Irrigation demand forecasting and its role in multi-scale system storage control

QS2 Final Report

ONE BASIN CRC

The One Basin Cooperative Research Centre (CRC) is an industry-led partnership established in 2022 to build a more productive, resilient and sustainable Murray–Darling Basin for current and future generations.

From Queensland to South Australia, we are facilitating collaboration between universities, industry, business, government, not-for-profit organisations and local communities, across the agriculture, environment, water and technology sectors, working towards our vision of growing the value of water in a changing world.

Acknowledgement of Country

We acknowledge and pay respect to the Tradition Owners of the Murray–Darling Basin and their Nations. We pay respect to the Traditional Owners of the lands and the waters upon and around which our organisations are situated. We acknowledge their deep cultural, social, spiritual, environmental and economic connection to their lands and waters. We pay respect to their Elders – past, present and future.

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Citation: Merritt, W.S., Sharma, S., Guillaume, J.H.A., Rosello, C., Zahir, A., Ali, W., Dunne, A., Hamilton, S., Simmons, A., Wang, Q.J., Western, A., Yenamandra, S., 2024, 'Irrigation demand forecasting and its role in multi-scale system storage control', Final report, One Basin CRC, Australia.

This report is a collaboration between the following organisations.

Contents

Tables

Figures

Executive summary

In the highly modified Murray-Darling Basin, achieving the best possible outcomes for a healthy Country and realising the full value of water depends heavily on how humans manage water across the landscape. We now live in a data rich world, with the potential for a step change in how we understand where water is in the landscape and where we would prefer it to be in future, and navigate a diversity of pathways to achieve better outcomes in the face of uncertain, constantly changing conditions. This transformation will come from progress over time rather than deploying one-off tech fixes. To achieve it, we need to 1) strengthen processes for continual improvement of knowledge systems supporting water management and 2) further integrate operational management across a wide variety of stakeholders to achieve environmental, social and economic outcomes across the region.

This project is therefore one of a suite of One Basin CRC collaborations striving to advance data science and knowledge systems for water delivery in the Murrumbidgee River and the Southern Connected Basin. While it targets demand forecasting, the project underpins a larger pivot towards organisational adoption of reproducible predictive modelling capabilities in integrated storage management, within human-in-the-loop and continuous integration processes, and hence provides a catalyst for further innovation in this space.

The premise for this One Basin CRC Quickstart project was to demonstrate the reliability and utility of demand forecasts within the partner organisations and other actors in the water resource system (e.g., river operators), shape the adoption and continual improvement of new cutting-edge demand forecasting algorithms and, connecting back to our longer-term vision, inform future research agendas and collaborations in this space. In the first work package, the team developed algorithms with the purpose of supporting the operational water orders of Murrumbidgee (MI) Irrigation and Coleambally Irrigation Cooperative Limited (CICL) and established assessment frameworks to support the operationalisation and continual improvement of the algorithms. The second package of work placed the first in context by investigating how new demand forecasting tools can improve water delivery across the landscape and across planning scales. This was achieved by describing uses cases (or decision contexts) around water delivery and integrated storage systems where demand forecasting technologies show promise (Figure A).

Irrigation water ordering by irrigation districts was the focus for algorithm development and evaluation in this project. Algorithms for forecasting total system daily demand (for 0-7 days in advance) were developed for the Main Canal of the Murrumbidgee Irrigation (MI) district and the main zone of the Coleambally Irrigation Cooperative Limited (CICL) area of operations. Two models were developed for the Main Canal in the MI district, one applying a hybrid (conceptual and data-driven) approach and the other a data-driven approach. A hybrid model was developed for CICL. The hybrid model [1], led by the University of Melbourne team, computes daily crop irrigation requirements based on weather, crop type and crop area variables using the conceptual component of the model. The data-driven module uses these computed outputs with 7 days of lagged and leading weather variables to reduce the likely errors in the modelled demand. The MI data science team used forecast and observed weather data and lagged actual daily demand (less daily diversions) to train a data-driven model. The hybrid and data-driven model developed highlighted the criticality of high-quality weather forecasts. Forecasts are generally more accurate in dry periods where conditions are more stable than during periods of high rainfall. Nonetheless, both approaches produced models with a level of performance that demonstrated the promise of the algorithms to support the CICL and MI operation teams moving forward as they transition to the use of reproducible predictive modelling capabilities. Both CICL and MI have initiated internal processes to formalise the algorithms operationalisation and continuous improvement beyond this project.

[1] Publicly shared code available as: One Basin CRC (2024). irrigation-district-demand-forecasting: Public release (v0.1.0). Zenodo. https://doi.org/10.5281/zenodo.14428758

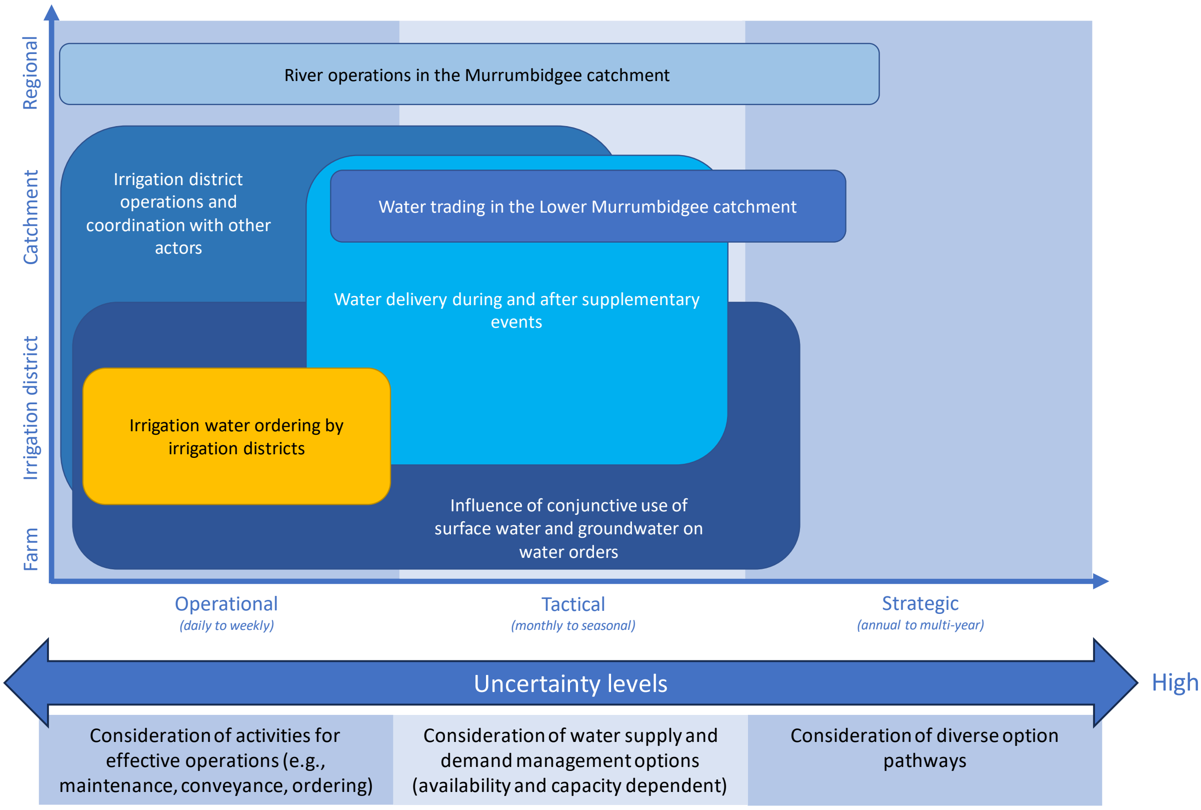

Figure A. Use cases, mapped across hierarchical planning levels and spatial scales, where demand forecasting approaches could support water ordering and delivery.

Beyond short term water ordering, demand forecasting advances could complement existing technologies and processes used by key actors involved in decisions across planning scales that relate to water ordering, delivery and use by environment, irrigation and consumptive users in the Murrumbidgee. The relative complexity of the decision contexts (Figure B) vary from use cases on focused issues (supplementary events) or users (irrigation districts) to more complex multi-actor, multi-scale (and ultimately transformative) use cases that lend themselves to exploration and advancements through the partnership model of the One Basin CRC. For example, achieving benefits from water delivery involves a broad range of decision makers and stakeholders. There is potential for even incremental changes to mechanisms for coordination and collaboration to transform management of the water system and river operations to improve the range of benefits to communities, environment and industry from water deliveries. Demand forecasting can help improve multi-stakeholder understanding of future water demand variability across the river system and associated uncertainties across time and space.

This QuickStart project has demonstrated that contemporary data science practices in demand forecasting are both valuable and achievable for water network operators. The last decade has seen unprecedented investment of over a half a billion dollars in modernisation and efficiency projects in the Murrumbidgee River system. As a result, reliable and accurate streams of real-time data are now being generated by thousands of field assets. This investment has transformed water infrastructure in the Murrumbidgee into a data-rich environment that lends itself to step change innovation in delivery modalities and to support continuous improvement in algorithms to support network management objectives. This project has also shaped how organisations can leverage extensive modernisation efforts to tackle river management and demonstrated the transferability of the methodologies employed in this QuickStart at the river scale. With Murrumbidgee River water entitlements currently estimated to be worth $13 billion, the value of these entitlements is underpinned in part by how infrastructure is managed and water is delivered. Initiatives that improve practices, techniques, tools and governance by leveraging modernised assets and data are expected to be hugely consequential moving forward.

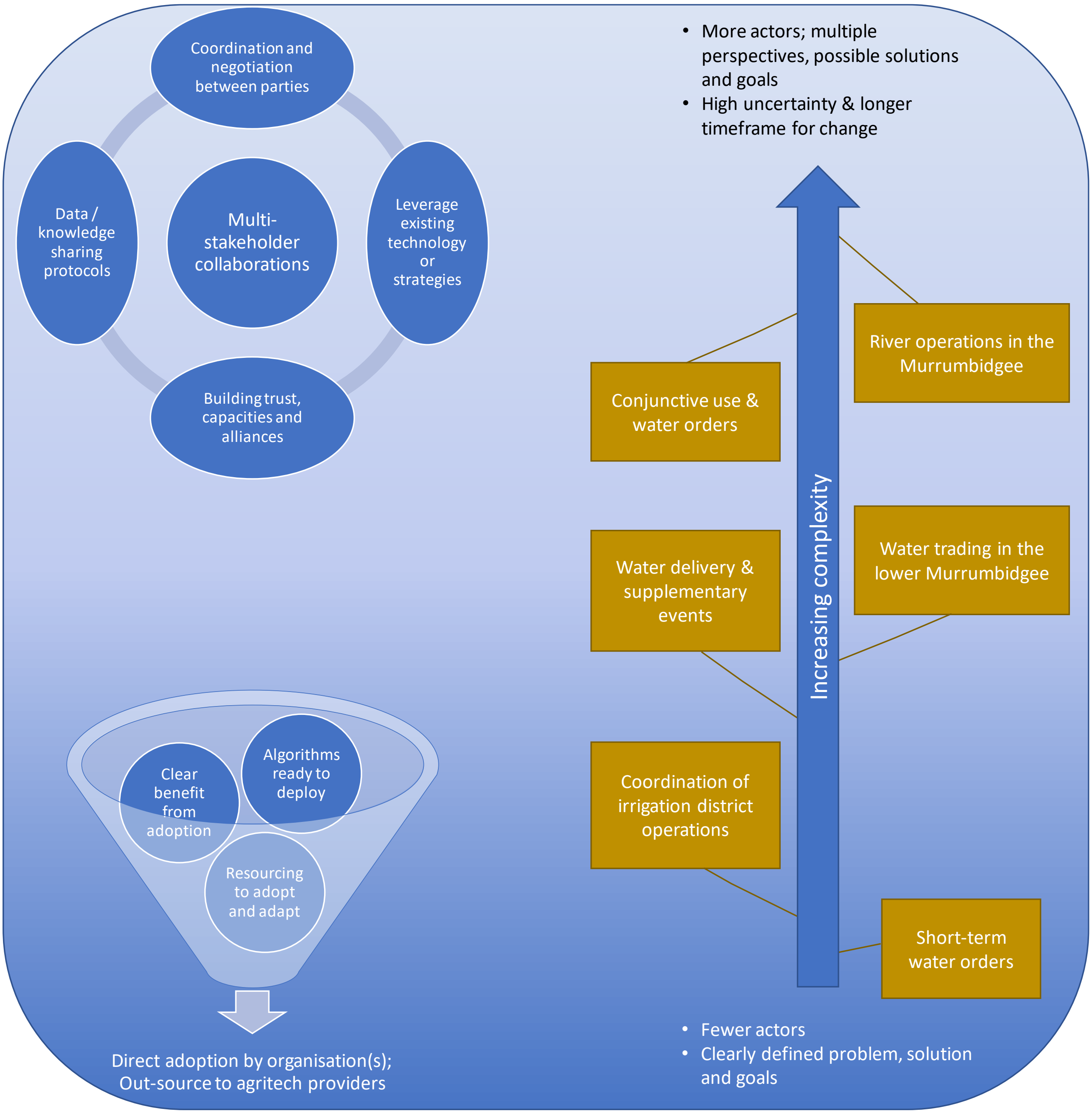

Figure B. Relative complexity of the use cases in relation to the advancement and uptake of demand forecasting approaches to support water delivery and integrated storage management in the Murrumbidgee.

This QuickStart project serves as a catalyst for future transformative innovations, having showcased the potential of predictive modelling capability in network management and in transforming water management practices through the development of algorithms and performance assessment framework. Beyond this, the use cases are being used to foster discussions beyond the life of this Quick Start project on how demand forecasting technologies might be developed and applied to support water delivery and river operation decisions, communities, the environment and industry.

1 Introduction

The *'Irrigation demand forecasting and its role in multi-scale system storage control'* Quickstart project (QS2) was a collaboration between the One Basin Cooperative Research Centre (One Basin CRC), Australian National University (ANU), University of Melbourne (UoM), Murrumbidgee Irrigation (MI) and Coleambally Irrigation Cooperative Limited (CICL). Using the Murrumbidgee River as a case study, the project aimed to evaluate the current state of the art of demand forecasting algorithms and their potential role in multi-scale multi-objective optimisation of system storage control. Critical to the project was an emphasis on the co-creation of the project scope and interactive development between academic and industry partners and, as the work progressed, reflective planning towards the adoption of models and processes. Two main work packages were conducted; in one, the team developed demand forecast algorithms with industry partners to demonstrate potential value in supporting short-term water orders and establish assessment frameworks to support operationalisation and continual improvement of the algorithms. The other package of work consisted of the development of other 'uses cases' or decision contexts around water delivery and integrated storage systems where demand forecasting technologies show promise.

1.1 Project motivation and scope

Water management in the Murray Darling has reached a watershed moment where long term extraction limits have been applied and substantial investment has been made in new monitoring and control equipment and techniques. Improving the integration of multi-stakeholder operational management of water storage in the landscape will broaden the option space for new water delivery solutions to emerge. As an entry point towards this longer-term vision, the premise for this project was to demonstrate the reliability and utility of demand forecasts within the partner organisations and other actors in the water resource system (e.g., river operators), shape the adoption (and continual improvement) of new cutting-edge demand forecasting algorithms and, connecting back to the longer-term vision, inform future research agendas and collaborations in this space.

1.2 A cross-scale framing of demand forecasting

Drawing on *Integrated Storage Systems* paradigm and the *Hierarchical Forecasting Framework* framings, this project takes a cross-scale view of demand forecasting spanning from farm through to catchment scales and daily through to seasonal or annual forecasts. A landscape view of storage includes not just reservoirs, the river and weirs, but also farm dams, channels, groundwater, and soil moisture. Improving demand forecasting and system storage control across these scales has the potential to improve benefits of water use for multiple purposes and improve efficiency, reliability and flexibility of irrigation water delivery.

The *Integrated Storage Systems* paradigm (Burke et al., 2023) takes the perspective that the suite of artificial and natural storages in a system provide services, at a particular time and place, with a given level of assurance, and that integrated systems should be developed that coordinate and manage these storages. Burke et al. (2023) suggest three broad services for water storages: improving the availability of water during drier periods, mitigating flood impacts, and regulating flows for different uses. Volume, adaptability and reliability attributes are critical for managing storage operations to effectively achieve such services [2]. These attributes are dynamic and evolve with changes between connected storages over time and space. Additionally, the performance of interconnected storages depends on contextual factors that influence water availability and demands including catchment characteristics, land use and management and climatic factors. Better accounting for these dynamic relationships and co-dependencies across scales should help managers to identify when and which storage(s) to operate within a specific landscape and contingency actions to manage water demands such as reducing operation losses and reallocating water (Burke et al., 2023). Factors influencing storage choices include location, timing, and management actions (Yu et al., 2021).

The *Hierarchical Forecasting Framework*, developed by Babai et al. (2022) for the field of supply chains, is a useful tool for exploring the potential roles of (and requirements for) demand forecasting across different planning and decision-making processes and levels. Hierarchical forecasting and combinations of forecasts across hierarchical levels acknowledges co-dependencies between planning levels and could contribute to coordinated processes across scales (Figure 1). The framework emphasises the importance of clarifying the role of forecasts to ensure coherence between strategic, tactical and operational decisions across short-, medium- and long-term time horizons. The choice of forecasting approach for different hierarchical and associated granularity levels should be based on accuracy considerations, subject to the constraint of data availability, as well as management of uncertainty (Babai et al., 2022). In the context of this project, water operations in the Murrumbidgee River system involve different stakeholders and sectoral uses of water across scales, presenting some similarities in operational logics to supply chain decision rules. Explaining different actors' behaviours and their influence on the effectiveness of the water supply chain through use cases could help formulate objectives for demand forecasting at different scales (e.g. Mitra et al., 2022). Different soft computing approaches could be used as reviewed by Ghalehkhondabi et al. (2017) or Niknam et al. (2022). Among them, machine learning methods, used alone or conjunctively with complementary approaches, could address challenges of accuracy and uncertainty (Makridakis et al., 2022, Umutoni and Samadi, 2024).

This project draws on the idea of a hierarchical approach of Babai et al. (2022), to demand forecasting by mapping out potential roles for demand forecasting (Figure 2) across different hierarchical levels (operational, tactical and strategic) and spatial scale (farm, irrigation district, catchment, regional). The strategic level is characterised by high uncertainty levels that influence decision-making and necessitate consideration of diverse option pathways to achieve desired societal and ecological outcomes. The tactical level involves decisions regarding different water supply and management options across various spatial levels, with the availability of (and capacity to use) different options being influential on the efficiency and effectiveness of processes, productions and service delivery. The operational level entails decisions related to controlling activities like storage maintenance, regulated water conveyance to offtakes and wetlands and other operational tasks. The development and evaluation of algorithms for short-term (0-7 day) forecasts in the Coleambally Irrigation Cooperative Limited (CICL) and Murrumbidgee Irrigation (MI) area of operations focus on this hierarchical level.

[2] The breadth of attributes identified by Burke et al. relate to volume, feasibility, adaptability, controllability, reliability, vulnerability, sphere of control, cost and environmental sustainability

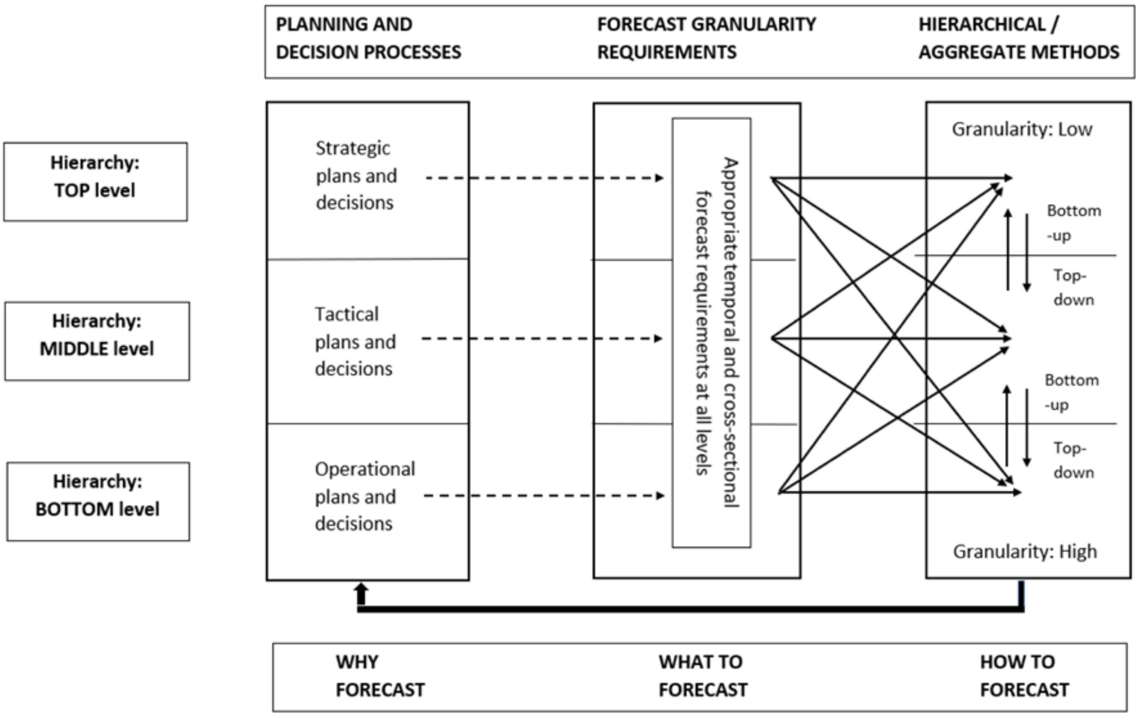

Figure 1. Hierarchical forecasting framework from Babai et al. (2022).

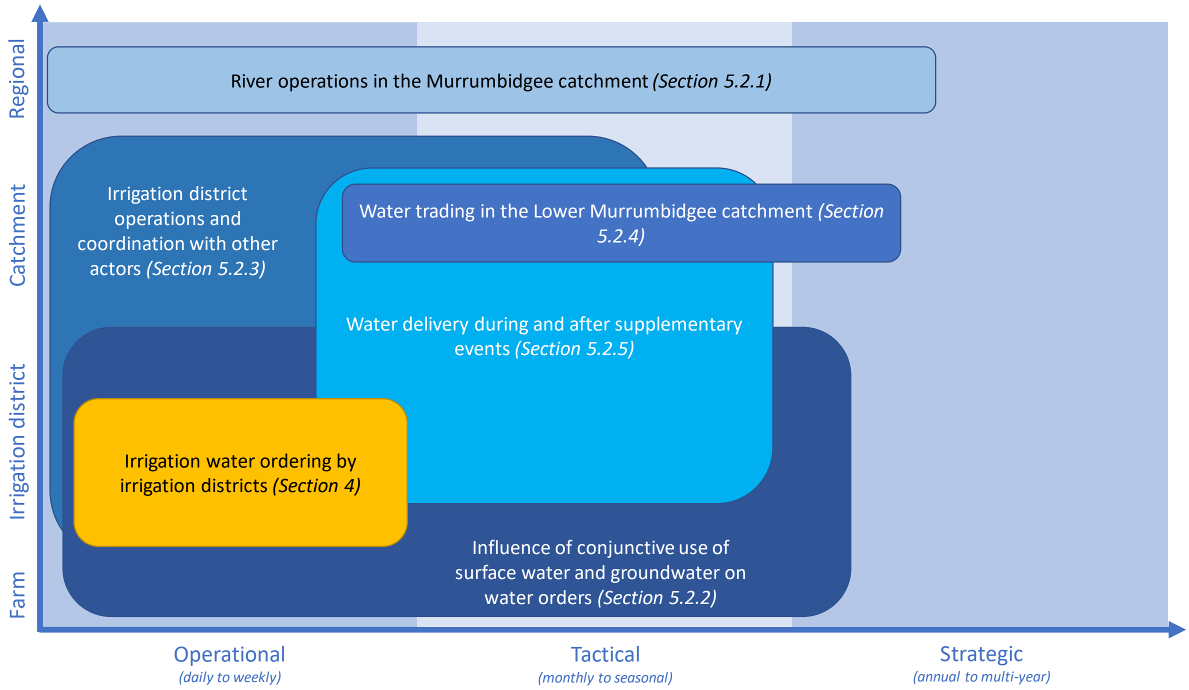

Figure 2. Mapping of the five use cases (blue) across hierarchical planning levels and spatial scales. The yellow frame highlights the position of "irrigation water ordering" (Section 4) within the two irrigation district companies (MI, CICL) in the Lower Murrumbidgee River Catchment.

Operational forecasts are typically short-term (hours to days) and involve detailed analyses of water demand, usually focusing on municipal and regional water suppliers (Renzetti, 2002). Short-term predictive models are crucial for optimizing the performance of irrigation system components like pumps and reservoirs (Kim et al., 2007, Niknam et al., 2022). These forecasts inform real-time management and operation decisions and facilitate decisions regarding the distribution and allocation of water resources (Jain et al., 2001, Niknam et al., 2022). Examples of demand forecasting models include process-based conceptual models such as

CropWat and AquaCrop (FAO, 2014, Vote et al., 2015), data-driven models like time-series models (e.g., ARMAX model (Perera et al., 2016), machine learning models such as Artificial Neural Network (ANN), metaheuristics and support vector machines (Ghalehkhondabi et al., 2017), and hybrid models (e.g., SVN-MLP model, Santos de Jesus and Silva Gomes, 2023). A comprehensive overview of operational demand forecasting models is provided in Section 4.1.

Tactical forecasts, covering months to seasons, aim to support specific user groups in making seasonal decisions regarding investments (Renzetti, 2002) or human and material/infrastructural capacity (e.g. Sagaert et al., 2018). These forecasts address uncertainties related to demand volume variability, timing of demand arrivals, and unforeseen events (Nikolopoulos, 2021). Based on Nikolopoulos (2021), trends and patterns such as local behavioural patterns from customers and suppliers can inform the development of the intermittent timeseries that are necessary for tactical forecasts. Timeseries could also be further decomposed by isolating 'peaks over thresholds' data points to capture the risk associated with a phenomenon (Nikolopoulos, 2021). Examples of tactical forecast models include shrinkage modelling approaches like LASSO regression (Sagaert et al., 2018), Naïve forecasting method to forecast ten trading days ahead (Nikolopoulos, 2021), season-ahead hydrological forecast for reservoir management applied in water-scarce regions (Delorit and Block, 2020), and data-driven models to forecast groundwater table regimes one to five months ahead in response to hydro-climatological forcing and water management actions (Delorit and Block, 2020).

Strategic forecasts provide a long-term perspective (annual to multiple years) for investigating the impact of structural, technological, and major policy changes on water demand (Renzetti, 2002). These forecasts can support strategic planning, irrigation system design, and water supply planning and management (de Souza Groppo et al., 2019). They contribute to gaining understanding about the factors influencing water demands like pricing or water policies and climate and socioeconomic contexts (Rinaudo, 2015). Examples of long-term demand forecasting models accounting for future socioeconomic changes include unit water demand analysis linked with Geographical Information Systems (Rinaudo, 2015) and ANN approaches for forecasting seasonal water allocations and water trading prices (Khan et al., 2010).

1.3 Report structure

This public report is the final project deliverable; this Section introduced the project motivation, framing and scope. The overarching methodology and Murrumbidgee case study are described in Section 2 and Section 3, respectively. The development, evaluation and operationalisation of demand forecasting algorithms to support short-term water ordering operations of CICL and MI is detailed in Section 4. Beyond this work, five use cases for demand forecasting to support water management across hierarchical planning levels (see Figure 2) and spatial scales are identified and documented in Section 5. Consideration is then given to deployment and adoption of demand forecasting technologies associated with the irrigation district algorithms and the broader use cases in Section 6.

2 Overarching Method

The project consisted of four components of work (Figure 3); the UoM team led a literature review that canvassed available demand forecasting techniques and relevant measures of performance, maturity assessment and benchmarking. This review informed the selection of specific assessment criteria and forecasting techniques for short-term (0-7 days) water orders that were developed and tested using data for the MI and CICL area of operations. Multi-scale conceptualisations of the Murrumbidgee system were developed to create shared understanding amongst the project team of current system storage control (including the implications for the operations of industry partners) and as the basis for identifying and visualising potential opportunities and decision contexts ('use cases') for demand forecasting.

