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# Water Markets for Climate Change Adaptation: Trade, Storage, and Investment Under Stochastic Water Supply

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**Abstract**
It is widely accepted that water markets can support adaptation to climate change. However, quantifying this adaptive capacity is difficult as it requires models that represent both stochastic water supplies and forward-looking behaviour by market participants. We develop a stochastic dynamic model of the Murray-Darling Basin water market in which irrigators form rational expectations over future water prices, and make monthly water use, annual crop planting, and long-run investment decisions. The model is solved using reinforcement learning methods to approximate expectations, combined with mathematical programming to estimate market equilibrium. We validate the model against observed prices and irrigation activity from 2008 to 09 to 2021–22 and apply it to an ensemble of 37 CMIP6 climate projections for the southern Basin. Under drier future climates, water markets support adaptation through increased inter-regional trade flows into the downstream Murray, and larger storage reserves through more conservative crop planting. However, under the driest projections, inter-regional trade constraints bind, price differences widen across zones, and long-run irrigation development contracts by up to 16 per cent. The results highlight both the value and the limits of market-based adaptation, with implications for the design of water market institutions under a non-stationary climate.

**Keywords** Water markets · Climate change · Murray-Darling Basin · Hydro-economic modelling · Rational expectations · Reinforcement learning

## 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. 2011; Young and McColl

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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 and 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 and 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).

These reductions in water availability have led to a range of adaptations including: improvements in technology (e.g., more efficient irrigation infrastructure) (Connor et al. 2014; Hughes et al. 2023) and changes in irrigation development (i.e., less pasture in the upper Murray, and more almonds in the lower Murray, see Zeleke and 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 and Luckett 2025).

Both within the MDB and internationally there is growing interest in understanding how water markets can be designed to support adaptation to future climate change (Bruno and Jessoe 2024). While there exists a large body of empirical research documenting successful water markets globally (Brennan 2006; Grafton et al. 2011; Easter and Huang 2014) this work cannot easily predict how markets might perform under future climate conditions outside the range of historical experience.

This paper develops a dynamic stochastic equilibrium model of the MDB water market that can simulate how trade, storage and investment respond to long-run shifts in climate. The model represents forward-looking irrigators making monthly water use, annual crop planting and long-run investment decisions who have "rational expectations" over future conditions and water prices.

To date, most model-based assessments of climate change in the MDB have relied largely on hydro-climate modelling (CSIRO 2008; Potter and Srikanthan 2008; Van Dijk et al. 2008), where catchment and river process models are used to simulate changes in streamflow and water supply under projected climate. While these models represent physical processes with high spatial and temporal resolution (i.e., daily), they adopt a simplistic static representation of water users and markets (based on historical observation) which understates the potential for adaptation.

Economic models of water markets have also been applied in the literature to simulate climate change in the basin (e.g., Jiang and Grafton 2012; Adamson et al. 2009; Goesch et al. 2009; Connor et al. 2009), however these studies have generally received less attention from policy makers and water agencies. This may be due to the more abstract nature of economic models, particularly their coarser spatial and temporal resolution. For example, Jiang and Grafton (2012), Adamson et al. (2009) and Goesch et al. (2009) each apply annual time-step models to simulate climate change (with Goesch et al. 2009 and Jiang and Grafton 2012 taking CSIRO 2008 water supply changes as inputs). While demonstrating the value of water trade as an adaptation, these models struggle to represent key features of real-world

water markets including seasonal effects (i.e., shortages during peak summer periods) and inter-regional trade constraints (see Hughes et al. 2023).

Commonly, water market models have also tended to ignore inter-temporal concerns, particularly storage dynamics, focusing instead on the trade of fixed water supplies across regions and sectors (via linear and non-linear programming methods). In studies where storage dynamics are modelled explicitly (via Stochastic Dynamic Programming and related methods, see Brennan 2010; Dudley 1988; Ahmad et al. 2014) markets are typically not represented. Hughes et al. (2023) presented an annual model of the southern MDB which represents both inter-regional trading and inter-temporal 'carryover' (storage). However, as with other economic models (including Connor et al. 2009; Qureshi et al. 2013 and Kirby 2014) Hughes et al. (2023) relies on reduced-form statistical relationships linking water supply with market prices. This backward-looking approach is not ideal for long-term climate scenarios where irrigation behaviour, investment and water demand are likely to vary from historical observation (see Connor et al. 2009).

