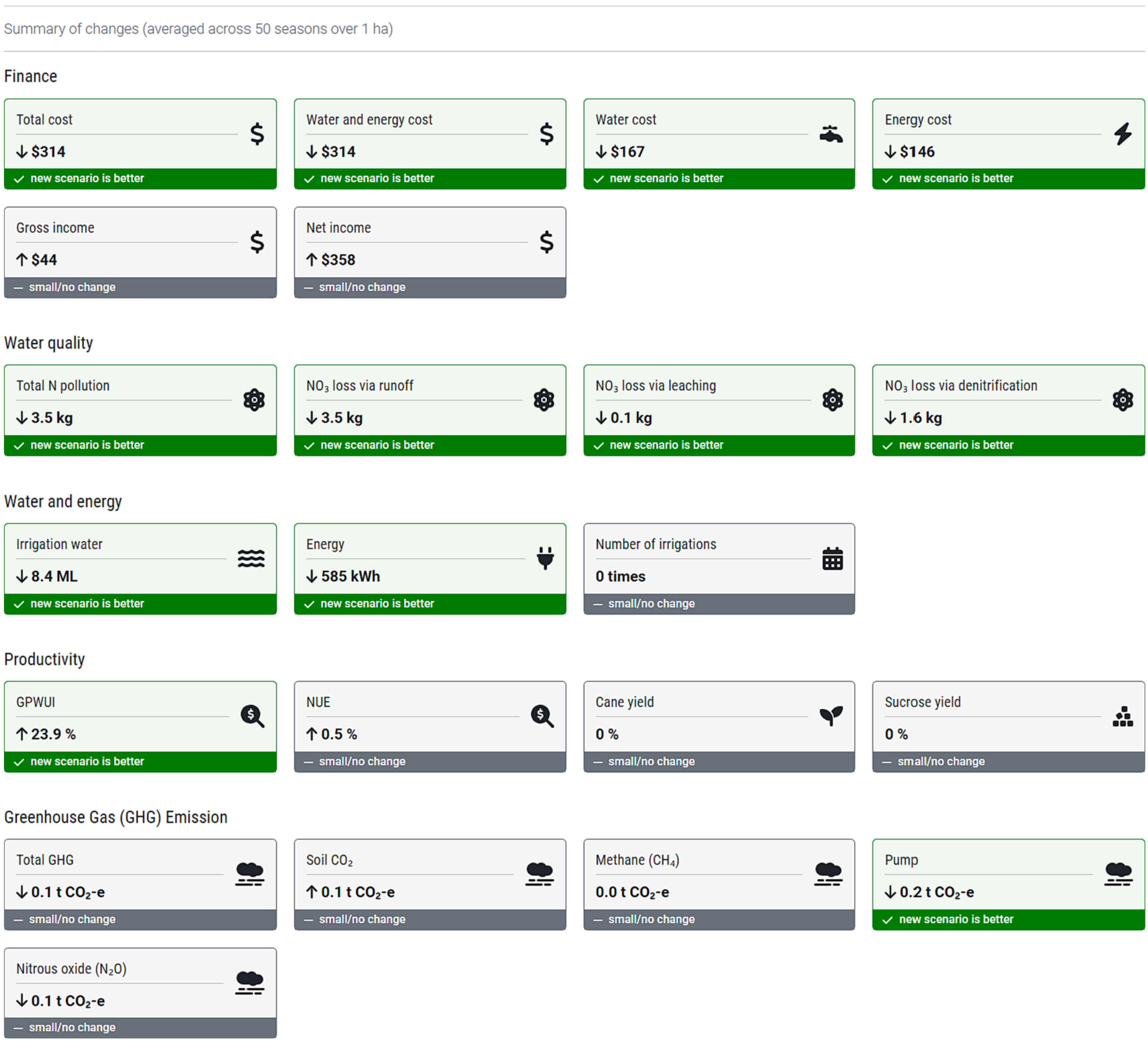


Fig. 5. The i-RAT's Summary Tab for an example 'What-If' analyses (reducing irrigation amount from 140 mm to 110 mm per irrigation event). Green (red) colour means the new scenario is better (worse) than the current scenario and grey colour shows small or no changes (see the text for definition).