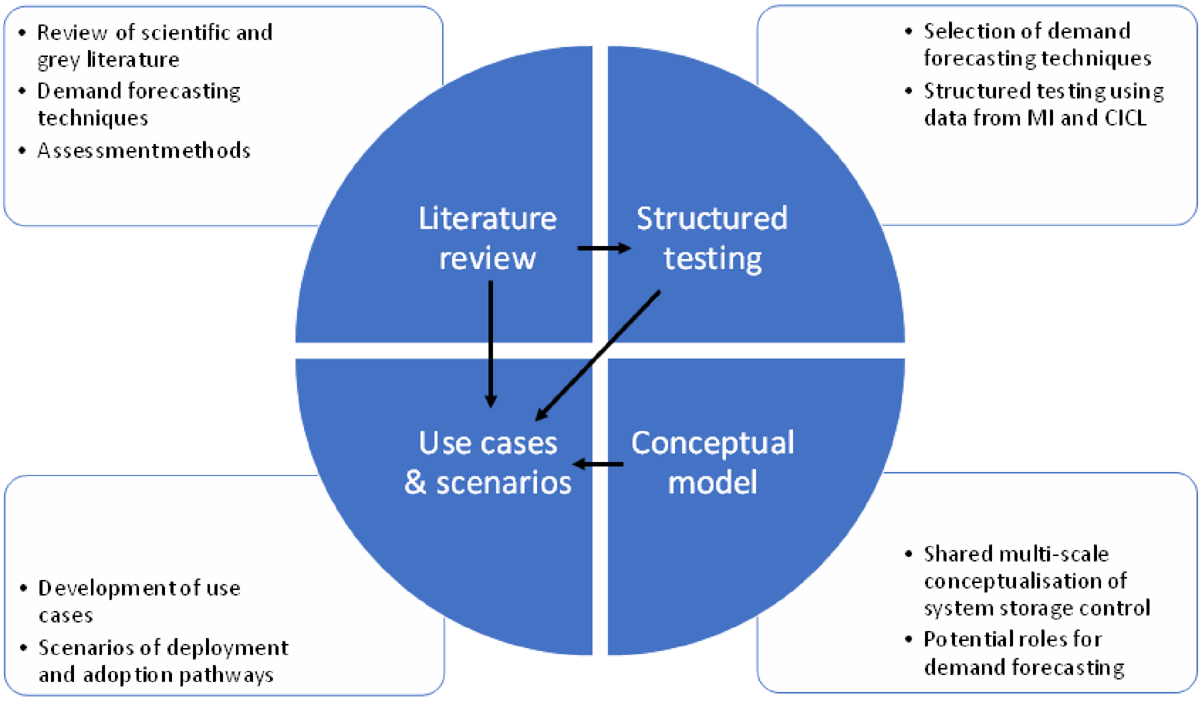

Figure 3. Schematic of the project components and overarching methodology

2.1 Demand forecasting algorithms for the CICL and MI area of operations

Detailed in Section 4, the structured testing led by UoM and MI team members employed a process of continuous improvement of both the demand forecast models and the evaluation framework and approach. Multiple models were developed with their evaluation focusing on performance at critical times for MI and CICL. The critical times for both irrigation districts are where there is an elevated risk of underordering but there are also challenges posed when overordering may occur. Initial activities focused on model development and testing using historical data. Later activities utilised live data and the project team met regularly with CICL and MI operations staff to evaluate the demand forecasting algorithms and the evaluation framework. During this phase the team explored the potential value and challenges to adoption, operationalisation and ongoing adaptation and development of the algorithms by the project industry partners.

2.2 Multi-scale conceptualisations and demand forecasting use cases

Conceptual models were developed in two phases of the project. Initial conceptualisations provided an entry point for the project team to develop a shared understanding of the Murrumbidgee catchment and integrate smaller scale conceptualisations (e.g. irrigation districts). A catchment scale conceptual diagram (Section 3.1) was developed from scientific publications, industry reports or websites; it described the location of water in the landscape, conceptualising possible water storages as broadly as possible, including reservoirs, rivers including unregulated tributaries, weirs, channels, off-channel storages, groundwater, farm dams, and soil moisture in both irrigation areas and upstream catchments. Irrigation district conceptualisations were developed by MI and CICL staff participating in a project workshop held in Griffith in May 2023. These mapped the location of water and water storages within the districts and key decision points for the CICL and MI (Section 3.3) and were used in the workshop to explore the implications of different conditions for operations, water orders and demand forecasting in the irrigation districts. Conceptual models were also constructed during the development of use cases (Section 5) to represent various actors' roles and their interactions, key constraints and potential ways in which demand forecasting approaches could support the operational, investment and strategic planning decisions of these actors.

2.3 Use cases, deployment and adoption pathways for demand forecasting

The identification and development of use cases involved a desktop review to situate demand forecasting approaches as a tool to support whole-of-water-cycle management and identify potential roles for demand forecasting to support water management in the Murrumbidgee catchment across temporal, spatial and governance scales. Five overarching themes emerged as the basis for use case development: river operations, conjunctive uses of surface and groundwater, coordination of river and irrigation districts' operations, water markets and supplementary water announcements. Each use case outlines the actors involved, the goal of demand forecasting and the context in which the use case occurs, the necessary requirements for demand forecasting to be useful, and alternative strategies that might also achieve the goals. These use cases are boundary objects with which to initiate and facilitate discussions with key actors regarding potential ways in which demand forecasting approaches could be used to inform the delivery of multiple benefits in integrated storage planning and operations (and the potential value gained and challenges in their application). For each use case presented in Section 5, opportunities for demand forecasting approaches are mapped across geographic scales and hierarchical levels highlighting the co-dependency of operational water delivery decisions between scales.

2.4 Engagement activities

As the industry partners for this project, and the intended user of the demand forecasting algorithms and evaluation framework developed in Section 4, data science and operations staff from CICL and MI have been the focus of project engagement. These activities have occurred through fortnightly project team meetings, a conceptual modelling workshop in Griffith in May 2023 and, as both the algorithms and evaluation framework matured, regular meetings with the UoM and MI model developers and the CICL and MI operations staff to evaluate and explore the operationalization of the algorithms and framework. Extensive engagement with non-partner organisations was not the priority of this one-year project although the modelling team from WaterNSW were engaged with at the commencement of the project and again in July 2024 to communicate the objectives, outputs and outcomes from the project. Our intent is that engagement with WaterNSW will continue beyond the project with the initiation of the Multiple Benefits project (CRC058). An overview of this Quickstart project and the identified use cases where demand forecasting could contribute to water delivery and operations across the Murrumbidgee landscape was presented at the Multiple Benefits project inception workshop in July 2024.

We recognise the importance of considering potential research impact and opportunities related to the First Nations people of the Murrumbidgee and acknowledge that they have often been locked out of conversations and decisions around irrigation development and water delivery operations on their country. The irrigation districts of MI and CICL both lie on the lands of the Wiradjuri People. Downstream, the western end of the catchment includes country of several smaller nations including the Barapa Barapa, Muthi Muthi, Nari Nari, Nyeri Nyeri, Wadi Wadi, Wamba Wamba, Weki Weki, and Wolgalu[3]. No engagement with First Nations peoples was conducted about this Quickstart project due to the short timeframe for the research, no prior relationships between the researchers and First Nations persons on country, and our intent to be guided by the One Basin CRC through their First Nations Engagement principles and the One Basin CRC engagement strategy that was being developed in parallel with the CRC Quickstart projects. With support from One Basin CRC staff, planning has commenced for First Nations engagement with peoples from the Murrumbidgee for the newly commenced or ongoing One Basin CRC activities in the catchment, including the Multiple Benefits project (CRC058).

[3] https://www.mdba.gov.au/basin/catchments/southern-basin-catchments/murrumbidgee-catchment, accessed 16 September 2024

3 Murrumbidgee case study

3.1 Geographic boundary of the case study

The catchment scale conceptualisation shown in Figure 4 was adapted from the Murrumbidgee River profile produced by the Murray Darling Basin Authority (MDBA)[4]. The focus was to describe the location of water in the landscape, conceptualising possible water storages as broadly as possible, including reservoirs, rivers including unregulated tributaries, weirs, channels, off-channel storages, groundwater, farm dams, and soil moisture in both irrigation areas and upstream catchments. The MDBA diagram included an elevation axis, distance axis and system elements above Burrinjuck dam which has been removed from the conceptualisation in Figure 4. The latter were removed as the geographic boundary of this project is the Blowering and Burrinjuck Dams and the catchment and river systems below them. Added to the diagram were Blowering Dam and the Tumut River below the dam, groundwater management areas, two Ramsar wetlands (Fivebough and Tuckerbill swamps), the governance of key water assets (e.g. owner or operator of storages), the return flows from Tombullen Storage to the Murrumbidgee River and the estimated volume of storages across the system.

3.2 Key actors in the Murrumbidgee

This section outlines the key actors involved in the water delivery for multiple benefits in the Murrumbidgee Region, drawing on a review of published and grey literature conducted to inform the use case development. The main actors include NSW Department of Climate Change, Energy, the Environment and Water (NSW DCCEEW), WaterNSW, MI, CICL and the Commonwealth and NSW Environment Water Holders (EWH) and environmental managers. These actors and irrigation district members are described further below. Additional stakeholders include private irrigators in the Lower Murrumbidgee River catchment, participants in water markets in the Murray River system, groundwater users within and outside of the Murrumbidgee Catchment, Snowy Hydro Limited and First Nations and broader communities, unregulated water users and other farmers and operating bodies in the Murrumbidgee Catchment. During the project proposal development, Agritech providers were identified as potential investors in demand forecasting and system storage control.

[4] https://www.mdba.gov.au/sites/default/files/publications/murrum-geographic-profile.pdf, accessed 2 September 2024

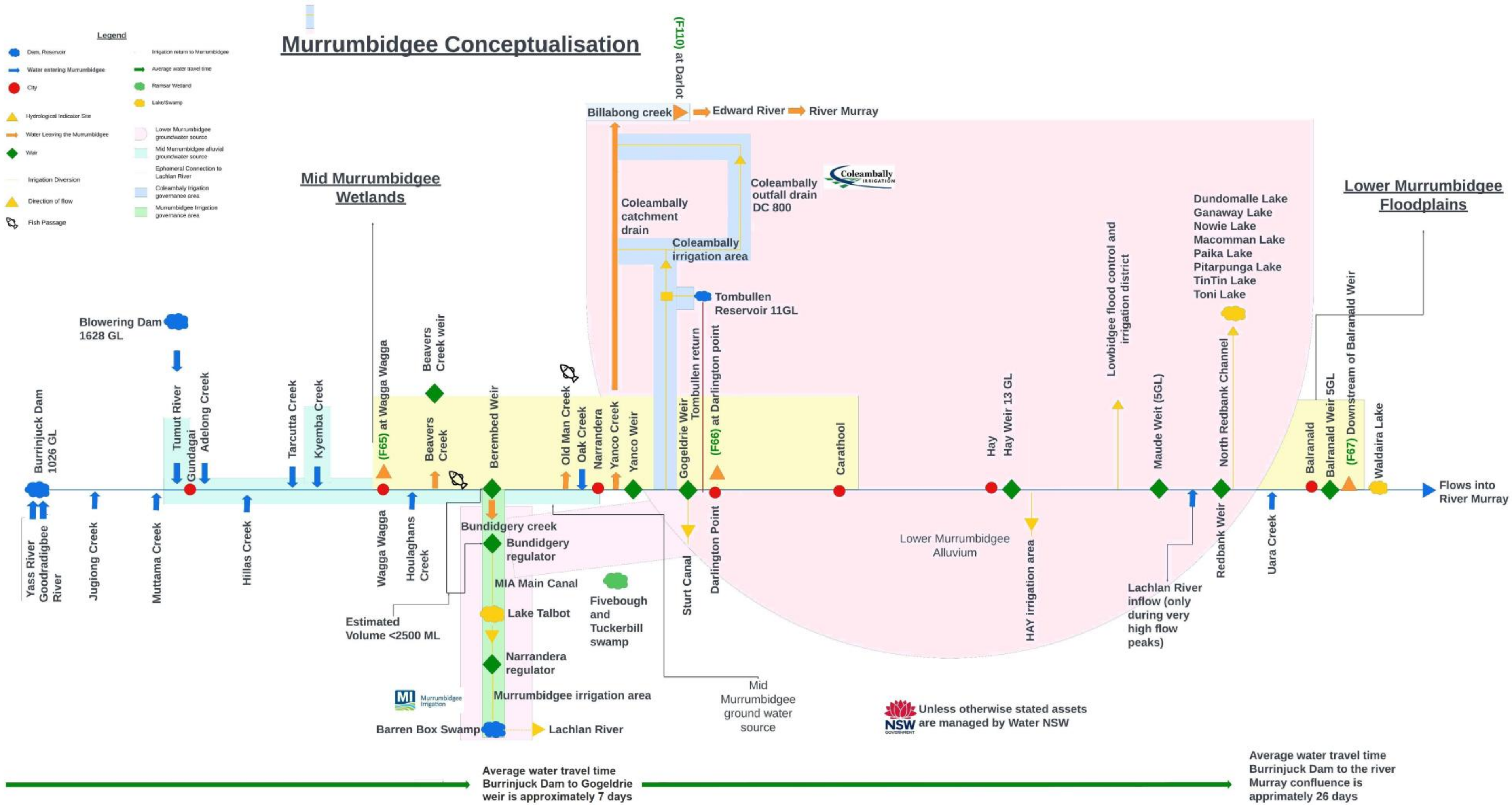

Figure 4. Geographic boundary of the Murrumbidgee case study.

3.2.1 Irrigation Infrastructure Operators

CICL and MI are the two main irrigation infrastructure operators (IIO) in the Lower Murrumbidgee River catchment. Their main responsibilities include: 1) daily orderings to WaterNSW for weekly deliveries of water to respective offtakes, 2) daily deliveries to customers, including WaterNSW, irrigators, and environmental assets based on agreements with Environmental Water Holders and NSW DCCEEW, 3) groundwater level and quality monitoring, 4) water quality within assets, 5) maintenance of assets (mostly in winter), 6) system enhancement for managing water demands during the peak season and maintenance time and, at the direction of local flood authorities, ensuring flood security, 7) ordering to WaterNSW and announcement of supplementary water events to respective customer bases (MI, 2016, CICL, 2023). For the announcement of supplementary events, they are themselves based on NSW DCCEEW Water announcements, with the specification of the time, location and duration of the events available from the WaterInsights website (DPI, 2015) [5]. Additionally, CICL is responsible for diverting water to the Tombullen storage in accordance with WaterNSW orders. Tombullen storage is principally used to ensure water deliveries to private irrigators between Darlington Point and Maude Weir (CICL, 2023).

Water orders are placed daily from WaterNSW at the irrigation district offtakes (two for MI and one for CICL). The water is then diverted in storages and channel systems to ensure reliable supply to irrigators, especially during the peak season. During winter, the main canal is closed during winter for CICL (CICL, 2023). To reduce the company's vulnerability to high flow events, limit rain rejections, and ensure timely water deliveries to customers, MI has built a new storage at the entrance of its system, the Roaches Surge Reservoir (MI, 2021).

Key decision points for water operations include factors such as water availability in channels and storages under different climate conditions; crop types, planting time and planting area; announcements of allocations and supplementary events; daily orders from customers; groundwater availability and likeliness to be used; timing for water orders (winter, summer) and crops' stage of development; timing for storage and channel maintenance; timing and likeliness to manage excess water within irrigation district systems, timing of supplementary events and risk of restriction following them (MI, 2016, CICL, 2023).

3.2.2 WaterNSW

WaterNSW is the State agency responsible for 1) managing water in both natural and artificial storages and weirs, 2) crediting the accounts of licensed water users and delivering water to licensees, including environmental flows, 3) ensuring that metering and compliance activities help water users understand their rights and obligations (Aither, 2017), 4) monitoring raw water quality of surface and groundwater systems, 5) announcing exceptional events such as supplementary water events and restrictions, 6) ensuring required end of system flows at Balranald and Yanco Creek are met (DPI, 2015)[6]), 7) collecting manual orders in anticipation of announcements of supplementary water events (MI, 2016, CICL, 2023), 8) managing rain rejection events at Bundidgerry Creek if water flows are reaching channel capacity (MI, 2016).

[5] WaterNSW (2023). *Learn how water is managed*. WaterInsights. Accessed 20 April 2024. https://waterinsights.waternsw.com.au/learn

[6] NSW Government (2024). *Schedule 1 - Roles and Responsibilities Schedule*. Roles and Responsibilities Agreement. Accessed 20 April 2024. https://water.dpie.nsw.gov.au/about-us/how-water-is-managed/roles-and-responsibilities-agreement#:~:text=The%20Agreement%20sets%20out%20in,of%20agencies%20against%20their%20responsibilities.

Key decision points include water availability and levels in rivers, creeks and channels as well as storages under different climate conditions throughout the year; timing and duration of maintenance work in regulated surface water systems (DPI, 2015); climate scenario and rules for delivering water to the environment and ensure Lower Murrumbidgee flows (SKM, 2011); weekly orderings (MI, 2016, CICL, 2023).

The potential interest of WaterNSW to invest in or use the outputs of this project are hypothesised to inform adoption, regulation and cooperation on demand forecasting and system storage control. For this potential to eventualise, the project would need to identify demand forecasting use cases and their implications which might include interactions between algorithms for regulation change. Opportunities at the river operation scale need to be identified which can be drawn on to scale up to other river systems; in the Murrumbidgee context opportunities should leverage and add value to the Computer Aided River Management system for the Murrumbidgee River (CARM) [7].

3.2.3 NSW DCCEEW

NSW DCCEEW is the NSW State government lead agency for developing a strategic approach to water at the State, regional and metropolitan levels. Its key responsibilities include 1) assessing water availability (surface and groundwater) and announcing Available Water Determination (AWD) from the 1st of July of each year and periodically throughout the year, 2) announcing supplementary water events, 3) setting trade and other management rules related to water trading and 4) maintaining and managing water accounts and reporting (Aither, 2017, DPI, 2015).

When assessing future water availability (i.e., for a year), NSW DCCEEW considers various factors such as BoM three month seasonal outlook (July to September) as well as the likelihood of rainfalls across mainland Australia, temperature likelihood across the Murrumbidgee Catchment, ENSO outlook and associated alert level for El Ninõ events. Decision points for assessing future water availability include water levels in storages, minimum expected natural inflows into storages, required annual releases (RAR) by Snowy Hydro Limited into the Blowering Dam, minimum volume to run the river (including evaporation and transmission losses and Lower Murrumbidgee flows), water sharing plan requirements (including storage reserves and credits to environmental water allowances (EWA)), forecast volume of carryover in general security (GS) and conveyance accounts (DPI, 2015)[8].

3.2.4 Environmental Water Holders

The Commonwealth and NSW environmental water holders (EWH) are primarily responsible for environmental management in the Murrumbidgee River Catchment. The EWH are tasked with maintaining and/or restoring connectivity between key riverine and wetland ecosystems in the Murrumbidgee River catchment. This includes water provisioning to key ecosystems in both the Murrumbidgee and Murray Rivers to ensure their functionality, services and biodiversity conservation. A reserve is agreed upon with NSW agencies to ensure end-of system flows to Balranald and Billabong

[7] The CARM (Computer Aided River Management) system was developed by DHI consulting for WaterNSW to enhance weirs and dams' operations in the Murrumbidgee River system and reduce operation losses. CARM integrates models reproducing key catchment and river processes with real-time measurements with the objective being to provide river operators with an overview of current and forecasted water inflows to inform operation decisions and ensure reliable deliveries to relevant locations at the right time.

[8] NSW Government (2024). *Water allocation guides for major river valleys – Murrumbidgee Regulated River Water Source*. Resources assessment process. Accessed 20 April 2024. https://water.dpie.nsw.gov.au/our-work/allocations-availability/allocations/how-water-is-allocated/resource-assessment-process

Creek. Watering actions are based on four main climate scenarios: extreme dry, dry, moderate and wet (Commonwealth, 2023).

The responsibilities of the EWH include 1) supporting watering actions to restore natural flow regimes, ensure connectivity between river, creeks and wetlands, and maintain function, services and biodiversity conservation, 2) managing environmental water allocations, including participation in water markets, or cancelling watering actions during extreme-rainfall events and/or availability of unregulated water, 3) ordering and agreeing on special releases to the Environment with irrigation companies (Commonwealth, 2023).

Key decision points relate to the consideration of climate scenarios and associated watering options; considering extreme rainfall events and availability of unregulated water, potentially influencing carry over decisions; evaluating unused water and ability to trade supplementary and general security (GS) entitlements; determining watering needs; fulfilling obligations to deliver water on-behalf of OEH; exploring potential for piggy backing or other 'en route' types of options, especially post-supplementary events; accounting for physical/operation constraints and infrastructural works when considering watering actions (SKM, 2011, Commonwealth, 2023). Two main challenges for ensuring sustainable environmental flows consist of the lack of consideration of antecedent watering condition for the four climate scenarios to anticipate when and where to prioritise environmental flows, on the one hand, and assumptions of meeting broad scale medium to long-term ecological and hydrological objectives can be achieved solely through environmental flows, on the other hand (SKM, 2011).

3.3 Irrigation districts

This subsection documents the irrigation scale conceptualisations developed by the project partners (led by MI and CICL) at a workshop in Griffith in May 2023. The location of water and water storages within the districts were mapped along with the key decision points for the organisations. The conceptualisations were used to explore the implications of different conditions for operations, water orders and demand forecasting in the irrigation districts.

3.3.1 CICL Area of Operations

A map of the CICL area of operations is provided in Figure 5. Water in the main CICL irrigation district is managed through a Total Channel Control (TCC™ [9]) system during the period of operation (mid-August to mid-May). CICL operates on a 7-day water order with WaterNSW, reflecting the time for water to travel from Burrinjuck and Blowering dams. Within the main area of operations, all users can give two-hour notice of orders or cancellations. The WCC, DC800 and CCD are channels that can drain water out of the main area or deliver water for stock or environmental purposes.

The environmental water holder (EWH) usually provides two to three weeks' notice and gives leeway on the specific timing which supports CICL to deliver environmental orders as part of its total order. Yanco Creek comes off the Murrumbidgee River above the CICL main canal offtake although CICL can deliver water to the Yanco system via its network. Delivering 300 ML/day through CICL main canal and the Coleambally Catchment Drain (CCD) outlet saves WaterNSW time to get water into the Yanco system. Water for operational purposes or to meet environmental targets can also be delivered for

[9] https://rubiconwater.com/irrigation-district-solutions/, Accessed 13 January 225

WaterNSW to the Yanco system via the DC800 drain. With two hours' notice from WaterNSW water can be moved into Tombullen Storage.

3.3.2 MI Area of Operations

The MIA encompasses 378,911 ha of land; the 190,000 ha irrigated area consists of permanent plantings (e.g. grapes, citrus) and seasonal broadacre crops (e.g. rice, cotton). Three zones are defined in Figure 6 - the Wah Wah, Main and Sturt. The Wah Wah area is supplied from Barren Box, Main and Sturt systems. The Sturt subsystem is mainly broadacre whilst the main zone encompasses Leeton and Griffith (with both towns solely reliant on the river) and much of the horticulture that is centred around the towns. Environmental water is supplied to 12 sites including two Ramsar sites (Fivebough and Tuckerbill Swamps).

MI operates all-year round on seven-day ordering to WaterNSW reflecting the time it takes for orders to travel from the Burrinjuck and Blowering Dams to the MI offtakes. Members can make orders to MI with 24 hours' notice and changes to their orders with two hours notice. MI operates a 24h/day control room, the 2-hour changes to orders often balance out to some extent, and MI has some surge capacity to help if there is a shortage. Temperature and the presence or absence of (un)predicted rainfall are common reasons for changes in orders by irrigators and any mismatch with the 7-day forecast. Horticulture with drip irrigation is centred around the towns where people might irrigate on different schedules depending on other work or time demands. To bridge the potential mismatch in the timing of orders between members and MI and MI and WaterNSW, MI undertake demand forecasting informed by the areas of plantings. Since 2013, MI have invested heavily in automation and high resolution and collecting accurate data on what water customers are taking. MI has also invested in 24 Rubicon weather stations across the network to capture real time weather data.

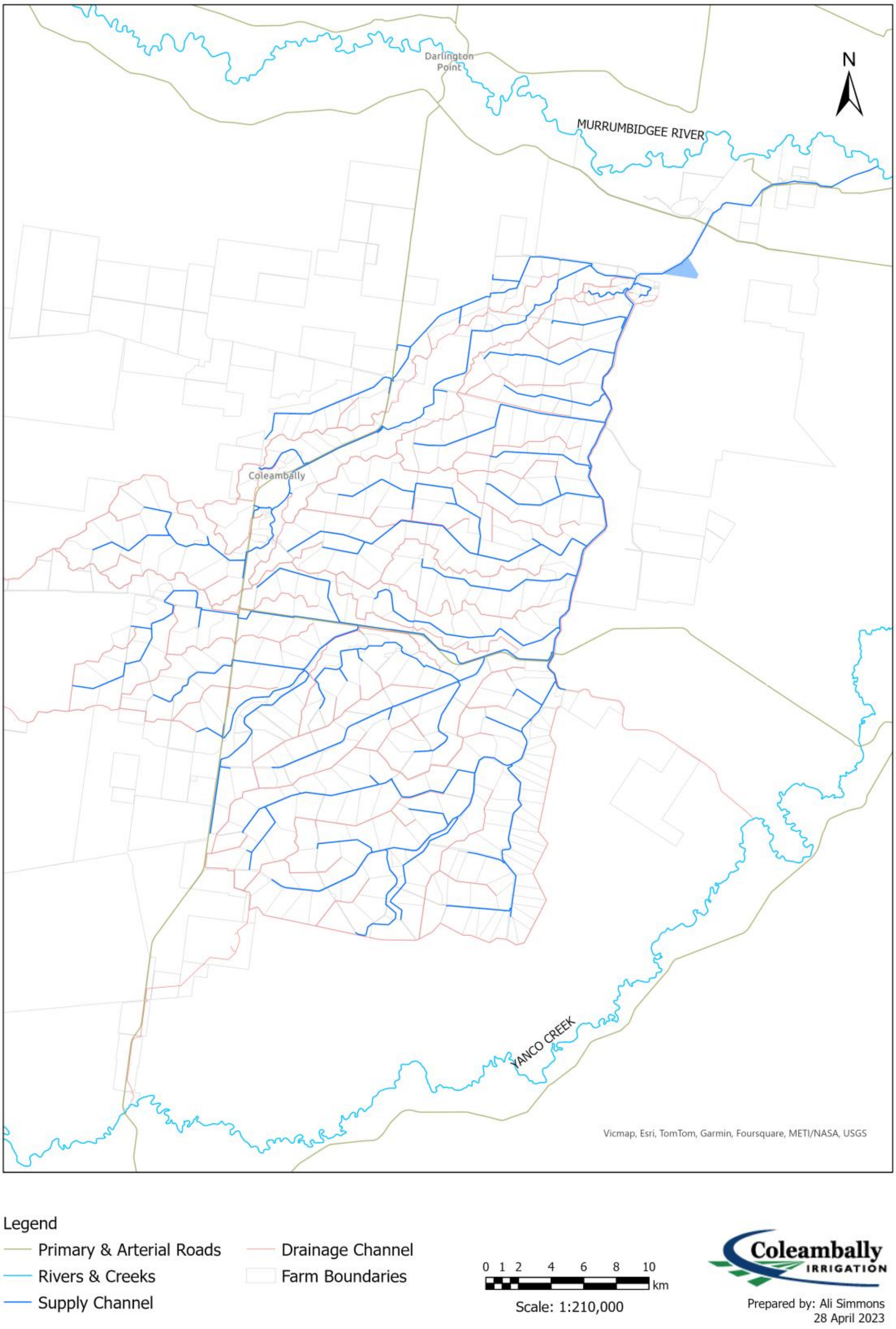

Figure 5. Map of the CICL Area of Operations

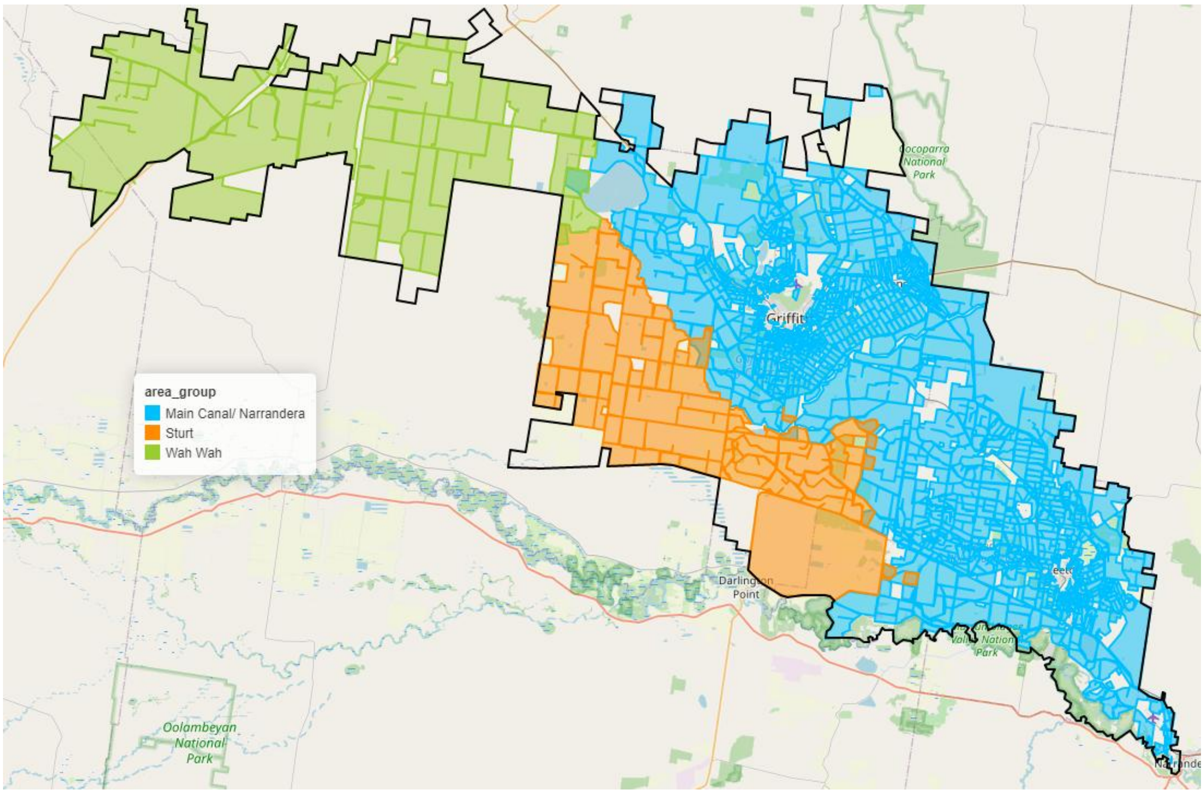

Figure 6. Murrumbidgee Irrigation area of operation, showing the three main zones: the Main Canal, Sturt and Wah Wah

3.3.3 Decision contexts

Following the development of the irrigation district conceptualisations, participants at the May 2023 Griffith workshop explored how decisions change under wet and dry conditions, supplementary events and rain rejections and the implications of these decisions for demand forecasting in the irrigation districts. CICL members typically operate family farms and predominantly irrigate during the week; MI customers include these types of irrigators but also small farm operators and hobby-farmers who may irrigate during the weekend (CICL, 2023, MI, 2016). Apart from MI and CICL farmers, private irrigators are also significant water users. Tombullen provides WaterNSW with a flow augmentation option for usage below Gogeldrie Weir or between Darlington Point and Balranald.

