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Water markets under climate change: a monthly model of the Murray-Darling Basin

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Abstract

The Australian Murray-Darling Basin is home to one of the world's most mature water markets. In recent decades, these markets have played a vital role supporting adaptation to the effects of drought, climate change and environmental reform. This study introduces a new monthly economic model of the water market with an emphasis on biophysical detail and empirical performance to enable integration with hydrological models. This model also contains significant economic structure, representing the stochastic and dynamic nature of water markets in storage-controlled rivers, including forward looking water users with rational expectations over future conditions. In this study, the model is applied to simulate the potential effects of climate change on water markets within the southern basin. The results show how markets support adaptation, with drier climates leading to increases in regional water trade volumes, particularly imports into the lower Murray. Drier scenarios are also associated with more conservative crop planting decisions, which increase storage reserves to maintain supply reliability. Under the driest future climates, the ability of markets to adapt is more limited, and the model simulates long-term declines in irrigation development. However, the future climate remains highly uncertain, with a majority of the projection ensemble involving increases in water supply and irrigation activity relative to recent conditions. In future, fully integrated hydro-economic models could help to design water market institutions that are robust to a non-stationary and uncertain climate.

Keywords

Water, Climate Change, Water market

Highlights

- A monthly timestep economic model of the Murray-Darling Basin water market is developed
- This model is applied to assess the potential impacts of climate change in the southern basin
- The results show how markets enable adaptation by reallocating water over space and time
- Under extreme dry scenarios the model simulates a decline in irrigation development
- In future, integrated hydro-economic models could better support adaptation planning

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1 Introduction

Water markets have emerged in many river systems around the world including in the Western US (Schwabe et al., 2020; Wight et al., 2024), Chile (Bauer, 2004) and the Australian Murray-Darling Basin (MDB) (Brennan, 2006; Grafton et al., 2012; Young & McColl, 2005). These markets play an important role in managing climate variability, particularly drought, by efficiently allocating scarce water resources among competing users. Increasingly, water markets are now also supporting longer-term adaptation to the effects of climate change (Bruno & Jessoe, 2024).

The Australian MDB has experienced a long-term decline in winter season rainfall over the last 20-30 years, a trend at least partly due to climate change (see Cai et al., 2012, 2014; Cai & Cowan, 2013). Lower rainfall has contributed to significant declines in streamflow and water supply in the basin in recent decades (Speer et al., 2021; Zhang et al., 2016). At the same time, governments have been securing water for environmental flows to improve ecological outcomes in the region (Crase et al., 2012; Hart, 2016; Leblanc et al., 2012). Since 2008, over 2,000 GL of water rights have been reallocated from farmers to the environment under the Murray-Darling Basin Plan; reducing consumptive supply by around 20 per cent.

These reductions in supply have led to a range of adaptation responses including improvements in technology (e.g., more efficient irrigation infrastructure) (Connor et al., 2014; Hughes et al., 2023) and changes in irrigation development across regions (i.e., less pasture in the upper Murray, and more almonds in the lower Murray, see Zeleke & Luckett, 2025). These changes have been enabled largely by water markets. Trading has allowed the spatial pattern of irrigation development to adjust across the basin. In addition, carryover (i.e., storage of unused water in on-river dams, see Brennan, 2010; Hughes et al., 2023) has increased the reliability of water supply supporting more intensive activities, particularly perennial tree crops (Hughes et al., 2023; Zeleke & Luckett, 2025).

Despite this, concerns remain over the future impacts of climate change in the region. Recent adaptations have increased the capital intensity of the irrigation sector raising the issue of stranded assets (see Bark et al., 2014; Hughes et al., 2020). To date, assessments of climate change in the MDB have relied mostly on hydro-climate modelling (CSIRO 2008; Potter & Srikanthan, 2008; A. Van Dijk et al., 2008), where catchment and river process models are used to simulate changes in streamflow and water supply under projected climate. For example, the CSIRO (2008) simulated a median decline in water availability by 2030 of 13 per cent in the southern MDB. While these models represent physical processes in detail, they largely ignore the economic behaviour of water users and markets, including potential adaptation responses.

This study presents a model of the MDB water market representing the economic behaviour of water users (i.e., irrigation farmers) including monthly water use, annual crop planting and long-run investment decisions. The water market is modelled as a spatio-temporal equilibrium problem, where market prices are the product of optimal water use, trade and storage behaviour, subject to physical and institutional constraints. This study extends the previous annual model presented in Hughes et al., (2023), drawing on a recently developed monthly bio-economic water demand system (described in Hughes et al., 2025). The model is demonstrated with an application to the southern MDB, simulating potential water market and irrigation responses to climate change.

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These simulations make use of an ensemble of climate and water supply scenarios derived from a separate hydro-climate model (John, Horne, & Hughes, 2025).

This combination of economic and hydrologic models places our study within the wider literature on integrated Hydro-Economic Modelling (HEM) (Brouwer & Hofkes, 2008). In particular, our study is related to the simplified monthly hydro-economic models of the MDB developed previously by Kirby et al., (2014) and Qureshi et al., (2013), which were both applied to simulate the effects of climate change. A key point of difference, is that our model is dynamic in the sense that water users make forward looking decisions subject to uncertainty over stochastic water supplies. The model is solved for a "rational expectations" equilibrium in which user behaviour reflects probabilities over future conditions drawn from a known distribution. As a result, the model can represent adaptation responses, such as changes in crop planting, water trade, carryover or even irrigation development in response to a change in the long-run climate (i.e., the probability distribution over water supply conditions).

Given the numerical complexities, most economic models of water markets (e.g., Grafton & Jiang, 2011; Quiggin et al., 2010; Wittwer & Griffith, 2011) tend to ignore storage dynamics, while economic and engineering models of water storage (e.g., Brennan, 2010; Dudley, 1988; Ahmad et al., 2014) tend to ignore markets. The model presented here represents both, using a combination of mathematical programming to solve the short-run water market (as a Mixed Complementarity Problem) and machine learning methods to resolve the stochastic-dynamics (i.e., obtain a long-run rational expectations equilibrium). In particular, the study employs methods from Reinforcement Learning to approximate user expectations over future water market prices.

In this paper we provide a brief description of the study region and then set out our economic model, including water accounting constraints and the spatial and intertemporal equilibrium conditions. We then provide an overview of the numerical methods applied to solve the model, before presenting simulation results detailing the potential effects of climate change on irrigation activity and water markets in the region.

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2 The Murray-Darling Basin

The Murray-Darling Basin (MDB) drains an area of over 1,000,000 km^2 across South-Eastern Australia. Irrigated agriculture accounts for more than 90% of total water use in the region. The southern MDB (sMDB)—which includes the Murray-river and its connected tributaries (Figure 1)—accounts for around three quarters of agricultural water use in the MDB (and around half of national agricultural use).

Figure 1: The Murray–Darling Basin

The sMDB is subject to a temperate climate with winter dominant inflows and relatively large on-river storages which support inter-year storage reserves. Irrigation within the sMDB is diverse with a mix of perennials (e.g., fruit and nut trees and grapevines), irrigated pasture and annual cropping (e.g., rice and cotton). Perennial crops are concentrated in the lower Murray (e.g., SA Murray and Vic. Murray Below Barmah regions), dairying / irrigated pasture in northern Victoria (e.g., Goulburn-Broken, Loddon, Campaspe) and rice and cotton in NSW

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(Murray and Murrumbidgee, see Figure 1). In contrast, irrigation in the northern MDB is dominated by cotton crops.

Water market reforms since the 1980s have seen the separation of water rights from land and the establishment and gradual refinement of cap-and-trade systems (Crase et al., 2004; Wheeler et al., 2014; Young & McColl, 2005). While water markets exist in many parts of Australia, the sMDB is by far the most active market (accounting for around 90% of water trade activity). Water property rights in the MDB involve a system of "entitlements" (perpetual rights to a share of water from a particular source / river) which receive annual water "allocations" (volumes of water available for use within the current year). Allocation volumes are determined by water authorities to reflect prevailing water availability (i.e., dam storage volumes).

Another key feature of the MDB are carryover rights (see Brennan, 2010; Hughes et al., 2023), which allow farmers to hold unused water allocations in public reservoirs: creating buffer stocks to reduce variability in water use and prices over time. These storage reserves are important in the sMDB given river inflows are highly variable, while alternatives to reservoir storage (e.g., groundwater recharge, on-farm dams) are limited. Both water trade and carryover are subject to regulatory limits, in the form of water accounting rules designed to reflect physical constraints on the delivery and storage of water within the river system. Together the system of water property rights and accounting rules are designed to represent key features of the physical river system (i.e., reservoirs and rivers) ensuring consistency between water market transactions and real-world water flows.

Under the Australian constitution, responsibility for water resource management lies primarily with the jurisdictions (i.e., state governments). As such, the implementation of water institutions varies considerably across the regions of the MDB, particularly the definition of water entitlements, water accounting and carryover rules and allocation determination processes. However, the annual water allocations held by end users remain relatively homogenous, such that trade across state borders can occur with low transaction costs.

3 Methods

3.1 The economic model

Figure 2 provides an overview of the economic model. The model takes hydro-climate data (monthly sequences of water allocations, rainfall and evapotranspiration), irrigation data (irrigation development and commodity prices), and water market rules (trade and carryover limits) as inputs, simulating monthly irrigation and water market outcomes (Figure 2a). The model includes seven southern MDB regions and five northern MDB regions (Figure 2b). Consistent with exiting MDB trading rules, inter-regional water trade is allowed in the "connected" southern MDB, but not among the "disconnected" northern MDB regions.

The model represents spatial and temporal equilibrium in water market, allowing for trade of water between regions and carryover of unused water between time periods. The supply side of the model includes a set of water accounting rules and trade limits, approximating those operating currently within each of the MDB regions. The demand side involves a detailed representation of irrigated agriculture, including crop production, revenue, costs and profits (drawing on Hughes et al., 2025).

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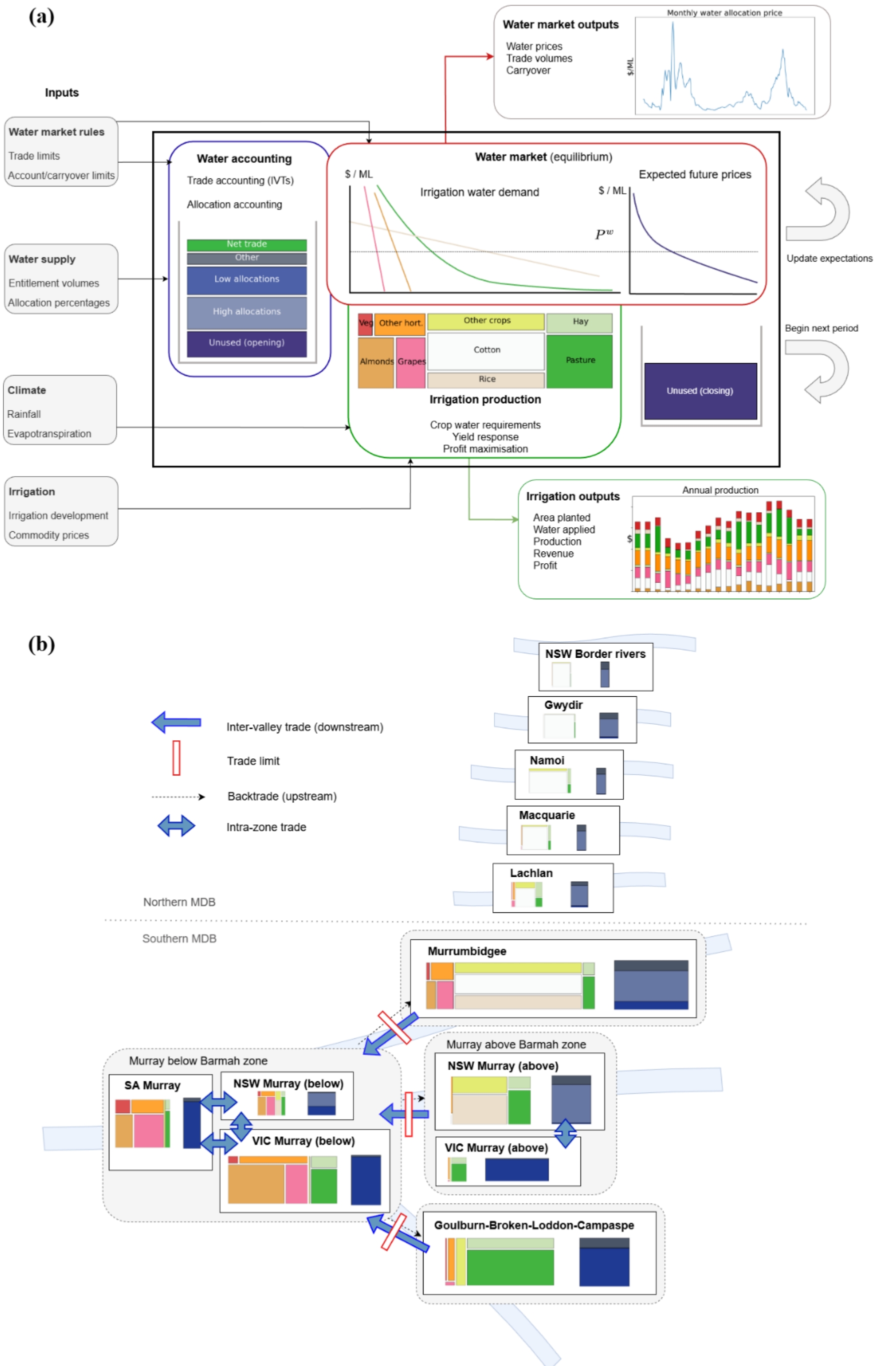

145 **Figure 2: Overview of the economic water market model (a) Stylised representation of the model for a single region, including input data, model processes (water accounting, irrigation production and water markets) and model outputs. (b) Spatial overview of the model including allowable inter-region water trade flows.**

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3.1.1 Water supply

Water accounting rules vary significantly across MDB regions and states, particularly in how they represent storage constraints (see Brennan, 2006; Hughes et al., 2023). The model adopts a simplified parametric representation of these accounting systems, which attempts to reflect the most relevant features within each region.