6.2. *Learning*

Fig. 5 shows i-RAT's Summary Tab for the first paddock representing the 140 mm to 110 mm scenario. i-RAT's outputs show that reducing irrigation amount from 140 mm to 110 mm per irrigation, without any change in irrigation frequency scenario (see Table 2), would lead to 314 AUD ha^{-1} of saving in water and energy cost in an average season. This saving would result from an 8.4 ML reduction in water consumption and a 585-kWh reduction in energy consumption. As cane and sucrose yield would not markedly change, the Gross Production Water Use Index (GPWUI) would be a direct function of water consumption and raised by 23.9%, on average. Given the assumed sugar and water price, the farmer could expect a 358 AUD ha^{-1} increase in net income.

From a water quality perspective, reducing water consumption would lead to substantially less N loss via run-off (3.5 kg ha^{-1}), though a reduction in N leaching via deep drainage would be relatively small (0.1 kg ha^{-1}) due to the low infiltration capacity of the soil (Fig. 6). This scenario would reduce total GHG emission by at least 5% in 8 out of 50 seasons (Fig. 7), leading to a small reduction in the average total emission from the paddock (0.1 t CO_2-e ha^{-1}), mostly due to a reduction (0.2 t CO_2-e ha^{-1}) in pumping-related emissions.

The same observations were made for other two paddocks (data not shown). Obviously, the more reduction in irrigation amount, the more saving in terms of water and energy cost and N loss via run-off and leaching. GHG emission would not change tangibly unless irrigation amount is reduced to 50 mm, which would lead to 1.1 t CO_2-e ha^{-1} reduction in GHG emission. However, on the other hand, the 140–50 scenario would lead, on average, to 7% reduction in cane yield which in turn would lower the gross income by 719 AUD ha^{1}. While even under such circumstances, the saving related to water and energy cost would cover the loss of income due to lower yield, this scenario would involve higher risk. It may be least appealing to the farmer and wider industry that relies on maximising cane volume.

Fig. 8 summarises the 'what-if' analyses by showing changes in

Fig. 6. Selected history charts from the i-RAT's N Balance Tab for an example 'What-If' analyses (reducing irrigation amount from 140 mm to 110 mm per irrigation event). Each plot depicts the 50 analysed seasons. Green colour means new scenario is better than current scenario, red means current scenario is better than new scenario, and grey colour shows small or no changes (see the text for definition).

selected financial (sucrose yield, and water and energy cost) and environmental (total N pollution and loss, soil carbon at harvest, and total GHG emission) indices due to change in irrigation rate from 140 mm per irrigation event to 110 mm, 80 mm, and 50 mm, respectively. As mentioned before, sucrose yield would only decrease significantly if the irrigation amount per irrigation event was to be reduced from 140 to 50 mm (Fig. 8A). Total N pollution (i.e., N loss via run-off + deep drainage) could be lowered by 10–20% with every 30 mm reduction in irrigation water (Fig. 8C). We can see that reduced water consumption would lead to a higher amount of C stored in the soil profile at harvest, though the impact is small (Fig. 8E).

From an environmental perspective, reducing water application per irrigation event would directly affect the amount of N pollution and GHG emission from the paddock (Fig. 8C, F). Therefore, while lower yield might be an important factor leading to the ruling-out of the 140–50 scenario, it could still be a viable option for the farmer if the loss of income (due to lower yield) was compensated through sustainability funds in recognition of lower N pollution and GHG emission. This option will be discussed in more detail.