Decision points for regulated water orders and alternative supply options are related to soil quality; crop types; planting area; planting time; irrigation system; on-farm water storage, water availability and water levels in storage(s); groundwater accessibility and dependency; energy costs; water prices; timing and opportunities for unregulated water (including supplementary events); in-crop rainfalls; reliability of entitlements; number of participants in water markets and heterogeneity of water uses for primary productions; trade rules within and between systems; opportunities for trading water based on system connectivity; location in the catchment; climate variability; ENSO and consecutive dry-wet year (MI, 2016, CICL, 2023, Aither, 2017).

Wet years: CICL prepare for flooding by checking infrastructure (namely the regulators) is in working order. They have forewarning 3 or more days before overland flows are seen in the irrigation district. If needed, water can be drained out the CCD and DC800 to the Yanco Creek system and west out the Billabong Creek system. Ordering in such times involves trying to make a determination of what customers need. In preparation for rain event, operators do not stop the river offtake straight away; this is done if people stop taking water and the TCC responds to levels in the main channel.

In the MIA, high flows in Mirrool Creek – which ends up in Barren Box – can cut off other supply channels within the district. In a high flow or if a flood is declared, MI works with the local flood authority to mitigate and manage the flows. In these wet periods, higher allocations are available and there is high demand for water.

Dry years: In dry years, MI tries to keep Barren Box empty as it will otherwise lose a lot of water to evapotranspiration. They work with customers, particularly those between Barren Box and Wah Wah, to coordinate orders so that 'every last drop' goes to customers and losses over time are minimised. This means understanding the needs of customers, particularly those with permanent crops at the bottom of the system. As these years have low demand, the TCC is turned off, the regulators are laid flat and channels are allowed to drain; water is only put down the channel when it is needed. Demand forecasting is relatively simple in these times as the variability in what customers order and take is reduced.

In dry times, the CICL system is run at minimum levels and some channels can be shut off. In 2019/20, CICL turned off the automated ordering system and switched to a manual approach, were able to operate off the bottom of (e.g.) pools to save water and (for the first time) halted the ability for members to lodge two-hour orders, etc. As per normal operation of the WCC channel, the stock water supply system was on a rotation-based ordering with two rostered events in the year.

Supplementary events: Supplementary announcements pose a challenge for both CICL and MI in their operations. Supplementary events during a normal or dry year create more uncertainty than if they occur in wet years as there is a heightened risk that restrictions might occur once the supplementary event ceases and the timing or eventuality of follow-up rains is highly uncertain. A supplementary event can also have the same effect as a major rain event in the CICL and MI systems, where all their customers get on the same cycle for their orders, with the flow-on impacts on operations and updating the 7-day orders to WaterNSW.

Rain rejections: Rain rejection can pose a problem for operators as the 'ramp-up' to approaching rains might see customers hold off on making or cancelling orders. Reduced orders as the rain event starts leads to a mismatch in the customer aggregated demand and the 7-day order to WaterNSW and widespread decent rains can see the orders almost completely cut. If this happens in the MI system, the channels overfill and water moves back up Bundidgerry Creek. If the storage capacity of Bundidgerry is already full then the 100-year-old gates have to be shut manually. Farmers do look at the 7 days weather forecast and a non-rain event is equally problematic for CICL and MI as a big rain event. However, in this situation, customers may have been relying on the rainfall to arrive (e.g. at planting time) after which they would need irrigation a set period later. Without the rainfall event, there may be no point in making the subsequent order.

Understanding their customers: The crop systems and irrigation patterns in the MI and CICL area of operations are quite different reflecting the decisions of their customers (

Table 1). Coleambally irrigators are mostly groups of families that own their farms and water during the week. They also tend to have recycling systems, allowing them to pump runoff and recirculate it around their farm. Whether or not they recycle water depends on the cost of the water relative to the cost of operating the pumps. Some customer behaviours might seem non-intuitive at first glance, such as decisions to keep growing crops like rice or cotton when conditions do not suit. In some cases, farmers might have to plant crops if they are locked into contracts or face the prospect of washout fees. In the MIA, there are many irrigators who irrigate on the weekend, either because they have off-farm jobs during the week or they decide to use off-peak power to pump water. Different customers can take very different approaches to how they buy and use water (e.g. the balance of entitlements and purchasing water from the market).

Table 1. Key factors influencing decisions of member irrigators in the MIA or CICL areas
Superscripts denote specificity of factors; A – annual/broadacre crops; D – dry years; CICL – CICL member irrigators; MI – irrigators in the MIA; P – perennial crops; W – wet years; WCC – West Coleambally Channel customers

	Key decisions				
	Irrigated area	**Crop choice(s)**	**Buy or sell water**	**Surface water order**	**Order cancellation**
Decision timeframe	[A] Early-October to mid-November [P] Annual to multi-year			Growing season; 2 [CICL] to 24 [MI] hour notification; [WCC] 7 day notification	Growing season; 2 hour notification
Indicative influencing factors					
Environmental / climate	Climate outlook; catchment conditions; dam volumes; soil moisture		Climate outlook	Soil moisture; anticipated (forecast) rainfall; temperature; humidity	Rain rejection events; non-rain 'events'; temperature
Agronomic				Crop water requirements; irrigation system	
Surface water	Allocation determination; announcement timing; carryover volumes		Cost of surface water	Available water allocation Supplementary announcements	
Groundwater			Cost of groundwater	Groundwater salinity	
Market	Commodity prices Input costs Contractual arrangements Washout fees	Commodity prices Input costs Contractual arrangements	Price of temporary water	Price of temporary water; Cost of allocated water [CICL] Electricity cost (water recycling) [MI] Electricity cost (off-peak irrigator)	
Irrigator / enterprise		Identity / past experience	Identity / desire to farm Farm typology Purchasing power Balance of entitlements	Farm typology Farm infrastructure (e.g. outlets)	
Irrigation district				[D,MI] MI order coordination needs Collated supplementary orders Channel constraints	

4 Demand forecasting for river ordering

This section reports on the activities and achievements in developing and operationalising short-term demand forecasting algorithms to support river ordering by IIO. In Section 4.1, the literature review describes the prevailing approaches to crop water demand modelling and identifies the potential value of hybrid methodologies. The review also highlights a predilection to applying a small number of metrics to 'evaluate' model performance raising the concern that there is limited evidence in the scientific literature that reported evaluation approaches explicitly reflect the decision contexts of potential users of demand forecasts. These findings, together with project team discussions around the decision context for CICL and MI river orders, informed the research design and methodology for this component of the project (Section 4.2). Section 4.3 describes the case study data used in the development and evaluation of the UoM-developed hybrid models (Section 4.4) and MI-developed data-driven models (Section 4.5). The section concludes with a discussion on the process and outcomes for the operationalisation of the algorithms and evaluation framework (Section 4.6).

4.1 Review of demand forecasting and assessment techniques

Effective and sustainable management of water supply plays a critical role in addressing the societal needs for health and well-being in both rural and urban environments (Niknam et al., 2022). It holds significant importance in areas such as public health, the economy, food production and irrigation (Vijai and Sivakumar, 2018). Having accurate information about water demand is vital for effectively managing water resources in extensive agricultural regions. Predicting water demand offers significant benefits in terms of designing, managing, and upgrading water supply and distribution systems (Pulido-Calvo and Gutiérrez-Estrada, 2009). An irrigation system that provides water on demand enables users to enjoy greater flexibility compared to other delivery schedules. Typically, water distribution system operators create a 24-hour operating plan to schedule pump and valve control settings (Alvisi et al., 2007). Consequently, irrigation system operators need an efficient and dependable system to promptly meet users' immediate water requirements. The travel time from the reservoir to the irrigated fields presents considerable difficulties for irrigation system operators. Irrigation system operators usually encounter challenges in promptly responding to rapid fluctuations in irrigation demand caused by sudden weather changes, such as extremely hot periods and rainfall events (Perera et al., 2015). Additionally, the demand fluctuates according to the decisions farmers make in response to other pressures and opportunities, further complicating the task for irrigation system operators. Efficient demand management and forecasting techniques are proposed as tools to support operators to deal with these problems.

Water demand forecasting can be done for strategic, investment (termed tactical in Section 1.2) or operational reasons (Renzetti, 2002). Strategic forecasts provide the longest and broadest perspective to investigate the impact of structural, technological, and major policy changes (Renzetti, 2002). They can be utilized for strategic planning, designing an irrigation system, and water supply planning and management (de Souza Groppo et al., 2019). Operational forecasts are short-term (hours to days) and detailed analyses of water demand usually focusing on municipal and regional water suppliers (Renzetti, 2002). Short-term predictive models have a significant impact on the optimal performance of pumps and reservoirs in the irrigation system (Kim et al., 2007, Niknam et al., 2022). In other words, short-term forecasting of water demand can provide useful information for planning real-time management and operation of important components in the irrigation system. It also provides valuable information to decision-makers regarding the distribution and allocation of water resources when required (Jain et al., 2001, Niknam et al., 2022).

There are two major approaches for forecasting irrigation water demand: process-based (conceptual) methods or data-driven (system theoretical) approaches. Conceptual modelling approaches develop daily water demand requirements for crop irrigation based on rates of percolation and evapotranspiration that have been predicted at the stage of irrigation planning (Pulido-Calvo and Gutiérrez-Estrada, 2009). Data-driven approaches involve using a model to establish a relationship between inputs and outputs without detailed consideration of the internal structure of the physical process (Pulido-Calvo and Gutiérrez-Estrada, 2009). Many researchers have investigated and implemented these techniques to predict short-term water demand in recent years (Niknam et al., 2022, Perera et al., 2015). With the advancement in artificial intelligence, several hybrid models and neural network models have been developed and these offer novel possibilities for prediction (Kavya et al., 2023).

This review includes the most used short-term demand forecasting models at a temporal time step from one to 10 days and a spatial scale from farm to the system level, influencing factors for the models, data requirements, and main indicators to evaluate the model's forecasting accuracy.

4.1.1 Exogenous factors influencing predictive models

The factors influencing predictive models are many and range from weather conditions to the geographical location of the target area. Climatic or weather extreme conditions have a prominent relationship with agricultural water use (Niknam et al., 2022). Both conceptual and data-driven models are based on historical and forecast weather data. Rainfall, temperature, humidity, and wind speed are standard inputs to the predictive models. Many models used short-term weather forecasts, especially rainfall and evapotranspiration to make irrigation decisions (Aly and Wanakule, 2004, Forouhar et al., 2022). Wang et al. (2015) concluded that the irrigation water requirement and prediction are mainly affected by interlinked climate change and human factors (irrigation area, management practices, planting structure, and agricultural water saving level). The result from Brentan et al. (2017) showed a correlation between the weather factors, mainly temperature, relative humidity, and hour of the day, as the most relevant factors for forecasting demand. Perera et al. (2016) determined the water supply deficit as the exogenous variable which reflects the effect of atmospheric forcing on irrigation demand as a combination of precipitation and evapotranspiration. The forecast and observed uncertainties in precipitation and evapotranspiration contribute to the irrigation demand uncertainties (Perera et al., 2016). For residential or urban water demand prediction, other influencing factors include the economic, socio-demographic, household properties, technological, location, and geographic factors (Niknam et al., 2022).

4.1.2 Short-term irrigation demand forecast models

4.1.2.1 Process-based (conceptual) models

Process-based (conceptual) models are formulated by deriving key elements of the irrigation process such as crop water needs and soil water content balance, and the relationship between the processes.

Conceptual models can be used to estimate crop water needs based on climate data and soil water balance which aids in optimizing the irrigation scheduling (Forouhar et al., 2022). Many types of models have been used to simulate these elements from empirical or functional (Allen et al., 1998) to mechanistic (Van Aelst et al., 1988). The Food and Agriculture Organization (FAO) has developed some empirical models that provide a more simplified mathematical model of crop physiological processes such as CropWat and AquaCrop (FAO, 2014, Vote et al., 2015). CropWat can be used to assess the irrigation methods employed by farmers. On a broader level, it can be utilized to create water distribution plans for various crop patterns in an irrigation system, accommodating up to 20 different types of crops, such as paddy and upland rice (FAO, 2014). Unlike other models, it can calculate crop water and irrigation requirements from crop and climate data with minimum input (Vote et al., 2015). The main meteorological inputs require daily, 10-day, or monthly rainfall data, and climatic data (sunshine hours, wind speed, humidity, maximum and minimum air temperature), and these data can be input directly or imported from FAO CLIMWAT 2.0 database, which provides long-term monthly values for more than 5000 meteorological stations globally (Sene, 2010). Crop-related coefficients (rooting depth, yield response factor, crop height) can be used either from a ground survey or the default values from a database including a wide range of crop types (Sene, 2010). Some user-supplied values are required including planting area, planting date, and cropping pattern (Sene, 2010).

AquaCrop was developed to facilitate the farmers, agronomists, engineers, water managers, economists, and policymakers to simulate biomass and yield response to water under varying agricultural practices and environmental conditions (FAO, 2014, Vote et al., 2015). The application of AquaCrop includes the development of irrigation schedules by farmers or water managers, optimizing irrigation practices, and assessing the effect of weather and climate on crop production and water use (Vote et al., 2015). Due to the requirement of large, predefined project files, the simulation time of AquaCrop is comparatively longer. In the process-based models, crop water needs are estimated based on daily weather variables (evapotranspiration and rainfall) during the growing season, and annual cropping area (Forouhar et al., 2022). The reference evapotranspiration is estimated using the Penman-Monteith equation which is described by (Allen et al., 1998).

$$ET_o = \frac{0.408\,\Delta(R_n - G) + \gamma\frac{900}{T+273}u_2\,(e_s - e_a)}{\Delta + \gamma(1+0.34u_2)} \tag{1}$$

where, ET_o is reference evapotranspiration, R_n is net radiation at the crop surface $MJm^{-2}day^{-1}$, G is soil heat flux density $MJm^{-2}day^{-1}$, T is air temperature at 2 m height C, u_2 is wind speed at 2 m height ms^{-1} , e_s is saturation vapour pressure kPa, e_a is actual vapour pressure kPa and $e_s - e_a$ is saturation vapour pressure deficit kPa, respectively.

Irrigation scheduling determines the timing and amount of water applied to an irrigated cropland during the growing season. For the irrigation distributors, forecasting irrigation schedules at a farmer's field level can be critical. A case study on corn production in the Havana Lowland region, Illinois by Wang and Cai (2009) by incorporating the publicly available weather forecasts and climate prediction soil water atmosphere plant (SWAP) model for supporting irrigation scheduling. The SWAP model integrated with genetic algorithm (GA) optimization to schedule irrigation using different types of rainfall forecasts. These methods are tested using real-time soil moisture, meteorological data, and weather forecasts collected during a 5-year period running from 2002–2006 to conduct a retrospective analysis on the impacts of weather forecasts on crop yield, net irrigation profit, and water use.

Cai et al. (2011) developed a simulation-optimization modelling framework for supporting irrigation scheduling using probabilistic rainfall forecast incorporated SWAP model (Wang and Cai, 2009). This simulation-optimization framework was developed to maximize farmers benefit over an irrigation season by deciding on the irrigation schedule. The SWAP model simulates soil moisture, crop ET, crop yield as farmers make decisions day by day. Irrigation decisions are made daily in a moving-window fashion, where today's irrigation decision on how much to irrigate is optimized on the basis of existing conditions (today) and forecasted weather conditions (future) over a maximum forecast horizon of 1 week. The comparison of the gain in seasonal profit and water saving in three scenarios, no rainfall forecast, imperfect rainfall forecast (NOAA's probabilistic values), and perfect rainfall forecast. The comparison showed that using short-term imperfect rainfall forecasts could lead to 2.4-8.5% seasonal profit gain (gross profit in terms of yield minus irrigation cost) and 22.0-26.9% water saving for the farmers and irrigation distributors (Cai et al., 2011).

Tian and Martinez (2014) developed an approach to evaluate daily ET forecasts using a global ensemble forecast system in the Southeastern US. Irrigation scheduling was evaluated by water deficit forecasts, which were determined based on the agricultural reference index for drought (ARID) model driven by the global ensemble forecast system (GEFS)-based ETo forecasts of up to 7 days lead (Tian and Martinez, 2014). Their finding showed that the water deficit forecasts driven by ET forecast provided higher accuracy and less uncertainty than the forecast provided by climatological data (Tian and Martinez, 2014). The evaluation of ensemble and deterministic forecast of water deficit in five locations provided the root mean square error (RMSE) in range 0.63-0.91 mm and Nash-Sutcliffe efficiency (NSE) of 0.87-0.82 from 1 to 5 lead days, respectively.

A data assimilation approach has been used for irrigation scheduling using SWAP model prediction updated with ET prediction from the Surface Energy Balance Algorithm for Land (SEBAL) (Bastiaanssen et al., 1998) model by Irmak and Kamble (2009). The main objective of this work was to develop an ET data integration scheme to optimize the parameters of an agro-hydrology model for on-demand irrigation scheduling. The study was conducted on the irrigated wheat field in Sirsa Irrigation Circle, northwest India using climatic data, soil data, and discharge from in a time-period between November 2001 and December 2002. SEBAL integrates radiation from visible, near-infrared, and thermal bands from satellite remote sensing (RS) along with the air temperature, relative humidity, wind speed, and solar radiation for quantifying actual ET (Irmak and Kamble, 2009). The optimized SWAP model based on the genetic algorithm (GA) to estimate soil water balance for irrigation scheduling showed improved results with higher yield and water use efficiency (Irmak and Kamble, 2009).

Similar research was reported by Ullah and Hafeez (2011), a holistic approach of integrating remote sensing derived ET from the SEBAL method with forecasted meteorological data and water-use efficiency was used to forecast net irrigation demand in the Coleambally Irrigation Area (Ullah and Hafeez, 2011). To capture the spatial variability, all hydrological data of inflow and outflow were estimated at 22 nodes based on direction of flow and connectivity to estimate water use efficiency. Results of irrigation demand forecasting indicate that the net irrigation demand forecast for fields at the node level shows a relatively high difference across the nodes. However, net irrigation demand forecast for fields at the system level shows no significant difference and has good agreement with actual water being delivered to fields. This study only incorporated data from a single year and therefore training and testing over several years would be required to further substantiate the results.

Daily water balances were simulated at the field level within an irrigation district in Southern Italy based on daily weather and rainfall data, crop coefficient, irrigation methods, and soil properties (Khadra and Lamaddalena, 2006). This study demonstrated the capacity to simulate hydrographs of discharge in hourly steps for a peak of 10 days that had a similar pattern to actual discharge hydrographs. However, the model did not account for the hydraulic and physical limitations of the irrigation network and seldom generated hourly discharges higher than the observed, and produced lower discharges even when simulated and registered daily volumes were comparable (Khadra and Lamaddalena, 2006).

Process-based models depend on soil water balance and forecast the irrigation demand by incorporating historical, real-time, and short-term weather forecast information at various spatial scales from the field to the system. The performance of these models is often influenced by the irrigation process, farmers' behaviour, model structure, and uncertainties in the input parameters. The inefficiency of process-based models in predicting volumetric irrigation stems from the inability to quantify behavioural factors, such as the attitudes of farmers and system operators, which greatly impact management decisions.

4.1.2.2 Data-driven models

Data-driven models draw a relationship between the exogenous factors (mainly weather data) and irrigation water demand without accounting for the physical process within the system (Forouhar et al., 2022). Several time-series and artificial intelligence models have been implemented to predict short-term irrigation water demand at regional scales (Pulido-Calvo et al., 2007, Pulido-Calvo et al., 2003). Compared with the process-based models, data-driven models require much less data to generate outputs (Pulido-Calvo and Gutiérrez-Estrada, 2009). These models are driven by climatic data (i.e. precipitation, temperature, relative humidity, wind speed, etc.) which are easily obtained from the publicly accessible meteorological database and weather station at the study site, making it more suitable for operational forecasting purposes (Pulido-Calvo and Gutiérrez-Estrada, 2009).

Time series models: Time-series models are traditional approaches that are commonly used for demand forecasting. Time-series models (univariate or multivariate) are highly explainable as they are based on past observations and associated error terms. Exponential smoothing, autoregressive (AR), moving average (MA), autoregressive-moving average (ARMA), autoregressive integrated moving average (ARIMA), and seasonal ARIMA (SARIMA) are examples of univariate forecasting models. Several inputs can be integrated as independent variables such as water demand of previous days, climatic data of previous days (temperature, wind speed, sunshine hours, precipitation, relative humidity), crop data, present water demands, and cropping pattern in developing a multivariate time series model (Pulido-Calvo et al., 2003). Literature from the urban water demand field indicate that ARIMA, SARIMA, and exponential smoothing techniques have been widely used for forecasting (Chen and Boccelli, 2014, Ristow et al., 2021).

Multivariate time series models have been successfully implemented to forecast short-term water demand in the system scale (Perera et al., 2015, Perera et al., 2016). An ARMA model with exogenous variables (ARMAX) model was developed to forecast short-term (5 lead days) irrigation demands concerning aggregated service points flows and off-take regulator flows based on five command areas (command area 280 km^2) and four irrigation channels in the Goulburn-Murray irrigation district. The major inputs for this model were weather data (daily minimum and maximum temperature, daily mean temperature, daily solar radiation) from automatic weather stations, reference evapotranspiration, normalized vegetation index (NDVI), and leaf area index (LAI) (8 and 16 days composite products from MODIS) collected for six irrigation years. To estimate crop water demand, another index known as water supply deficit (WSD) was calculated using the soil water bucket model based on precipitation and evapotranspiration. During the evaluation period, cross-validation NSE across five command areas ranged between 0.98–0.78 for forecast lead times of up to five days. Whilst the overall performance was promising (Perera et al., 2015), the systematic bias was higher from the model during the period of rapid change in demand. This possibly indicates that the crop coefficient should be accounted for in the model with the more accurate method. Since this research was based on perfect weather forecasts, uncertainties associated with the weather forecast were not evaluated.

Further research was conducted by Perera et al. (2016) which examined the characteristics and incorporated the impacts of uncertainty in the measure of weather input data, model parameters, and real-time weather forecast. The forecast performance for the ensemble irrigation demand predictions were evaluated for lead times of one to five days across the four command areas plus the full study area. Both the average forecasts (ensemble means) and the uncertainty estimates (ensemble spread) performed well overall. NSEs for forecast conditions were up to 0.97 for one day lead time and larger command areas and remained above 0.65 for five-day lead times, except in the two smallest command areas.

Machine learning-based models: Ticlavilca et al. (2013) presented a robust machine-learning approach to forecast the short term (two days lead) diversion demands for three irrigation canals in the lower Sevier River Basin in Utah (command area 280 km^2). The models were developed in the form of a multivariate relevance vector machine (MVRVM) that is based on a Bayesian learning machine approach for regression. Daily flow data from 2001 to 2006 integrated with minimum and maximum temperature, retrieved from The National Oceanic and Atmospheric Administration (NOAA), was used as model input and model performance was tested on the irrigation seasons in the year 2007. The comparison between MVRVM and Artificial neural network (ANN) showed that both methods could achieve reliable results for forecasting irrigation demand. However, the MVRVM model does not include rainfall as the major input (since the average rainfall is relatively low in the study site) which could introduce uncertainties in the model transferability to the irrigation areas with high rainfall.

A comparison study was done using two nonlinear ANN models and one linear ARIMA model to forecast water demand for the water supply system in Canada (Bata et al., 2020). The nonlinear model was developed with five years of historical outflow data with or without introducing exogenous variables. Results show that nonlinear (Nonlinear autoregressive ANN) models are much more efficient compared to the linear (ARIMA and SARIMA) models in forecasting water demand 24 hours and one week ahead. Nonlinear models can capture the non-linearity and linearity in the time-series, providing an advantage over using traditional linear models (Bata et al., 2020).

Perea et al. (2015) developed a new methodology to optimize deep neural network structure by genetic algorithm (ANN-GA) to forecast short-term daily irrigation demand in the irrigation district level. The model has been calibrated and validated using water demand, climatic variables (average temperature, solar radiation and reference ET of two previous days. Water demands were aggregated at daily level for the years 2010, 2012, and 2013. The model has predicted 93 % of the variability of the observed water demand with a standard error of 12.63 %.

While data-driven models have frequently demonstrated improvements in the predictive accuracy of irrigation water demand (IWD) forecasting, there are certain concerns associated with these models. One notable issue is the potential for overfitting, as the models capture system interactions implicitly. Overfitting is a common problem that was highlighted in a study by Wu et al. (2014). Another concern is that data-driven models tend to underperform during periods of exceptionally high or low demand, which would be particularly concerning for operators. As indicated by studies conducted by Perera et al. (2015) and Pulido-Calvo and Gutiérrez-Estrada (2009), this limitation primarily stems from the over-generalization of these models during their development.

4.1.2.3 Hybrid models

Table 2 show examples of literature where hybrid models have been developed for shorter term irrigation demand forecasting at field and system level. Forouhar et al. (2022) created a hybrid framework that combined both existing physical knowledge and data-driven modelling techniques to forecast irrigation water demand for up to seven days in an irrigation district located in Victoria, Australia. They incorporated a conceptual model that utilized observation data to understand the various factors influencing crop water requirements within the system. By integrating this knowledge with data-driven modelling, they aimed to improve the accuracy of predicting irrigation water demand in advance.

In their study, Perea et al. (2021) created a system that could forecast water demand at the farm level, specifically looking ahead to the next seven days. This innovative method involved integrating artificial intelligence methods, satellite remote sensing, and freely available climate data to improve the accuracy of predicting irrigation water requirements in advance. However, it is worth noting that even though the model achieved Standard Error of Prediction (SEP) values ranging from 17% to 19%, the one-week estimation provided a single value without distinguishing between individual days within that week.

Perea et al. (2021) applied a methodology to the Canal del Zujar Irrigation District in Spain for obtaining a set of ANN models optimum for water user association. The accuracy of the developed forecasting models ranged from 17% to 19% and representativeness was higher than 80%. In addition, they reported that by analysing the input variables of the forecasting model automatically identified with fuzzy logic, the knowledge of the irrigator's behaviour in water use can be increased.

4.1.3 Model performance metrics

Forecast model validation indicators calculate the forecast error rate as difference between forecast value and actual value. Niknam et al. (2022) highlight that the most used validation indictors are the root mean squared error (RMSE), standard error of prediction (SEP), coefficient of determination (R^2) mean absolute percentage error (MAPE), mean absolute error (MAE) and Nash-Sutcliffe efficiency (NSE) indices.

$$RMSE = \sum \frac{(P_i - O_i)}{n} \tag{2}$$

$$NSE = 1 - \frac{\sum (P_i - O_i)^2}{\sum (O_i - \overline{O_i})^2} \tag{3}$$

$$MAPE = \frac{\sum \frac{Abs(O_i - P_i)}{O_i} \times 100}{N} \tag{4}$$

$$MAE = \frac{\sum_{i=1}^{N} Abs(P_i - O_i)}{N} \tag{5}$$

$$SEP = \frac{100}{\overline{O_v}} \times RMSE \tag{6}$$

P_i= forecast or predicted value; O_i = Observed or actual value, N= total number of samples; $\overline{O_v}$ = average of observed water demand in validation set (L s^{-1}) (Perea et al., 2015). RMSE is suitable to compare errors using the same dataset. MAPE is considered to give the error in percentage or proportion, lower the MAPE higher is the model performance. MAE and RMSE give similar overview only MAE provide the error in absolute value. NSE represents the gain of using the model versus using the mean, NSE = 1 represents perfect fit and NSE = 0 represents model has a similar performance as the mean of the historical time series (Niknam et al., 2022).

4.2 Research design and methodology

With the focus problem being to assess the potential role of using demand forecasts to inform river orders, the process is represented as a model learning loop in Figure 7. Multiple models were developed with their evaluation focusing on performance at critical times for MI and CICL (Table 3). The critical times for both irrigation districts are when there is an elevated risk of underordering. Initial activities focused on model development and testing using historical data. As the modelling matured, data from the 2023-2024 season was used to test the models. Regular project meetings between project team members and CICL and MI operations staff were held to evaluate the demand forecasting algorithms and the evaluation framework. Further development of either the algorithms or the framework was prioritized based on their ability to meet the operational needs of the industry partners. Through this process, the team explored the potential value and challenges to adoption, operationalisation and ongoing adaptation and development of the algorithms by the project industry partners. For MI, an output of this process was the development of a software application for reporting demand forecasts for the Main Canal.