The model presented here represents both spatial water markets and inter-temporal decision making on a monthly basis, 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, we employ numerical methods from Reinforcement Learning to approximate user expectations over future water market prices. Our model draws on a recently developed bio-economic water demand system (presented in Hughes et al. 2026) involving a system of structural equations representing production technology and bio-physical processes.

We apply this monthly model to simulate potential water market and irrigation sector responses to climate change in the southern MDB, using an ensemble of climate and water supply scenarios derived from a purpose built linked hydro-climate model (Hughes et al. 2026). This combination of economic and hydrologic models places our study within the wider literature on integrated Hydro-Economic Modelling (HEM) (Brouwer and 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). A key difference is that our model is dynamic, in the sense that water users make forward-looking decisions subject to uncertainty over stochastic water supplies, allowing it to better capture adaptation responses to shifts in the long-run climate distribution.

Watto et al. (2026) provide a timely review of HEM research relating to climate change in the MDB between 2000 and 2025. Our study helps address two key limitations of existing research identified by Watto et al. (2026): the need for better treatment of uncertainty through the simulation of large climate ensembles, and a more realistic representation of irrigation behaviour and adaptation dynamics (Watto et al. 2026, p. 14).

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.

## 2 Methods

### 2.1 Study Region: 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 (Fig. 1)—accounts for around three quarters of agricultural water use in the MDB, and around half of national agricultural use.

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 and

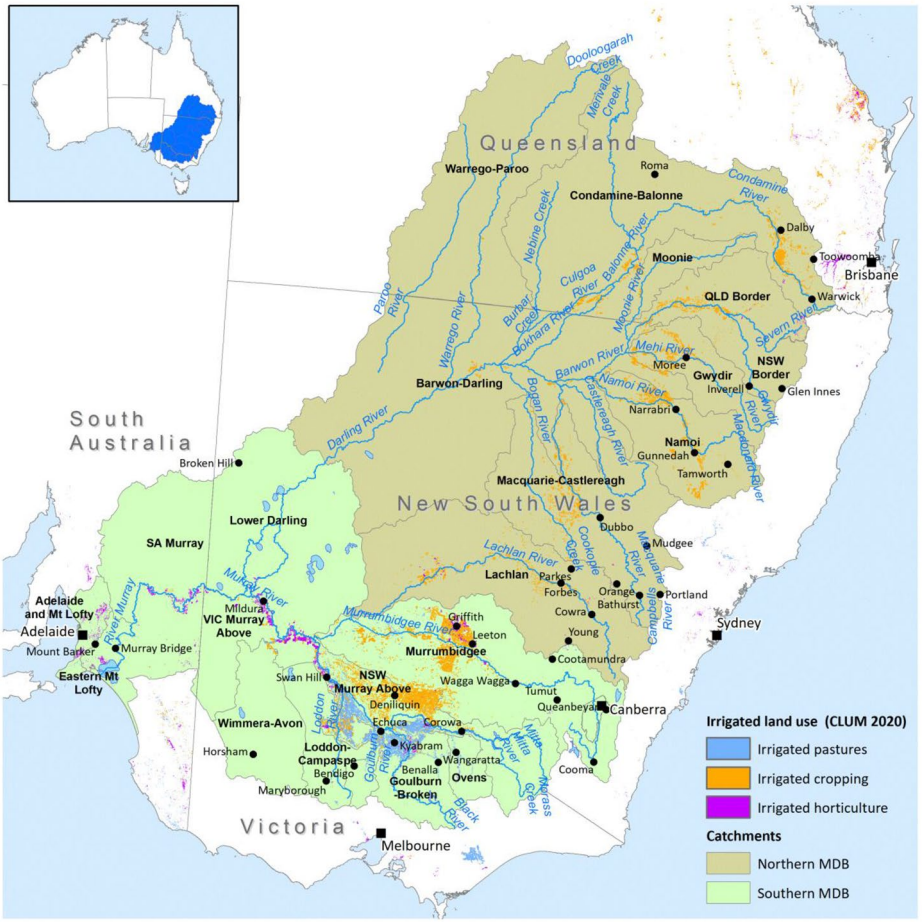



**Fig. 1** The Murray–Darling Basin. Source: Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES): Catchment Scale Land Use of Australia (CLUM): https://www.agriculture.gov.au/abares/aclump/catchment-scale-land-use-of-australia-update-december-2020