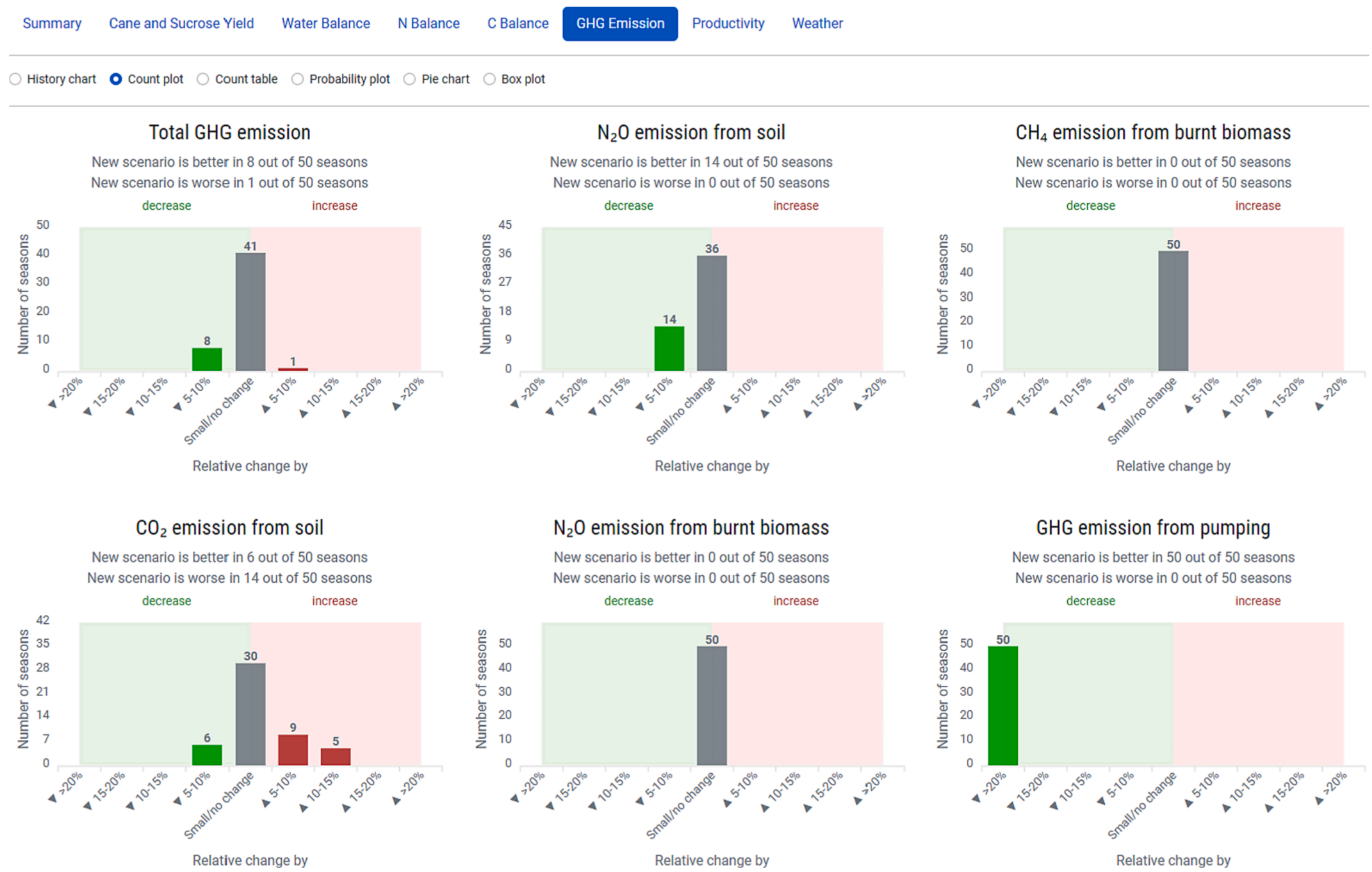


Fig. 7. Selected count plots from the i-RAT's GHG Emission Tab for an example 'What-If' analyses (reducing irrigation amount from 140 mm to 110 mm per irrigation event). Each plot shows the number of analysed seasons in which the target variable increased or decreased or did not change markedly. Green colour means new scenario is better than current scenario, red means current scenario is better than new scenario, and grey colour shows small or no changes (see the text for definition).