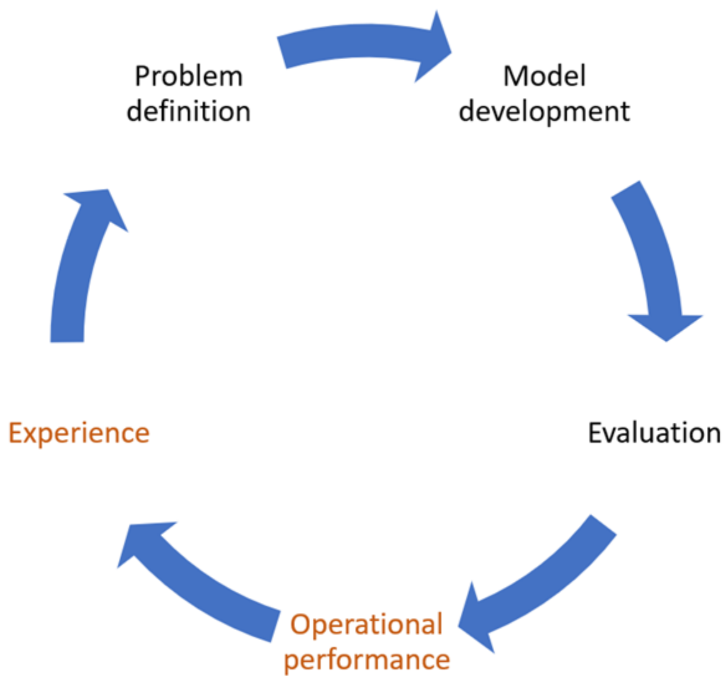

Figure 7. Model learning loop for the development of demand forecasting algorithms and the evaluation framework

Table 2. Examples of hybrid models and their use for short-term irrigation demand forecasting at field and system level.

Title	Temporal	Spatial scale	Data	Methods	Variables	Accuracy	
A hybrid framework for short term irrigation demand forecasting (Forouhar et al., 2022)	Daily (7 lead days)	Red cliffs irrigation district, Australia	2012-2020	Hybrid model (Conceptual method for crop water need estimation and data driven model (ANN))	Daily rainfall, minimum and maximum temperature, relative humidity, bright sunshine hours, wind speed, sea level pressure, daily reference ET (calculated from air temperature, humidity, wind speed, radiation), cropping data, daily climate variables, seven lags of daily pumped volume	RMSE = 22-25	NSE = 0.92-0.90 from 1 to 7 lead days
Demand Forecasting for Irrigation Water Distribution Systems (Pulido-Calvo et al., 2003)	Daily	System scale (Fuenta Palmera irrigation district, Spain)	1988-1991	CNN and ARIMA	Water demand of 5 previous days, climatic data of previous days (maximum temperature, minimum temperature, average temperature, precipitation, relative humidity, wind speed, and sunshine duration), crop data surfaces and crop coefficients	ARIMA (R^2 = 0.973, SEP = 85.53)	CNN (R^2 = 0.90, SEP = 34.11 %)
Improved irrigation water demand forecasting using a soft-computing hybrid model (Pulido-Calvo and Gutiérrez-Estrada, 2009)	Daily (1 lead day)	System scale (Fuenta Palmera irrigation district, Spain)	1988-1991	CNN models (Extended-Delta-Bar-Delta algorithm), ARIMA model, CNN and Fuzzy logic hybrid models	Daily irrigation demand data (mm day^{-1}), crop data (crop coefficient and growth stage), weather data (rainfall, mean temperature and daily evapotranspiration)	Correlation coefficient (R); CNN= 0.88-0.91; ARIMA = 0.93; hybrid model = 0.93-0.94	SEP of CNN= 25.5-29.67 %; ARIMA = 26.81%; hybrid model = 20.27-22.65 %

Table 1 continued

Title	Temporal	Spatial scale	Data	Methods	Variables	Accuracy	
Deep learning with long short-term memory neural networks combining wavelet transform and principal component analysis for daily urban water demand forecasting (Du et al., 2021)	Daily	Waters supply network in Suzhau, China	2016-2020	Hybrid discrete wavelet transform (DWT)-principal component analysis (PCA)-long short-term memory (LSTM) method	Min-max temperature, weather, calendar information and holidays	R =0.9803	MAPE =0.0183
Short-term water demand forecasting using hybrid supervised and unsupervised machine learning mode (Bata et al., 2020)	Hourly and daily (7 lead days)	Water utility from Southwestern Ontario, Canada	4 months (Aug-Nov)	Hybrid regression tree (RT) and Self -Organizing Maps (SOM) along with seasonal autoregressive integrated moving average (SARIMA) model	Outflow previous day same hour, outflow previous week same hour, outflow average previous 24 h, month of the year, hour of the day, day of the month	NRMSE: 5.18% (1hr), 6.24% (8hr), 6.78% (24hr), 8.62% (7days)	MAPE: 0.0484 (1hr), 0.0582 (8hr), 0.6120 (24hr) 0.0680(7days)
Irrigation Demand Forecasting Using Artificial Neuro-Genetic Networks (Perea et al., 2015)	Daily (1 lead day)	Bembézar M.D. Irrigation District (BMD), Spain	2010, 2012, 2013	ANN combined with Genetic algorithm (GA)	Water demand in the previous day, water demand in the two previous days, average temperature, solar radiation, reference ET	R^2 = 0.90-0.93	SEP = 12.72-13.48 %
Water and energy demand forecasting in large-scale water distribution networks for irrigation using open data and machine learning algorithms (Perea et al., 2021)	Daily (7 lead days)	The Canal del Zujar Irrigation District (CZID)	2015, 2016, 2017 and 2018	ANN combined with Genetic algorithm (GA)	Aggregated daily water demand, daily: temperature (max, min, average), relative humidity, solar radiation, wind speed, precipitation, effective rainfall, net solar radiation, reference evapotranspiration, mean NDVI at farm level	R^2 = 0.66-0.81	SEP = 17.1-18.2 %

Within the literature, there was limited evidence that evaluation approaches considered the context of potential users of demand forecasts or crop models. Supporting this, engagement with industry partners through project team meetings and the conceptual modelling workshop held in May 2023 in Griffith indicated that the metrics that are typically reported in the literature are not always fit-for-purpose in practice. Recognising this, the evaluation framework developed and employed in this project identified basic (which are most applied in the literature), risk (or control) informed and diagnostic metrics (Table 4).

Table 3. Overview of models developed by the project team.

Irrigation district zone	Model	Training period	Testing period	Scenarios
MIA – Main canal	UoM Hybrid model (Section 4.4.3)	2018-2022	2023-2024	• Actual forecast • Perfect knowledge of forecast rainfall and temperature • Perfect knowledge of all model features
	MI data-driven model (Section 4.5)		2023-2024	
CICL	UoM Hybrid model (Section 4.4.4)	2019-2022	2023-2024	• Perfect forecast • No forecast

Table 4. Examples of metrics that are relevant to evaluation of demand forecasting (note that not all metrics used in the project are suitable for public release)

Basic metrics	Risk (or control) informed	Diagnostic
Under-ordering focused • Absolute error timeseries • Relative error timeseries • Total absolute bias • Relative bias • Graph of cumulative error over time • Cumulative distribution function Other metrics • RMSE (over and underestimates have equal weight) • NSE (relative to mean)	• Error as percentage of total surge capacity (within district) • Error as percentage of available surge capacity • Cumulative error as percentage of total river surge capacity • Cumulative (spatial and temporal) error at offtakes and zones • Total 3-day running error • Evaluation of probabilistic forecasts (reliability, sharpness)	• Performance on specific sub-periods • Missed rain events • Other high customer order-take mismatch periods • Key crop development periods • During planting window • Heatwave/high evaporative demand periods • Performance as a function of flow (expect higher error with higher flow) • Highest 10% demand days

In the context of continuous improvement, the intention is that end-users of forecast are provided with the information and tools needed to be able to form their own assessment of the performance of the forecast in terms meaningful to them, to be able to identify periods of time when the forecast may perform poorly, and report failures of the model to inform further model development. The assessment framework developed in the project was intended to fit within a regular performance review process that considered (1) issues faced in forecasting and ordering since the previous review meeting, (2) evaluation of operational, staging and experimental forecasts and (3) discussion of future changes such as the identification of test cases and hypotheses for model improvement or possible changes to performance metrics. The outcomes of this process are documented in Section 4.6.

4.3 Case study data

4.3.1 MI Area of Operations

There are two key offtakes, namely Narrandera (main canal) and Sturt, which are the key decision points for demand forecasting in MI. The Sturt subsystem is mainly broadacre with a smaller (although still considerable) demand for water than the Main Canal; the channel capacity limits how MI can operate this part of the system. During periods of very low demand, demand can be met purely through the main channel system (the Narrandera offtake).

Weather variables were obtained from Griffith Airport weather station by MI for the period between January 2010 and August 2023. These variables include daily minimum and maximum temperature (C), daily relative humidity (%), solar radiation (MJ/m^2), wind speed (m/s), and vapor pressure (kPa). MI provided the long-term factors such as the cropping area and crop types for the main and Sturt channels.

4.3.2 CICL Area of Operations

The CICL main channel offtake, upstream of Gogeldrie weir, can be used to fill the Tombullen storage owned and operated by WaterNSW as well as the CICL system of channels, the off-stream storage, and delivering water outside the system via the Coleambally Catchment Drain (CCD) and DC800. Water is mainly regulated by the total channel control (TCC™ [10]) system in the CICL irrigation district.

Weather variables were obtained from the Bureau of Meteorology (BoM) Coleambally Irrigation station (74249) for the period between January 2010 and August 2023. These variables include daily minimum and maximum temperature (C), daily relative humidity (%), solar radiation (MJ/m^2), wind speed (m/s), and vapor pressure (kPa).

CICL provided the long-term factors such as cropping area and crop types as well as thedaily net diversion volume (ML) diverted through CICL main offtake (minus WaterNSW deliveries for Tombullen, CCD and DC800).

4.3.3 Role of Uncertainty

Uncertainty within river ordering is currently approached primarily from the point of view of maturity/utility of information products and their relatability to the tacit knowledge of operators. Other framings of uncertainty (Guillaume et al., 2017) take a secondary role. Operators draw on multiple information sources ("triangulation") and would not rely solely on a single demand forecast but do not explicitly quantify uncertainty. Operators show interest in historical performance of algorithmic forecasts but do not yet use probabilistic information. Operators use different assumptions in different circumstances, which potentially lends itself to switching between different forecast models in future.

[10] https://rubiconwater.com/irrigation-district-solutions/, Accessed 13 January 2025

This project deliberately adopted continuous improvement as the primary mechanism for managing model uncertainty. Development of a first generation of algorithmic demand forecasts and their adoption for river ordering builds the foundation for progressively reducing uncertainty over time, with new experiments in demand forecasting providing steps towards a longer-term goal. Currently, the forecasts presented in this chapter are deterministic. In the future, ensemble forecasts could be considered to consider the implications and effects of (for example) different decisions or possible states that can change across the season in presence of uncertainties.

A continuous improvement approach to uncertainty is considered essential for a context in which user behaviour is expected to change over time and is far from fully characterised. A combination of conceptual and data-driven modelling allows forecasts to fit behaviour during a training period, but model performance is expected to both vary across different conditions and to drift over time. While differentiation of classes of users is possible, it is expected that fundamental limits would be reached due to privacy considerations and lack of predictability of human behaviour. In addition, diminishing returns are likely to be encountered given the effectiveness of data-driven modelling of emergent behaviour at the system level. Unknown unknowns form an important part of user behaviour. If those unknowns are present in the training data, data-driven models may be able to capture their effect at system level. If unknown unknowns are not present in the data, in a river ordering context they can still be managed as they emerge (when they become known unknowns) by being aware of the limitations of model and ceasing its use. For example, extreme events such as floods, long droughts, fire, and crop disease may cause major changes to water demand in the region that operators can react to if the model lacks skill. Maintaining a human in the loop is an important part of uncertainty management of demand forecasts for river ordering.

Information about future weather, soil moisture, and crop water use are all incomplete and uncertain, with missing spatial variation and coarse approximation of behaviours. It is expected that uncertainty on all these factors could be gradually reduced over time through additional data collection, data sharing, or uncertainty quantification. Explicit uncertainty quantification, e.g., ensemble weather forecasts, could both feed into probabilistic demand forecasts and inform additional data collection to improve skill at longer lead times, using value of information and design of experiment methodologies.

In general, the modelling problem is characterised by an abundance of uncertain and potentially inconsistent data points about a variety of possible forecasting outputs. Consistent with the tension between simple and complex models, there is temptation to err towards more complex mechanistic models of water balances and user behaviours that produce estimates of demand at the finest scale possible, and then to aggregate these demands to a variety of scales. However, weather does vary across the region, neither point-wise soil moisture data nor satellite soil moisture provide generalisable high-fidelity information, user-reported and remotely sensed crop data are both uncertain and not necessarily timely, the uncertainty aggregation behaviour of customer outlet data is not known, and the state of user behaviour modelling involves hypotheses of heuristic rules in use with limited historical evidence. While increasing model complexity is likely to be worthwhile, this project has elected to tackle uncertainty by starting simple, building on existing lumped regional modelling techniques. Data at the main offtakes is regularly audited for regulatory purposes, and other necessary data is publicly available with potential to use more local and/or more accurate data sources when available.

Each model is considered a digital asset in its own right. As with other assets, its lifecycle needs to be managed, including maintenance and replacement. Maintenance includes ongoing verification of whether performance is degrading, as well as gradual improvement of understanding of its domain of applicability - understanding under which conditions it performs well and poorly. As with other assets, failure of a model's forecast to meet defined requirements may cause cascading failures in water delivery processes, and therefore need to be identified quickly, and anticipated where possible. As understanding of limits of existing models improves, a business case is made for replacement with a new model that improves performance according to all defined criteria. Given the location-specific nature of the models in use, collaboration with research institutions can form part of the replacement strategy - building a critical mass of experts on the local system who provide data science services rather than just providing a model as a product.

Overall, the management of uncertainty aims to draw on best practice in 1) use of forecasts in water operations, 2) continuous delivery of software products, e.g., as seen in "MLops" deployment of machine learning models. While there is extensive history of these concepts in other application areas, development of best practice guidelines in water delivery and integrated storage management in systems like the Murrumbidgee is still at its early stages and will need further development between One Basin CRC partners before its formalisation.

4.4 Case study: UoM hybrid model application

4.4.1 Rationale for model selection

Three major approaches for short-term irrigation water demand forecasting have been elaborated in the literature (and detailed in Section 4.1). These involve conceptual (process-based), data-driven (system theoretical) and hybrid modelling, respectively. Conceptual models are developed by modelling key elements of the irrigation process such as soil water balance or crop water needs and the relationships between them (Forouhar et al., 2022). Several approaches have been reported for simulating crop water needs based on empirical, functional, and mechanistic relationships within the conceptual models. Data-driven models are developed to map the relationship between the influential factors and irrigation demand with no detailed consideration of the internal structure of the physical process (Perera et al., 2015). There are also hybrid models that try to draw on the benefits of both the conceptual and data-driven approaches. All these models generally aim to generate the daily crop water needs for irrigation water demand forecasting using climate variables and crop properties.

Conceptual models aim to determine the optimal timing and quantity of irrigation water to maximize yield or economic benefits based on different criteria, including farmer assessment of crop water needs, estimating crop water needs based on historical climate data, and/or prediction of irrigation water requirement based on soil water data obtained from soil moisture sensor (García et al., 2018, Perea et al., 2021, Forouhar et al., 2022). An advantage of conceptual models is that they aim to build theoretical and experiential knowledge into the model structure; however, the performance of conceptual models is influenced by the way the various processes are represented in the model and the quality of input data (Cai et al., 2011, Wang and Cai, 2009, Forouhar et al., 2022). The primary drawback of conceptual models is that only some of the interactions between physical understanding of the system elements are included and thus modelled as they mainly consider the irrigation requirement equivalent to crop water needs (Forouhar et al., 2022).

Data-driven models aim to identify a direct empirical relationship between inputs and outputs without detailed consideration of the internal structure involved in the biophysical system. An advantage of data-driven models over conceptual models is that they have lower data requirements. Data-driven models have improved the predictive performance of water demand forecasting models (Pulido-Calvo and Gutiérrez-Estrada, 2009) although limitations are inevitable. Data-driven models typically learn patterns from training data that may not accurately represent the broader population or future data points, sometimes leading to overfitting and failure to perform accurately in unseen or extreme demand conditions.

Hybrid models have proven to be more versatile for short-term water demand forecasting by combining conceptual and data-driven techniques (Pulido-Calvo and Gutiérrez-Estrada, 2009, Forouhar et al., 2022). The efficacy of the hybrid approach becomes apparent when compared to an independent approach using either conceptual or data-driven models (Forouhar et al., 2022). Integrating a conceptual understanding of the physical system into data-driven models has shown promising results in improving prediction performance. For instance, Forouhar et al. (2022) devised a hybrid framework that incorporated existing physical knowledge into a data-driven model by utilizing a conceptual model to comprehend factors influencing crop water needs through observation data. This integrated approach successfully forecasts short-term irrigation water demand up to 7 days ahead for an irrigation district in Victoria, Australia. Perera et al. (2016) developed a multivariate time series model integrating both conceptual and data-driven approaches into a single structure to forecast irrigation water demand for a lead time of up to 5 days. In a different application, Sushanth et al. (2023) applied a hybrid approach to accurately forecast inflows in a reservoir-regulated basin 1-5 days in advance, showcasing its effectiveness. Consistent results were also reported by Perea et al. (2023) in the middle-term water demand forecasting for irrigated areas. This hybrid approach not only demonstrates the potential for effective short-term water demand forecasting but also provides helpful insights into daily operational decisions for water suppliers as well as agricultural businesses (Perera et al., 2016). This section of the report develops (Section 4.4.2) and evaluates a hybrid modelling approach for MI (Section 4.4.3) and CICL (Section 4.4.4) case study applications.[11]

4.4.2 Model development

The structure of the hybrid model is depicted in Figure 8. In the conceptual segment of the model, daily crop water needs are computed based on weather, crop type and crop area variables. The soil water balance model was introduced in the conceptual part of the module to derive the crop irrigation requirement (CIR), considering the effect of rainfall on irrigation water demand. The data-driven model then incorporates 7 days of lagged and leading weather variables, along with the CIR and reference evapotranspiration (ETo) obtained from the conceptual module, serving as potential features. Recognizing the likelihood of relatively higher errors in the conceptual model, we assume that these errors can be further minimized in the data-driven component of the model.

[11] Publicly shared code available as: One Basin CRC (2024). irrigation-district-demand-forecasting: Public release (v0.1.0). Zenodo. https://doi.org/10.5281/zenodo.14428758

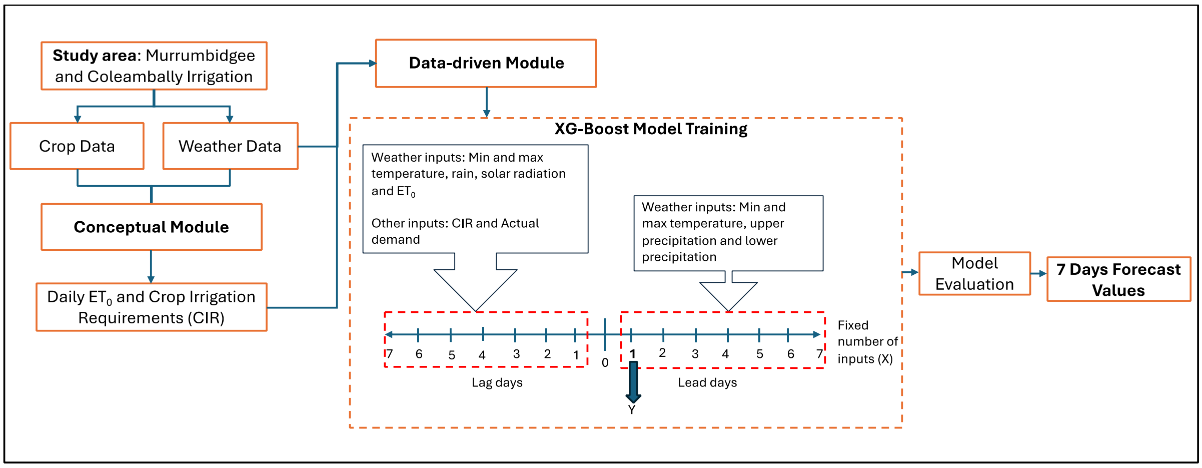

Figure 8. Overall framework of the hybrid model.

4.4.2.1 Conceptual module

The conceptual model is mainly based on weather variables (minimum temperature, maximum temperature, wind, vapour pressure, humidity and rainfall) and crop data (cropping area and crop type) which are used to calculate daily crop irrigation requirements (CIR). Firstly, daily reference evapotranspiration is estimated using the Penman-Monteith equation described by Allen et al. (1998).

$$ET_o = \frac{0.408\,\Delta(R_n - G) + \gamma\frac{900}{T+273}u_2\,(e_s - e_a)}{\Delta + \gamma(1+0.34u_2)} \quad (1)$$

where, ET_o is reference evapotranspiration, R_n is net radiation at the crop surface $MJm^{-2}day^{-1}$, G is soil heat flux density $MJm^{-2}day^{-1}$, T is air temperature at 2 m height C, u_2 is wind speed at 2 m height ms^{-1}, e_s is saturation vapour pressure kPa, e_a is actual vapour pressure kPa and $e_s - e_a$ is saturation vapour pressure deficit kPa, respectively.

Crop evapotranspiration (ET_c) under standard conditions is defined as the evapotranspiration from disease-free, well-fertilized crops grown in large fields under optimum soil water conditions and achieving full production under the given climatic conditions (Allen et al., 1998). The crop coefficient, K_c, is the ratio of the crop *ETc* to the reference *ETo*, and it represents an integration of the effects of four primary characteristics that distinguish the crop from reference grass (Allen et al., 1998). K_c is specific to a given crop and is usually determined experimentally. k_c values represent the integrated effects of changes in leaf area, plant height, crop characteristics, irrigation method, rate of crop development, crop planting date, degree of canopy cover, canopy resistance, soil and climate conditions, and management practices (Pokorny, 2019). Each crop will have a set of specific crop coefficients and will predict different water use for different crops for different growth stages.

Using the crop coefficient approach is under standard conditions ET_c given by (2).

$$ET_c = K_c \times ET_o \quad (2)$$

k_c values for the initial stage, mid-season and harvest were obtained from the literatures (Humphreys et al., 1994, Shuttleworth and Wallace, 2009, Meyer et al., 1999, MDBA, 2018, Lewis and Randall, 2017, North et al., 2008). In the FAO56 method used here, K_c values for the development stage and late season (see

Figure 9) are interpolated using equation (3).

$$K_c = K_{c\,prev} + \left[\frac{i - \sum L_{prev}}{L_{stage}}\right] \times \left(K_{c\,next} - K_{c\,prev}\right) \quad (3)$$

where, i: day number within the growing season,

$K_{c\,i}$: crop coefficient on day i,

L_{stage} : length of the stage under consideration [days],

$\sum L_{prev}$: sum of length of all previous stages [days]

In addition, a representation of soil water conditions was introduced to incorporate the effect of rainfall in the crop water needs estimation (Figure 10). We recognise that along with heavy rainfall, other factors impacting irrigation demands for the following days could include soil water recharge, surface runoff and deep percolation.

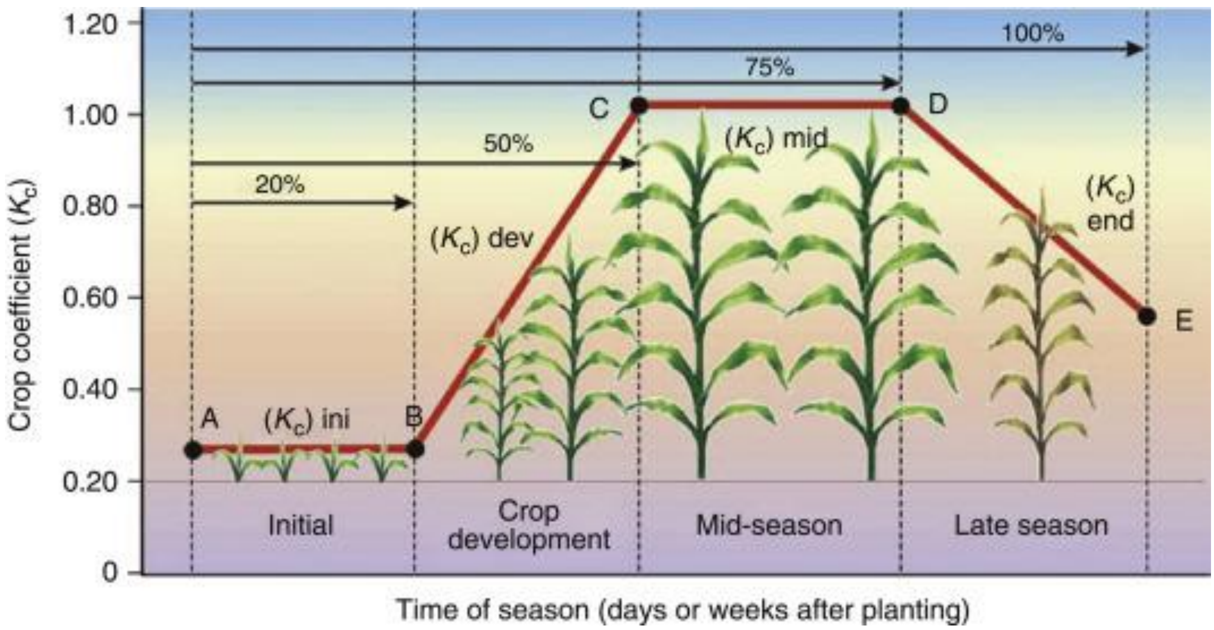

Figure 9. Schematic representation of increase and decrease in crop coefficient based on different plan development stages (Imrak, 2008).

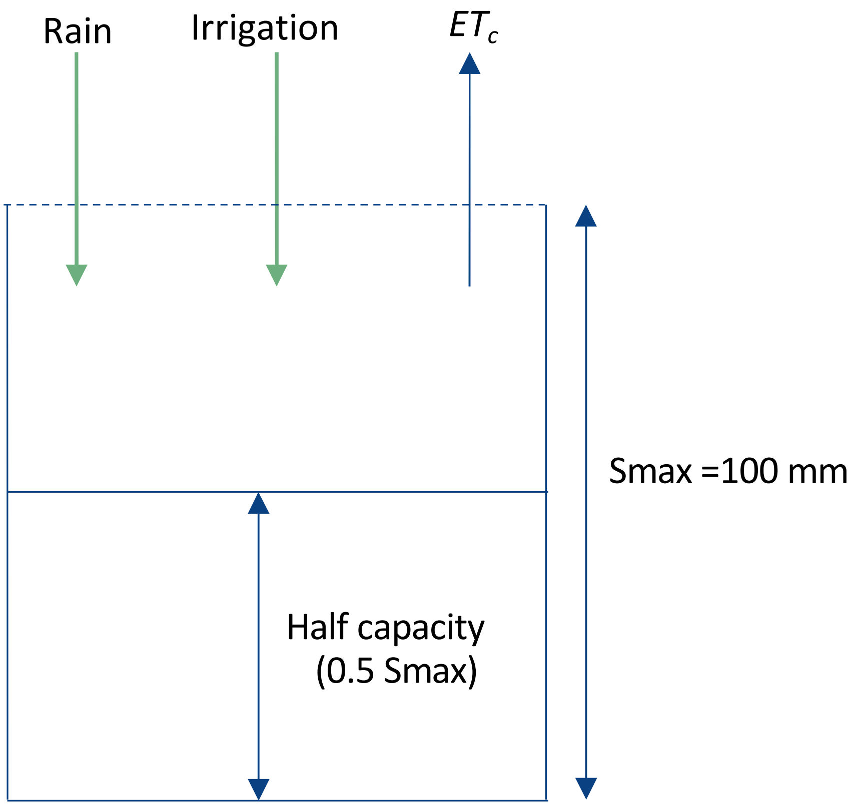

Figure 10. Schematic diagram for a simple soil water balance model.

Crop water needs is the amount of water required to compensate for the evapotranspiration loss from the cropped field. Crop water needs and ET_c are identical, as one represents the amount of water needed, and the other refers to the amount of water lost.

Based on the soil water balance model, the crop irrigation requirement (CIR) can be represented as;

$$CIR_i = S_{i-1} + Rain_i - ET_c \tag{4}$$

Where, i: day counter, Area: cropping area, S_i: Soil moisture content; ET_c: crop evapotranspiration.

A soil saturation threshold (Smax) has been defined to simulate runoff generations in reaction to rainfall. The soil saturation threshold is the maximum amount of water that the soil can hold. Beyond this point, any additional water will either runoff or move downwards through the soil profile, potentially contributing to the factors such as groundwater recharge. Likewise, we assume that the fields are always maintained at the half capacity of the total soil saturation threshold, giving us the irrigation requirement for each day concerning the rain, and ET_c. In this case, we have considered the soil saturation threshold at 100 mm. This assumption, whilst somewhat crude, reflects that at an irrigation district level, there is a spectrum from some fields being fully irrigated through to others being dry and needs to be irrigated immediately. After a rain event, the soil capacity can be filled up to full and irrigation is not necessary until the moisture is drawn down to half level. The CIR for each crop type is then aggregated for the whole area to compare with the daily demand values.

Table 5 lists the major crop types grown between the 2018-2023 period for MI and CICL, respectively which were considered in the model; some crop types in either irrigation area, which collectively account for less than 2 percent of the total irrigated area, were excluded. The area of each crop used in the model was provided by CICL and MI staff who also checked the suitability of the planting and harvest dates initially derived from the available literature.

Table 5. Description of major crop types in Murrumbidgee irrigation district.

District	Plantation area (ha) range
MI	Citrus, Cotton, Nuts, Rice, Summer cereals, Summer oilseeds, Summer pasture, Vegetables, Vines, Winter oilseed, Winter cereals, Winter pasture
CICL	Rice, Cotton, Winter Wheat, Almonds, Corn, Annual Pasture, Almonds, Corn, Annual Pasture, Barley, Oats, Oilseeds, Sorghum, Soybeans

4.4.2.2 Data-driven module

After estimating crop irrigation requirements (CIR) and reference evapotranspiration (ET_0), the input features for the data-driven module were selected from the dataset. This included seven lags of all prospective input variables: Tmin, Tmax, solar radiation, rain, ET_0, CIR and actual demand. Additionally, forecasts of the weather variables for the next seven days were incorporated as inputs. As shown in Figure 7, seven models were trained using the same set of X variables and varying the target Y variables from lead day 1 to 7. The perfect weather forecast assumption was considered for comparison, utilizing observation values of the weather variables. The model was developed based on three scenarios: assuming perfect forecast, no forecast and actual forecast.