Within the model, the volume of allocations A_{it} available at end of of period t (i.e., unused water) evolves according to:

$$A_{it} = f^A(A_{i,t-1}) + \sum_h \Delta A_{hit} - U_{it} + T_{it} - F_{it} \qquad (1)$$

$$\Delta A_{iht} = (a_{hiy,m} - a_{hiy,m-1}).E_{hi} + A_{it}^{other}$$

$$f^A(A_{i,t-1}) = \min\left((1-\alpha_{im}^G)A_{i,t-1}, \alpha_{im}^C \sum_h E_{ih}\right)$$

$$\tau_{it}^l \le T_{it} \le \tau_{it}^u$$

$$0 < A_{it} < \bar{A}_{it}$$

where ΔA_{iht} are new allocation volumes made available in period t (implicitly reflecting inflows into storages), U_{it} is allocation use, T_{it} is net inter-region trade and F_{it} are forfeits (reflecting storage constraints / losses). Note that in general we use t to refer to the current time-period (month), but where necessary separately index the (financial) year y and month m.

The model represents two water entitlement types in each region with varying reliability levels $h \in \{high, low\}$ (i.e., General and High Security in NSW and High and Low Reliability in Victoria). These water entitlements each receive annual allocations of water $a_{hi,t}.E_{hi}$, where $a_{hi,t}$ is an annual allocation percentage updated monthly, and E_{hi} is a fixed (i.e., maximum) annual supply volume. Finally, the term A_{it}^{other} reflects volumes of water available against other surface water rights not explicitly represented in the model, including conveyance losses and urban water (for details see Appendix A3).

3.1.2 Water storage and trade limits

The function f^A governs the transfer (carryover) of unused water from one period to the next. Different rules are imposed across regions, including in some cases limits on the transfer of water between financial years (from June to July). Carryover rules are represented in the model via alternative specifications for f^A, F_{it} and $\bar{A}_{it}$ as set out in Appendix A1.

The model includes four trading zones in the southern MDB (see Figure 2b) which represent the key physical constraints on inter-regional water trade. Net flows of water downstream on the Murray-river (into the Murray below Barmah) are constrained by the “Barmah Choke” a narrow section of the river which limits delivery capacity. Downstream deliveries from the Murrumbidgee and Goulburn tributaries are also subject to constraints.

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Trade within these zones is unconstrained but trade between zones is subject to volumetric limits: τ_{it}^{u}, τ_{it}^{l}. These "Inter-valley Transfer" (IVT) limits evolve overtime in response to accumulated trade volumes and physical river flows, with specific accounting rules applied in each case (see Appendix A2). In general, upstream inter-regional trade is only possible where it offsets other downstream flows (referred to as "back-trade", Figure 2b).

3.1.3 Irrigation water demand

The demand side of the economic model is based on the monthly bio-economic water demand system developed by Hughes et al., (2025). This system represents 12 irrigation activities $j \in J$ in each region including perennial crops (Almonds, Grapes, Vegetables and Other horticulture), summer crops (Rice, Cotton), winter/perennial crops (Hay, Pasture) winter/summer crops (Other). The parameters of the demand system $\boldsymbol{\beta}_{ijt}$ are estimated from historical data over the period 2004-05 to 2021-22. The parameters vary over-time in line with observed technological trends (e.g., water use efficiency, irrigation development). The values applied in this study are based the 2021-22 estimates (intended to reflect current irrigation development and technology).

A brief summary of the water demand models is provided below (for a complete description see Hughes et al., 2025). The demand model adopts a crop water balance equation in which monthly crop irrigation requirements (ML per hectare) $\overline{w}_{ijt}$ are a function of effective rainfall ER_{it} (moisture in) and evapo-transpiration ET_{it}^{0} (moisture out):

$$\overline{w}_{ijt} = \frac{1}{100} \cdot \frac{1}{\beta_{ij}^{w0}} \max\left(k_{jm}^{c} ET_{it}^{0} - ER_{it}, 0\right) \qquad (2)$$

where k_{jm}^{c} are crop and month specific coefficients and β_{ij}^{w0} is an estimated (water use efficiency) parameter. Here ER_{it} is a parametric function of actual rainfall R_{it} while both ET_{it}^{0} and R_{it} are random variables. Irrigators are required to make annual planting decisions, and monthly irrigation decisions to maximize expected profits. Annual crop areas planted L_{ijt}^{p} are constrained by the level of irrigation development, represented by $\bar{L}_{ij}$: the maximum area set-up for crop type j in region i (as estimated in Hughes et al., 2025). For perennial crops annual area is fixed $L_{ijt}^{p} = \bar{L}_{ij}$. The model allows for deficit irrigation, where water applied W_{ijt} is less than the full requirement $\overline{w}_{ijt}.L_{ijt}^{p}$ resulting in yield penalties. Note that planting decisions have a dynamic component as they depend on expectations (in the planting month) over weather, water supplies and any deficit irrigation over the rest of the crop growing season (see Appendix A.5).

In the model, profits to irrigation farmers are equal to crop production revenue, less water and planting costs:

$$\pi_{ijy} = P_{jy}^{y} \cdot y_{ijy} - \sum_{m} \left(P_{iym}^{w} + \beta_{i}^{c0}\right) W_{ijym} - \beta_{j}^{c2} L_{ijy}^{p} \left(1 + \beta^{c1} . L_{ijy}^{p} / 2\bar{L}_{ijy}\right) \qquad (3)$$

where P_{jy}^{y} is the crop output price and y_{ijy} is crop production (a quadratic function of water applied), W_{ijym} is monthly water use, P_{iym}^{w} is the water price, and β_{i}^{c0} a per unit water delivery charge. Reduced-form water demand functions (derived from the irrigation profit maximisation problem, see Hughes et al., 2025) then link area planted (i.e., $L_{ijt}^{p} \leq \bar{L}_{ij}$) and water use (i.e., $W_{ijt} \leq \overline{w}_{ijt}.L_{ijt}^{p}$) with water and crop prices, weather

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conditions and model parameters. The specific functional forms vary by crop, for details see Hughes et al., (2025) or Appendix A.5.

3.1.4 Total water demand

While irrigation remains the major water user, some surface water allocations are used for other purposes including urban needs and environmental flows. As a result of the Murray-Darling Basin Plan "Held environmental water" (consumptive water entitlements recovered for environmental flows) now represent a significant share of total allocation 'use', the order of around 20-30 per cent depending on the region.

Following Hughes et al., (2025) total use of water allocations U_{it} is defined as:

$$U_{it} = \beta_i^{u0} W_{it} + \beta_i^{u1} U_{it}^{env} + \beta_i^{u2} + \beta_i^{u3} R_{it}/\bar{R}_{im} \qquad (4)$$

where $R_{iym}/\bar{R}_{im}$ is monthly rainfall relative to the long-run monthly mean and U_{iy}^{env} is an estimate of environmental water use in region i (calibrated to historical data, see Appendix A4).

3.1.5 Equilibrium conditions

For a single month, the model can be formulated as a Mixed Complementary Problem (MCP), in which water prices are required to equalise across space and time subject to trade, carryover, supply and market clearing constraints:

$$P_t^{w*} - P_{it}^{w} \perp \tau_{it}^{l} < T_{it} < \tau_{it}^{u} \qquad (5)$$

$$P_{it}^{w} - \left(\frac{1}{1+r}\right) \mathbf{E_t}\left[\frac{\partial f^A}{\partial A_{it}} . P_{i,t+1}^{w}\right] \perp 0 < A_{it} < \bar{A}_{it} \qquad (6)$$

$$\frac{\partial f^A}{\partial A_{it}} = \begin{cases} 0 & \text{if } F_{it} > 0 \\ (1 - \alpha_{im}^{G}) & \text{otherwise} \end{cases}$$

Subject to:

$$\sum_i T_{it} = 0$$

$$A_{it}^{op} = f^A(A_{i,t-1}) + \sum_h \Delta A_{hit} - U_{it} + T_{it} - F_{it}$$

Here equilibrium in the water market in period t requires the equalisation of water prices across each region, subject to trade constraints (Eq. 5). Above P_t^{w*} refers to the 'unrestricted' water market price (effectively the price prevailing in the terminal Murray below Barmah region). Equilibrium also requires equalization of period t water prices with the expected marginal value of water in period $t+1$ (Eq. 6). Here r is the time (monthly) discount rate and $\mathbf{E_t}\left[\frac{\partial f^A}{\partial A_{it}} . P_{i,t+1}^{w}\right]$ is the expected marginal value of unused allocations A_{it} from period t in period $t+1$. The term $\frac{\partial f^A}{\partial A_{it}}$ is the marginal rate at which allocations can be transferred between time periods. This rate of

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transformation is one in most cases but goes to zero if allocation account limits are reached in the next period (as any unused water is forfeited by users).

Note that these conditions are dynamic (i.e., recursive): calculation of equilibrium prices in P_t^{w*} is dependent on expected future prices. This recursion is resolved via an iterative "learning" approach outlined in the next section.

3.2 Simulations

3.2.1 Solving the model

While a static (i.e., single period) MCP is easy to solve numerically, a dynamic stochastic problem presents some challenges. Notionally, the agents in this model (i.e., irrigation farmers) are making repeated water use-storage decisions subject to uncertainty over future climate conditions. As such, the economic model has some similarities with reservoir operation problems (see Stedinger et al., 1984): limiting current use U_{it} in-order to increase reserves A_{it} may be beneficial if future conditions are dry, but wasteful if future conditions are wet. Commonly, Stochastic Dynamic Programming (SDP) methods are applied to solve such problems, however these suffer from well known computational issues.

For this study, we follow the approach of economists Williams and Wright (1992) in solving the equilibrium conditions iteratively to resolve the recursive dynamics (similar to the methods implemented by Brennan, 2010; Hughes et al., 2023). Typically, with this approach the unknown expectations (i.e., in our case $\mathbf{E_t}\left[\frac{\partial f^A}{\partial A_{it}} . P_{i,t+1}^w\right]$) are replaced with a simple parametric approximation fit by least-squares. However, here we adopt non-parametric approximation methods from the field of Reinforcement Learning (RL) as summarised below.

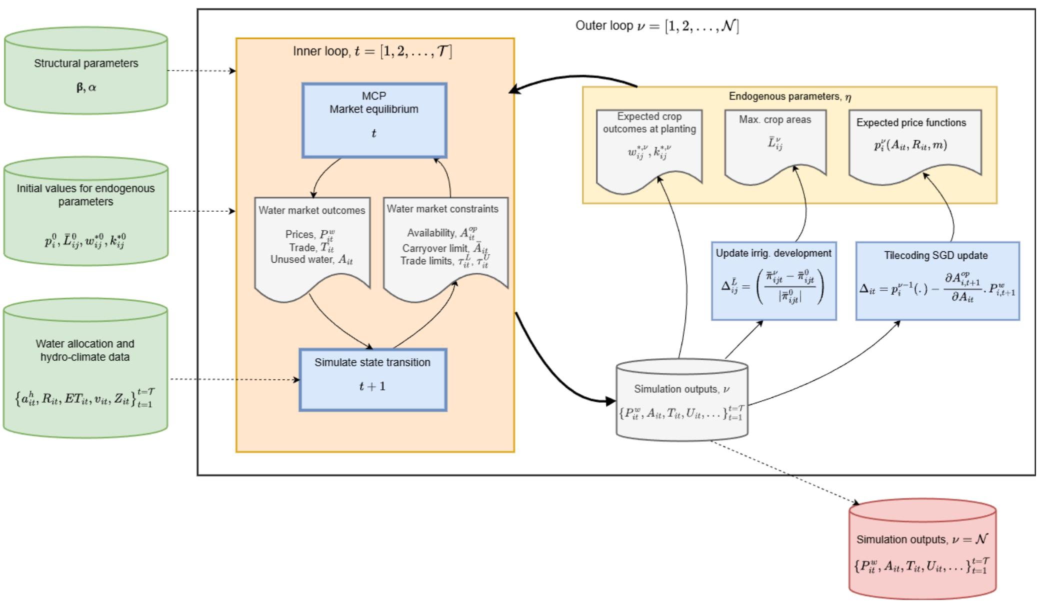

Figure 3: Solving the economic model: an iterative RL-MCP approach

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This process takes three main inputs: an extended sequence of hydro-climate data $\{a_{hit}, R_{it}, ET^0_{it}, \}_{t=0}^{T}$; fixed parameter vectors $\boldsymbol{\beta}$, $\boldsymbol{\alpha}$; and an initial approximation for the unknown expectations (i.e., some function $p_i^0(.) \approx \mathbf{E_t}\left[\frac{\partial f^A}{\partial A_{it}} . P^w_{i,t+1}\right]$) Given these inputs the problem can be solved as series of sequential MCPs, as shown in the 'Inner loop' in Figure 3.

Here expected future prices are represented by a function defined over the state variables $p_i(A_{it}, R_{it}, m)$. We employ Tilecoding a non-parametric approximation scheme drawn from the field of Reinforcement Learning (Sutton & Barto, 1998) to approximate this function. Tilecoding can be viewed as a simplistic Neural Network with discrete (binary) basis functions defined on regular grids over the input space (see Appendix B). In each iteration of the 'Outer loop' (Figure 3) the Tilecoding weights are trained on the latest batch of simulation data via Stochastic Gradient Descent (SGD) (see Appendix B). For the initial values $p_i^0(.)$ we train the tilecoding weights on historical observed data. For the model we implement a locally linear form of Tilecoding, described further in Appendix B.

This approach differs from previous studies (including Hughes et al., 2023; Brennan, 2010) in solving directly on sequences of hydro-climate data without estimating explicit state transition probabilities (a 'model free' approach in the language of Reinforcement Learning). This offers some numerical efficiencies and supports integration with hydrologic models where simulation of historical climate sequences is common practice.