irrigated pasture in northern Victoria (e.g., Goulburn-Broken, Loddon, Campaspe) and rice and cotton in NSW (Murray and Murrumbidgee, see Fig. 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 and 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 specific source) which receive annual water "allocations" (water available for use within the current year). Allocations are determined by water authorities to reflect prevailing water availability (i.e., dam storage volumes).

Another key feature of the MDB is carryover (see Brennan 2010; Hughes et al. 2023), which allows 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 (see Hughes et al. 2013). 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 (see Hughes et al. 2013). However, the annual water allocations held by end users remain relatively homogenous, such that trade across state borders can occur with low transaction costs.

### 2.2 The Economic Model

Figure 2 provides an overview of the 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, and simulates monthly irrigation and water allocation market outcomes (Fig. 2a). The model involves three main components: a representation of *water accounting* systems, a model of *irrigation production* and a model of *water market equilibrium* (Fig. 2a). The water accounting system represents the key trade and water account / carryover rules operating within each of the MDB regions, which determine the volumes of water allocations available for use in each region and month. The market model represents both spatial and temporal equilibrium in the water allocation market, allowing for trade of water allocations between regions and carryover of unused water between time periods. The demand side involves a detailed representation of irrigated agriculture, including crop production, revenue, costs and profits (drawing on Hughes et al. 2026).

The spatial structure of the model is summarised in Fig. 2b. The model includes seven southern MDB regions and five northern MDB regions (Fig. 2b). Consistent with existing