The prediction model for actual water demand utilized Extreme Gradient Boosting (XGBoost), an algorithm based on decision trees that employs gradient descent to generate new trees. XGBoost is known for its effectiveness in classification and regression tasks. For the regression task, the XGBoost model sequentially generated new trees and fit residuals from the previous model, allowing for parallel execution based on boosted trees and efficient handling of complex data (Shan et al., 2023). The XGBoost model was trained using the feature set from year 2018 to 2022. Hyperparameter optimization was performed using GridSearchCV from the scikit-learn package, involving cross-validation techniques to select the optimum hyperparameters. A leave-one-year-out cross-validation technique was applied. The model's performance was evaluated during the independent testing period in the season 2023-2024. Using the 7 pre-trained models, the forecast values are generated at daily time steps.

4.4.3 Application to the MI area of operations

The conceptual part of the model involved calculating both the reference evapotranspiration (ETo) and daily crop water needs. Figure 11 displays the annual trend of daily ET0 from 2018 to 2024, while

Table 6 provides the monthly average, minimum, and maximum ET0 values. Figure 11 shows that average ET0 values are lower during winter months, specifically from April to August, and gradually increase from September to March each year. Figure 12 shows the residuals on the y-axis representing the difference between the actual irrigation demand and the CIR over time, from 2018 to 2024. Positive values indicate that the demand was higher than the requirement. The residuals during 2018-2019 show significant variability, with frequent swings between positive and negative values. The large variability suggests that there may have been inconsistencies possibly due to erratic weather patterns, changes in irrigation practices, or errors in estimating crop areas. As the plot moves into 2019 and 2020, the residuals tend to be more negative, with several large dips below zero, although the overall variability is somewhat reduced compared to 2018. In late 2020 and 2021, the residuals show significant positive spikes reaching values as high as 4000 ML. The positive spikes could indicate a period of over-irrigation, possibly due to conservative irrigation practices to avoid under-watering during critical growth periods or adjustments made in response to extreme weather. In 2022-2023, the plot shows a decrease in the overall variability of residuals, with less frequent extreme spikes, though both positive and negative residuals indicate there is still room for improvement in matching irrigation demand with crop needs. Towards the end of the time series, particularly in 2023 and 2024, the residuals stabilise, with fewer extreme fluctuations and more residuals closer to zero.

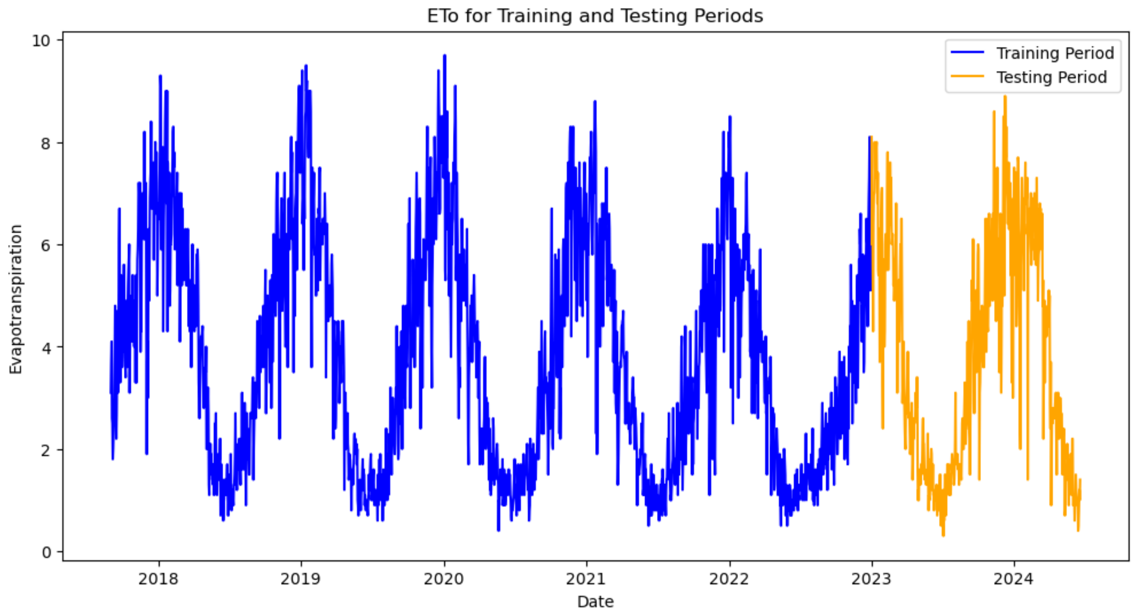

Figure 11. Annual trend of reference evapotranspiration in Murrumbidgee Irrigation district.

The concept of CIR can be complemented by irrigation water requirements (IWR). IWR is a net depth of water that must be applied to a crop to satisfy CIR fully. It is the fraction of CIR not satisfied by rainfall, soil water storage and groundwater contribution. In the current approach, CIR acts as an IWR without considering the effect of groundwater. The availability of groundwater can be crucial in sustaining agricultural activities, as farmers often rely on wells to extract groundwater for irrigation. The unaccountability of groundwater storage the model could also be the reason for having higher CIR than actual demand. The scatter plot shows the correlation between actual demand and CIR which attained a coefficient of determination (R^2) of 0.72 (Figure 13).

Table 6. Monthly statistics of ETo calculated using FAO 56.

Months	Eto		
	Average	Max	Min
Jan	7.1	11.5	1.9
Feb	6.3	9.9	2.8
Mar	4.6	8.4	1.3
Apr	2.9	7.2	0.9
May	1.6	3.9	0.5
Jun	1.1	2.7	0.5
Jul	1.2	3.5	0.4
Aug	1.7	4.7	0.6
Sep	3.0	6.3	1.2
Oct	4.2	8.8	1.8
Nov	5.4	10.4	1.1
Dec	6.8	12.0	3.7

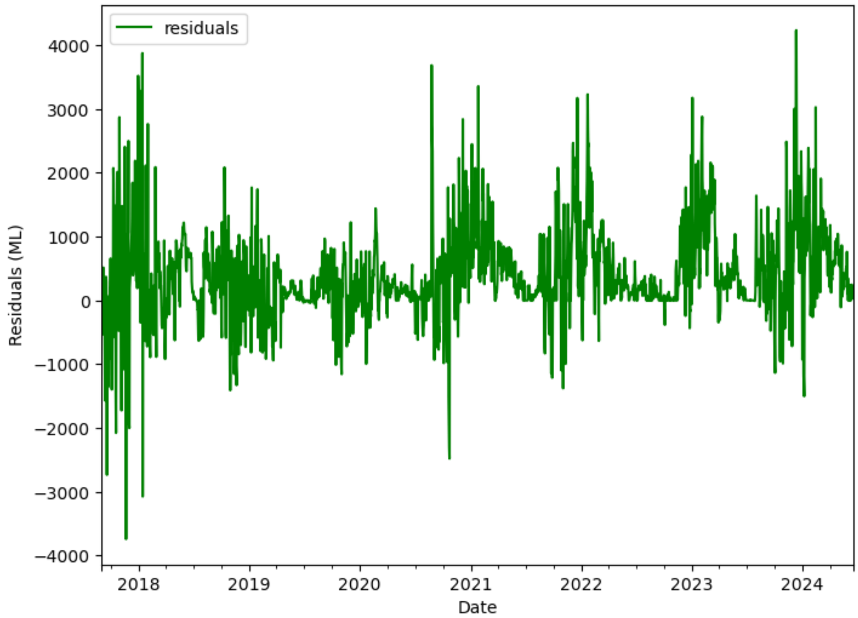

Figure 12. A residual plot showing the difference between the actual demand of MI and crop irrigation requirements.

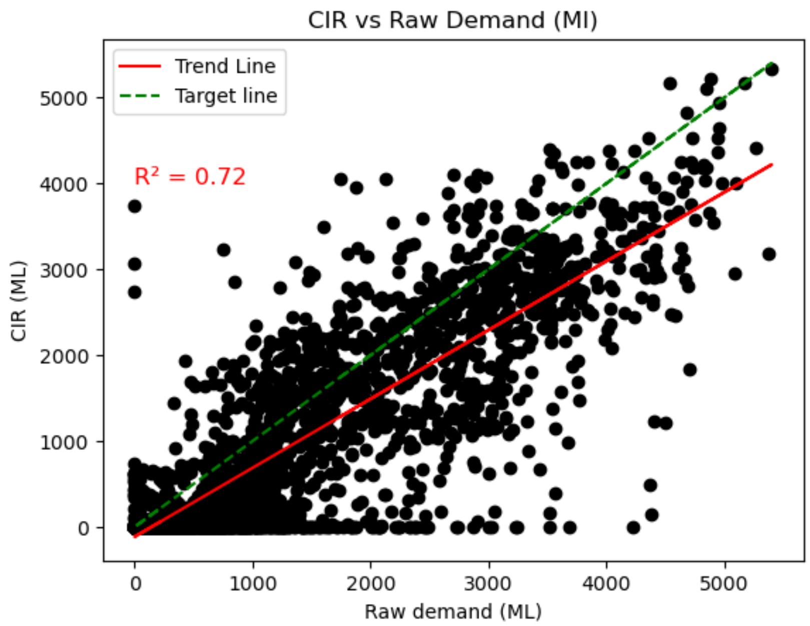

Figure 13. Scatter plot showing actual demand versus predicted crop irrigation requirements.

4.4.3.1 Extreme gradient boosting model

Table 7 gives the comparison of the XG-Boost model performance in three scenarios. Figure 14 shows the RMSE for three models across a 7-day lead time. The perfect forecast of temperature and rain, means that these variables are assumed to be known accurately based on observed data. The RMSE for this scenario starts around 409 ML on lead day 1 and gradually increases to about 677 ML by day 7. The blue dashed line represents the model using actual temperature and rain forecast from BoM, which introduces real-world forecasting uncertainties. The RMSE for this case is higher across all lead days compared to the perfect forecast model, starting at 417 ML on day 1 and rising to 728 ML by day 7. The third scenario is assuming the model has perfect knowledge of all input variables for the next 7 days, i.e. the perfect forecast for all feature inputs. It shows the lowest RMSE value on lead day 1 starting at 380 ML and increasing more slowly to 637 ML by lead day 7.

All three models show an increase in RMSE as the lead time increases from 1 to 7 days. This trend is expected because the uncertainty in forecasting generally grows as the lead time increases. The actual forecast model has the highest RMSE at all the lead times, highlighting the impact of real-world forecast errors on irrigation demand prediction. The gap between this model and the perfect forecast models increases over time, especially after lead day 3. The result shows the model performs better with the perfect knowledge of all inputs as it incorporates a comprehensive set of features, minimising errors even over longer lead times. The significant difference in RMSE between the actual forecast and the perfect forecast models emphasises the importance of accurate input data.

The graph in Figure 15 shows the absolute forecast error for the 7th lead day and rainfall data over a period spanning from January 1, 2023, to June 1, 2024. The forecast error fluctuates significantly over time, with periods of low error interspersed with spikes reaching up to approximately 2000 ML. The error tends to be higher during certain periods, indicating the model struggles more with accuracy during these times. In early January 2023, several heavy rainfall events coincide with high forecast errors, exceeding 1500 ML. Similar patterns are observed in mid-July 2023 and January 2021, where intense rainfall events are followed by large forecast errors. This suggests that the model has difficulty accurately predicting the demand when there is heavy rainfall, possibly because the actual water needs of crops are significantly influenced by these extreme events and the model may not account fully for these variations. During period of lower rainfall, the forecast error generally decreases, as seen in April 2023, November 2023 and May 2023. The model's performance is better under stable and less extreme weather conditions. The error seems to follow a seasonal pattern, with higher errors during wetter months and lower errors during drier months. This could reflect the model's performance across different season, where it struggles more in wet seasons due to the complexity introduced by rainfall. Figure 16 shows the correlation plot between actual demand and predicted demand for the 7th lead day.

Table 7. Results from the XGBoost Murrumbidgee model with perfect and actual forecast weather inputs.

Lead	Perfect temp and rain forecast	Perfect forecast for all feature inputs	Actual temp and rain forecasts		
	RMSE (ML)	RMSE (ML)	RMSE (ML)	NSE	MSSS
1	409.8	380.6	**417.6**	**0.902**	**0.0334**
2	472.3	431.3	**483.1**	**0.874**	**0.0570**
3	524.3	504.5	**559.0**	**0.840**	**0.0553**
4	559.4	502.5	**596.5**	**0.798**	**0.0596**
5	589.6	515.4	**649.5**	**0.776**	**0.098**
6	585.8	531.3	**682.2**	**0.757**	**0.0996**
7	677.6	637.4	**728.6**	**0.727**	**0.1419**

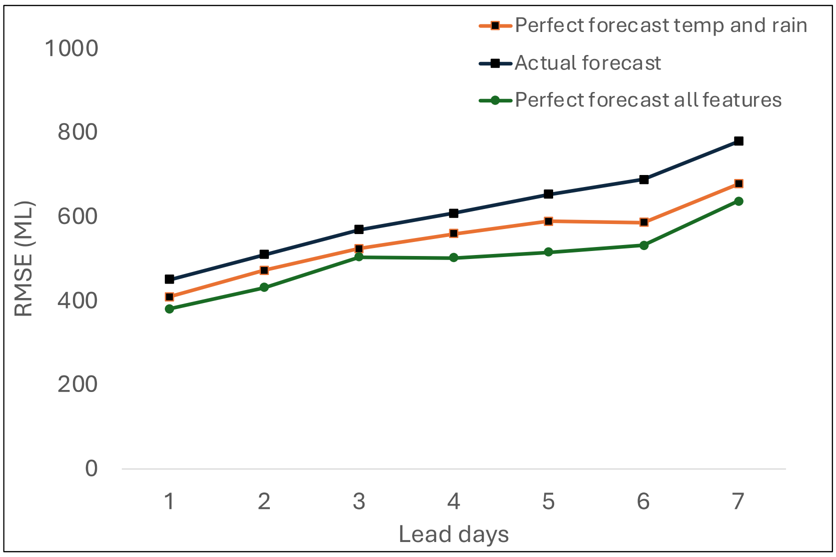

Figure 14. Comparison of RMSE attained for the lead days using two scenarios for the model development.

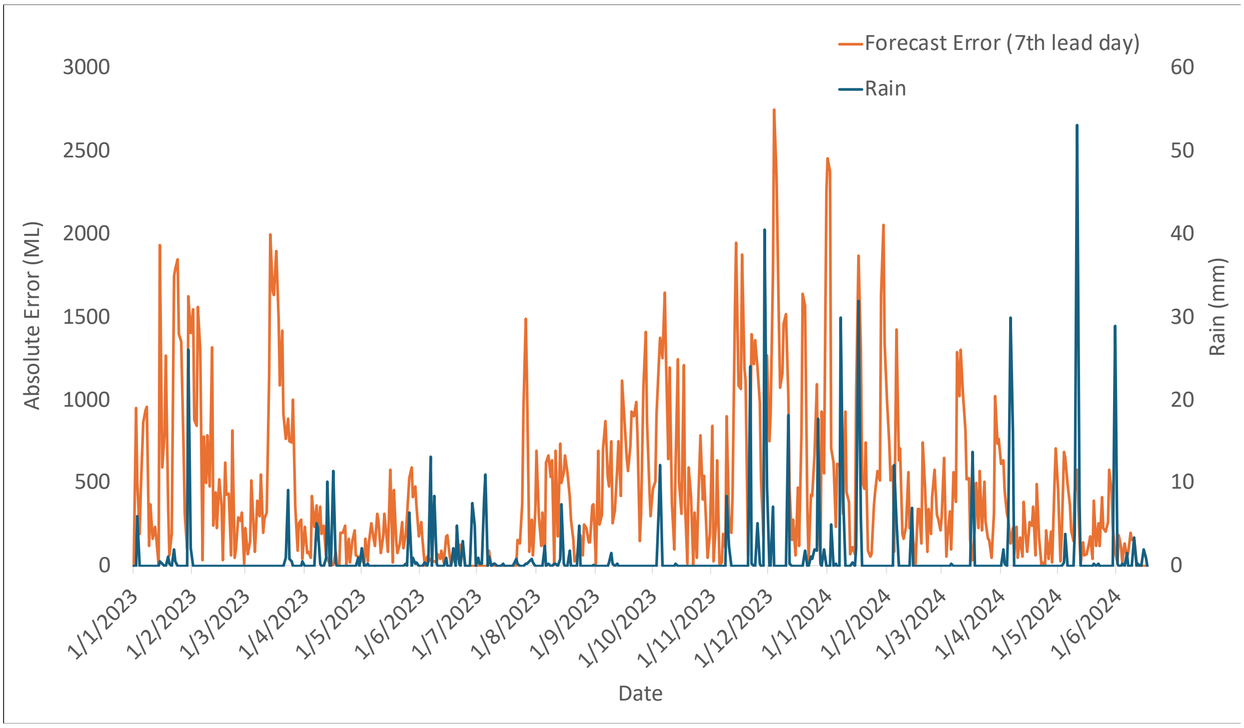

Figure 15. Line plot showing the absolute error for the 7th lead day and daily rain 2023-2024 (MI).

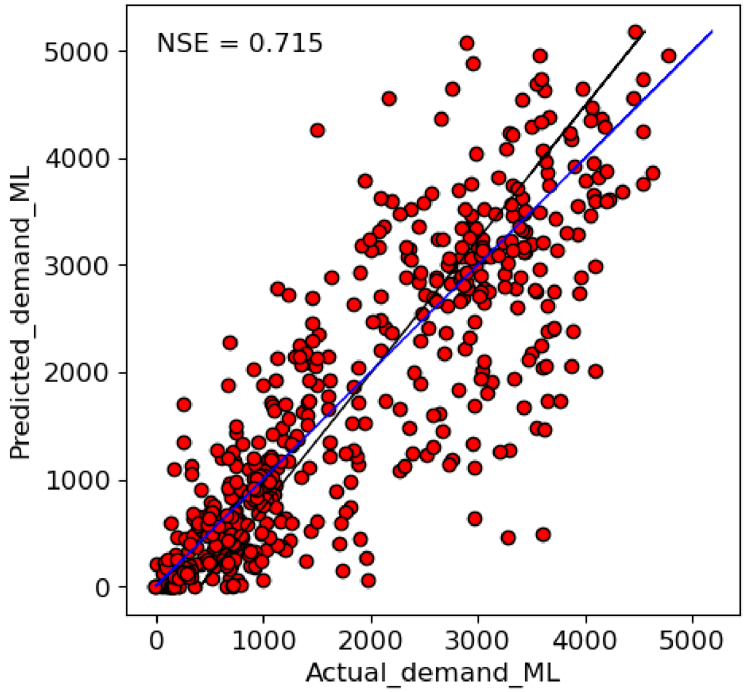

Figure 16. Scatter plot showing actual versus predicted demand on 7th lead day using actual forecast.

Figure 17 explains the important variables for generating the forecast values which include the demand values of previous days (actual_demand_m1, actual_demand_m2, actual_demand_m3, actual_demand_m6 and actual_demand_m7). Other influencing variables include radiation and rain of the previous day and the forecast maximum air temperature and precipitation.

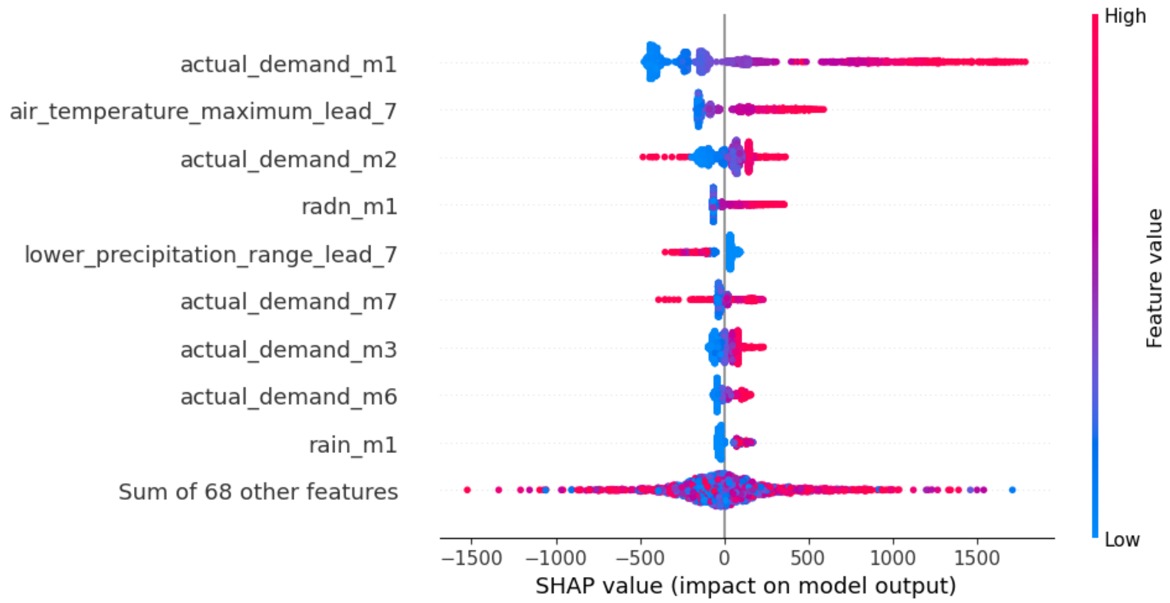

Figure 17. SHAP score from XGBoost model for 7th lead day using actual forecast information (p: lead days and m: lag days).

4.4.4 Application to the CICL area of operations

Figure 18 shows that the average ET_0 values exhibit a lower trend during winter months, specifically from April to August, and gradually increase from September to March each year. Figure 19 shows the residual plot showing the difference between actual irrigation water demand and crop irrigation requirements over time, spanning from 2019 to 2024. In the starting year 2019 to 2020, the residuals are relatively stable with a smaller fluctuation around zero. Later in 2021, there was a noticeable increase in the amplitude of the residuals, with peaks reaching up to around 2000 ML and troughs down to -1000 ML. The residuals continue to show high variability, similar to 2021 in 2022, though with slightly less extreme values. The peaks are lower than in 2021, generally staying below 1500 ML. There are several notable spikes, particularly negative ones, with residuals dropping to nearly 1500 ML from 2023 to 2024. This indicates periods where the actual demand was significantly lower than crop irrigation requirements. Over the five years, the residuals show increasing variability, particularly from 2021 onwards. These increased fluctuations could be attributed to several factors, including changes in weather patterns, irrigation practices, crop types, or forecasting errors. Figure 20 shows the correlation between net diversion and CIR which provided a R^2 of 0.54.

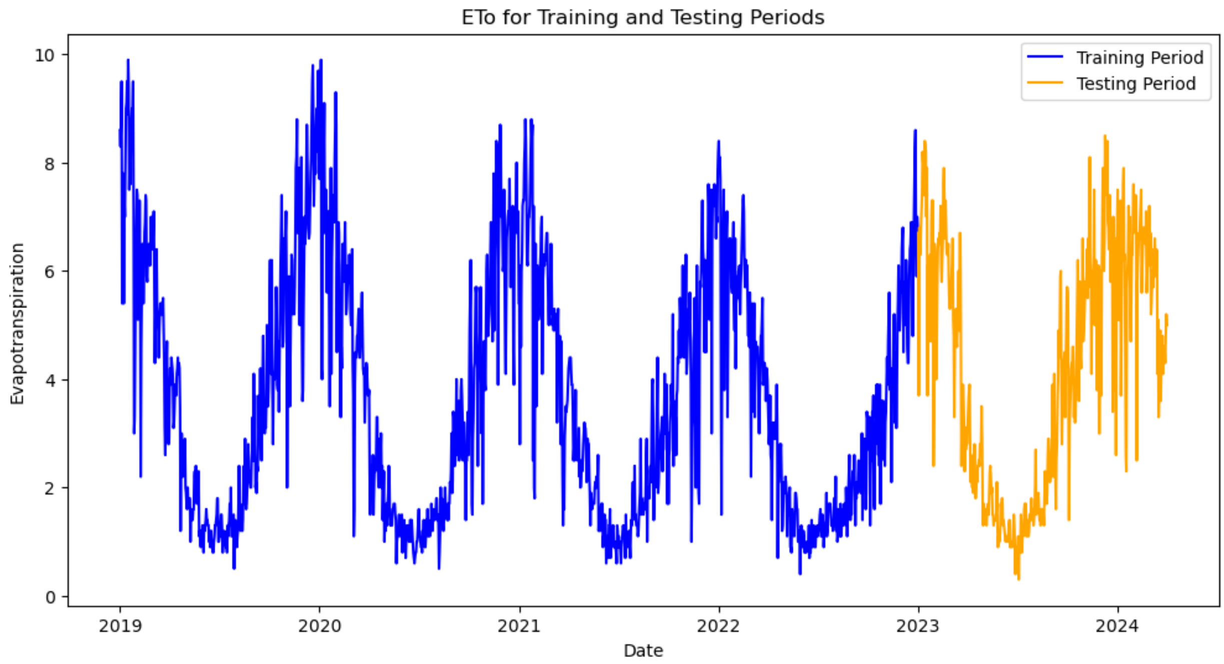

Figure 18. Annual trend of reference evapotranspiration in Coleambally Irrigation district.

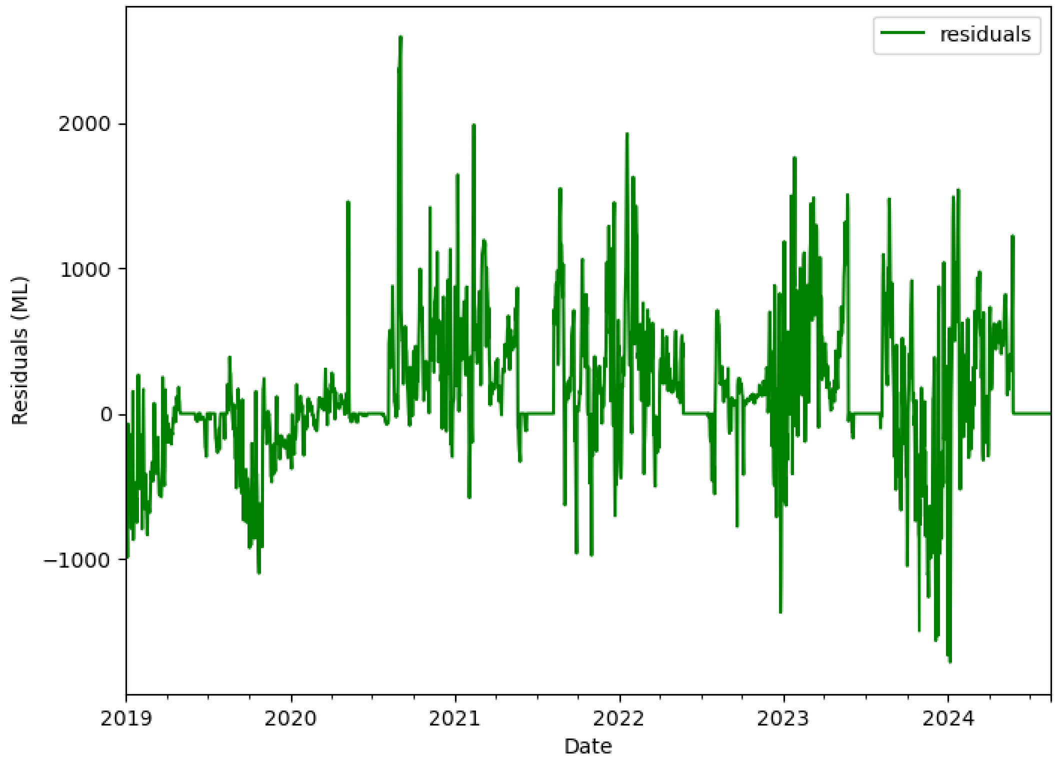

Figure 19. A residual plot showing the difference between the actual demand of CICL and crop irrigation requirements.

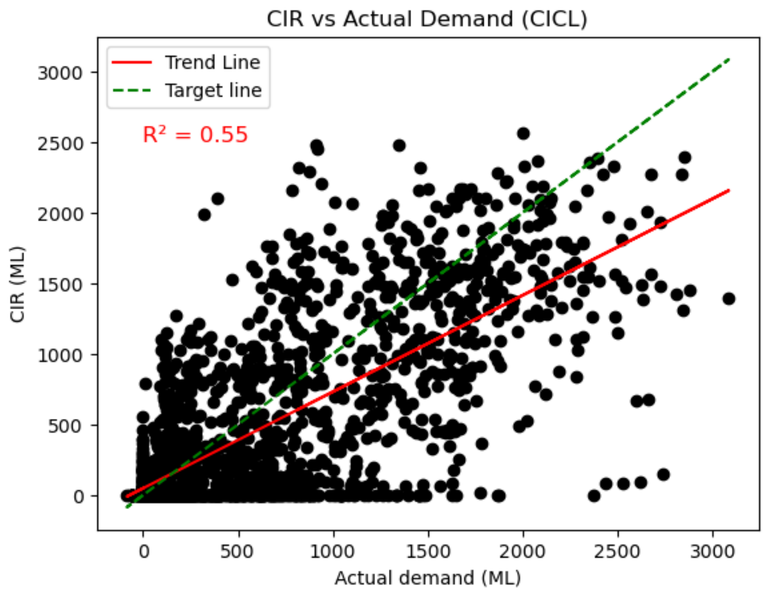

Figure 20. Scatter plot showing actual demand and crop irrigation requirements for CICL.