While novel in the context of water markets, the general approach (i.e., use of adaptive learning to estimate rational expectations in a stochastic-dynamic market) is relatively common in other fields of economics, particularly macro-economic stochastic growth models (Den Haan & Marcet, 1990). The use of non-parametric machine learning methods in this context is also not uncommon (Heinemann, 2000).

Note that in this study, learning algorithms are used purely as numerical method to derive a rational expectations solution. While learning algorithms can have an intuitive interpretation as an approximation of real-world adaptive behaviour, we resist that leap in this study, reporting only results at the completion of the outer loop (an example of the convergence path of is presented in Appendix B.3)

3.2.2 Annual crop planting decisions

Expectations over water prices are not the only dynamic aspect of the economic model. In the irrigation water demand functions crop area planted L^p_{ijy} is also subject to recursion, as these decisions are made at planting time subject to uncertainty over weather conditions and water allocations (and hence crop revenues and costs) for the remainder of the growing season (see Appendix A.5). At each iteration of the outer loop, inputs for the crop planting decision, including expected crop water requirements and yield penalties, are also updated from the simulation data (Figure 3), although here a simple parametric (linear least squares) approximation scheme is adopted (see Appendix B.2)

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3.2.3 Long-term irrigation investment

The economic model also allows for adjustment in the level of irrigation development (including the area of perennial tree crops) in response to long-term changes in climate or commodity prices. In the model, the level of development is represented by maximum crop areas $\bar{L}_{it}$, which can be adjusted at each iteration of the simulation outer loop (Figure 3).

At each iteration, long-run average profit per hectare by region and crop is compared with to a baseline level $\bar{\pi}^{0}_{it}$ (estimated from a model scenario intended to reflect current expectations of climate conditions and commodity prices). $\bar{L}_{it}$ is then updated via the rule:

$$\bar{L}^{\nu}_{ijt} = \min\left(\bar{L}^{\nu-1}_{ijt} + \eta^{\bar{L}}\Delta^{\bar{L}}_{ij}, \bar{L}^{0}_{ijt}\right) \qquad (7)$$

$$\Delta^{\bar{L}}_{ij} = \left(\frac{\bar{\pi}^{\nu}_{ijt} - \bar{\pi}^{0}_{ijt}}{\left|\bar{\pi}^{0}_{ijt}\right|}\right), \bar{\pi}^{\nu}_{ijt} = \frac{1}{\mathcal{T}}\sum_{t=0}^{\mathcal{T}} \frac{\pi^{\nu}_{ijt}}{\bar{L}_{ij}}$$

where $\eta^{\bar{L}}$ is a learning rate parameter. This update is applied iteratively until profit levels are equal (or above) baseline levels. Note that in this study the update rule only allows for decreases in investment from baseline levels.

This approach involves several implicit assumptions. Firstly, it assumes initial (i.e., currently observed) irrigation development levels ($\bar{L}^{0}_{it}$) represent a long-run equilibrium that is sustainable under a continuation of baseline scenario conditions. Secondly, it assumes the productivity and suitability of different crops in each region remains unchanged from baseline levels (in practice temperature increases could make some horticultural crops less suitable in warmer regions, and more suitable in cooler regions). Finally, it assumes fixed irrigation capital costs per hectare, fixed commodity prices, and ignores any adjustment cost or asset life-cycle issues.

Importantly, the model generally assumes that while seasonal conditions are uncertain, the long-run climate (i.e., the mean and variance of water supply as represented by a given hydro-climate sequence) is known and stationary. As such, results for different climate scenarios (including the equilibrium levels of irrigation development) are to be interpreted as "long-term" outcomes with no attempt to account for a realistic transition path. In practice, ambiguity over climate change along with other practical constraints (i.e., adjustment costs) will limit the speed adjustment in the short to medium term (see Discussion and Conclusions).

3.3 Hydro-climate data

The climate change scenarios presented in this study draw on a hydro-climate data derived from a monthly timestep hydrological model of the southern MDB (John et al. 2025). These data are based on an ensemble of 37 CMIP6 GCM projections for the SSP5-8.5 (high-emissions) scenario. Bias-corrected rainfall and temperature change factors from the GCM ensemble (as at 2050) are applied to historic climate data for the period 1895-96 to 2021-22. These rainfall and temperature data are then used to simulate monthly catchment runoff, inflow, storage volumes and allocation percentages for the southern MDB (see John, Horne, Trail, et al., 2025). While using historical data sequences to represent climate variability, these simulations all assume contemporary levels of irrigation development, water institutions and river operating rules.

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We also highlight three additional climate scenarios, consistent with the common practice of developing a smaller number of 'bounding' scenarios (François et al., 2024). These three scenarios represent the minimum, median and maximum of the ensemble in terms of mean total water allocation volume, and are labelled: *Future (Dry)*, *Future (Medium)* and *Future (Wet)* respectively. We contrast these against the *Historical* scenario which uses historically climate observations but otherwise identical model settings (i.e., contemporary irrigation development, water institutions and river operating rules).

A summary of the hydro-climate scenario data is presented in Figure 4. Figure 4a shows the percentage change in long-run mean (water allocation volumes across the climate projection ensemble relative to a historical scenario, showing a median decline in water supply of 10.1% for total sMDB). Figure 4b shows the distribution of annual water supply for the three representative scenarios, relative to the historical scenario. Given upper limits on annual water supply, drier scenarios lead to an increase in the variance of annual allocations (i.e., more years with less than 100% allocations).

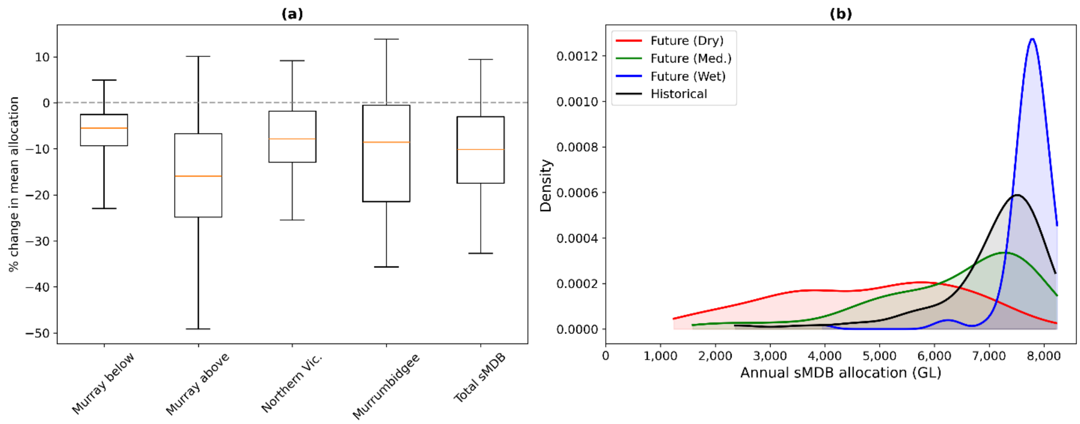

Figure 4: Hydro-climate scenarios: (a) Percentage changes in long-run mean water supply (end-of-year allocation) for the climate scenario ensemble by trading zone. (b) Distribution of annual water supply (end of year allocation) for three future climate scenarios: Future (Dry), Future (Med.) and Future (Wet) historical scenario.

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4 Results

4.1 Model validation

Validation results for the economic model are presented in Figure 5, with further detail in Appendix C.1. These scenarios, test the ability of the model to replicate observed outcomes, including monthly water market prices, and annual water use and irrigation activity over the period 2008-09 to 2021-22. For each year in this range the model is used to simulate water market and irrigation outcomes, given the estimated level of irrigation development in that year and the prevailing climate, water supply (allocations), commodity prices and opening carryover.

The accuracy of these predictions depends on three main factors: the irrigation demand models (considered separately in Hughes et al. 2025), the assumed water market constraints (water trade and carryover rules, see Appendix A.1 and A.2) and importantly, the calibration of expected market prices.

This calibration process requires an assumption over the distribution of water supply and climate conditions in the form of a specific hydro-climate sequence. This is challenging given the historical record is clearly non-stationary: being subject to a long-term drying trend related to climate change. For validation purposes we adopt a rolling 32-year climate and water supply sequence to represent of contemporary market perceptions of climate. For example, the validation results for the year 2021-22 are based on a sequence of observed climate and water supply data over the period 1990-91 to 2021-22 (which we refer to as the Baseline scenario, see Appendix B.4).

With this approach, the model can predict historical variation in water market prices and irrigation activity over-time and across regions relatively well (Figure 5, Appendix C.1). In comparison with the annual model of Hughes et al., (2023) the monthly model better reflects observed water market prices, particularly in cases where water supplies increase late in the year (i.e., after the summer cropping season has started) as occurred in 2019-20.

In general, the accuracy of the model is best over the peak summer period (November to February) and weaker during winter (May to August), which is understandable given real markets have more information available to forecast future allocations (including current storage volumes). For example, modelled prices are lower than actuals at the end of the 2018-19 water year, with real markets better anticipating the drought conditions of 2019-20. Modelled prices reach zero during the flood years of 2011 and 2012 due to binding carryover constraints in the model. Actual prices were slightly higher over this period, partly because the recently introduced spill rules in northern Victoria were ineffective during this period (see Hughes et al. 2016).

Importantly, the results suggest that water market participants believe the current climate distribution (i.e., the mean and variance of water availability) is better represented by the drier recent period than the long-term historical record (although not shown here validation scenarios based on the full historical record led to underestimation of observed market prices). Water allocations over the 1990-2022 period (the Baseline scenario) are 21% drier than the Historical (1896-2022) scenario (in terms of southern MDB mean annual water allocations)[1].

[1] Comparisons between the 32-year *Baseline* scenario and the 127-year hydro-climate scenarios are not straightforward given the hydro-climate data for the later are derived from a hydrologic simulation model (with an assumption of fixed

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This period also remains drier than a majority of the climate projection ensemble (sitting around the 19th percentile of the ensemble in terms of water allocation volumes).

The results are consistent with other evidence (see Hughes et al. 2022) suggesting Australian farmers have updated their perceptions of climate in-line with recent rainfall changes. While largely beyond the scope of this study, non-stationarity in observational data and related climate ambiguity has important implications for real-world adaptation responses (an issue considered further in the Discussion and Conclusions).

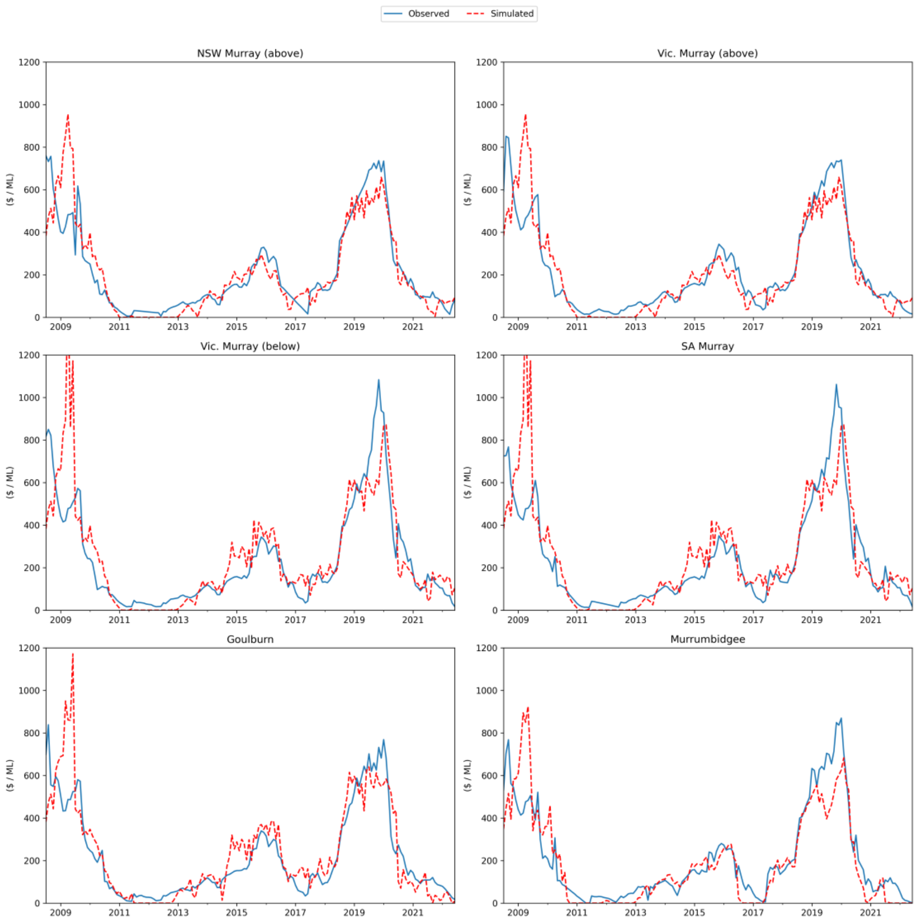

Figure 5: Simulated and observed monthly water allocation market prices P^w_{it} by region in the southern MDB, July-2009 to June 2022.

development, water accounting and operational rules) while the former are based on observed climate and allocations, see Appendix B.4. However, the differences mostly reflect drier conditions observed in recent decades (i.e., lower mean rainfall) particularly the presence of multi-year droughts including the "Millenium Drought" (A. Van Dijk et al., 2013) and the "Tinderbox drought" (Devanand et al., 2024).

4.2 Climate scenarios

Simulation results for the southern MDB climate scenarios (127-year hydro-climate sequences reflecting 2050 climate projections, see section 4.4) are summarised in Figures 6 to 8, with further detail in Appendix C2. The results show a wide range of potential outcomes due to the substantial spread in the water supply volumes across the climate ensemble. This is typical of Australian climate change impact studies, given the significant variation across climate models in future projected rainfall (particularly in south-east Australia). As discussed, most of the climate scenarios used in this paper involve water supply levels that are higher than recent experience in the region (as represented in Figure 6 by the Baseline scenario which is a model simulation based on observed hydro-climate data between 1990-91 and 2021-22).