7. Discussion

7.1. Modelling: A solution to a multifaceted problem

The rising costs of electricity and water have inflated the importance of adopting more efficient irrigation practices and state-of-the-art technologies that are usually embedded in decision/discussion support systems. Better irrigation practices, through increased water use efficiency, can deliver economic, environmental, and social outcomes to agroecological systems (Mueller et al. 2017; Wang et al. 2020). Improving irrigation practices requires quality data on crop water requirement during the season. In Queensland, the total crop water requirement is usually calculated using the concept of reference evapotranspiration (ET_0; Allen et al. 1998). This approach is simple and easy to implement but does not consider the impact of soil and crop status on its water and nutrition requirements. For proper irrigation scheduling, the atmospheric demand for water vapour, soil characteristics, and plant-specific features must be considered (Anadranistakis et al. 2000).

A crop model, like APSIM-Sugar, simulates many processes to model the soil–plant-atmosphere continuum as a dynamic system. Application of such models can lead to improved water requirement estimation and irrigation scheduling. However, it requires a considerable amount of data on soil, weather, plant, and management along with a high level of expertise and experience. A DSS built upon data generated by a crop model, like i-RAT, removes the complexity of such models and provides ready-to-use data to users without requiring them to know anything about the setting up of a crop model.

Implementation of the GBR 2050 Plan (State of Queensland 2018) marked a significant shift in how the federal and state governments should lead collaborations in addressing challenges that face the GBR. However, achieving tangible outcomes has proven difficult, partly due to a lack of quality paddock-scale data on N pollution and GHG emission from vast and diverse agricultural lands in the region. To assess the relative importance of various N loss pathways (run-off, deep drainage, and denitrification) along with CO_2, N_2O, and CH_4 emissions from agricultural production systems, and to suggest possible procedures for mitigating these air and water pollutants, obtaining quality data on GHG and N pollution generated at a paddock level is essential. However, measuring these emissions and losses at a paddock level is extremely time-consuming and costly, if not impossible. Once again, crop models can reasonably reproduce processes involved in the soil-atmosphere C/N cycle and provide reliable estimates, which can then replace and/or complement such field measurements.

7.2. Environmental markets and incentives

i-RAT is a tool that can help farmers, extension staff, and local advisors trial scenarios that can mitigate the main threats to the GBR and potentially benefit from existing and emerging environmental markets and financial incentives. Climate change or land-based run-off (i.e., water quality) present a very high-risk to the GBR's ecosystem and heritage values (GBRMPA 2019). At the same time, increasing GHG emissions from human activities continue to pressure the agricultural sector to mitigate emission (de Figueiredo et al. 2010).

In response to these and other environmental challenges, the Australian federal government recently passed the Climate Change Bill 2022, which targets a 43% reduction in carbon emissions by 2030,