Extreme gradient boosting model:

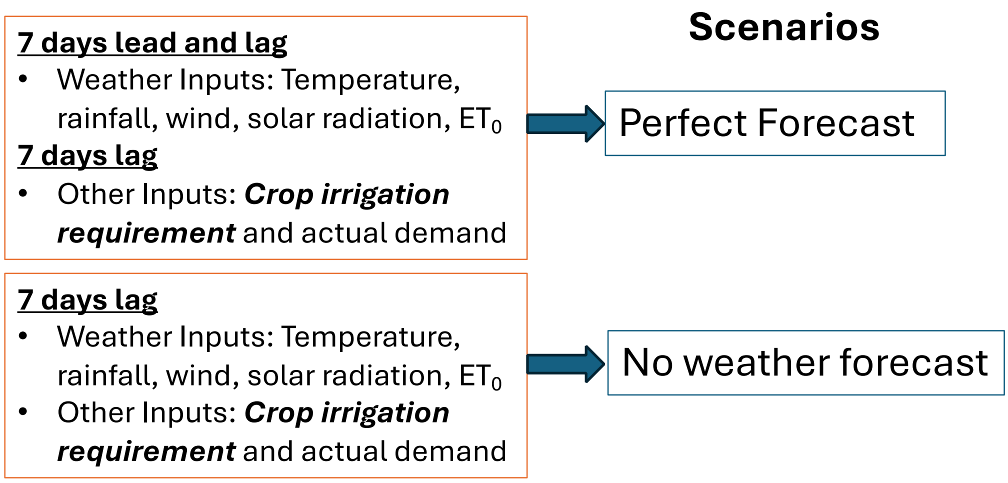

Figure 21. Inputs to the scenarios

Results in

Table 8 show the forecast RMSE values range between 310 and 445 ML using perfect forecast scenarios. In the ideal case for CICL, where no weather forecast information is used in the model, RMSE lies between 340 and 532 ML. Figure 22 shows the RMSE of irrigation demand forecasts over a 7-day lead time using two scenarios. The perfect forecast model consistently outperforms the no-weather forecast model across all lead days, indicating that accurate forecast information significantly improved the model's predictive accuracy. No weather forecast model is fully relied on historical data or static input, meaning it does not account for the dynamic changes in key variables that influences more sharply, reaching nearly 500 ML by day 7.

Figure 23 relationship between the forecast error (in ML) for a 7-day lead time and the observed rainfall (in mm) over the period from August 2023 to March 2024. The absolute errors fluctuate significantly over time, with peaks reaching as high as 1800 ML. The graph shows a series of high forecast errors, particularly in early to mid-August 2023. Rainfall during this time is sporadic but intense, leading to significant forecast errors. In the summer months, from October to mid-November, the error is lower with relatively less rainfall events. In December and January the spikes get high followed by rain around 20 mm. During the dry period in late January to March, the forecast errors are significantly lower, this might be because the model's inputs (such as past demand, temperature and evapotranspiration) remains stable, reducing the likelihood of large deviations between the forecasted and actual irrigation demand.

Figure 24 explains the important variables for generating the forecast values which include the demand values of previous days (actual_demand_m1, actual_demand_m2, actual_demand_m6 and actual_demand_m7). Other influencing variables include radiation and evapotranspiration. The model's reliance on the past 7 days demand values could create a lag in its response to changing conditions. This lag could explain why the forecast errors are particularly large during periods of significant deviation from normal conditions, such as during heavy rainfall.

Table 8. Results from the XGBoost Coleambally model with perfect and no forecast scenarios

Lead	Perfect weather forecast	No weather forecast		
	RMSE (ML)	RMSE (ML)	NSE	MSSS
1	313.1	**340.6**	**0.780**	**0.242**
2	359.8	**412.9**	**0.668**	**0.359**
3	396.7	**455.6**	**0.601**	**0.416**
4	424.8	**485.6**	**0.504**	**0.489**
5	434.3	**508.1**	**0.480**	**0.513**
6	453.0	**531.8**	**0.456**	**0.552**
7	442.1	**532.7**	**0.461**	**0.556**

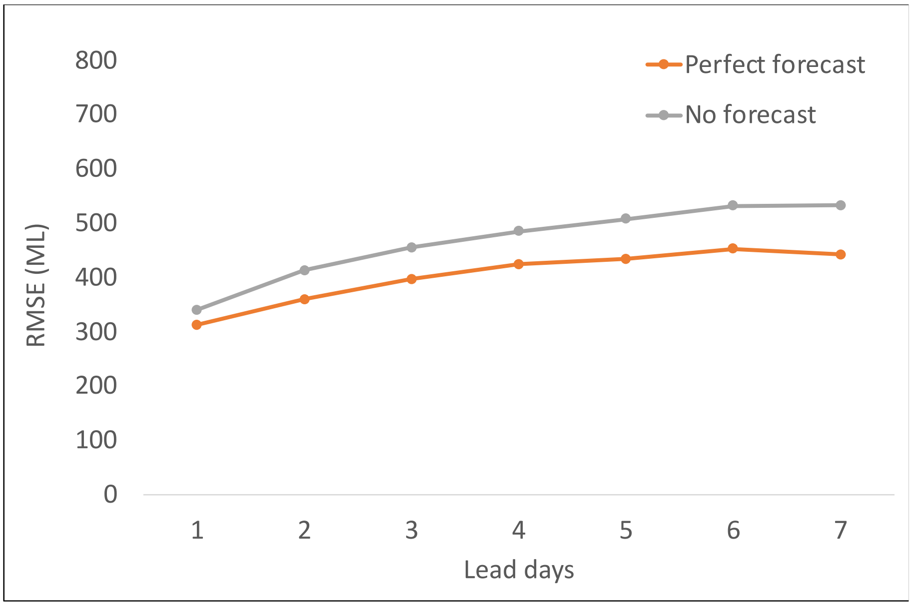

Figure 22. Comparison of RMSE attained for the lead days using two scenarios for the model development.

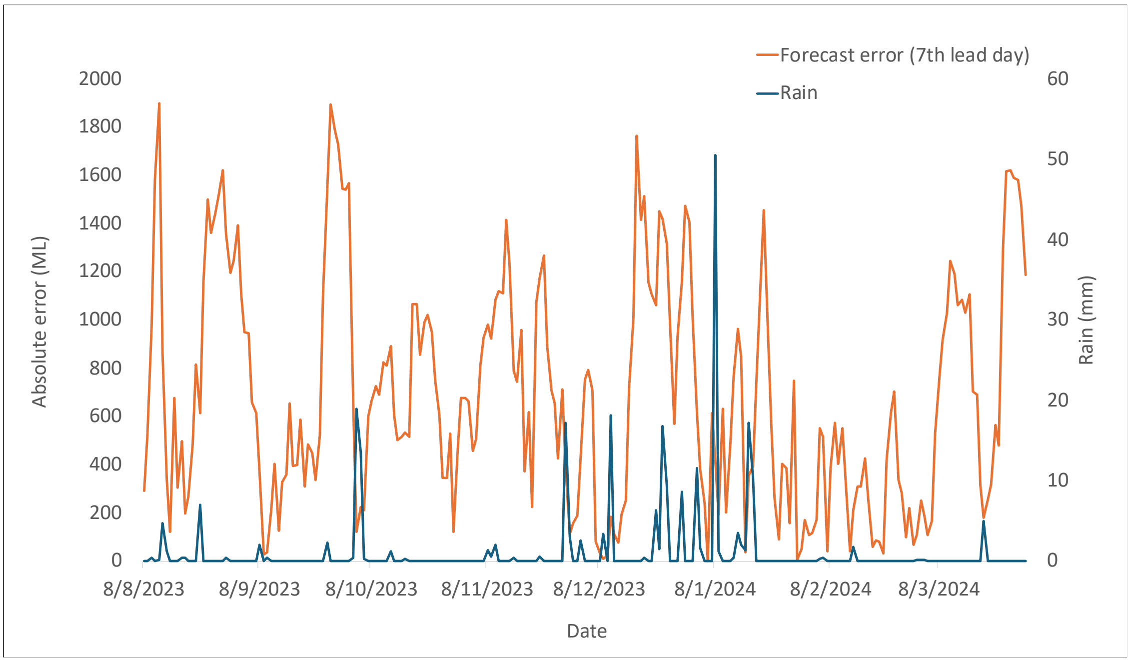

Figure 23. Line plot showing the absolute error for the 7th lead day and daily rain 2023-2034 (CICL).

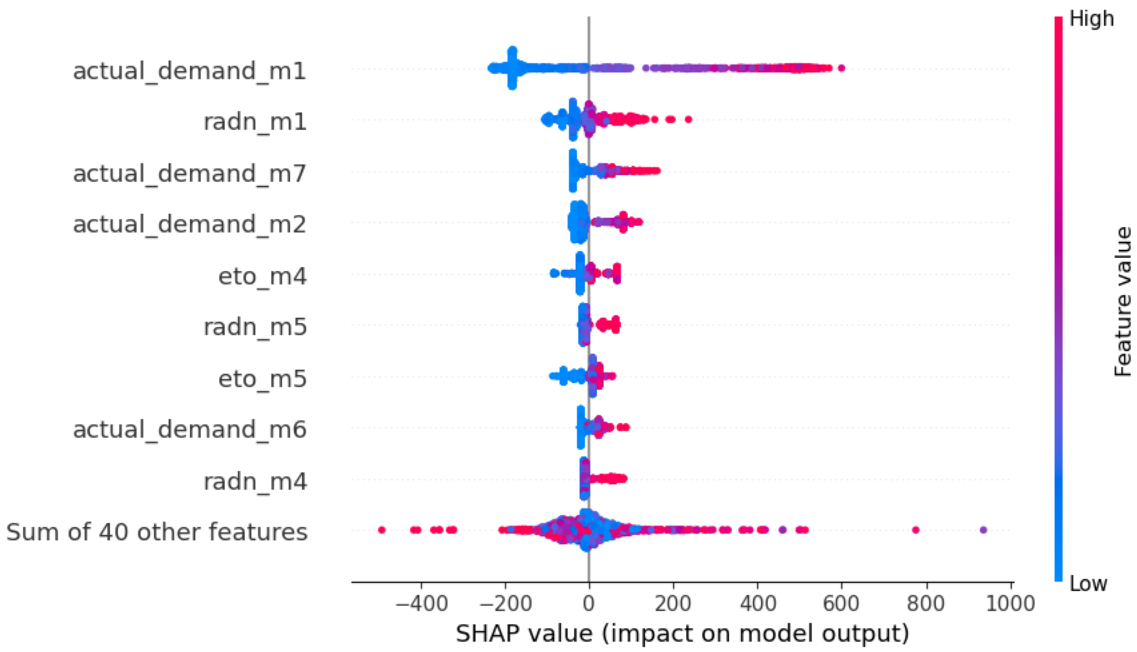

Figure 24. SHAP score from XGBoost model for 7th lead day using actual forecast information (p: lead days and m: lag days).

In both case studies, MI and CICL, the results suggest that the model's forecast errors increase significantly during periods of heavy rainfall. This indicates that extreme weather events, particularly rainfall, introduce significant uncertainty into the model's predictions of irrigation demand. The model may not fully capture the complex relationship between rainfall and crop water needs, leading to larger errors during these times. Conversely, during the dry periods, the forecast errors are generally lower, suggesting that the model performs better under more predictable, stable weather conditions. Understanding these patterns can help in managing irrigation practices better by recognizing when forecast errors are likely to be high. During periods of extreme events, more caution may be needed in relying on the forecast for irrigation decisions.

4.5 Case study: MI data-driven model

4.5.1 Methodology

The Operations team at MI is responsible for the river orders. Weather, storage volume, channel works are all factors that go into their decision-making process. Often excess water is ordered from the river so that the water can be diverted off the main canal to meet system operational needs (e.g. surge refills). Non-compliance is also a big issue (farmers taking water without ordering it). Using data for the main offtake, it is not realistic to forecast diversions and non-compliance. MI's demand forecast model will look to forecast for the residual, i.e. water demand less the diversions. It will then be up to the operators to adjust for the diversions and non-compliance.

Parameters used in MI's model (so far) are:

- Weather forecast (temperature & rain)
- Observed Weather (temperature & rain)
- Lagged actual daily demand (less daily diversions)

The Skforecast library is utilised to build and train the model. The model is built using the *ForecasterAutoregMultivariate* class, since it is suitable for dependent multi-series forecasting. In dependent multi-series forecasting (multivariate time series), all series are modelled together in a single model, considering that each time series depends not only on its past values but also on the past values of the other series. The forecaster is expected not only to learn the information of each series separately but also to relate them.

Since as many training matrices are created as there are series in the dataset, it must be decided on which level (in this case – demand) the forecasting will be performed. To predict the next n steps (in this case 7) a model is trained for each step to be predicted. In this case, the level is the water demand.

Backtesting is carried out using the *backtesting_forecaster_multiseries* class. In time series forecasting, the process of backtesting consists of evaluating the performance of a predictive model by applying it retrospectively to historical data. Therefore, it is a special type of cross-validation applied to the previous period(s). The purpose of backtesting is to evaluate the accuracy and effectiveness of a model and identify any potential issues or areas of improvement. By testing the model on historical data, one can assess how well it performs on data that it has not seen before. This is an important step in the modeling process, as it helps to ensure that the model is robust and reliable.

The backtesting strategy used is *Backtesting with refit and increasing training size (fixed origin)*. Instead of randomizing the data, this backtesting sequentially increases the size of the training set while maintaining the temporal order of the data. By doing this, the model can be tested on progressively larger amounts of historical data, providing a more accurate assessment of its predictive capabilities.

4.5.2 Results

The backtest error for the period shown in Figure 25 is 353.99 ML/d; this statistic is the mean absolute error, calculated as the average of the absolute difference between the predicted and actual demand values $\sum_{i=0}^{N} \frac{(\dot{y}_i - y_i)}{N}$. It is calculated only for the main canal (focus of this forecasting exercise so far). A gradient boosting algorithm, XGBoost, was used to carry out the predictive modelling task.

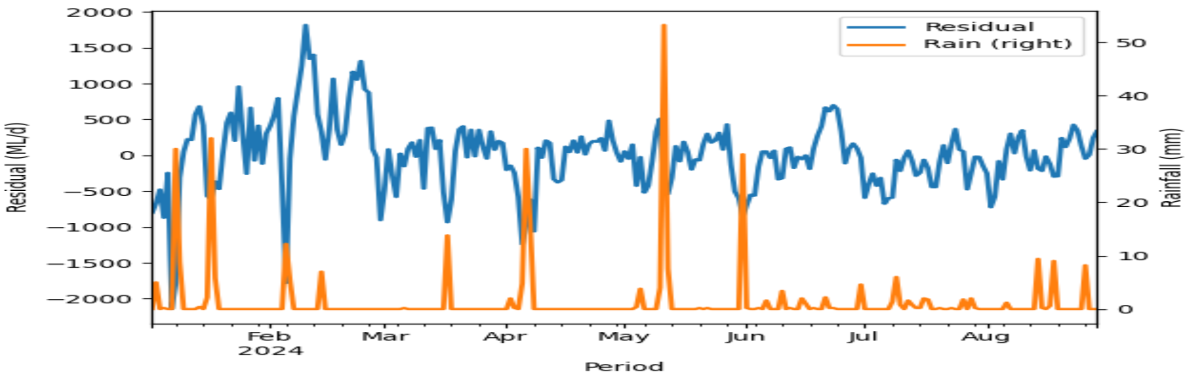

Figure 25. Plot of residual (Actual vs Predicted Demand)

The metrics used to assess model performance are shown in Table 9. This brings us to the results section. The negative bias suggests that the model is underestimating the demand.

The RMSE suggests that the typical difference between the model's predictions and the actual demand is 498.05 ML/d. Given that the demand ranges from 0 to 5000 ML/d, the average error rate sits at around 9.9%. Max_Error is the maximum difference between a forecasted demand and actual demand for a day (ML/d). As for NSE (0.81), a value close to 1 suggests that the model has good predictive skills.

Next the model performance was assessed against a *Naive Estimator*, i.e. we simply set all forecasts to be the value of the last observation, $\dot{y}_{t+h|t|} = y_t$. We then compared the performance of the naive model against the XGBoost model (Figure: Not Shown). The naive model seemed more lagged. The XGBoost model also outperformed in terms of Mean Absolute Error by 84.9 ML/d (MAE of the Naive model > MAE of XGBoost model).

4.6 Operationalisation

4.6.1 Operationalisation within a context of continual improvement

While the analysis above has focused on fundamental metrics, our ultimate intention is that end-users of forecast are provided with the information and tools needed to be able to form their own assessment of the performance of the forecast in terms meaningful to them, to be able to identify periods of time when the forecast may perform poorly, and report failures of the model to inform further model development. Operationalisation of the models presented in this report is therefore expected to include 1) production of demand forecasts using live data, 2) processes for regular performance review of the demand forecasts, and 3) communication of suitable performance information.

Table 9. Metrics used to assess the model performance

Metrics	Score	Description	Formula
RMSE (ML/d)	498.05	Root Mean Square Error (model)	$\sqrt{\frac{1}{N}\sum_{i=1}^{N}(\dot{y}_i - y_i^i)^2}$
MAE (ML/d)	353.99	Mean Absolute Error (model)	$\sum_{i=0}^{N}\frac{\lvert(\dot{y}_i - y_i)\rvert}{N}$
Max_Error (ML/d)	2147.25	Maximum Error value (model)	
Bias	-1.71	Bias (model)	$\frac{\sum_{i=0}^{N}(y_i - \dot{y}_i)}{N}$
Relative_Bias	0.00	Relative Bias (model)	$\frac{\sum_{i=0}^{N}(y_i - \dot{y}_i)}{N \cdot \overline{y}}$
NSE	0.81	Nash-Sutcliffe Efficiency	$1 - \frac{\sum_{i=0}^{N}(y_i - \dot{y}_i)^2}{\sum_{i=0}^{N}(y_i - \overline{y})^2}$

Production of demand forecasts using live data involves ingestion of live weather forecasts, SCADA information and any other necessary time-varying inputs. The output of forecasts needs to be stored and archived (for performance review) and delivered to the operations team placing river orders. In general, deployment and maintenance would be handled by a combination of external expert support and in-house IT staff. As with any new IT asset, minimising downtime would be expected to require some level of ongoing attention.

Regular performance review requires input from at least the operations team and staff with sufficient data science training to be able to interrogate problems raised and formulate descriptions of forecast defects in an actionable manner, producing unambiguous test cases and testable hypotheses for further model development.

In the context of the One Basin CRC, it is proposed that in addition to any in-house support, there is potential for long-term input from researchers to play this role. Where in-house support or consultants may be able to address obvious defects or well-defined issues, integration with research allows for broader experimentation with more difficult hypotheses and increased transferability of fundamental knowledge and learning across regions.

The review process provides a mechanism for the team to document issues that the currently operational algorithms are facing, as well as to run new algorithms in parallel and evaluate how they would have performed if they were operational. It is anticipated that three demand forecasts would be reviewed: the current operational model, a “staging” model in contention to be adopted as the new standard, and an experimental/”unstable” model used to test new ideas.

The speed with which new models would be adopted depends on resourcing and the maturity of processes in the organisation. Initially, it is expected that a high number of failures may be observed given the relative simplicity of the model and initial assessment framework. Staging models that fix the observed defects would be quickly adopted. Over time, diminishing returns are expected, and more extensive research and development may be required to address defects. However, as the assessment framework will also have matured, it should become easier to demonstrate the superiority of a new model, and therefore shorten time to adoption.

It is expected that ongoing evaluation of the operational model will gradually accumulate examples of failures of a forecast. Diagnostic metrics will support root cause analysis of the failure. Within a quality assurance framework, the archived forecast will be flagged, and time periods will be logged as test cases that demonstrate a system behaviour that is meaningful to operators and that future forecasting models need to be able to adequately simulate. These test cases will generally be associated with specific hypotheses about patterns of system behaviour. For example, a collection of missed rain events could be produced on which it is hypothesised that either weather forecast improvement is needed (which would reduce the number of missed rain events) or better modelling of irrigator behaviour is required. In some cases, the time periods may instead be flagged as outside the scope of demand forecasting, e.g., it may not be necessary for the model to perform well in times of flood.

A "staging" model may be adopted if the test cases effectively communicate that it is superior over the operational model according to suitable performance information. Not all test cases may be of equal interest – performance is judged through risk or control informed metrics. The regular performance review would document the risk management mechanisms that were used with the existing operational model. For example, if the operator believes the model to have a systematic bias in certain conditions, they may have added a larger than usual margin of safety. They may have refilled storages as insurance or drawn down storages to compensate for unexpected changes elsewhere in the system. Performance is therefore judged taking into account these management mechanisms and the cost, effort or desirability of their use.

To summarise, the assessment framework is intended to fit within a regular performance review process that addresses the questions:

- Issues faced in forecasting and ordering in the last period
- Evaluation of operational, staging and experimental forecasts
- How well did they do?
  - What risk management mechanisms were used?
  - What were the underlying causes of good or poor performance? How do we know?
- Discussion of future changes
  - Logging of forecast defects
  - Identification of test cases and hypotheses for model improvement
  - Identification of possible changes to performance metrics

4.6.2 Risk management considered within assessment framework

Strategic business risks to be tackled by the assessment framework include:

- Ability to meet demand needs of customers across the short term
- Ability to adjust to customer ordering preferences due to flexible levels of service, adverse weather conditions etc.
- Ability to adjust to supply side factors such as river resource availability, transmission losses and diversions, losses and storage levels in the short term
- Ability to adjust to organisational interventions to mitigate demand and supply side risks

These business risks bear similarity with other problems in which balancing supply and demand are important, e.g., in the electricity industry.

Meeting customer demand is a core business obligation. The forecast gap between demand and supply needs to be able to be managed through organisational risk management, in particular use of storages. Due to time delays in water delivery, any errors in 24-hour forecasts already need to be able to be managed through surge reservoirs and drawing down channel water levels or airspace. Errors in longer forecasts (7-day in particular) are additionally managed by adjusting orders over time as well as by river operations anticipating changing conditions. As water can be moved through the landscape, there is potential for complementary forecasting of, for example, flows between surge reservoirs, which was outside the scope of this case study.

It is additionally desirable to be able to meet actual customer consumption even if it changes at short notice. Water users face uncertainties, particularly related to weather conditions, and irrigation infrastructure operators already share this risk by providing flexibility to change orders. Demand forecasts are expected to become more precise as lead-time decreases (their uncertainty decreases), but longer term forecasts are still expected to already be accurate, i.e., they already include consideration of potential for customer consumption to change. This depends on performance of weather forecasts in particular, but is also likely to require forecasting of differences in customer behaviours in future.

Errors in demand forecasts may be either compensated or aggravated by errors in supply forecasts. Errors in demand have more impact when supply is constrained. Conversely, for other conditions, investment in complementary forecasts may be more valuable than investments in improving demand forecasts. Forecasting network losses and river resource availability can reduce error in forecast supply-demand gap. Forecasting storage and diversion volumes provides more precise information on the gap that can be tolerated across zones in the network. This may be affected by asset failures that affect both delivery reliability and quality of data inputs to forecasts. Both demand and complementary forecasts should consider this risk. Volume discrepancies and higher than expected flows may also cause water level stability disturbances within gravity irrigation systems – forecasts of demands should be sufficiently accurate to minimise their occurrence.

Demand and supply risks are mitigated by management of water storages and water levels across the irrigation network, with consideration of demand across zones, storage and flow capacities and their degradation over time, and location and severity of the resulting constraints. Performance is also affected by how upstream and downstream actors (e.g. river operators and water users) manage their risk. Ultimately, demand forecasting performance is therefore one component of broader delivery reliability performance. It also worth noting that this, and other metrics are likely to be commercially sensitive and may also affect negotiations between actors within the system. Who each metric is computed by and shared with therefore depends on the use case and the organisations involved.

5 Use cases to support whole-of-cycle water management

Short-term demand forecasting to support irrigation district water ordering constitutes one possible use case for demand forecasting algorithms. The remit of this component of the project was to identify and scope a broader suite of potential use cases for demand forecasting than that which was explicitly developed and tested in Section 4 with project industry partners. Five tentative use cases have been developed which are in intended as boundary objects to facilitate discussions between One Basin CRC partners as well as other key stakeholders around future opportunities for demand forecasting technologies to support multi-stakeholder water delivery and storage management to achieve multiple benefits.

5.1 Methodology

The process of identifying and developing use cases draws on a Design Science Research (DSR) methodology, aiming at developing and testing innovative “artifacts” such as processes or models. The primary objective is to enhance existing practices, advance research knowledge, address real-world problems, and facilitate transformative societal changes (Vom Brocke et al., 2020). Typically, three iterative and interacting steps are defined: problem identification, solution design and evaluation (Offermann et al., 2009); a conceptualisation of each phase for this project is shown in Figure 26.

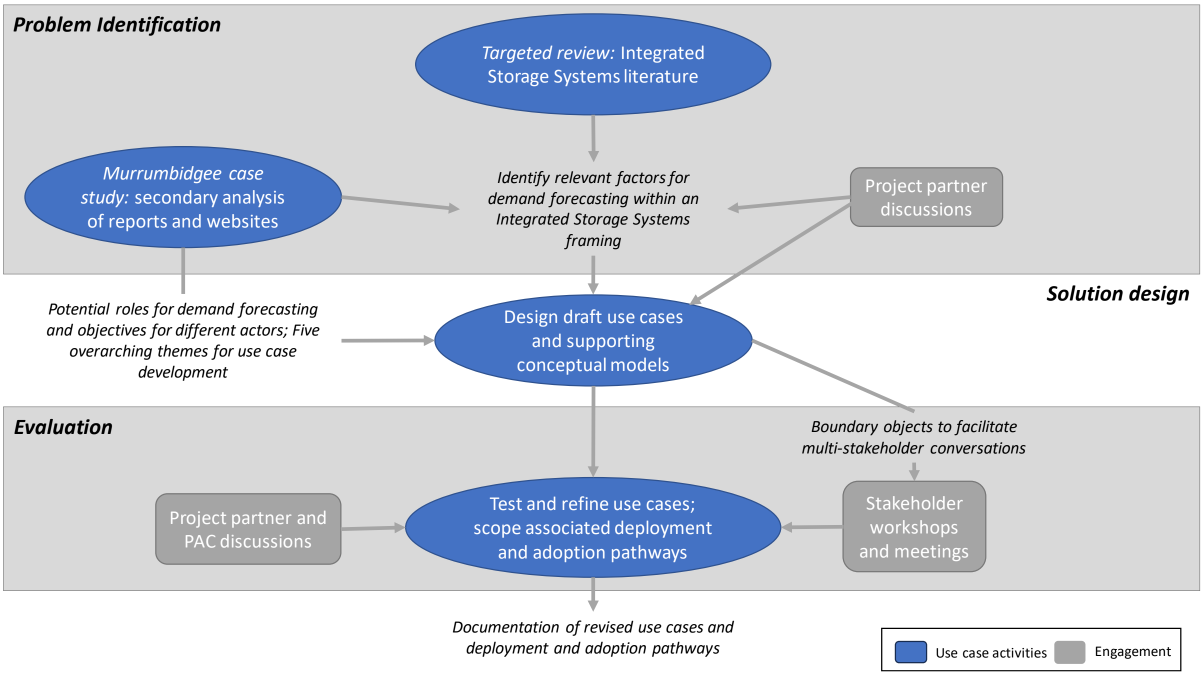

Figure 26. Conceptual process for developing and evaluating use cases and their associated deployment and adoption pathways (adapted from Offermann et al., 2009)

5.1.1 Problem identification

The *problem identification* phase initially involved a targeted literature review on the concept of 'Integrated Storage System' (see Section 1.2). The intent was to contextualise demand forecasting approaches as a tool to support whole-of-water-cycle management and to identify relevant factors for framing use cases for demand forecasting models. A case study analysis of the Murrumbidgee River Catchment was then conducted to identify potential roles for demand forecasting across temporal, spatial and governance scales. This was achieved through analysis of secondary data sources such as NSW and federal government reports, irrigation district compliance reports and relevant published and grey literature, and discussions with project partners. Through this analysis, key actors, their roles and responsibilities, and their main challenges were identified, alongside potential ways in which demand forecasting might enhance their planning and decision-making processes. Five overarching themes emerged as the basis for use case development: river operations, conjunctive uses of surface and groundwater, coordination of river and irrigation districts' operations, water markets, and supplementary water announcements.

5.1.2 Solution design

The *solution design* phase entailed the iterative development of use cases guided by the five overarching themes. Conceptual models have been developed to depict various actors' roles and their interactions, key constraints and potential ways in which demand forecasting approaches could support the operational, investment and strategic planning decisions of these actors. A targeted literature review was conducted to explore the types of demand forecasting models and approaches that have been applied in similar decision contexts. Each preliminary use case has been summarised in a tabular template that outlines the actors involved, the goal of demand forecasting and the context in which the use case occurs, the necessary requirements for demand forecasting to be useful, and alternative strategies that might also achieve the goals.

5.1.3 Evaluation

The *evaluation* phase comprises the iterative evaluation and refinement of the use cases guided by feedback from partners and stakeholders. Internal testing with the project research team and industry partners has been conducted and further engagement has commenced with project partner organisations and key stakeholders (non-partners) involved in water delivery and management of the Murrumbidgee River catchment. Within this project, the use cases have not been comprehensively tested with stakeholders external to the project. There may be some redundancies or overlap in the opportunities identified across the use cases and that some might not be considered desirable or feasible. Opportunities to further test these use cases will be sought through engagement with the 'Reducing uncertainties and enabling multiple benefits in water delivery operations (CRC058)' project.