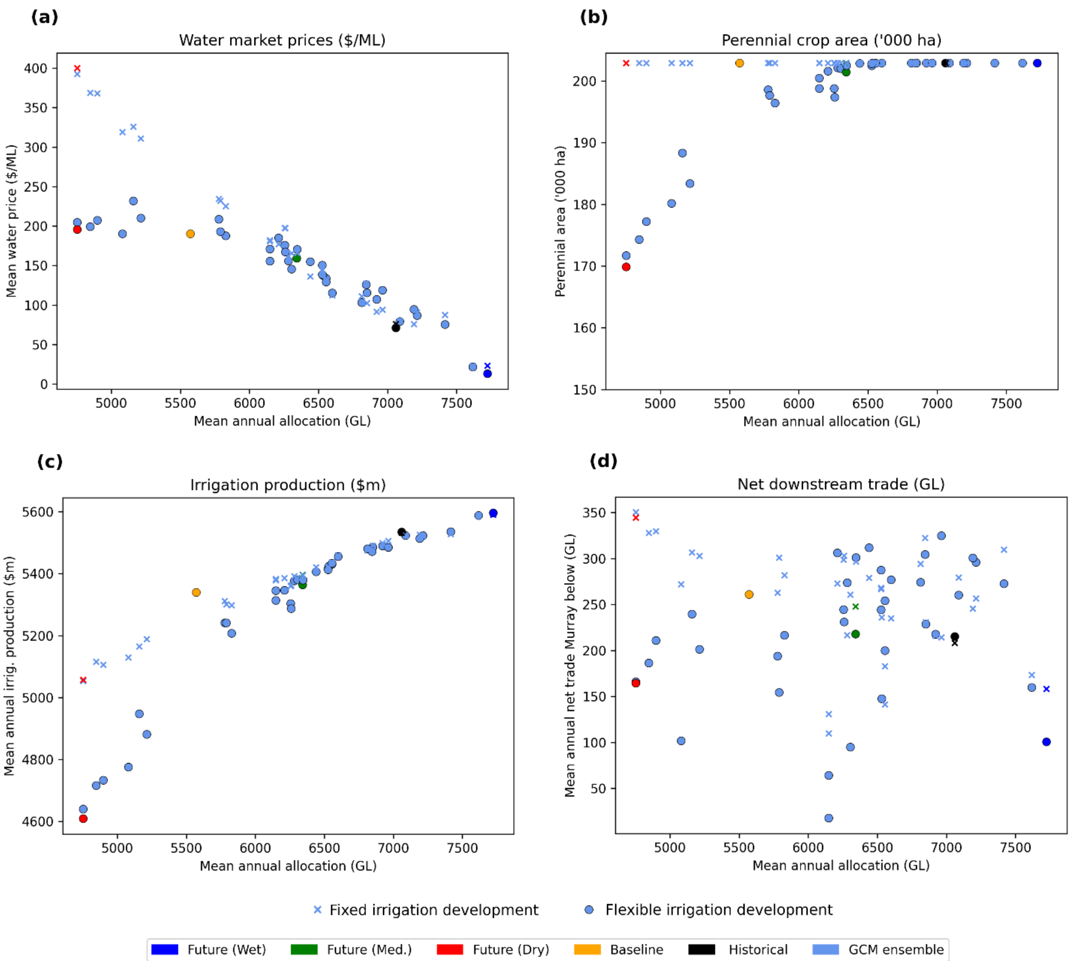

Figure 6: Climate scenario long-run mean outcomes versus long-run mean water supply for the total southern MDB, with both fixed and flexible irrigation development (a) Monthly water market prices (b) Total perennial crop area (Almonds, Grapes, Other Horticulture and Vegetables) (c) Gross value of irrigation production (revenue) (d) Net downstream water market trade (imports into the Murray below Barmah zone).

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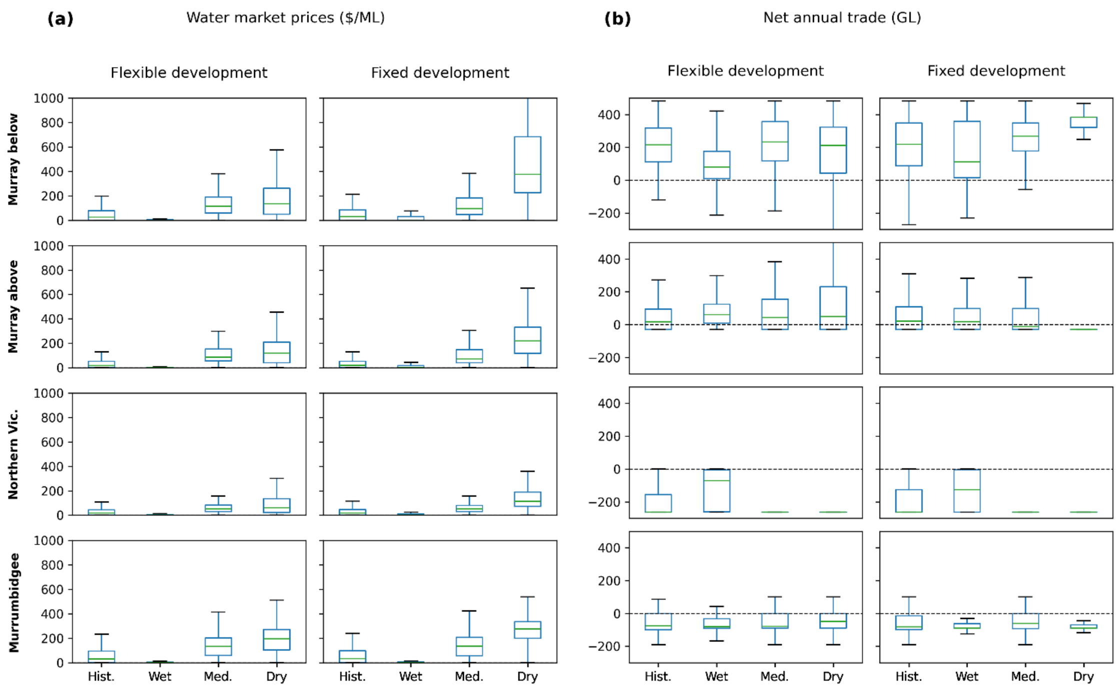

Figure 7: (a) Distribution of monthly water market prices for selected climate scenarios by trading zone ($ / ML) for selected climate scenarios. (b) Distribution of annual net trade volumes (GL) by trading zone for selected climate scenarios

While each of the climate scenarios are subject to unique and subtle changes in rainfall and temperature, including differences in spatial and seasonal patterns, most of the variation in simulated outcomes (i.e., water prices and production) can be explained by the total long-run mean water supply volume of each scenario (as shown in Figure 6a and c). This reflects the flexibility offered by water markets, where small changes in spatial or seasonal patterns of water supply can be managed through adjustments in trade flows between regions or transfers of water across time via carryover (subject to trade and carryover limits). As shown in Figure 6d water trade flows are highly sensitive to small changes in the distribution of water supply, with this flexibility in trade serving to limit variation in outcomes (i.e., water prices and production).

While markets can limit the impacts of climate change to some extent, reductions in mean supply (for a given level of irrigation development) ultimately lead to increases in water prices (Figure 6a, Figure 8a). With fixed irrigation development, the driest scenarios result in large increases in simulated water market prices, particularly in the Murray below trading zones, as shortages in dry years become pronounced impacting higher value perennial tree crops. In the *Future (Dry)* scenario water prices increase to a mean of over $500 per ML in the Murray below zone, compared to the *Historical* scenario mean of $70 (see Table C1).

Under these dry scenarios water markets literally hit their limits, with constraints on trade out of the Murrumbidgee, Goulburn, and Murray above zones (and into the Murray below) binding most of the time, leading to persistently higher prices in the Murray below zone compared with the upstream regions (Figure 8). In the

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Future (Dry) scenario (with fixed irrigation development) the Murrumbidgee trade limit is binding 64% of the time, the Goulburn limit 95% and the Murray limit 79% (compared with 35%, 49% and 41% respectively in the Historical scenario).

Water market prices in these dry scenarios, reflect an imbalance between the supply of water and the current level of irrigation development. Within the model, long-run adjustment is represented via reductions and in the level of development (by region crop type) which lower mean water prices and return irrigation profits back to Baseline levels. As shown in Figure 6, with "Flexible irrigation development" the level of development declines under drier climate scenarios, with a reduction in southern MDB perennial crops under the Future (Dry) scenario of 16% (Figure 6b), driven largely by declines in almonds and grapes in the Murray below Barmah zone (see Figure C8). In addition to lowering water market prices this long-term adjustment also alleviates pressure on inter-regional trade limits (Figure 7b).

In Figure 6 the Baseline scenario is included as a reference point, however it should be remembered that this scenario involves a different variability profile (being based on the last 32 years rather than the full 127 record). In particular, the Future scenarios tend to include more dry and wet extremes relative to the Baseline scenario. This helps to explain why Future scenarios with comparable mean supply volumes lead to slightly lower mean irrigation development and production.

While the reductions in water supply lead to declines in the value of irrigation production (Figure 6b), markets limit the impact by ensuring water is allocated to the highest value (i.e., most profitable activities) across the basin. As such, the percentage reductions in production value are smaller than the reductions in water supply (18% decline in mean production under the Future (Dry) scenario for a 35% decline in water supply). Generally, the results in Figure 6 highlight the non-linear nature of system responses to changes in water availability. This reinforces the value of producing large ensembles of projections, as non-linearities and threshold information may be less apparent when relying on a smaller number of 'bounding' scenarios.

In addition to water trade, carryover also plays an important role in supporting adaptation to climate change. Figure 8 shows the storage-utilisation curve for selected climate scenarios, comparing the annual volume of water used to the volume available (with the difference forming carryover for future years). As discussed, drier climate scenarios tend to increase the volatility of water allocations. In response users increase the proportion of available water that is stored to maintain supply reliability. Since drier scenarios involve lower mean inflows (relative to a fixed dam storage capacity) they also tend to reduce the likelihood and size of spills which further increases the benefits of carryover. As shown in Appendix C (Figure C9), this lower utilisation rate under drier climate scenarios is associated with a change in crop planting behaviour, including a significant reduction in summer crop areas planted for a given amount of water available at planting time.

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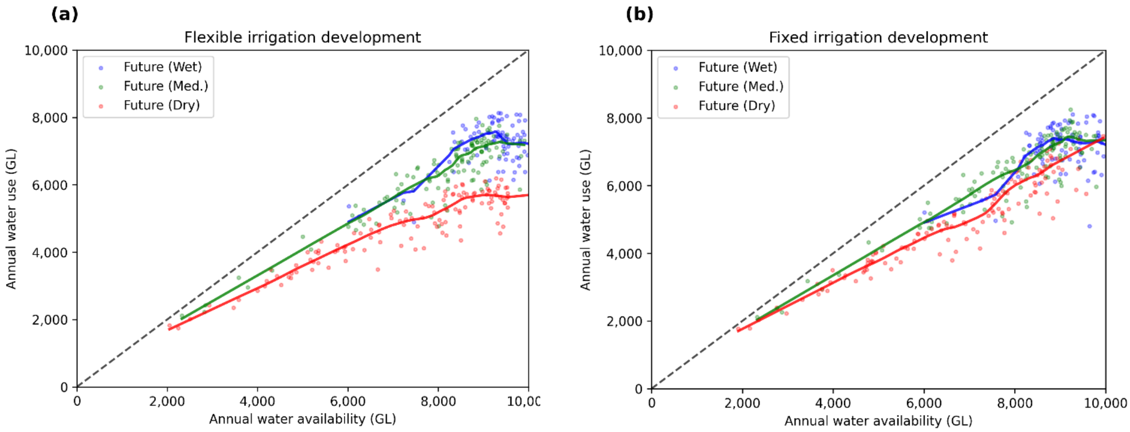

Figure 8: Simulated annual water use relative to available annual water supply (opening carryover plus annual allocations plus other water) for the total southern MDB (1896-97 to 2021-22). Scatter points represent individual years within each climate scenario sequence (a) Flexible irrigation development (b) Fixed irrigation development.

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5 Discussion and conclusions

This study presents a new monthly economic model of the Murray-Darling Basin (MDB) water market, which combines bio-physical and economic structure, with a data-driven approach to estimation and validation. The model offers two key advantages over the prior literature. Firstly, the monthly timestep, bio-physical detail and empirical performance make this model more suitable for integration with hydrological models at a basin-scale. Secondly, the model represents forward-looking dynamic behaviour, where market participants have "rational expectations" over future conditions and prices. As such, the model is suited to analysing adaptation responses to shifts in water supply and demand, including the potential impacts of climate change.

Validation results show the model can replicate observed variation in water prices and irrigation activity in the basin between 2008-09 and 2021-22 with good accuracy. Validating a dynamic model over this period is complicated by the large structural changes observed in both water demand (e.g., growth in almonds, decline in pasture, new environmental demands) and water supply (reduced rainfall and inflows). These long-term trends in water supply and demand likely led to some adjustment in the expectations of market participants over the period. To address this, the model was solved under the assumption that expectations reflect climate observations over the prior 32 years, consistent with the idea that water users implement some form of Bayesian updating (see Eisele et al., 2021; Guthrie, 2019; Hobbs, 1997).

In this study the economic model was combined with hydro-climate scenarios for the southern MDB, to simulate water market and irrigation sector outcomes under an ensemble of future climates (as at 2050 under SSP-8.5). The results demonstrate the ability of water markets to support adaptation. Under drier future climates, users adapt by increasing inter-regional water trade flows, particularly into the downstream Murray below Barmah zone, to prevent water shortages for perennial tree crops in drought years. Under drier scenarios, users also adopt more conservative crop planting and irrigation behaviour, accumulating additional carryover reserves to maintain water supply variability and limit the extent of drought shortages.

Under the most severe dry future scenarios, the ability of users and markets to adapt is more limited. Inter-regional trade flows reach their limits, leading to large differences in water prices between zones, including higher prices in the Murray below Barmah zone as drought water shortages impact tree crops. In these dry scenarios, the modelling suggests a reduction in the level of irrigation development would be required to bring water prices and irrigation profits back to sustainable levels. Under the worst-case *Future (Dry)* scenario (involving a 35 per cent reduction in long-term mean water supply, relative to the 127-year *Historical* scenario), perennial crop areas are simulated to decrease by 16 per cent and the mean value of irrigation production to decrease by 18 per cent.