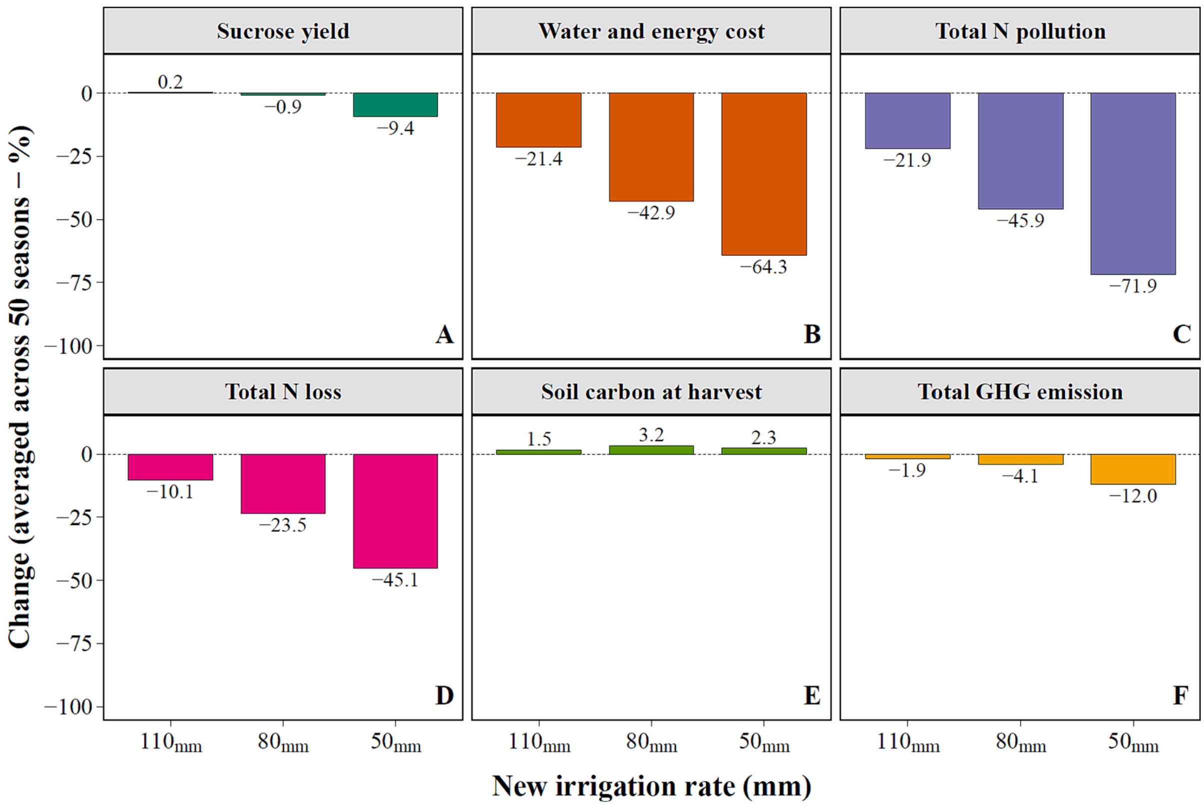


Fig. 8. Summary of the 'What-If' analyses: Changes in selected financial (sucrose yield, and water and energy cost) and environmental (total N pollution and loss, soil carbon at harvest, and total GHG emission) indices due to change in irrigation rate from 140 mm per irrigation event to 110 mm, 80 mm, and 50 mm, respectively. Unlike N loss, N pollution (run-off + leaching) does not include denitrification.

compared to 2005 levels and net zero by 2050. Achieving the ambitious net-zero goals by 2050 will require further incentivisation. Moreover, the federal government is now promoting accounting systems and trading infrastructure needed to grow Australia's carbon markets. Some of these environmental markets address the issue of improving water quality flowing into the GBR and its lagoons by paying land managers for reduced water pollutants resulting from their on-farm actions without compromising the productivity of their land. Performing 'what-if' scenario analyses in i-RAT will allow landholders to better understand the impact of different management practices on economic and environmental outcomes and provide guidance on benefits that can be generated from such markets. Examples of schemes that i-RAT outputs can be linked to include the Federal Government's Carbon + Biodiversity Pilot (Department of Agriculture, Fisheries and Forestry; DAWE 2021) and the Reef Credit Scheme, administered by Eco-markets Australia (Eco-Markets Australia 2021).

7.3. *i-RAT development: reflection on the approach*

Previous researchers have discussed challenges that surround the adoption of DSSs (Carberry et al. 2009; Ascough II et al. 2010; Thorburn et al. 2011b; Hochman and Carberry 2011; Cahn et al. 2017; Rose et al. 2018; Aversa et al. 2018; Car 2018; Gallardo et al. 2020; Baldin et al. 2021; Ara et al. 2021). These challenges include, but are not limited to, (1) the DSS (especially the information and communications technology-based DSSs) being too complex and not doing what end-users need or want it to do; (2) the DSS being developed in a top-down fashion by researchers rather than being demand-driven by end-user needs, (3) end-users not engaging with the DSS as a co-learning or educational tool; (4) the lack of effective procedures to train and support end-users; (5) a perception that the outputs from the DSS are not sufficiently accurate to reflect reality; (6) limited interest to reduce water/energy use due to the perceived risk (e.g., reduced yield), physical limits, and the effort/investment (e.g., labour) required relative to the perceived benefits; and (7) lack of the DSS's application outside the region(s) where it was originally developed.