5.2 Potential use cases

Figure 2 positioned the five use cases across the hierarchical levels (operational, tactical and strategic) and four spatial scales (farm, irrigation district, catchment and region) where decisions and activities of key actors are currently focused. All are positioned across the operational and tactical levels, with the use cases related to water trading and conjunctive use of water sources also extending to the strategic level. This emphasis on operational and tactical levels aligns with this project's aim of enhancing irrigation district companies' ability to coordinate water orders with river operators and EWH as well as to ensure reliable water supply to their customers. Their operational decisions typically focus on short (hourly)- to medium-term (seasonal) time horizons but do extend to longer-term strategic planning.

Opportunities for demand forecasting were identified that could address critical challenges identified during the literature review and analysis of secondary data. These opportunities – which are summarised in Figure 27 to Figure 31. and subsections 5.2.1 to 5.2.5 for each use case – can extend across the hierarchical planning scales and spatial levels. This reflects the types of demand forecasting approaches identified from the literature and the time horizons at which they have been applied to similar decision contexts; the spatial scales represent the breadth of actors (from farmers to government agencies) who might be interested in the challenges and demand forecasting opportunities.

5.2.1 River operations in the Murrumbidgee River catchment

Achieving benefits from water delivery involves a broad range of decision makers and stakeholders. There is potential for even incremental changes to mechanisms for coordination and collaboration to transform management of the water system and river operations to improve the range of benefits to communities, environment and industry from water deliveries. Demand forecasting can help improve multi-stakeholder understanding of future water demand variability across the river system and associated uncertainties across time and space. In addition to better forecasts, this could involve models of changes in behaviour over time, and more systematic coordination of water deliveries for different stakeholders. This opportunity will be further explored in the 'Multiple Benefits' project, which will examine how water system operators make decisions and why, including their decision criteria, the rights and responsibilities for water delivery and water accounting, and the information or tools operators use to support decisions.

Water users within the Murrumbidgee River Basin rely heavily on water releases from the Burrinjuck and Blowering dams, particularly in the dry season when there is about 60% reliance on the Burrinjuck dam for water deliveries to MI and CICL offtakes (DPE, 2021). NSW DCCEEW determines water allocations for entitlement holders by considering factors related to water in storages, future inflow estimations, consideration of evaporation, transmission and operation losses, minimal flows for the end of system and environment, and carryover (DPE, 2021). The responsibilities of WaterNSW include managing water in storages (natural and artificial) and water deliveries to licensees which include the IIO and their customers, private irrigators and EWH.

The timing of orders and deliveries varies by allocation (and other announcements), different types of licensees, their location along the river system and their water needs over time. Orders made by irrigators vary based on crop types, planting area and planting time, especially for water-intensive crops, and other factors that influence when they choose to water (e.g. off-farm employment; off-peak energy periods). Crop types and planting areas may also fluctuate based on crop and fuel prices as well as rainfall event opportunities (CICL, 2023, MI, 2016).

WaterNSW and the IIO deliver water to the environment on behalf of the EWH and environmental managers to support watering actions. Key wetlands include the Mid-Murrumbidgee Wetlands between Gundagai and Hay, the Lowbidgee wetlands, wetlands in the MI area of operations including

Fivebough, Tuckerbil and the Barren Box Swamps, the Lower Mirrool Creek floodplain, the Yanco and Billabong Creek systems and wetlands within the CICL area of operations which include wetlands on private or CICL managed reserves that support breeding subpopulations of the southern bell frog (*Litoria raniformis*). Ecological objectives across these wetlands include maintaining or restoring ecological function, the extent and condition of water-dependent vegetation communities and supporting the diversity and abundance of wetland fauna populations (SKM, 2011). Watering actions aimed at achieving these objectives vary depending on the prevailing climate scenario and conditions in previous years.

Three opportunities have been identified for the use of demand forecasting approaches to support river operations (Figure 27 and Appendix A).

1. ***Estimate future demands and uncertainty:*** Aggregate water demands within irrigation districts are inherently uncertain reflecting the spectrum of individual customer decisions taken from day-to-day and over and between seasons. These decisions can be influenced by numerous agronomic, climate, environmental, water availability, commodity and market, and irrigator enterprise factors. Long-term sectoral demand forecast accounting, such as the unit water demand analysis method (Rinaudo, 2015) could be applied at the irrigation district scale.
2. ***Update forecast models to account for changes in water demands:*** A critical challenge for IIO is to accurately anticipate the (sub-)daily decisions of their customers. Timeseries data are used to forecast demand in practice, although they may fall short of effectively anticipating real-time decisions if not applied at the right spatial scale. Additionally, they have limited capacity to capture the impacts of unforeseen events like high rainfall events on customers' decisions. Enhancing the reliability of timeseries data for long-term horizons (above two years) and better capturing factors influencing changes in water demands could be realised using adaptive forecasting algorithms. These algorithms can estimate adaptive parameters and if the alternative set of parameters performs better than the current one, the algorithm automatically updates the current parameters and reports a model switch (Chen and Boccelli, 2014).
3. ***Coordinate water deliveries for irrigation and the environment:*** WaterNSW and the irrigation districts are responsible for delivering water to the environment on behalf of the EWH and environmental managers. Flow regime requirements and associated watering actions are informed by seasonal climate scenarios (extreme dry, dry, moderate and wet). Physical and operational constraints as well as infrastructure works may affect actual water deliveries actions and possible alternative watering options or carryover (SKM, 2011). Short-term (e.g., daily) and long-term (e.g., seasonal) ensemble flow forecasting (Ahmad and Hossain, 2020) for the prevailing climate scenario could support the irrigation companies, WaterNSW, regulatory bodies and environmental agencies in their efforts to coordinate irrigation and environmental watering actions. Approaches could be developed in the context of river operations through multi-level partnerships with IIO's, river operators and EWH, that can build on and complement existing technologies, notably the CARM (Computer Aided River Management) system developed by DHI consulting for WaterNSW[12].

[12] CARM integrates models reproducing key catchment and river processes with real-time measurements. The system is intended to provide users with an overview of current and forecasted water inflows to inform operational decisions and ensure reliable and timely deliveries to particular locations. This is achieved in part by providing automated processes to import future water demands as well as 13
[13] forecast and data series archiving (https://water.dpie.nsw.gov.au/__data/assets/pdf_file/0005/491576/Computer-Aided-River-Management-System-for-the-Murrumbidgee-River.pdf).

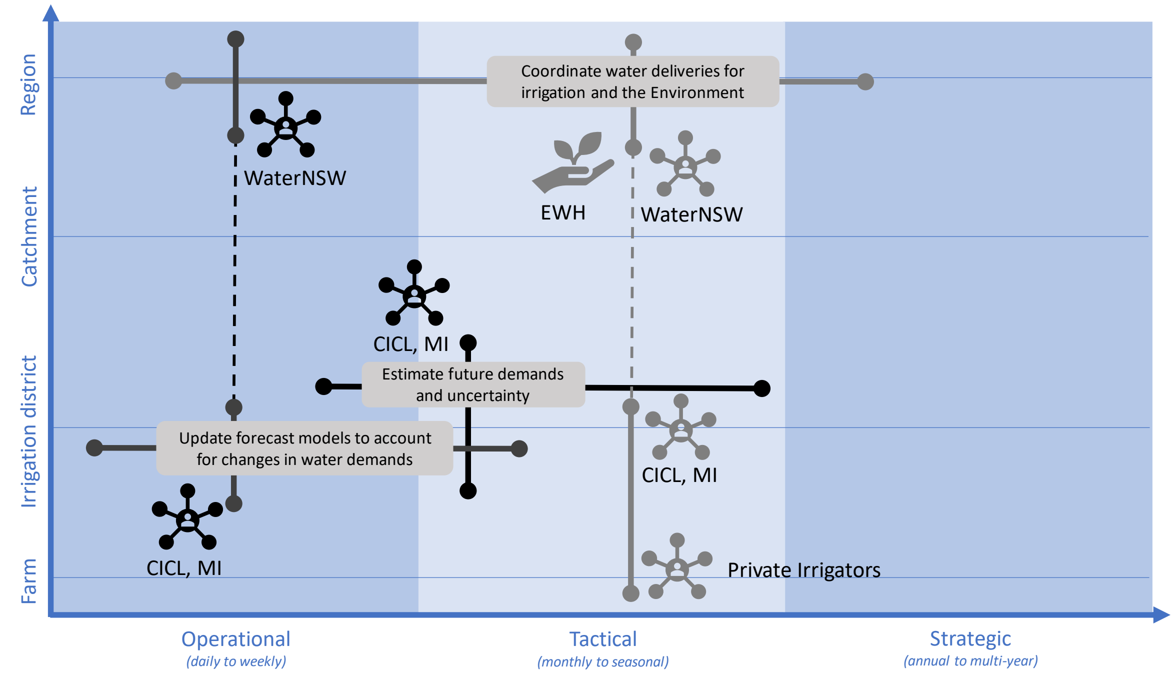

Figure 27. Mapping of possible demand forecasting opportunities across hierarchical levels and spatial scales for the 'Enhancing river operations in the Murrumbidgee River Region' use case. Icons represent types of decisions or purposes: operations or water orders ( ) and environmental water ( ).

5.2.2 Influence of conjunctive use of surface water and groundwater on water orderings from irrigation districts

Groundwater and surface water are both used in the Murrumbidgee, and there is potential to better understand how they are used and to better coordinate between users and across scales to maximise benefits, particularly for dry years. The Lower Murrumbidgee Alluvium – comprised of the Lower Murrumbidgee Shallow Groundwater Source (Shepparton formation) and deposits in the Calivil Formation and Renmark Group that comprise the Lower Murrumbidgee Deep Groundwater Source – underlies the MI and CICL districts and nearby areas. The latter is the more productive aquifer in which the majority of bores registered for production purposes extract from (DPE, 2022). Changes in water tables and salinity in these aquifers are influenced by factors such as rainfall patterns, irrigation system, pumping intensity and land management. The area between Hay, Coleambally and Griffith was identified in 2007 as an area of concern due to groundwater extractions and their due to cumulative impacts on the aquifer and other groundwater users, leading to the establishment of two local trade management areas (DPE, 2022).

Diversification of water supply (e.g., groundwater, recycled water) and demand (e.g., on-farm storages, smart technologies, water trading) options complicates the anticipation of IIO customer demand for regulated surface water. Access to diverse water supply alternatives can significantly enhance the reliability of irrigation water for farmers. These alternatives, including groundwater, recycling systems, on-farm water storages, reticulated water, unregulated water and soil moisture, play a pivotal role in farmers' decisions to invest (or not) in water allocation licenses. Factors such as storage levels, seasonality, potential for rainfalls, climate variability, fuel costs, and water availability and prices impact farmers' decisions to order regulated surface water (CICL, 2023, MI, 2016).

Three opportunities for demand forecasting are identified (Figure 28 and Appendix B) to support a shared understanding of interactions between groundwater extractions and regulated surface water orders from irrigation districts:

1. Evaluate the influence of changes in energy costs and technological access on groundwater extraction
2. Estimate crop application rates (i.e., the amount of water from available supplies to water crops according to their development stage) based on integrating surface water, groundwater and soil moisture data and

Evaluate the implications of relative availability and quality of groundwater and surface water under prolonged dry conditions.

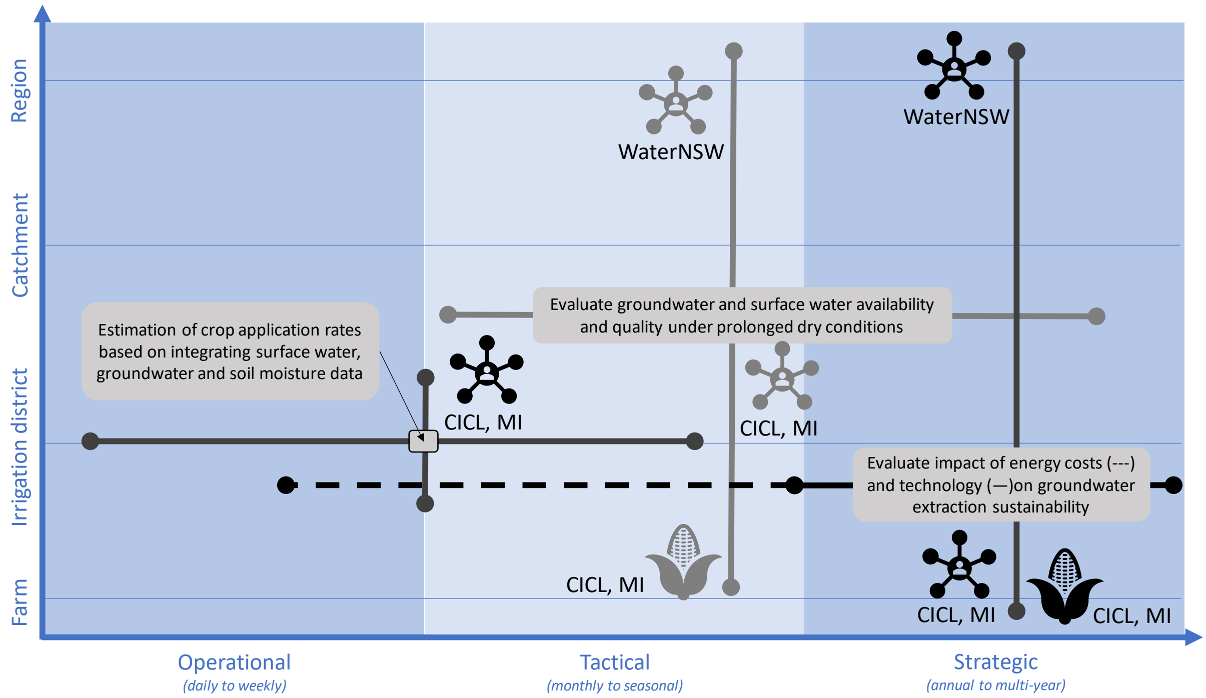

Figure 28. Mapping of possible demand forecasting opportunities across hierarchical levels and spatial scales for the 'Influence of conjunctive use of surface water and groundwater on water orders' use case. Icons represent types of decisions or purposes: operations or water orders ( ) and crop choices or agronomic decisions ( ).

5.2.3 Irrigation district operations and coordination with other actors

Within the MI and CICL irrigation districts coordination is needed between the IIO and other actors (irrigator members, WaterNSW, EWH and NSW DCCEEW) to deliver water for multiple uses, over space and time and under different climate conditions. This use case can be considered a subset of "River operations in the Murrumbidgee catchment" (Section 5.2.1) focused on management of risk by irrigation districts.

In the Lower Murrumbidgee River Catchment, aligning water orders is crucial for effective river and irrigation district operations as well as farmers and environmental water managers' watering actions, among other water users. The timing for orders poses a major source of uncertainty for water operators and could potentially lead to water restrictions if available flow rates fall below daily orders (CICL, 2022a). Farmers within districts can adjust their orders within a two-hour window (CICL, 2023, MI, 2016). Climate conditions and opportunities for in-crop rainfalls significantly influence irrigator orders.

Different storages and wetlands within CICL and MI aim to buffer potential changes in water orders during the peak season, reducing the risk of misalignments with WaterNSW (CICL, 2023, MI, 2016, MI, 2021). Orders from private irrigators after Darlington Point are directed to WaterNSW, with conveyance times varying based on location and channel capacity. The Tombullen Storage in CICL serves as a buffer to manage water orders during the peak season, with WaterNSW placing orders for filling or releasing water with a two-hour window. This timing impacts flow rate availability in CICL drainage system and water delivery reliability to different water users, including the Environment (CICL, 2023). Additionally, this storage enhances peak height and duration during piggyback events (Allen, 2019).

Environment water requirements also influence water order alignment, with monthly flow regimes varying according to four climate scenarios for various assets within and outside of Irrigation District areas, including the Murray River system (SKM, 2011). Agreement between the Environmental Water Holders (EWH), NSW DCCEEW and MI facilitate the delivery of water to wetlands, typically before or after the peak season (SKM, 2011). As for CICL, recent agreements with NSW DCCEEW (formerly DPIE) allow private landowners in the western part of the district to voluntarily water wetlands within CICL (CICL, 2022b).

Four opportunities for demand forecasting are identified to explicitly consider the integrated operation of storages within the district (Figure 29 and Appendix C).

1. Anticipate water restriction events under different climate scenarios. This role includes the consideration of prolonged dry conditions and high flow events that could hinder monitoring of surface water availability.
2. Anticipate climate and maintenance impacts on the alignment of water orders and flow regime requirements.
3. Estimate off-stream storages' lag time to refill/ emptying events. This role aims to inform operation decisions, including investments in supply and demand management options.
4. Estimate the risk from contract agreements or incentives. This role aims to consider the influence of farmers' locks-in contracts or incentives on farmers' behaviour and planting of water intensive crops, especially under inadequate climate conditions.

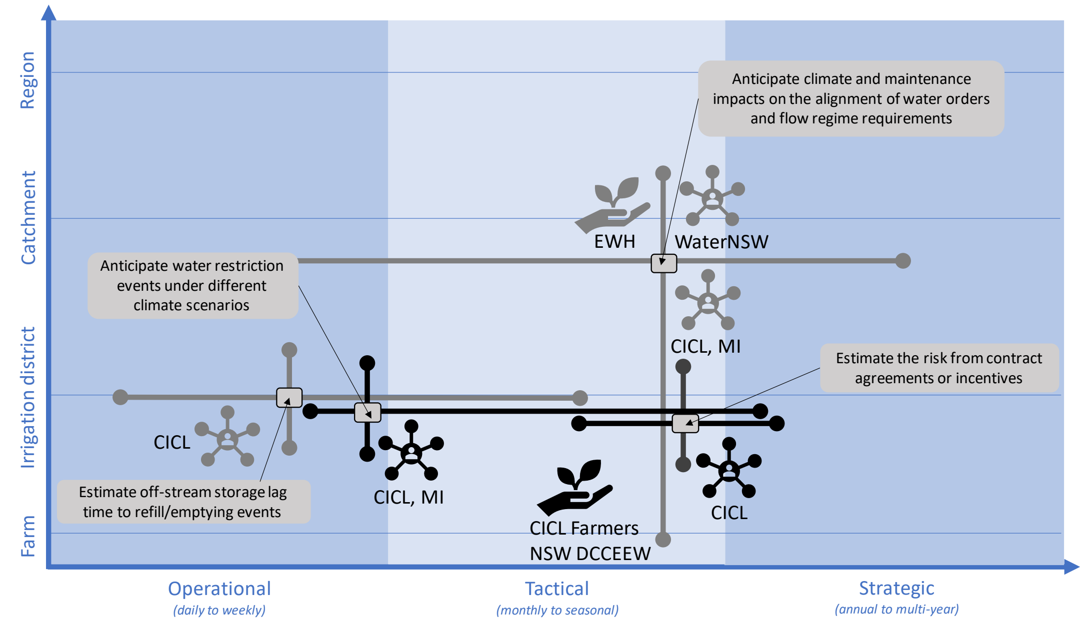

Figure 29. Mapping of possible demand forecasting opportunities across hierarchical levels and spatial scales for the 'Irrigation district operations and coordination with other actors' use case. Icons represent types of decisions or purposes: operations or water orders ( ) and environmental water ( ).

5.2.4 Water trading in the lower Murrumbidgee River Catchment

Water trading affects where and when water is used and conversely, forecast water demand can influence water trading behaviours. NSW Government or delegated entities are responsible for effectively operating, approving and processing water trades based on relevant rules and regulations. Key drivers of water entitlement market outcomes include the value and price of water entitlements, which rely on the level of security as well as by longer-term production decisions and characteristics of different users, including their risk tolerance. Water allocation market outcomes are primarily influenced by water allocated to water access license (WAL) holders each year and opportunities for in-crop rainfalls (Aither, 2017).

The Murrumbidgee River Catchment represents the largest market in NSW by volume of entitlements issued, totalising 3,934,823 ML of water. Most of the water is allocated to general security (GS, 52%) compared to 10% for high security (HS), with 23% of general security held for the environment. General security entitlements are generally less secured but offer more flexible trading, with up to 30% eligible for carry-over each year.

Other main entitlements include Aquifer and Supplementary entitlements. These entitlements are typically the most secure with limited flexibility for carry-over (up to 2 ML per unit share) or trading (restricted). Supplementary entitlements, representing 26% of the total entitlement issued, are mainly held for the environment and can only be accessed on announcements during high flow events, with no carry-over and restricted trading.

Intervalley trading is feasible with a number of connected systems (Murray and Lower Darling as well as to Victoria and South Australia) but limits apply. Surface water trading generally outweighs groundwater trades, with more GS trades than HS trades. Key factors influencing trade include water availability in the system and potential for users to obtain water resources through other means;

variability in water resources within and between years and across geographic areas, connections between systems and water users, minimum number of participants in water markets, heterogeneity in demands for water, net increase in water demand over time driven by new investments or activities, changes in response (e.g., crop type, land irrigated) to external pressures such as in global commodity markets. Additionally, releases from Snowy Hydro Schemes (Aither, 2017) can impact water availability and trade, with energy demands influencing trading dynamics.

Four opportunities for demand forecasting are identified (Figure 30 and Appendix D).

1. Evaluate the implications of trading unregulated water, new trading products, and changes to trading rules and processes on regulated water demand and type of water allocation licenses.
2. Anticipate farmers' water trading behaviour. This role includes the consideration of climate, agronomic, global demand for primary productions, diversification of incomes from primary productions, irrigation system, availability of other water supply and demand management options.
3. Evaluate the implications of socioeconomic and ecological changes on water prices and trading opportunities.
4. Anticipate the impacts of releases from Snowy Hydro Scheme on water trading dynamics, noting that increased recycling of water with Snowy 2.0 mean suggests that outflows will be increasingly dependent on release requirements.

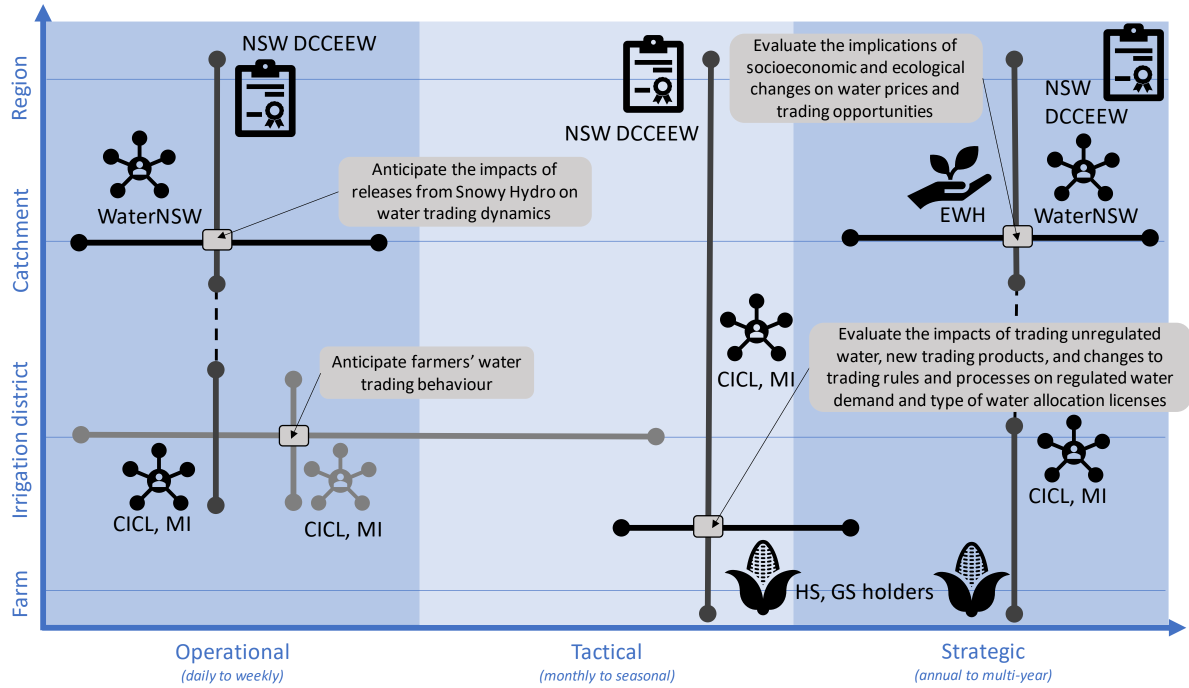

Figure 30. Mapping of possible demand forecasting opportunities across hierarchical levels and spatial scales for the 'Water trading in the lower Murrumbidgee catchment' use case. Icons represent types of decisions or purposes: operations or water orders ( ), regulation and/or compliance ( ), environmental water ( ) and crop choices or agronomic decisions ( ).

The first two aim to capture or support the tactical or strategic level decisions of the breadth of stakeholders (entitlement holders, irrigation districts, government agencies), whilst the last two are positioned to support the operational planning of the irrigation districts and WaterNSW.

5.2.5 Water delivery during and after supplementary events

Maximising benefits of supplementary water events is time sensitive, requiring anticipating demand and supply and management of storages. NSW DCCEEW approves WaterNSW announcements which specify the location and duration of supplementary water events. Both Supplementary and General Security (GS) entitlement holders can divert supplementary flows in accordance with the *Water Sharing Plan for the Murrumbidgee Regulated River Water Source 2016* (NSW, 2016) . High rainfall events or releases from Snowy Hydro Schemes can trigger supplementary events (DPI, 2015). During supplementary announcements, environmental watering actions are cancelled and a portion of the allocated water carried over (Commonwealth, 2023). GS and conveyance license holders may be able to carryover water if water allocations remaining in the water allocation accounts from one year to the next remain up to 0.3 ML per unit share (NSW, 2016).

MI and CICL provide an estimation of supplementary water orders to WaterNSW, communicate the location and duration of supplementary events to their customers and manage any excess water through their system. The timing of supplementary events poses challenges for both IIO, especially during low allocation years when demand from customers might exceed the available volume of supplementary water. Their capacity to determine the volume of supplementary flows that can be extracted by customers is further limited by a lack of knowledge about how much water could be stored in on-farm storages. Water delivery is also complicated if the end of supplementary events result in customers all ordering at the same time, possibly exceeding availability or capacity (CICL, 2023, MI, 2016).

EWH need to decide how supplementary allocations will be used for watering actions (and whether some may be held as carry over) and work with WaterNSW and the irrigation districts to achieve intended outcomes. Subject to system constraints, piggybacking opportunities may exist to prolong watering actions beyond the end of the supplementary event. Piggybacking on irrigation or other releases or flow, particularly in Mid-Murrumbidgee wetlands, can be used to prolong high and flood flows (SKM, 2011). However, physical or operational constraints and infrastructure works may reduce supplementary flows opportunities by limiting channel capacity or flow deliveries (Commonwealth, 2023).

Four opportunities for demand forecasting are identified (Figure 31 and Appendix E), namely to:

- Anticipate risks of restriction after supplementary events.
- Evaluate the potential for piggybacking for Mid-Murrumbidgee wetlands.
- Anticipate event timing and capacity to store supplementary water.
- Anticipate farmers’ demand for supplementary water.
- Anticipate the costs for maintaining and managing assets.

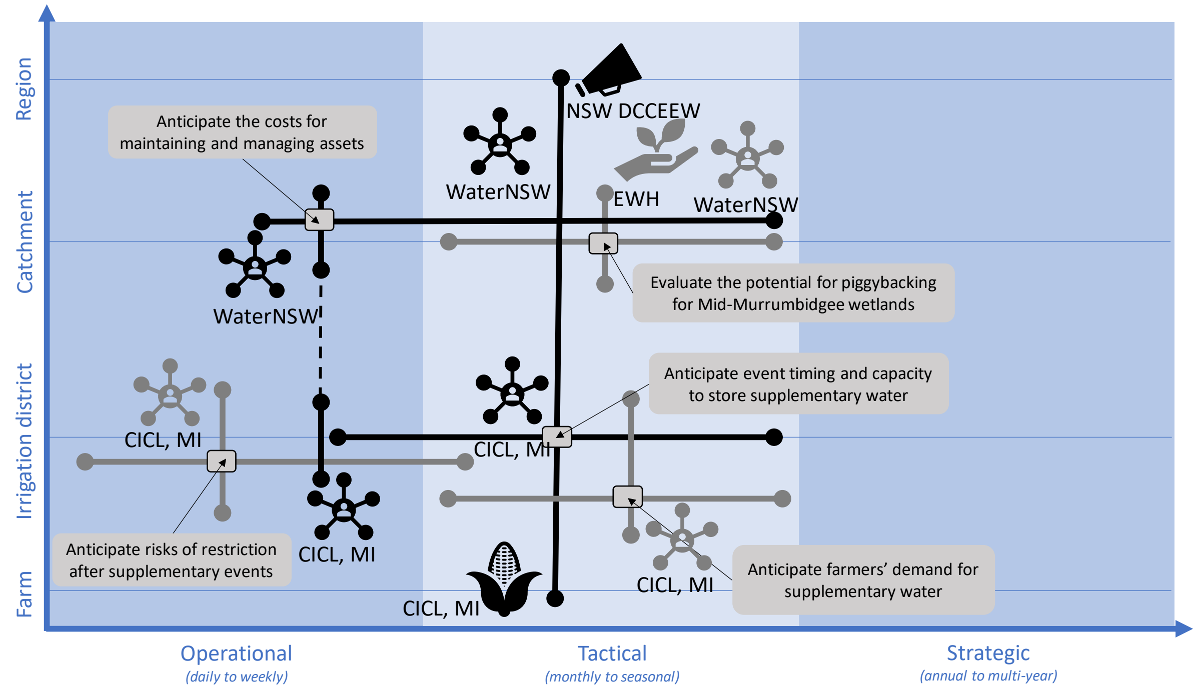

Figure 31. Mapping of possible demand forecasting opportunities across hierarchical levels and spatial scales for the 'Water delivery during and after supplementary events' use case. Icons represent types of decisions or purposes: operations or water orders ( ), supplementary announcements ( ), environmental water ( ) and crop choices or agronomic decisions ( ).