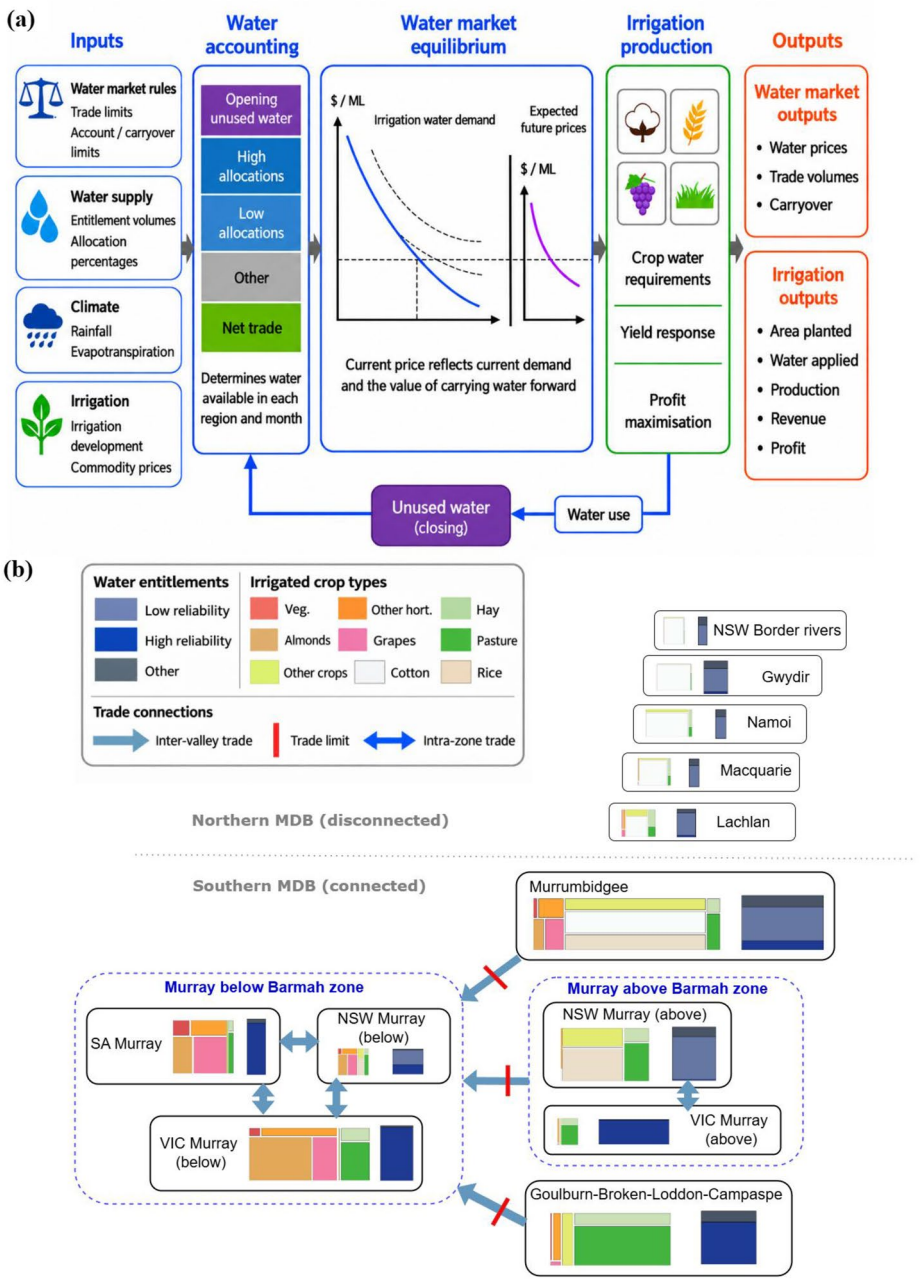



**Fig. 2** Overview of the economic water market model (**a**) Stylised representation of the model for a single region, including input data, model processes (water accounting, irrigation production and water markets) and model outputs. (**b**) Spatial overview of the model including allowable inter-region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

MDB trading rules, inter-regional water trade is allowed in the "connected" southern MDB, but not among the "disconnected" northern MDB regions. Trade within the southern MDB occurs across four main "trading zones" (Murray above, Murray below, Murrumbidgee, Goulburn) with trade between zones subject to specific volumetric limits. Data sources for the model are outlined in Appendix A.1.

### 2.2.1 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 the end of period $t$ (i.e., unused water) evolves according to:

$$A_{it} = f^{A}\left(A_{i,t-1}\right) + \sum_{h} \Delta A_{hit} - U_{it} + T_{it} - F_{it} \tag{1}$$

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

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

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

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

where $\Delta A_{iht}$ are new allocation volumes made available in period $t$ (implicitly reflecting inflows into storages), $U_{it}$ is allocation use, $T_{it}$ is net inter-regional 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.

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 A.2.

The model includes four trading zones in the southern MDB (see Fig. 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. Trade within these zones is unconstrained but trade between zones is subject to volumetric limits: $\tau^{u}_{it}$, $\tau^{l}_{it}$. These "Inter-valley Transfer" (IVT) limits evolve over time in response to accumulated trade volumes and physical river flows, with specific accounting rules applied in each case (see Appendix A.3). In general, upstream inter-regional trade is only possible where it offsets other downstream flows (referred to as "back-trade"; Fig. 2b).

Finally, the term $A^{other}_{it}$ reflects volumes of water available against other surface water rights not explicitly represented in the model, including conveyance losses and urban water (see Appendix A.4).

### 2.2.2 Irrigation Water Demand

The demand side of the economic model is based on the monthly bio-economic water demand system discussed in detail in Hughes et al. (2026). This system represents 12 irrigation activities $j \in J$ in each region including perennial crops (Almonds, Grapes, Vegetables and Other horticulture), summer crops (rice and cotton), winter and perennial crops (hay and pasture), and other winter and summer crops. The model also includes a simplistic representation of environmental water demands based on historical observation (see Sect. 2.2.3 and Appendix A.5).

The parameters of the water demand system $\boldsymbol{\beta}_{ijt}$ are estimated from historical data from a variety of sources over the period 2004-05 to 2021-22 (Hughes et al. 2026). The parameters vary over time in line with observed technological trends (e.g., water use efficiency, irrigation development). The values applied here are based on the 2021-22 estimates.