While these results shed some light on the potential effects on climate change in the basin, they are subject to several limitations and uncertainties. Firstly, the prediction of long-term adjustment in irrigation investment requires strong simplifying assumptions. For example, this study does not allow for changes in crop suitability resulting from higher temperatures. Water market outcomes in dry scenarios reflect the difficulty of delivering water to high-value tree crops (e.g., almonds) in the warmer downstream regions of the Murray. However, future warmer climates could change the locations at which crops can be feasibly grown (including for

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example allowing almonds to be grown further upstream) which could alter these results. These results also only allow for decreases in irrigation development from current levels. Under wetter future climates some expansion in development might be possible (although this would be subject to complex infrastructure, land and environmental constraints).

Secondly, as with most climate impact studies of this kind, the projection ensemble involves wide range of mean supply volumes, due to uncertainty over projected rainfall. Importantly, a majority of the projection ensemble (derived from the full 127-year historical record) involve higher mean water supply and lower mean water prices than the *Baseline* period (1990-91 to 2021-22) due largely to the recent drying trend.

Non-stationarity in observational data is a general challenge in hydrological assessments of climate change (see Bayazit, 2015; Mondal & Mujumdar, 2017). In keeping with standard practices, this study measures climate change impact as the difference between two steady state scenarios in which the climate (i.e., the long run mean and variance of rainfall, temperature and water availability) is known with certainty. In reality, the climate is non-stationary and the "true" distribution unknown, such that each year of observations provides new information, an environment conducing to adaptive learning, i.e., Bayesian updating).

For example, in recent years (i.e., 2022-23 to 2025-26) above-average water supply volumes have been observed in the sMDB (at least relative to the 1990-91 to 2021-22 *Baseline* scenario presented here). During this period irrigation investment has remained strong with further expansion in perennial crops in some regions. These recent observations are entirely consistent with the results presented in this study. While extreme dry climates could require a long-term contraction in development, investors may rightly consider these scenarios unlikely over the investment horizon. Further, under uncertainty there can be value in delaying investment decisions and more generally keeping adaptation options open (see Guthrie, 2019; Pindyck, 1990). Given long investment horizons, non-trivial adjustment costs and high uncertainty (i.e., option value) irrigation adjustment to climate change is likely to be slow in practice.

Since uncertainty in projections is unlikely to be resolved in the near term, research into the impacts of extreme events could have more immediate practical value than predictions of long-term outcomes. Recent experience in the MDB has shown that extreme events play a key role in motivating and to some extent forcing adaptation. Given current levels of development, the southern Basin remains vulnerable to the effects of extreme drought, particularly droughts beyond the range of historical observation. While such events are inherently unpredictable, modelling can be used to examine how water markets can be designed to be robust to extremes.

In future, this type of policy analysis could be supported by the development of 'holistic' integrated hydro-economic models: models with two-way feedback between river systems and water markets (Brouwer & Hofkes, 2008). To date, most applied climate change impact and water policy assessments have adopted a narrow hydrological perspective (Hall & Melvold, 2025), especially in the MDB (John, Young, Nathan, et al., 2025). In contrast, integrated models would enable analysis of water policy issues involving complex interactions between hydrology and economics: including the design of water markets (e.g., trade and carryover limits), river operations, new infrastructure (e.g., water supply or water saving projects) and environmental water management (e.g., short-term environmental-irrigator trading, see Connor et al., 2013). Ultimately, this research direction would aim to progress beyond projections, offering water managers and policy makers a testing environment to design robust institutions for an uncertain future.

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Data availability

A data repository is available on Mendeley Data (DOI: 10.17632/cf5sk9n5bn.1)

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Appendix A: Additional model detail

A.1 Water account limits (carryover rules)

The function f^A governs the transfer of unused water from one period to the next:

$$f^A(A_{i,t-1}) = \min\left((1-\alpha^G_{im})A_{i,t-1}, \alpha^C_{im}\sum_h E_{ih}\right)$$

Under the annual accounting systems of the southern MDB (ACO), special limits are imposed in some regions on carryover between the final water (financial) year month of June and opening month of July (α^C_{i6} = 0.30 in the Murrumbidgee and 0.50 in the NSW Murray). In Northern Victoria there are no limits imposed on annual carryover volumes as such, however an annual loss factor is applied to reflect storage evaporation losses (α^G_{i6} = 0.05).

In addition, most regions within the MDB impose some form of account limit at all times of the year, designed to represent storage capacity constraints and related spill losses. When account limits are reached any further allocations are forfeited (via the term F_{it}). In southern NSW there is a monthly limit imposed on the sum of annual carryover and allocation (aka the 100% rule):

$$F_{it} = \sum_h \max\left(C_{iy} + a_{iht}E_{ih} - \alpha^A_{ih}E_{ih}, 0\right) - \sum_{m<t} F_{iym}$$

$$F_{it} = \sum_h \max\left(C_{iy} + a_{iht}E_{ih} - \alpha^A_{ih}, 0\right) - \sum_h \max\left(C_{iy} + a_{iht}E_{ih} - \Delta A_{hit} - \alpha^A_{ih}.E_{ih}, 0\right)$$

For the northern basin regions the model represents the NSW system of "Continuous Accounting" (CA), where the financial year transition (June-July) has no special significance, and users are able to carryover water each month subject to a fixed account limit specified as a proportion of entitlement volume, α^A_{ih}, such that forfeits are:

$$F_{it} = \max\left(A_{i,t-1} + \sum_h \Delta A_{hit} - \sum_h E_{ih}\,\alpha^A_{ih}, 0\right)$$

In Victoria carryover of water within "Allocation Bank Accounts" works similarly to continuous accounting in NSW, however any unused water more than entitlement volume is not immediately lost, being transferred to a "Spillable Water Account" (SWA) which is then only subject to forfeits in the event of physical storage spills. In the absence of any explicit hydrology, we predict spills via a simple annual statistical function calibrated to observed SWA spill forfeit data, as below (where I_{iy} refers to annual inflow):

$$F_{it} = \min\left(\max\left(A_{i,t-1} + \sum_h \Delta A_{hit} - \sum_h E_{ih}\,\alpha^A_{ih}, 0\right), Z_{it}\right)$$

$$Z_{iym} = max\left(z_{iy} - \sum_{s=7}^{m} F_{iys}, 0\right)$$

$$z_{iy} = max\left(\beta^{z0}_i + \beta^{z1}_i(A_{i,y-1,6} + \sum_h \Delta A_{hit}) + \beta^{z2}_i I_{iy} + \beta^{z3}_i(A_{i,y-1,6} + \sum_h \Delta A_{hit}).I_{iy}, 0\right)$$

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The water accounting rules vary across each region as defined by the below parameters α_{ih}^{A}, α_{ih}^{C} and α_{i}^{G}. Note that α_{ih}^{C} and α_{i}^{G} are set to zero in all months except June (as NSW and Vic. carryover limits are imposed only at the end of the financial year). Water accounting limits α_{ih}^{A} are applied consistently across all months. For SA Murray the model assumes no annual carryover. While annual carryover rules do currently exist in the region, they remain highly limited in practice and have resulted in negligible effective carryover of water in the region since being adopted.

Table A1: Water accounting parameters

		Account limit		**Carryover limit**		**Storage loss**
Region, $i \in I$	**Account type**	$\alpha_{low,i}^{A}$	$\alpha_{high,i}^{A}$	$\alpha_{low,i}^{C}$	$\alpha_{high,i}^{C}$	α_{i}^{G}
Murrumbidgee	ACO	1	1	0.30	0	0
Goulburn	SWA	1.1	1.1	0	0	0.05
NSW Murray above	ACO	1.1	1	0.50	0	0
Vic. Murray above	SWA	1.1	1.1	-	-	0.05
NSW Murray below	ACO	1.1	1	0.50	0	0
Vic. Murray below	SWA	1.1	1.1	-	-	0.05
SA Murray below	ACO	1	1	0	0	0
Lachlan	CA	2	0	-	-	0
Macquarie	CA	1	1	-	-	0
Namoi	CA	2	1	-	-	0
Gwydir	CA	1.5	1	-	-	0
NSW Border rivers	CA	1	1	-	-	0

A.2 Water trading rules (IVT limits)

The Murrumbidgee adopts a rolling monthly limit, based on the evolution of an 'Inter-valley Transfer' (IVT) account:

$$V_{it} = V_{i,t-1} - T_{i,t-1} - v_{it}$$

$$\tau_{it}^{l} = V_{it} - \alpha_{i}^{VL}, \tau_{it}^{u} = V_{it}$$

Here T_{it} is the net trade volume for region i in period t (negative values reflecting exports, positive values imports), V_{it} is the IVT account volume at the end of period t, α_{i}^{VL} the IVT account limit (100GL in the Murrumbidgee) and v_{it} are physical trade deliveries (aka IVT callouts).

The Goulburn and Barmah Choke trade rules operate slightly differently, with an IVT account that resets on an annual basis:

$$V_{it} = V'_{i,t-1} - T_{i,t-1} - v_{it}$$

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$$V'_{i,t-1} = \begin{cases} 0 & \text{if } m = 7 \\ V_{i,t-1} & \text{otherwise} \end{cases}$$

$$\tau_{it}^{l} = V_{it} - \alpha_i^{VL}, \tau_{it}^{u} = -\sum_{m \le t} T_{iym}$$

Trade limits are dependent on IVT account limits α^{VL} and α^{VL} specified below (Table A2) in GL units. Here a value of -1 implies no limit. Note that within the model (and in practice) effective limits on inter-region trade depend heavily on monthly trade opportunities / IVT 'callouts' v_{it}. Trade opportunities are dependent on hydrological factors and are therefore assumed exogenous in model simulations. The default assumptions for v_{it} are outlined in Table A3.

Table A2: Water trade parameters

Trading zone	IVT type	IVT limit α^{VL}	α^{VU}
Murrumbidgee	Rolling	100	0
Northern Vic.	Annual	0	0
Murray above	Annual	0	0
Murray below	NA	-1	-1

Table A3: IVT trade opportunities

Month	Murrumbidgee	Northern Vic.	Murray above
January	15,000	0	0
February	15,000	0	0
March	15,000	0	0
April	0	0	0
May	0	0	0
June	0	0	0
July	0	232,500	30,000
August	0	0	0
September	0	0	0
October	15,000	15,000	0
November	15,000	15,000	0
December	15,000	0	0

A.3 Other water allocations

Given historical data on all other components A_{iym}^{other} can be computed as a residual, by exploiting changes in opening carryover between years (see Hughes et al., 2023). For the simulation model, we develop a simple statistical model predicting annual A_{iy}^{other} as a function of annual allocations, entitlements and rainfall:

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$$A_{iy}^{other} = \beta^{a0} + \beta^{a1}.A_{iy}\beta^{a2}.R_{iy} + \beta^{a3}A_{iy}.R_{iy} + \beta^{a4}.\sum_h E_{ih}$$

$$A_{iy} = \sum_h \max_m \{a_{iym}\}.E_{ih}$$

Within the southern MDB regions A_{iy}^{other} primarily reflects conveyance water, which is strongly correlated with irrigation water deliveries (and therefore allocation volumes). In the northern MDB, a larger component of this other water is derived from supplementary / unregulated water licenses and is therefore more strongly correlated with current and lagged rainfall data. Annual predictions are applied pro-rata across the months of the year. Validation results for A_{iy}^{other} are provided in Appendix C.1.

A.4 Environmental water use

Historical environmental water use data is obtained from MDBA annual 'take' reports for each region over the period 2004-05 to 2020-21. A simple reduced from statistical model is estimated from this historical data, predicting environmental use as a function of held environmental water rights (entitlements and allocations) and rainfall:

$$U_{iy}^{env} = \beta^{env0}.A_{iy}^{env} + \beta^{e1}A_{iy}^{env}.R_{iy} + \beta^{e2}E_{iy}^{env} + \beta^{env3}E_{iy}^{env}.R_{i,y-1}$$

$$A_{iy}^{env} = \sum_h \max_m \{a_{iym}\}.\delta_{ihy}.E_{ih}$$

$$E_{iy}^{env} = \sum_h \delta_{ihy}.E_{ih}$$

where δ_{ihy} is the share of entitlement class h held by the environment in region i year y. In the model annual U_{iy}^{env} is applied pro-rata across the months of the year (see Hughes et al., 2025).

A.5 Water demand functions

The monthly water demand system of Hughes et al., (2025) includes two functional forms Area Deficit (AD) (quadratic land productivity) and Water Deficit (quadratic yield response). Below are the water demand functions for the WD form, which apply for almonds, grapes, cotton and pasture crops:

$$W_{ijt} = \bar{w}_{ijt}.L_{ijt}^{p}\left(1 - \frac{\bar{w}_{ijt}\left(P_{ijt}^{w} + \beta_{j}^{c0}\right)}{2.P_{jt}^{y}.\beta_{ij}^{y0}.\dot{k}_{ijt}^{s}}\right)$$

$$L_{ijt}^{p} = \bar{L}_{ijt}.\frac{1}{\beta_{ij}^{c1}\beta_{ij}^{c2}}.\left(P_{jt}^{y}\beta_{ij}^{y0}.\left(1 - k_{ij,m0}^{*}\right) - \beta_{ij}^{c2} - \left(\beta_{ij}^{c0} + P_{ij}^{w}\right).w_{ij,m0}^{*}\right)$$

$$k_{ij,m0}^{*} = \mathbf{E}_{m=m0}\left[\sum_m \dot{k}_{ijt}^{s}\left(\frac{w_{ijt}}{\bar{w}_{ijt}} - 1\right)^2\right]$$

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$$w^*_{ij,m0} = \mathbf{E}_{m=m0}\left[\sum_m w_{ijt}\right]$$

Here both crop area planted, and area irrigated are increasing in commodity (output) prices P^y_{jt}, and decreasing in water (input) prices P^w_{it}. Monthly irrigation decisions are increasing in water stress $\dot{k}^s_{ijt}$ (higher water stress reduces the gains from deficit irrigation), while crop planting decisions are decreasing in water stress (more water stress reduces the profitability of planting crops). Note that crop planting decisions are made once per year in the planting month $m0$ (October for Summer crops and April for Winter crops) subject to uncertainty over outcomes for the remainder of the cropping season. As such, area planted in year y depend on prices in the planting month: $P^w_{iy,m0}$ and expected annual water requirements and crop yield penalties at planting time: $\$w^*_{ij,m0}, k^*_{ij,m0}$. For full details see Hughes et al., (2025).