i-RAT was designed and developed with these challenges in mind while remaining simple, easy-to-use, and relevant: (1) i-RAT user interface provides sufficient information to the user and reduces the complexity of a DSS to simple rules, which can improve the chance of its adoption (Thorburn et al. 2011b), (2) the participatory approach that underpinned the development of i-RAT involved engagement by the Extension and Farming focus groups as part of action- and co-learning cycles throughout the project. This process was especially important during the early phases of the project, wherein the 'problem' and 'potential solutions' were formulated, (3) i-RAT has been adopted by an industry body who has embedded i-RAT into their district management plan as the only available tool that allowed farmers to answer the question, "Is it possible to reduce water and energy consumption without compromising productivity, profitability, and sustainability?". Moreover, several workshops and one-on-one interviews were held to train and support end-users, (4) i-RAT scenarios help advisors confidently guide farmers towards more efficient irrigation practices by showing that in most cases, efficient irrigation practices do not result in reduced yield and can be implemented with limited investment and effort, (5) external drivers and incentives such as the upcoming rises in the cost of water and electricity, stricter environmental regulations, and social awareness are new forces that can lead to a higher chance of adoption for i-RAT, (6) i-RAT does not collect any data and thus eliminates concerns farmers have with sharing their data, (7) i-RAT framework is extensible and easily transferable to other regions. The positive feedback from the focus groups and the funding body (the GBRF) has already led to the funding of the i-RAT extension to the Mackay-Whitsunday region.

7.4. Limitations and future works

In current version, i-RAT displays other irrigation related variables as well, including soil loss, crop transpiration, soil evaporation, and N update by the plant. In the future, there is the potential for other parameters to be made adjustable and/or other variables be outputted/displayed. New features may also be added while some of the available features may be discarded from the future versions. These changes will be conditional on the feedback from i-RAT users and requests from the industry partners.

It is essential to note that the outputs of i-RAT strongly depend on (i) the crop model used, (ii) the choice of sugarcane cultivar and its parameterisation, and (iii) the choice of management practices. Outputs from any crop model are subject to uncertainty, of which the user must be aware. APSIM parametrisation was done based on previous peer-reviewed research studies. Currently, i-RAT captures a representative range of scenarios, but it is possible to increase the range of predefined scenarios. i-RAT currently provides simulations utilising historical climate data, but it can potentially integrate climate change scenarios in the future, contingent upon funding availability. Although i-RAT may accommodate a larger number of management scenarios in its future versions, for now, it is critical that the user chooses scenarios that best resemble real management practices on the paddock.

8. Conclusion

This paper demonstrated how fundamental learnings about more (drought) resilient farming systems and more sustainable irrigation practices can be extracted from a paddock-scale 'discussion' support system. We overviewed the industry involvement that guided the development of the DSS by taking a participatory approach. Via a "what-if" scenario example, it was demonstrated that it is possible to reduce water/energy consumption and N pollution without compromising productivity and profitability.

i-RAT, through an easy-to-use web interface, enables its users to take advantage of the power of a crop model and perform many other 'what-if' analyses without any need to collect or store individual growers' data. It also provides measures of sustainability that can be used to assess the impact of proposed changes in irrigation practices not only on the financial status of a paddock/farm, but also on the water quality of the GBR and GHG emissions. Such information not only helps sugarcane farmers make informed decisions regarding irrigation practices, but it also brings about opportunities provided by, for example, carbon markets. Although i-RAT, in its current functional form, has been developed for sugarcane grown in the Burdekin region, the methodology and framework are readily extendable to other crops and/or other regions globally.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Brian Collins, Yvette Everingham, Steve Attard reports financial support was provided by The Great Barrier Reef Foundation.

Data availability

Data will be made available on request.

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Ethics approval

Not applicable.

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