A brief summary of the irrigation water demand models is provided below (for a complete description see Hughes et al. 2026). The demand model adopts a crop water balance equation in which monthly crop irrigation requirements (ML per hectare) $\bar{w}_{ijt}$ are a function of effective rainfall $ER_{it}$ (moisture in) and evapo-transpiration $ET^{0}_{it}$ (moisture out):

$$\bar{w}_{ijt} \propto \frac{1}{\beta^{w0}_{ij}} \max\left(k^{c}_{jm} ET^{0}_{it} - ER_{it}, 0\right) \tag{2}$$

where $k^{c}_{jm}$ are crop- and month-specific coefficients and $\beta^{w0}_{ij}$ is an estimated (water use efficiency) parameter. Irrigators are required to make annual planting decisions, and monthly watering decisions to maximize expected profits. Annual crop areas planted $L^{p}_{ijt}$ 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. 2026). For perennial crops annual area is fixed $L^{p}_{ijt} = \bar{L}_{ij}$. The model allows for deficit irrigation, where water applied $W_{ijt}$ is less than the full requirement $\bar{w}_{ijt}.L^{p}_{ijt}$ 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.6).

In the model, profits to irrigation farmers are equal to crop production revenue, less water and planting costs (reflecting costs of all other inputs associated with planting):

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

where $P^{y}_{jy}$ is the crop output price and $y_{ijy}$ is crop production (a quadratic function of water applied), $W_{ijym}$ is monthly water use, $P^{w}_{iym}$ is the water price, and $\beta^{c0}_{i}$ a per unit water delivery charge, while the term $\beta^{c2}_{j}L^{p}_{ijy}\left(1 + \beta^{c1}.L^{p}_{ijy}/2\bar{L}_{ijy}\right)$ reflects calibrated quadratic crop planting costs (see Hughes et al. 2026). Reduced-form water demand functions (derived from the irrigation profit maximisation problem, see Hughes et al. 2026) then link area planted (i.e., $L^{p}_{ijt} \leq \overset{?}{L}_{ij}$) and water use (i.e., $W_{ijt} \leq \bar{w}_{ijt}.L^{p}_{ijt}$) with water and crop prices, weather conditions and model parameters. The specific functional forms vary by crop, for details see Hughes et al. 2026 or Appendix A.6.

### 2.2.3 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 recent environmental reforms (see Hart 2016) "Held environmental water" (consumptive water entitlements recovered for environmental flows) now represents a significant share of total allocation 'use', the order of around 20–30 per cent depending on the region.

Following Hughes et al. (2026) total use of water allocations $U_{it}$ is defined as:

$$U_{it} = \beta^{u0}_{i}W_{it} + \beta^{u1}_{i}U^{env}_{it} + \beta^{u2}_{i} + \beta^{u3}_{i}R_{it}/\tilde{R}_{im} \quad (4)$$

where $R_{iym}/\tilde{R}_{im}$ is monthly rainfall relative to the long-run monthly mean and $U^{env}_{iy}$ is an estimate of environmental water use in region $i$ (and $\beta$ are parameters calibrated to historical data, see Appendix A.5).

### 2.2.4 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:

$$P^{w*}_{t} - P^{w}_{it} \perp \tau^{l}_{it} < T_{it} < \tau^{u}_{it} \quad (5)$$

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

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

.

Subject to:

$$\sum {}_{i} T_{it} = 0$$

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

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 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.

### 2.3 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 (1991) 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.

This process takes three main inputs: an extended sequence of hydro-climate data $\left\{a_{hit}, R_{it}, ET_{it}^{0}, \right\}_{t=0}^{\mathcal{T}}$; fixed parameter vectors $\beta$, $\alpha$; and an initial approximation for the unknown expectations (i.e., some function $p_i^0(.) \approx \mathbf{E_t}\left[\frac{\partial f^A}{\partial A_{it}}.P_{i,t+1}^{w}\right]$) Given these inputs the problem can be solved as a series of sequential MCPs, as shown in the 'Inner loop' in Fig. 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 and 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.1). In each iteration of the 'Outer loop' (Fig. 3) the Tilecoding weights are trained on the latest batch of simulation data via Stochastic Gradient Descent (SGD) (see Appendix B.1). For the initial values $p_i^0(.)$ we train the tilecoding weights on historical observed data. In the model, we implement a locally linear form of Tilecoding, described further in Appendix B.1.