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Appendix B: Model solution methods

B.1 Tilecoding

Tilecoding function approximation scheme commonly used in reinforcement learning (Sutton & Barto, 1998). Tilecoding works by dividing the state space into a set of overlapping, rectangular regions or 'tiles', and then
770 associating a set of weights with each tile (Figure B1). The approximated function is then given by the weighted sum of the set of tiles that intersect with a given state.

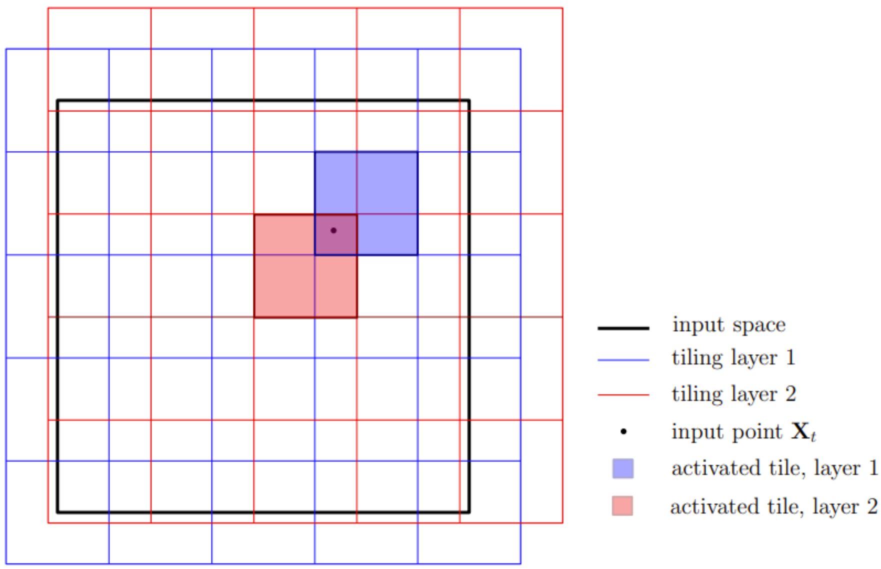

Figure B1: Simple example of Tilecoding with two input dimensions and 2 layers

In the model, we represent the expected future price of water (or more precisely the marginal returns from water
775 storage) in region i at time t via a locally linear form of Tilecoding:

$$\mathbf{E_t}\left[\frac{\partial f^A}{\partial A_{it}}.P^w_{i,t+1}\right] \approx p_i^0(\boldsymbol{X}_{it}) + p_i^0(\boldsymbol{X}_{it}).A_{it}$$

$$p_i^0(\boldsymbol{X}_{it}) = \sum_{j\in\mathcal{J}} \mathbf{1}_{j\in\mathcal{J}_t}\,\theta^0_{\mathrm{ij}}, \qquad p_i^1(\boldsymbol{X}_{it}) = \sum_{j\in\mathcal{J}} \mathbf{1}_{j\in\mathcal{J}_t}\,\theta^1_{\mathrm{ij}}$$

$$\boldsymbol{X}_{it} = \{A^{op}_{it},\ \bar{I}_{it}, m\}$$

$$A^{op}_{it} = f^A(A_{i,t-1}) + \sum_h \Delta A_{hit} - F_{it}$$

780 Here for a given region and month expected prices are linear with respect to unused water A_{it} (allowing the monthly MCP to be solved over simple parametric functions). Both the intercept and slope coefficients of this linear scheme are represented as Tilecoding functions defined over the state space $p_i(\boldsymbol{X}_{it})$. Above $\mathcal{J}_t$ is the set of

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tiles that intersect with the state $\boldsymbol{X}_{it}$, $\mathbf{1}_{j\in\mathcal{J}_t}$ is an indicator function equal to one if tile j intersects with the state and zero otherwise, and θ^0_{ij}, θ^1_{ij} are weights associated with tile j in region i (for p^0_i and p^1_i respectively). The state (input features) for each Tilecoding scheme is defined as $\{A^v_{it},\ \bar{I}_{it}, m\}$, where A^{op}_{it} is the opening availability of water allocations (before use and trade), and $\bar{I}_{it}$ is the 12 month moving average of region inflow (taken from the hydro-climate data). In the northern regions, the 12 month moving average of rainfall is used in place of $\bar{I}_{it}$.

The weights of each Tilecoding scheme are updated in each iteration of the outer loop using stochastic gradient descent:

$$\theta^0_{ij} \leftarrow \theta^0_{ij} - \eta \frac{1}{T}\sum_t \epsilon_{it}$$

$$\theta^1_{ij} \leftarrow \theta^1_{ij} - \eta \frac{1}{T}\sum_t \epsilon_{it} \, . A_{it}$$

$$\epsilon_{it} = p^{0/1}_i(A^v_{it},\ \bar{I}_{it}, m) - \frac{\partial f^A}{\partial A_{it}} . P^w_{i,t+1}$$

where η is the learning rate and ϵ_{it} is the prediction error.

B.2 Crop planting decision

As outlined in Appendix A.5 (and detailed in Hughes et al. 2025) crop planting decisions depend on expectations over future crop water requirements $w^*_{ij,m0}$ and crop stress $k^*_{ij,m0}$ penalties. When solving the model, these expectations are updated at each stage of the outer loop as simple linear function of planting time prices:

$$k^*_{ij,m0} \approx max\{\beta^{ek0}_{ij} + \beta^{ek1}_{ij} . P^w_{i,m0}, 0\}$$

$$w^*_{ij,m0} \approx max\{\beta^{ew0}_{ij} + \beta^{ew1}_{ij} . P^w_{i,m0}, 0\}$$

Here the parameters β are fit by minimising the prediction error over the latest round of simulation data:

$$min_\beta \left(\hat{k}^*_{ijt} - \max\{\beta^{ek0}_{ij} + \beta^{ek1}_{ij} . P^w_{i,m0}, 0\}\right)^2$$

$$min_\beta \left(\widehat{w}^*_{ijt} - \max\{\beta^{ew0}_{ij} + \beta^{ew1}_{ij} . P^w_{i,m0}, 0\}\right)^2$$

$$\hat{k}^*_{ijt} = \sum_m \dot{k}^s_{ijt} \left(\frac{w_{ijt}}{\bar{w}_{ijt}} - 1\right)^2$$

$$\widehat{w}^*_{ijt} = \sum_m w_{ijt}$$

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B.3 Convergence

Figures B2 and B3 below provide an example of the convergence of the learning algorithm across the outer loop.

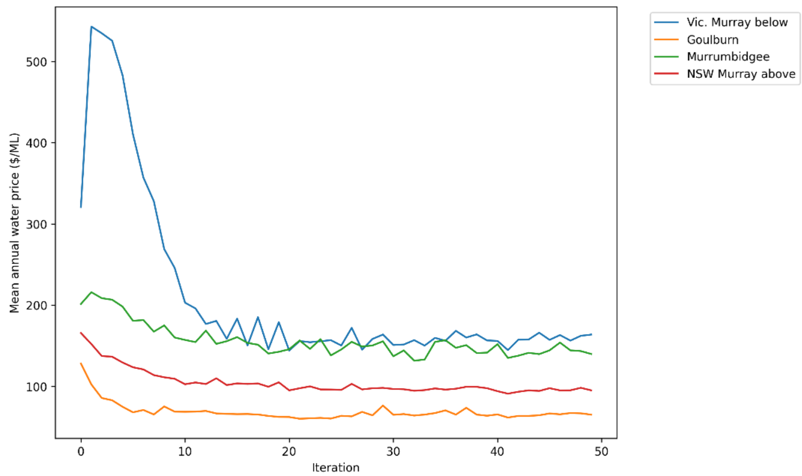

Figure B2: Evolution of mean water prices P_{it}^{w} by southern MDB region during the outer loop, *Future (Med.)* scenario with flexible irrigation development

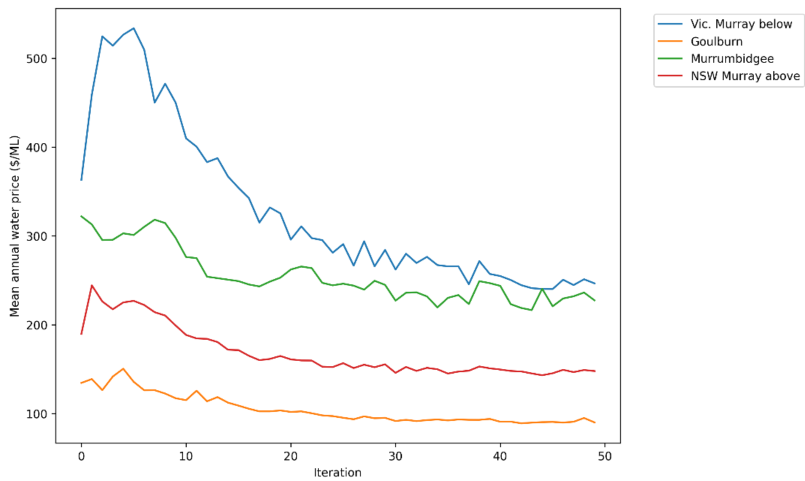

Figure B2: Evolution of mean water prices P_{it}^{w} by southern MDB region during the outer loop, *Future (Dry)* scenario with flexible irrigation development

B.4 Validation scenarios

The validation scenarios (used to derive the simulation results in Appendix C.1 and Section 4.1) involve a rolling 32-year window where results simulated for year *x* are generated from a climate and water supply sequence for the period *x - 31* to *x*. For example, the validation results for the year 2021-22 (referred to in this paper as the *Baseline* scenario) are based on a climate and water supply sequence for the period 1990-91 to 2021-22.

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Unlike the 127 hydro-climate scenarios (see Section 3.3) thesevalidation scenarios draw on historically observed climate data. Here rainfall and temperature data are based on historical monthly SILO observations. Between 2000-01 and 2021-22 allocation percentages are obtained from historical observations (collated from state government websites (see Hughes et al., 2025). For years prior to 2000-01 to 2022 synthetic observational data is derived by sampling from the 2000-01 to 2021-22 period using an analogue year approach (where analogue years are identified based on annual rainfall and lagged annual rainfall).

Validation scenarios adopt the default IVT trade opportunities (as set out in Table A.3) with some allowances made for additional trade volumes in observed in specific drought years (Murrumbidgee 3 factor increase in 2008-09, and 2 factor increase in 2020-21, Northern Vic. 30% increase in 2017-18 and 2018-19).

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Appendix C: Additional results

C.1 Validation results

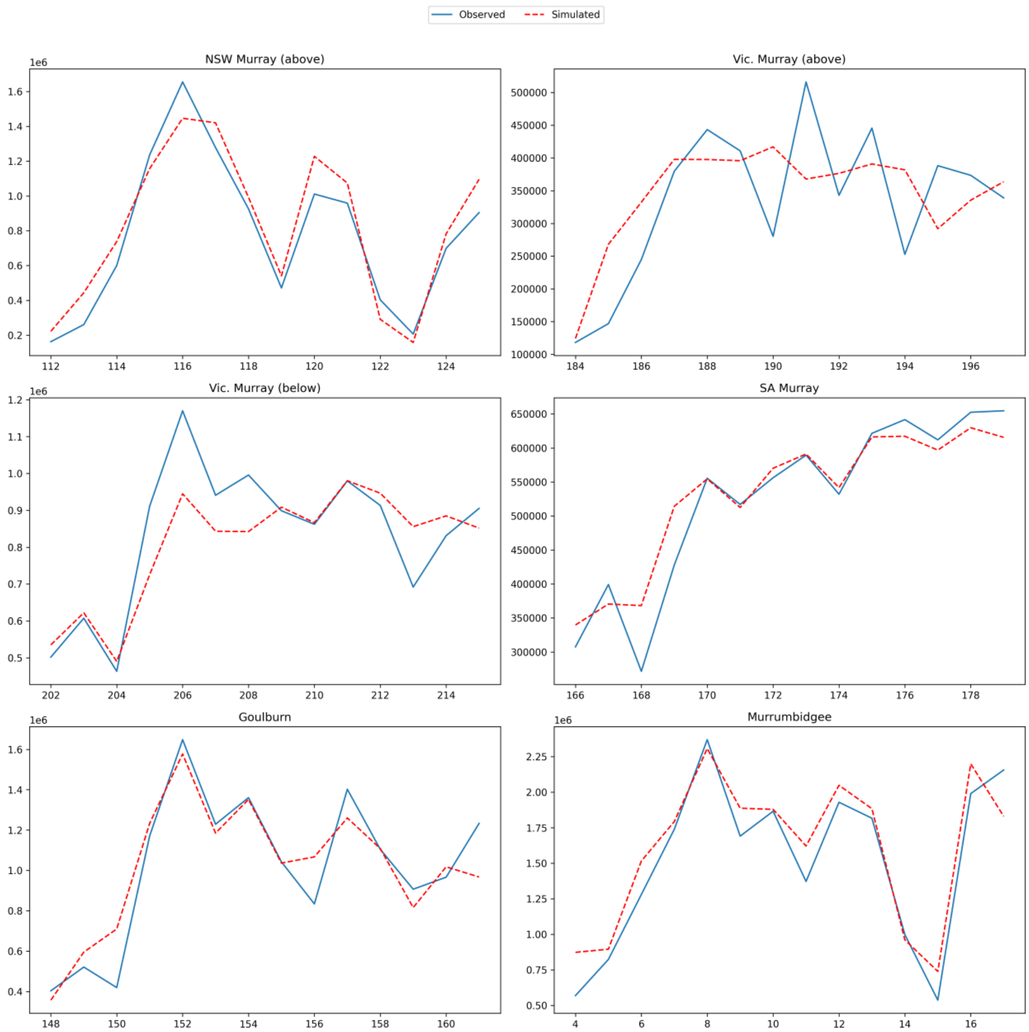

Figure C1: Simulated and observed annual water use U_{it} by southern MDB region, 2008-09 to 2021-22.