6 Demand forecasting adoption and deployment options

Demand forecasting approaches and tools developed for the use cases presented in Section 5.2 would vary in how they are deployed and the pathways to them being adopted. Deployment could occur through adoption by irrigation districts, by third party forecasting services, through state or federal government services or collaborations across organisations (Figure 32).

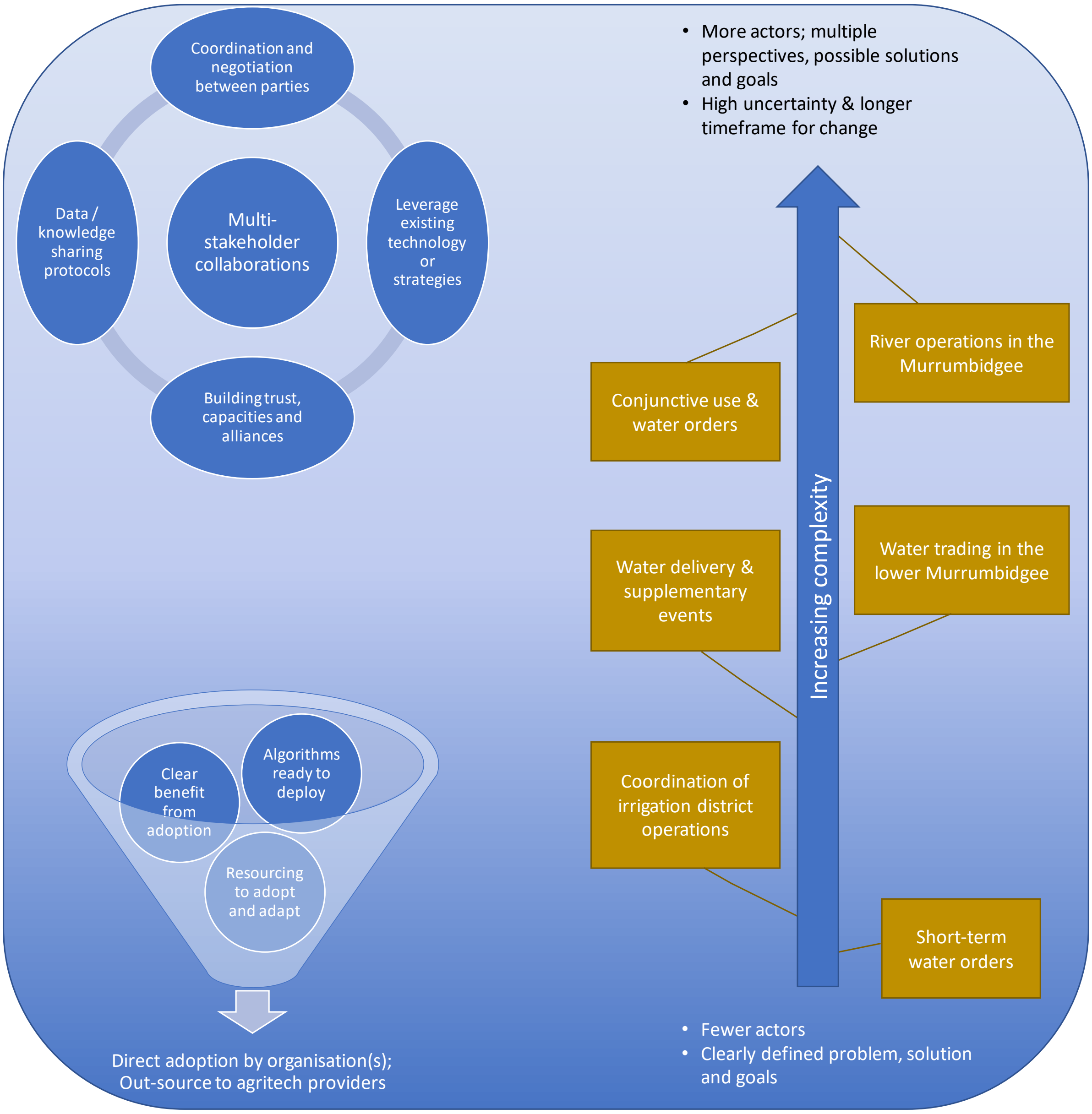

Figure 32. A systems complexity perspective of the use cases in relation to the advancement and uptake of demand forecasting approaches to support water delivery and integrated storage management in the Murrumbidgee.

Taking a systems complexity perspective, deployment and adoption pathways will be more obvious and feasible where a use case addresses a clearly defined problem (and associated goals) and where there are few actors involved in the decision-making and /or implementation of the technology. As demonstrated with the algorithms and process for operationalisation developed in this project, short-term demand forecasting to support irrigation district water ordering could be deployed and adopted directly through the irrigation district data science and operations teams. Alternatively, agritech providers could provide the technical expertise and infrastructure to deploy, implement (with their clients) and adapt demand forecasting algorithms. The *'Coordination of irrigation district operations'* use case is an extension beyond orders for irrigation to planning and coordination (across hierarchical planning levels) for the breadth of water deliveries to irrigator and consumptive users and the environment. The 'Water delivery during and after supplementary events' use case has a relatively narrower focus than the other use cases defined in Section 5. For IIO, these relatively rare events require time sensitive decisions where demand for supplementary water by customers are influenced by antecedent conditions (allocations, available storage) and where operational risks to the IIO can arise if (e.g.) restrictions occur or customer orders become synchronized. For EWH, supplementary events are an opportunity to implement or prolong watering actions. Given the gamut of constraints affecting delivery of water to assets across the Murrumbidgee, these actions require multi-stakeholder cooperation and planning across hierarchical levels to achieve intended outcomes.

Use cases that imply transformative change involve more (diverse) parties, each with their own (possibly conflicting) goals, processes and responsibilities. Here, deployment options and adoption pathways will be less certain and there will be a longer timeframe for change. Emphasis needs to be given to negotiation and coordination between parties and identifying opportunities to leverage and add value to existing demand forecasting or alternative technologies or strategies. 'River operations' is the most complex of the use cases defined in Section 5, arguing that improved coordination and collaboration of the water system and river operations to improve the outcomes for communities, environment and industry. The use cases spans all actors involved in water use and operations decisions (with WaterNSW acting as the custodian of the State's water resources and the conduit to IIO, EWH and other customers) and planning across geographic and planning scale. There is little demand currently from operators and water uses for coordinated and conjunctive management of water use and orders. Shifting to a paradigm of conjunctive use is a large change from the current paradigm, although the local geographic scale reduces the complexity of this use case relative to 'River operations'. Similarly, 'Water trading in the Murrumbidgee' is relatively less complex as a use case for demand forecasting as it is situated within the existing rules and water markets paradigm. The complexity of this use case stems from the breadth of actors involved and geographic scales at play.

Incremental progress on the less complex use cases can arguably be made by working with these key actors or groups. The One Basin CRC offers the opportunity to make progress on the more complex uses cases through the partnerships between universities, government agencies, industry groups, IIO, NRM agencies and communities. The potential for this work to develop further through the Multiple Benefits (CRC058) project was outlined in Section 5.2.1. The potential exists to progress opportunities identified through the conjunctive use and water trading through the 'Water Banking for Drought Resilience' (CRC054) and 'Unlocking Collaborations for Transformation' (CRC050) projects respectively.

7 Conclusion

This report introduced the project motivation, framing and scope for the *'Irrigation demand forecasting and its role in multi-scale system storage control'* collaboration. The project developed, evaluated and initiated the operationalisation of demand forecasting algorithms to support the short-term water ordering operations of CICL and MI. Beyond this component, the team identified other use cases where new or existing demand forecasting tools can improve water delivery across the landscape and considered the pathways for deployment and adoption of demand forecasting technologies. This QuickStart project is a catalyst for incremental transformation by building and implementing predictive modelling capability in network management and by documenting our understanding of how the Murrumbidgee catchment operates and the potential leverage points to improve water operations and delivery.

Short-term (0-7 day) algorithms for forecasting total system daily demand were developed for the Main Canal of Murrumbidgee Irrigation (MI) and the main area of the Coleambally Irrigation Cooperative Limited (CICL) districts. Evaluation focused on performance at critical times for MI and CICL and involved the project team meeting regularly with operations staff to work through the opportunities and challenges to operationalisation and continuously improve the algorithms beyond the project; both CICL and MI have initiated internal processes to formalise this. Demand forecasting has been demonstrated through this component to be both valuable and achievable for water network operators and that the increasingly data-rich environment will support continuous improvement of the algorithms to support network management objectives.

Beyond short term water ordering, demand forecasting advances could complement existing technologies and processes used by key actors involved in decisions across planning scales that relate to water ordering, delivery and use by environment, irrigation and consumptive users in the Murrumbidgee. The project identified five further use cases for which demand forecasting technologies might be developed and applied to support water delivery and river operation decisions. The relative complexity of the decision contexts vary from use cases on focused issues (supplementary events) or users (irrigation districts) to more complex multi-actor, multi-scale (and ultimately transformative) use cases that lend themselves to exploration and advancements through the partnership model of the One Basin CRC.

Acknowledgements

This project is funded by the One Basin CRC. Our gratitude goes to operations staff from CICL and MI for working with the project team to test the performance of the demand forecasting algorithms and evaluation framework; staff from CICL and MI were also instrumental in the system conceptualisation workshop early in the project. We thank the members of the Project Advisory Committee (PAC), Professor Seth Westra as One Basin CRC Program Lead for Technology and Opportunity and the One Basin CRC Regional Hub Managers and administration team for their support throughout the project. The ANU team acknowledge the considerable support provided by the Institute for Water Futures (IWF) and the Fenner School of Environment and Society (FSES).

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Appendix A. River operations in the Murrumbidgee River Catchment

Opportunities for demand forecasting to tackle some challenges related to the use case. *(Numbers under brackets aim to link comments to the example demand forecast models)*
What role(s) could demand forecasting fill? [1] Estimate future demands and uncertainty (e.g., changes in crop types and planting areas during the peak season of November-December, fluctuations in Tombullen storage due to private farmers' demand or the impact of maintenance works on conveyance). [2] Update forecast models to account for changes in water demands. This role considers adaptive updates of demand forecasts). [3] Coordinate water deliveries for irrigation and the Environment. This role includes the alignment of watering actions with irrigation, according to four climate scenarios (extreme dry, dry, moderate, wet).
Do existing demand forecasting or alternative algorithms or strategies exist to fill these roles? • [1] Unit water demand analysis method to develop sectoral demand forecast accounting for expected population growth, change in economic activity per branch. With demand represented spatially using GIS information (Rinaudo, 2015). • [2] Vectorised double-seasonal ARI (autoregressive integrated) model to capture both temporal correlations and spatial variations in demands. Adaptive forecasting algorithm: GLR (Generalised Likelihood Ratio), monitoring the ratios of likelihoods for a current set of parameters and an alternative set of parameters computed from recent observations. If the alternative set of parameters perform better than the current one, the algorithm automatically updates the current parameters and reports a model switch (Chen & Boccelli, 2018). • [3] Short-term (daily) and long-term (season) ensemble flow forecasting using ANN and co-optimisation of multiple reservoir operations. Ensemble forecast forcings from publicly available numerical weather predictions were used to generate daily and monthly scale inflow forecasts (scenario years: dry, moderate, wet) (Ahmad & Hossain, 2020). • CARM (Computer Aided River Management) system, developed by DHI consulting for WaterNSW to enhance weirs and dams' operations in the Murrumbidgee River system and reduce operation losses. CARM is driven by MIKE OPERATIONS and integrates models reproducing key catchment and river processes with real-time measurements. The objective is to provide river operators with an overview of current and forecasted water inflows to inform operation decisions and ensure reliable deliveries to relevant locations at the right time. Build-in models consist of NAM Rainfall Runoff model (MIKE 11 NAM) to describe rainfall and runoff; MIKE for evaluating groundwater seepage and surface water evaporation; MIKE 11 (MIKE HYDRO River) to account for river hydraulics and storages in the river, at weirs and in wetlands (Van Kalken et al., 2012). In 2018, rolling-out a derived version of CARM, CARM Lite across all regulated valleys in NSW was considered by the NSW Government to predict tributary inflows and improve the effectiveness of water operations (IPART, 2019).
What is needed for demand forecasting to be useful / feasible? • **Data / knowledge**: Under different climate scenarios: [1] unit water consumption coefficients (per user types) and estimated future number of users per category (Rinaudo, 2015). [2] hydraulic information; observed demand timeseries: total system demands and regionally aggregated demands (in the paper), the latter aiming to capture the spatial variability in demands across a network (Chen & Boccelli, 2018). • **Institutional / relational processes**: multi-level partnerships with water users, regulatory bodies, (Snowy Hydro) and environmental agencies to optimise water management practices (Wang, 2021); co-innovation processes including on-farm and off-farm stakeholders for coordination of on-farm water uses and

management; consideration of the influence of regulatory, climatic, infrastructural and hydrological factors on on-farm irrigation decisions (Srinivasan et al., 2017).

Key opportunities and constraints/risks associated with role(s)

- [1] **constraint**: does not account for possible future changes in unit water consumption due to evolving water tariffs or household incomes among others; opportunity: consumption coefficients could be considered as variable with time, extrapolating their future direction from past trends. Advantages: useful where little or no data are available, provide transparency, easily understood by stakeholders.
- [2] **constraint/opportunity**: adaptive forecasting algorithms are expected to aid in reducing forecast errors for long-term time horizons (above 1-2 years) and account for factors driving water consumption changes.

Potential stakeholders

- *MI and CICL:* responsible for water operations (ordering, deliveries, asset maintenance, groundwater and water quality monitoring, environmental watering) in their area of operations.
- *Environmental water holder:* Ensure connectivity of and water provisioning to key ecosystems in the Murrumbidgee Catchment and Murray River to ensure functionality, services, and biodiversity conservation.
- *WaterNSW:* responsible for managing water in storages (natural and artificial), water deliveries to licensees (including environmental flows), raw water quality monitoring (surface and groundwater), announcements of exceptional events (e.g., supplementary water, restrictions).
- *Private irrigators below Gogeldrie Weir*: orders may vary according to the location along the Low Murrumbidgee River system.
- *DHI consulting*: mandated to develop the CARM system by WaterNSW to improve river operations and better account for evaporation, transmission and operation losses affecting water availability and the reliability of deliveries to customers (including the Environment).

Information source used to identify and develop the use case

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Appendix B. Influence of conjunctive use of surface water and groundwater on water orderings from irrigation districts

Opportunities for demand forecasting to tackle some challenges related to the use case. *(Numbers under brackets aim to link comments to the example demand forecast models)*
What role(s) could demand forecasting fill? [1] Evaluate the influence of changes in energy costs and technological access on groundwater extraction sustainability. [2] Estimate crop application rates (i.e., the amount of water from available supplies to water crops according to their development stage) based on integrating surface water, groundwater and soil moisture data. [3] Evaluate the relative availability and quality of groundwater and surface water under prolonged dry conditions.
Do existing demand forecasting or alternative algorithms or strategies exist to fill these roles? • [1] DT, optimised with a Genetic Algorithm (GA) to predict irrigation amount based on farmers' decisions about when to irrigate, providing information of when to schedule irrigation and aiding in coordinating irrigation activities to minimize energy and water losses. Realised with drip-irrigated tomato and maize and flood-irrigated rice (González Perea et al., 2019). • [2] AQUACROP coupled with LSTM model to develop a predictive irrigation scheduling system to maintain soil moisture within a set of lower and upper bound, with the irrigation amount defined as the water depth necessary for replenishing soil water to a certain threshold (Adeyemi et al., 2018). • [3] Data-driven models (DDM) to forecast different regimes of water tables one to five months ahead (lead times) in response to hydro-climatological forcings and water management. In water shortage conditions, extreme learning machines and Genetic Programming (GP) providing higher forecast accuracy for short lead times, while ANNs were less sensitive to increase in the forecasting horizon (Amaranto et al., 2018). • [4] Near ecological forecasts to predict ecological responses to droughts and floods, changes in carbon and biochemical cycles, algal blooms, wildfires, among others (Dietze et al., 2018). • [5] Transformer neural network (TNNs) model, optimised by NSGA-II to forecast daily irrigation water 7 days ahead and automatically adaptation throughout the irrigation season. Account for water management and energy contracting in irrigation districts considering current and expected scenarios of water scarcity and high energy prices (González Perea et al., 2024).
What is needed for demand forecasting to be useful / feasible? • **Data / knowledge:** [1] daily climate and daily irrigation data over one year; [2] historical soil moisture and climate data to predict water in soil. [3] consideration of monthly crop water demand as a proxy for human impacts on groundwater (including irrigation system), monthly precipitation, monthly snowmelt, monthly evapotranspiration. Could include pumping data if available. Water table monitoring timeseries data over three years, daily and monthly, using USGS. [4] For decision-making, due to long-term consequences based on present decisions, need for relevant decision metrics at appropriate spatial and temporal scales; inclusion of uncertainty in risk management decisions. [5] information about the position within the input vector to the forecasting model (e.g., daily average temperature of 4 days before), information about the real day of each input variable (e.g., time series) • **Institutional / relational processes**: [4] training in statistics and best practices in data, coding and informatics, theoretical knowledge, leadership, interdisciplinary collaboration and communication skills; organisational support with phased funding transition to move from research to operations and sustain operational forecasting capabilities; shifts in scientific culture to encourage engagement in iterative forecasting; for

decision-making, long-term partnerships between researchers and managers to improve both forecasts and their uses.
- **Others:** [4] open and reproducible science, with reducing data latency and increasing automation for problems amenable to frequent forecasts; development of a forecasting synthesis centre for technology, training, theory, and methods development.

Key opportunities and constraints/risks associated with role(s)

- **Opportunities:**

  [1] align irrigation and orderings, with reducing evaporation and operation losses.

  [2] Prevent impacts of waterlogging and rising water tables and enhance water use efficiency.

  [3] account for regime changes under different dry, moderate and wet scenarios and integrate surface with groundwater data. To address uncertainty of hydrometeorological estimates, quantification of the sensitivity of groundwater variability to the uncertainty in the meteorological input estimation and development of the approach at the aquifer scale.

  [4] evaluate and identify options better accounting for ecological requirements; link iterative near-term forecasts with adaptive management and other iterative policy rules.

- **Risk:**

  [3] absence of pumping data and use of crop water demand as a proxy for human impacts. Assumption that the amount of water pumped, and available surface water are proportional to the evapotranspirative needs of crops. Use of monthly hydrometeorological forecasts as inputs.

  [4] Mindsets and resources

1. Potential stakeholders

- *MI, CICL:* scheduling water charges annually, ordering and delivery of regulated water, environmental watering, storage and channel maintenance; water quality and groundwater monitoring (September and March). For CICL, setting and enforcing sustainable extraction limits for groundwater.
- *Department of Water and Energy (DWE):* Monitoring of groundwater levels and quality in CICL.
- *WaterNSW:* Provision of water to Berembed and Gogeldrie Weirs, at MI and CICL offtakes.
- *Farmers in MI and CICL:* Decision choice of water sources; purchase of GS and HS licences for using groundwater and surface water; ordering of regulated surface water.
- *Independent Pricing and Regulatory Tribunal (IPART):* Influence water prices for water in irrigation districts by setting bulk water charges to be recovered and returned to the MDBA and WaterNSW.

2. Information source used to identify and the develop use case

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Appendix C. Irrigation district operations and coordination with other actors

Opportunities for demand forecasting to tackle some challenges related to the use case. *(Numbers under brackets aim to link comments to the example demand forecast models)*
What role(s) could demand forecasting fill? [1] Anticipate water restriction events under different climate scenarios. This role includes the consideration of prolonged dry conditions and high flow events that could hinder monitoring of surface water availability. [2] Anticipate climate and maintenance impacts on the alignment of water orders and flow regime requirements. [3] Estimate off-stream storages' lag time to refill/ emptying events. This role aims to inform operation decisions, including investments in supply and demand management options. [4] Estimate the risk from contract agreements or incentives. This role aims to consider the influence of farmers' locks-in contracts or incentives on farmers' behaviour and planting of water intensive crops, especially under inadequate climate conditions.
Do existing demand forecasting or alternative algorithms exist to fill these roles? • [1] Transformer neural network (TNNs) model, optimised by NSGA-II to forecast daily irrigation water 7 days ahead and automatically adaptation throughout the irrigation season. Account for water management and energy contracting in irrigation districts considering current and expected scenarios of water scarcity and high energy prices (González Perea et al., 2024). • [2] Joint structured and unstructured information sharing i.e., mixed demand forecasting and engagement approaches for operation and strategic coordination under different levels of demand uncertainty (Li et al., 2019). • CARM (Computer Aided River Management) system, developed by DHI consulting for WaterNSW to enhance weirs and dams' operations in the Murrumbidgee River system and reduce operation losses. CARM is driven by MIKE OPERATIONS and integrates models reproducing key catchment and river processes with real-time measurements. The objective is to provide river operators with an overview of current and forecasted water inflows to inform operation decisions and ensure reliable deliveries to relevant locations at the right time. Build-in models consist of NAM Rainfall Runoff model (MIKE 11 NAM) to describe rainfall and runoff; MIKE for evaluating groundwater seepage and surface water evaporation; MIKE 11 (MIKE HYDRO River) to account for river hydraulics and storages in the river, at weirs and in wetlands (van Kalken, 2012). In 2018, rolling-out a derived version of CARM, CARM Lite across all regulated valleys in NSW was considered by the NSW Government to predict tributary inflows and improve the effectiveness of water operations (IPART, 2019).
What is needed for demand forecasting to be useful / feasible? • **Data / knowledge**: [1] information about the position within the input vector to the forecasting model (e.g., daily average temperature of 4 days before), information about the real day of each input variable (e.g., time series)
Key opportunities and constraints/risks associated with role(s) • **Opportunities**: (CICL, 2023) Accessibility to high-resolution temporal data and consideration of soil water balance models to enhance the estimate of ETa values, especially capturing ETa from rainfall events, and get a more comprehensive understanding of water use dynamics. [2] Research applications in the Australia contexts to evaluate coordination practices across strategic and operational levels.

Potential stakeholders

- *MI, CICL:* ordering and delivery of regulated water, environmental watering, storage and channel maintenance; surface water monitoring; system upgrade; manual or automatic operations of the irrigation system; water quality monitoring. For CICL, fill/release to Tombullen Storage.
- *WaterNSW:* Provision of water to Berembed and Gogeldrie Weirs, at MI, CICL and private irrigation companies' offtakes; conveyance of minimum flows to ecological systems (Lowbidgee wetlands and Yanco Creek); management of water in Tombullen storage.
- *Farmers in MI and CICL, private irrigators:* daily ordering of regulated surface water. For private land owners in CICL (western), voluntary involvement in environmental watering actions.
- *DPIE:* assessment of annual water availability; since 2015, works with CICL to deliver water to natural wetlands with Coleambally Irrigation Area
- *Environmental water holder and OEH:* Ensure connectivity of and water provisioning to key ecosystems in the Murrumbidgee Catchment and Murray River to ensure functionality, services, and biodiversity conservation.

Information source used to identify and develop the use case

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Appendix D. Water trading in the Lower Murrumbidgee River Catchment

Opportunities for demand forecasting to tackle some challenges related to the use case. *(Numbers under brackets aim to link comments to the example demand forecast models)*
What role(s) could demand forecasting fill? [1] Evaluate the implications of trading unregulated water, new trading products, and changes to trading rules and processes on regulated water demand and type of water allocation licenses. [2] Anticipate farmers' water trading behaviour. [3] Evaluate the implications of socioeconomic and ecological changes on water prices and trading opportunities. [4] Anticipate the impacts of releases from Snowy Hydro on water trading dynamics.
Do existing demand forecasting or alternative algorithms or strategies exist to fill these roles? • [1] ANN approach for forecasting seasonal water allocations and water trading prices, to aid farmers in land and water management (Khan et al., 2010). Khan et al. (2010) explored management of uncertain water allocations and water trading prices in the Murray River Basin and in relation to water operations from Murray Irrigation Limited • [2] Season-ahead hydrologic forecast to anticipate water user decision making (trading or not trading) in semi-arid regions. Use of a five-phase forecast approach of (1) streamflow and allocation estimates, (2) crop-water and farm-scale profit optimisation, (3) endowment-based water trade rulesets based on market-scale trade, (4) inter-cooperative water trade (option contract trading) forecast, (5) risk tolerance effect on forecast uptake (Delorit & Block, 2020).
What is needed for demand forecasting to be useful / feasible? • **Data / knowledge**: land use and water use per crop types as proxies for change in irrigation water production (Aither, 2017). [1] global sea surface temperature, Southern Oscillation Index for the past 100 years, average monthly rainfall data over 8 years, average monthly water trading volumes and prices over 8 years. [2] season-ahead inflows in reservoirs, mean annual allocation values, estimation of yields and profit from crops (crop type cooperatives, per ha), market prices of crop products with a 6-month lead. • **Institutional / relational processes**: education on water trade; enhanced transparency and pace for assessment and approval processes; refinement of the operation of some trade rules; improved information delivery about water availability and water trade on DPI websites; improved information on key trading rules (Aither, 2017). [2] interactions with farmers of varied crop types to understand decisions. • **Other elements**: investigation of demand for unregulated trade and impacts of new trading products or changes to rules and processes to ease trade (Aither, 2017).
Key opportunities and constraints/risks associated with role(s) • **Benefits/opportunities**: [2] Ground-truthing risk attitudes through focused interactions with farmers of varied crop types to confirm risk attitude modelling. • **Risk**: [2] unknown true nature of risk attitude towards confidence in forecasts; limitation to the total number of alternative simulated for trading options.
Potential stakeholders

• *NSW DCCEEW*: assessment of water availability and announcement of Available Water Determination (AWD) on the 1st of July and periodically throughout the year; announcement of supplementary water events; set trade and other management rules; responsible for water accounting and reporting. • *Environmental water holder and OEH:* decisions for carry-over or trading supplementary and GS entitlements based on unused water, watering needs, generation of revenues, delivery of water on behalf of OEH (NSW Office of Environment and Heritage), potential for piggy backing. • *WaterNSW:* Based on AWD, credit the accounts of licenced water users with the volume of water specified and allow licensees to take additional water based on their account balance and licence conditions; responsible for metering and compliance activities facilitating water users understanding of their rights and obligations. • *Small entitlement holders*: Expected to participate more in water trades based on less reliable allocations (GS), based on water prices for irrigation or opportunities for paying charges or improving farm operations. • *HS farmers:* expected to participate less in water trading due to more reliable entitlements. • *Aquifer entitlement holders:* expected to participate in trade when surface water allocations are low, but restricted to 2 ML per unit share.
Information source used to identify and develop the use case
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Appendix E. Water delivery during and after supplementary events in dry years

Opportunities for demand forecasting to tackle some challenges related to the use case. *(Numbers under brackets aim link comments to the example demand forecast models)*
What role(s) could demand forecasting fill? [1] Anticipate risks of restriction after supplementary events [2] Evaluate the potential for piggybacking for Mid-Murrumbidgee wetlands [3] Anticipate event timing and capacity to store supplementary water [4] Anticipate farmers' demand for supplementary water [5] Anticipate the costs for maintaining and managing assets
Do existing demand forecasting or alternative algorithms or strategies exist to fill these roles? • [1] Synthetic short-term forecasts using a policy tree optimization algorithm for improving reservoir operations for flood control and water supply objectives and informing forecast-based policies. Based on increasing conjunctive use capacity (Nayak et al., 2018) • [2] Probabilistic fluvial flood forecasts for flood early warning (Arnal et al., 2020)
What is needed for demand forecasting to be useful / feasible? • **Data / knowledge**: On-farm storage data; [1] daily inflow to reservoirs based on daily precipitation and maximum temperatures over 100 years; 1-30 days ahead daily precipitation and temperature numerical weather prediction model forecasts based on sub-seasonal to seasonal prediction project database from more recent data over 12 years. • **Institutional / relational processes**: [2] enabling co-design of the probabilistic forecasting system and a risk-based decision-making framework between forecasters and national/state agencies; define guidelines for operating procedures for using probabilistic forecasts in practice in combination with tools currently used; communicate with internal and external players to inform about the use of probabilistic forecasts and their benefits over deterministic forecasts. • **Other:** [2] Adapting existing wider flood management priorities (e.g., warning lead times)
Key opportunities and constraints/risks with role(s) • **Constraints:** [2] complex and require a full understanding of probabilities, risks, uncertainty and the systems modelled as well as set rules, such as threshold exceedance, to avoid missing an event. Other influential factors include identifying the type of event (e.g., localised small event or large-scale), costs of taking action, decision-makers' experience, trust in the forecast, risk aversion, cultural context in which decisions are made. • **Opportunities:** [1] consider hourly data for improving reservoir operations, especially for high flow event control. Support banking groundwater in a conjunctive use system and forecast skills. Could support multi-reservoir policies.
Potential stakeholders • *DPI Water*: Announcement of supplementary events • *MI and CICL:* Estimation of supplementary water orders to WaterNSW; announcement of the location and duration of supplementary events; management of excess water. • *Environmental water holder:* Consideration of supplementary allocations for watering actions or carry over of a proportion. Consideration of potentially prolongation of watering actions post-supplementary events based on piggyback. Payment of charges for using CICL network. • *WaterNSW:* Ordering of water a week in advance, in anticipation of announcements of supplementary events; Management of rain rejections at Bundidgerry Creek. • *Farmers in MI and CICL:* storage of supplementary water on-farm

Information source used to identify and develop the use case

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