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 and Marcet 1990). The use of non-parametric machine learning methods in this context is also not uncommon (Heinemann 2000).

Note that in this study, these learning algorithms are used purely as a numerical method to derive a rational expectations solution for the model. While learning algorithms can have an intuitive interpretation as an approximation of real-world adaptive behaviour, we resist that leap here, reporting only results at the completion of the outer loop (an example of the convergence path is presented in Appendix B.2).

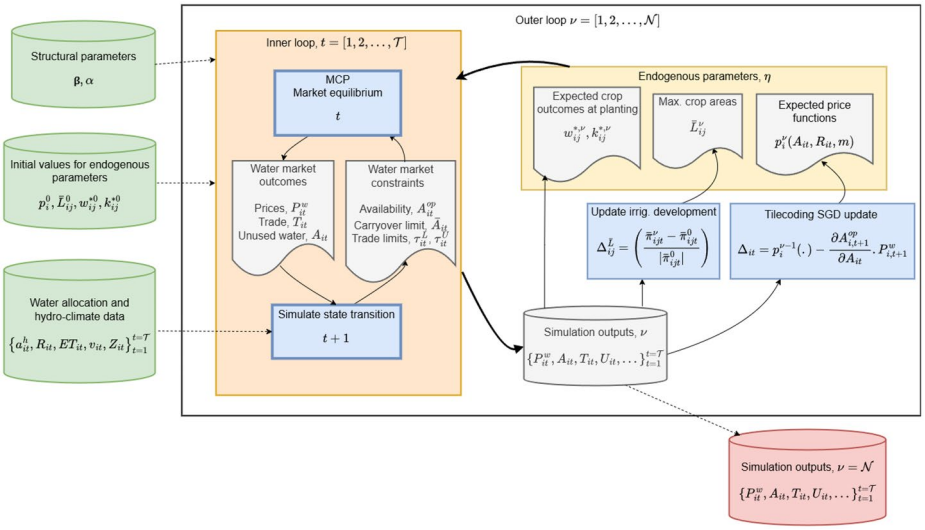



**Fig. 3** Solving the economic model: an iterative RL-MCP approach

### 2.3.1 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.6). 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 (Fig. 3), although here a simple parametric (linear least squares) approximation scheme is adopted (see Appendix B.3).

### 2.3.2 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 $\overleftarrow{L}_{it}$, which can be adjusted at each iteration of the simulation outer loop (Fig. 3).

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

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

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

where $\eta^{\overleftarrow{L}}$ 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 $\left(\overleftarrow{L}^{o}_{it}\right)$ 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 of adjustment in the short to medium term (see Discussion and Conclusions).

### 2.3.3 Hydro-Climate Data

The climate change scenarios draw on hydro-climate data derived from a monthly timestep hydrological model of the southern MDB (John et al. 2026). These data are based on an ensemble of 37 Coupled Model Intercomparison Project Phase 6 (CMIP6) General Circulation Model (GCM) projections for the Shared Socioeconomic Pathway 5-8.5 (SSP5-8.5; i.e., 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. While using historical data sequences to represent climate variability, these simulations all assume contemporary levels of irrigation development, water institutions and river operating rules.

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 Fig. 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