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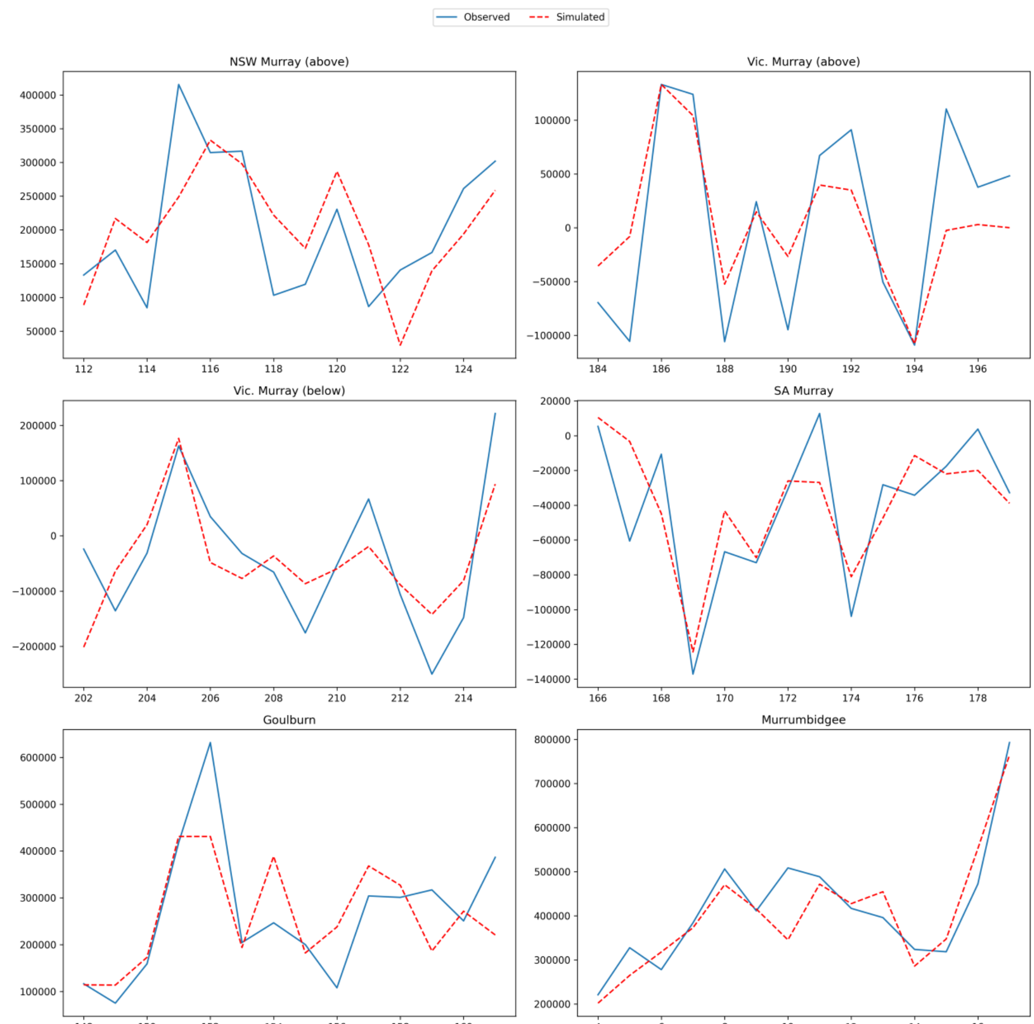

Figure C2: Simulated and observed other water supply A_{it}^{other} by southern MDB region, 2008-09 to 2021-22.

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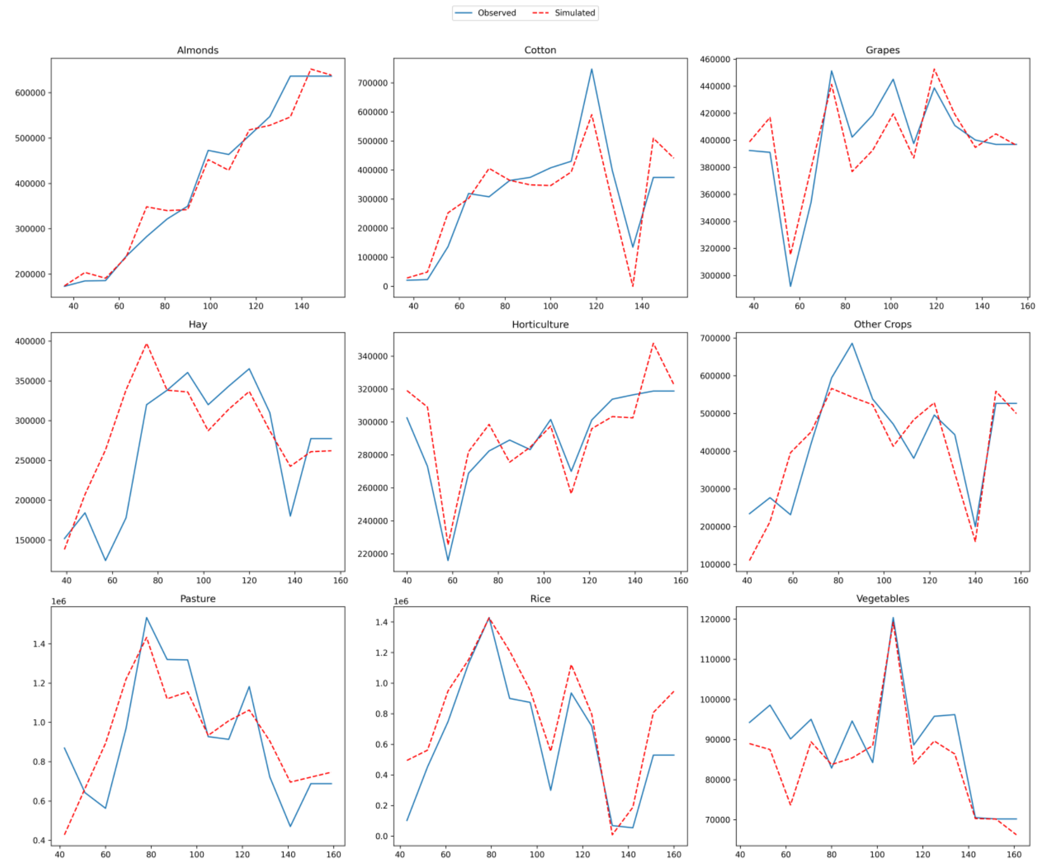

Figure C3: Simulated and observed water applied W_{ijt} by crop for the southern MDB, 2008-09 to 2021-22.

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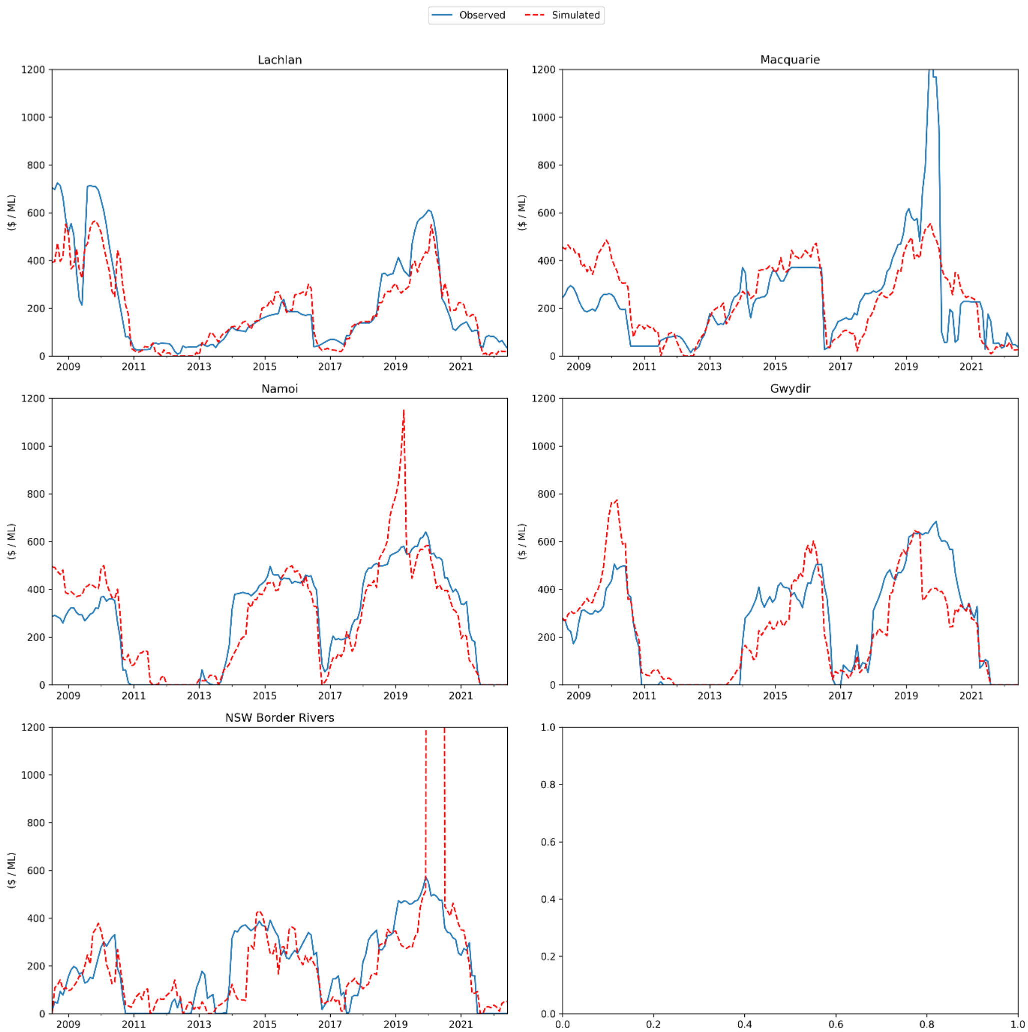

Figure C4: Simulated allocation market prices by northern MDB region, July 2009 to June 2022. Namoi, Gwydir and NSW Border Rivers "observed" series are estimated shadow prices from Hughes et al. (2025), while Macquarie and Lachlan are actual observations.

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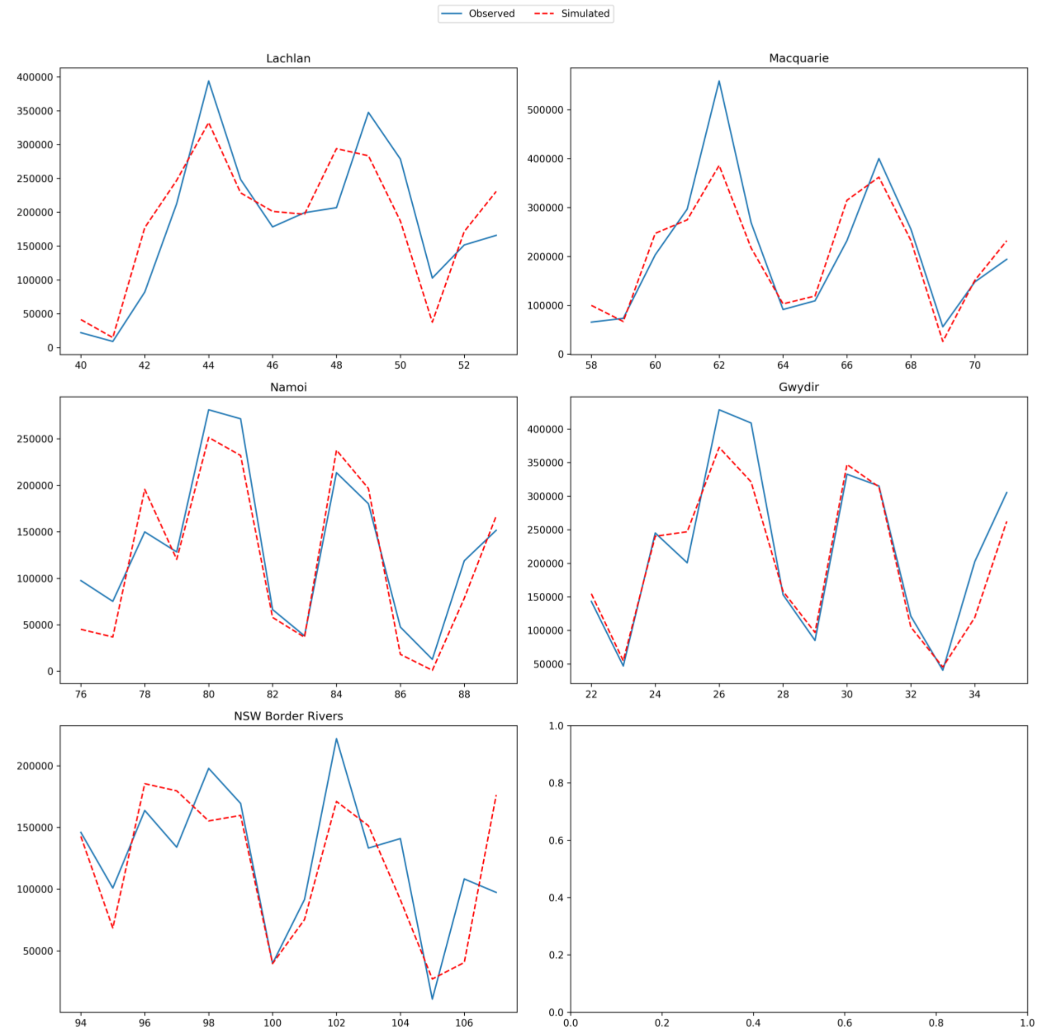

Figure C5: Simulated and observed annual water use U_{it} by northern MDB region, 2008-09 to 2021-22.

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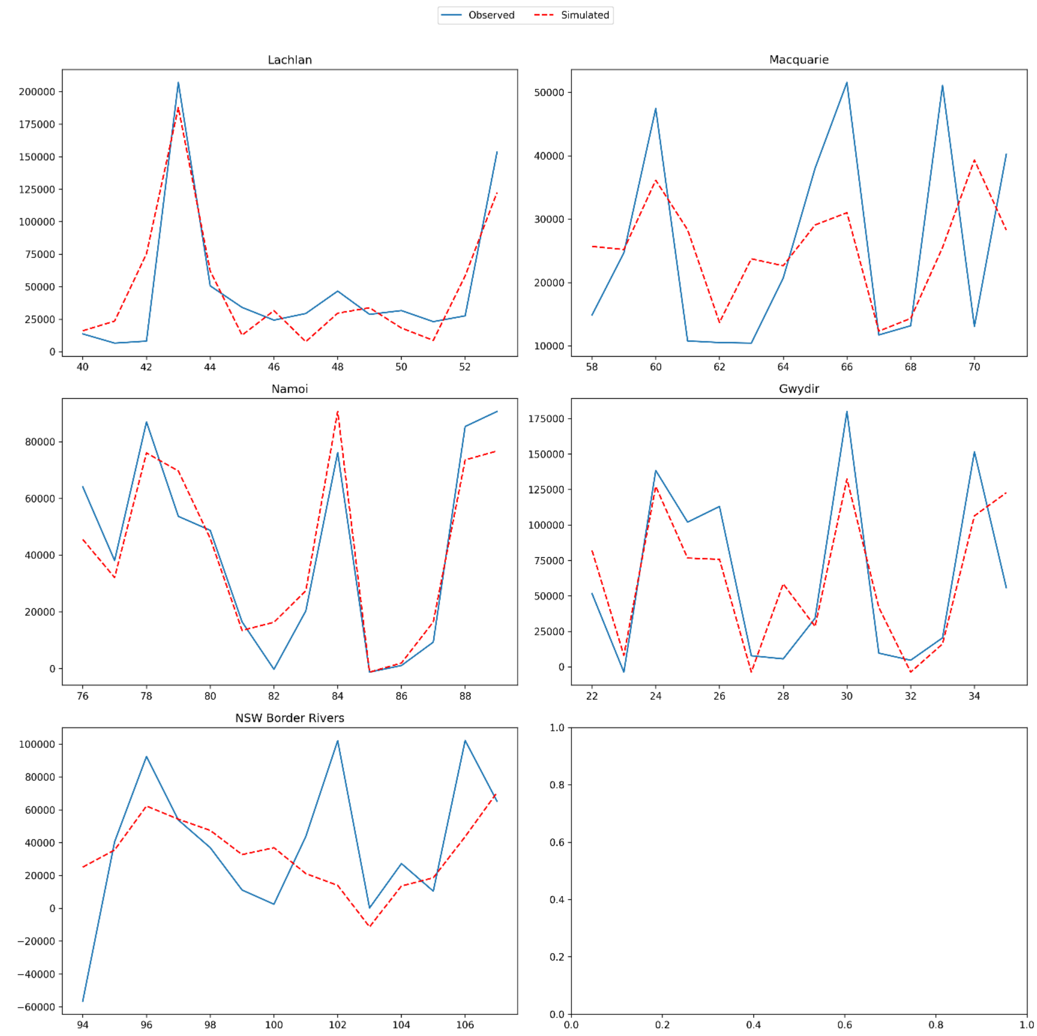

Figure C6: Simulated and observed other water supply A_{it}^{other} by northern MDB region, 2008-09 to 2021-22.

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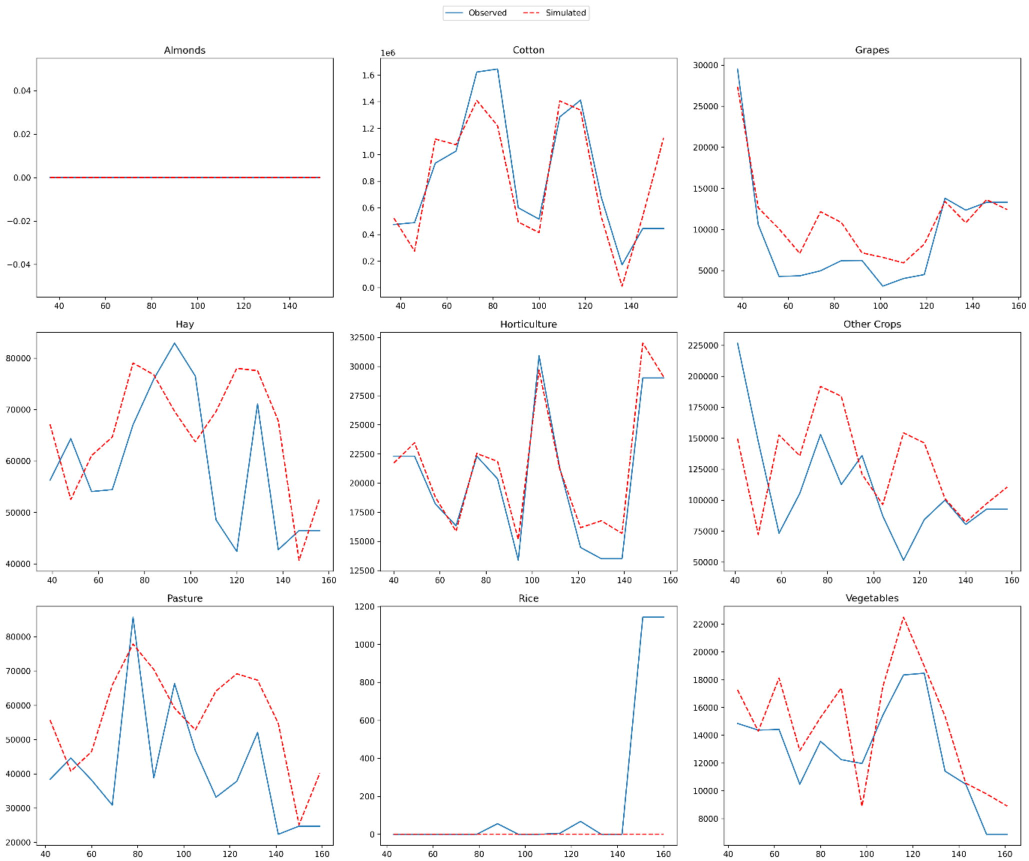

850 **Figure C7: Simulated and observed water applied W_{ijt} by crop for the northern MDB, 2008-09 to 2021-22.**

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C.2 Climate scenarios

Table C1: Mean simulated prices, trade volumes and irrigation production by climate scenario and region

Region	Flexible development				Fixed development			
	Hist.	Wet	Med.	Dry	Hist.	Wet	Med.	Dry
Mean water market prices ($ / ML)								
Murrumbidgee	64.5	25.0	123.8	188.0	64.4	26.6	122.0	259.1
Goulburn	26.3	10.9	50.0	84.5	26.1	13.0	51.2	134.7
NSW Murray (above)	37.0	12.5	85.7	140.1	37.5	12.5	87.4	243.6
NSW Murray (below)	70.2	19.1	159.6	256.1	71.0	19.9	159.6	505.5
SA Murray	70.2	19.1	159.6	256.1	71.0	19.9	159.6	505.5
Vic. Murray (above)	37.0	12.5	85.7	140.1	37.5	12.5	87.4	243.6
Vic. Murray (below)	70.2	19.1	159.6	256.1	71.0	19.9	159.6	505.5
Mean net annual trade volume (GL)								
Murrumbidgee	-54.7	-67.0	-58.4	-40.9	-54.7	-62.0	-59.2	-60.8
Goulburn	-183.6	-164.5	-245.7	-194.0	-184.5	-143.5	-241.6	-255.2
NSW Murray (above)	-85.7	-57.2	-93.0	9.5	-97.9	-94.4	-90.7	-42.1
NSW Murray (below)	34.0	9.3	63.1	6.4	38.2	-5.8	55.9	36.1
SA Murray	79.3	112.0	73.4	-2.3	75.2	112.7	77.0	26.8
Vic. Murray (above)	129.6	124.3	119.8	68.1	146.0	141.7	114.3	54.1
Vic. Murray (below)	81.1	43.2	140.8	153.2	77.7	51.4	144.4	241.1
Mean annual gross value of irrigation production ($m)								
Murrumbidgee	1450	1468	1409	1184	1450	1467	1409	1268
Goulburn	780	786	772	728	781	785	772	744
NSW Murray (above)	419	430	394	316	419	430	394	309
NSW Murray (below)	358	360	353	294	358	360	353	331
SA Murray	1164	1166	1157	1058	1164	1166	1158	1141
Vic. Murray (above)	134	135	132	117	134	135	132	123
Vic. Murray (below)	1223	1228	1209	1026	1223	1228	1210	1166

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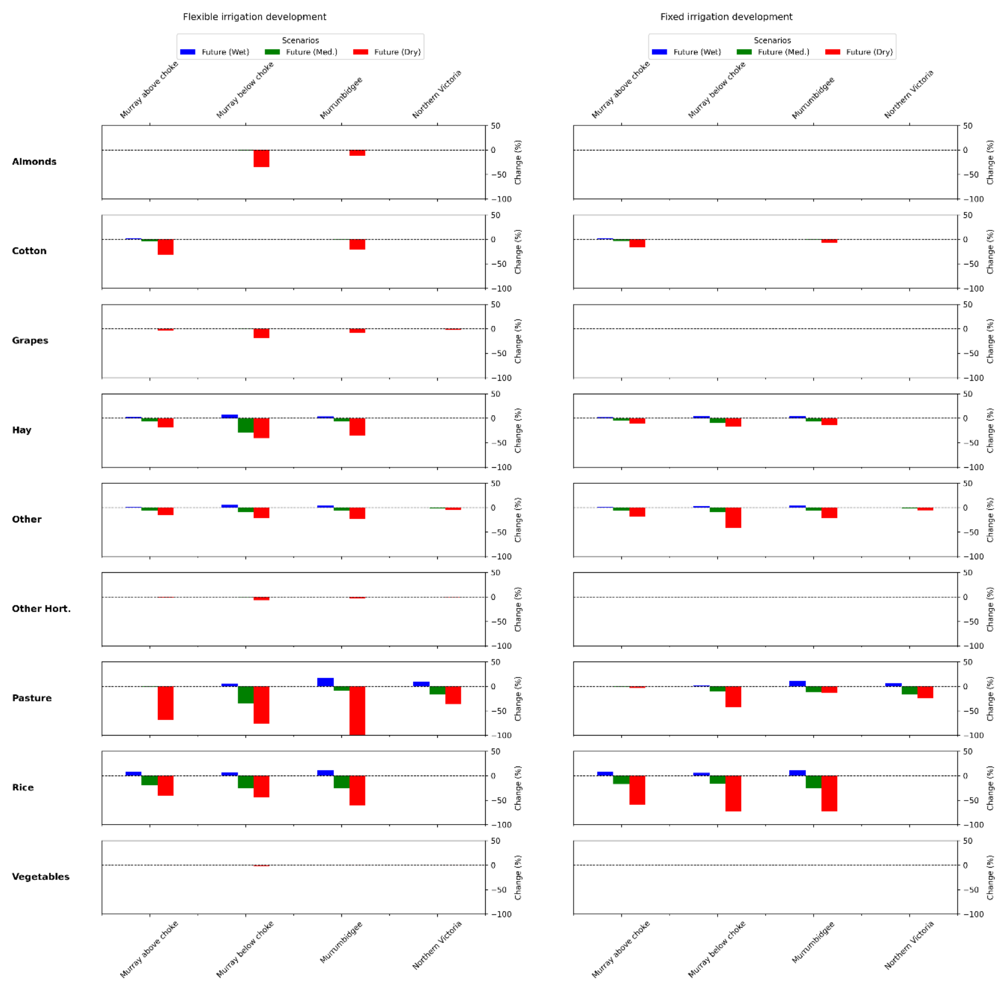

Figure C8: Percentage change in long-run mean crop area irrigated for selected climate scenarios relative to the *Historical* scenario by southern MDB trading zone, for both flexible and fixed irrigation development.

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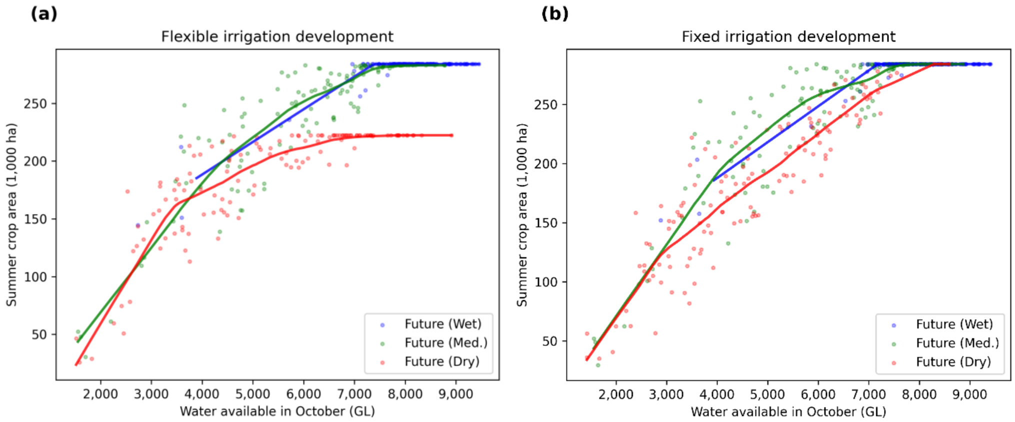

Figure C9: Simulated summer crop area planted (rice, cotton and other) versus available water in October for the total southern MDB (1896-87 to 2021-22). Scatter points represent individual years within each climate scenario (a) Flexible irrigation development (b) Fixed irrigation development.

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