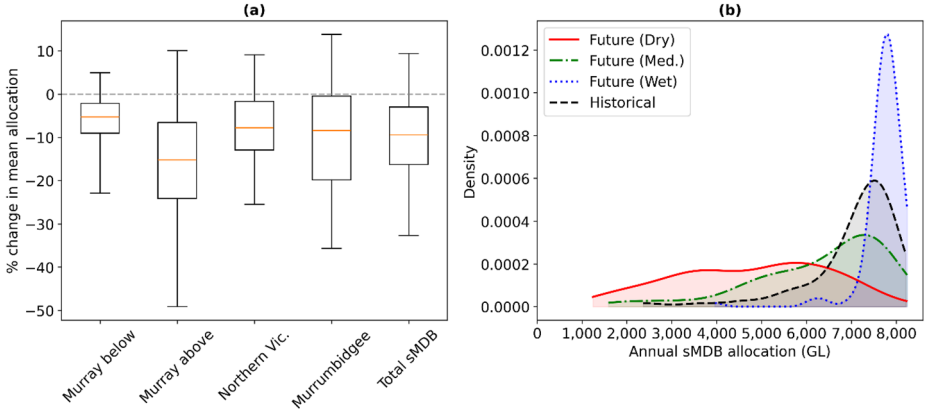



**Fig. 4** Hydro-climate scenarios: (**a**) Percentage changes in long-run mean water supply (end-of-year allocation) for the climate scenario ensemble by trading zone. (**b**) Distribution of annual water supply (end of year allocation) for three future climate scenarios: Future (Dry), Future (Med.)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

of 10.1% for the total sMDB. Figure 4b shows the distribution of annual water supply for the three representative scenarios and the historical scenario. Drier scenarios are associated with both lower mean allocations and higher variance. Wetter scenarios lead to a very high frequency of full supply years (i.e., 100% storages and allocations).

## 3 Results

### 3.1 Model Validation

Validation results for the economic model are presented in Fig. 5. 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

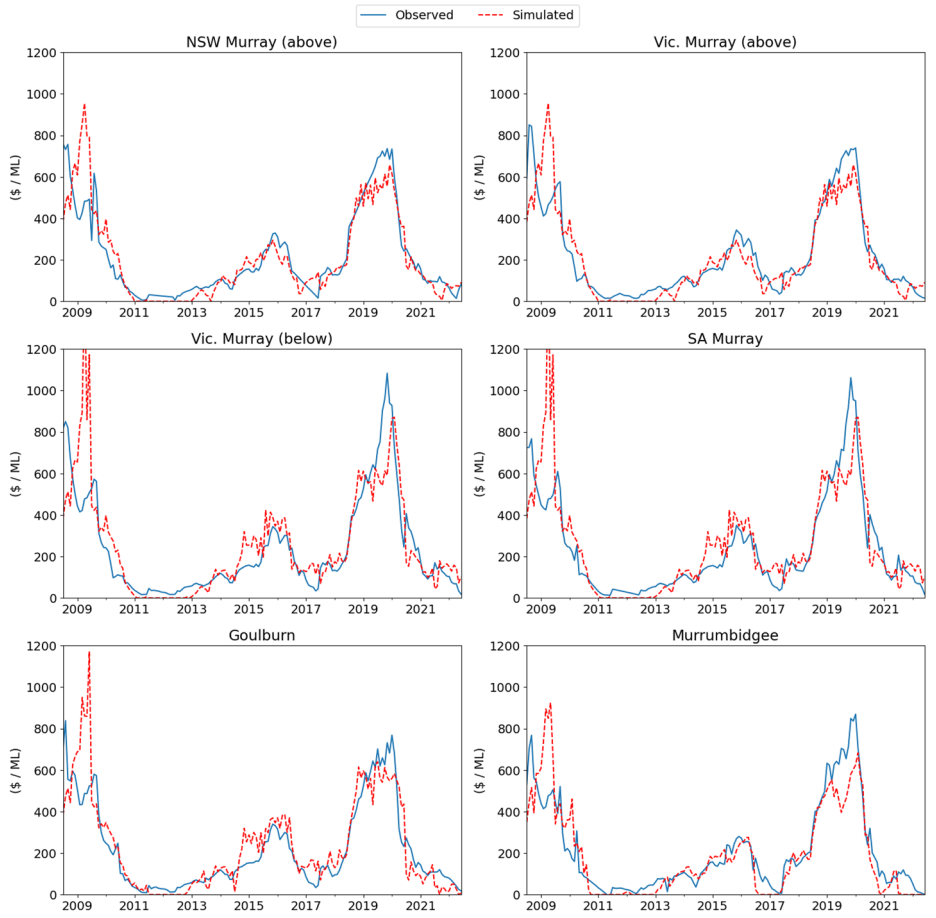



**Fig. 5** Observed (blue line) and simulated (red-dash line) monthly water allocation market prices $P_{it}^{w}$ by region in the southern MDB, July-2009 to June

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. 2026), the assumed water market constraints (water trade and carryover rules) and importantly, the estimation of expected market prices (i.e., the rational expectations equilibrium).

This estimation 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: 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 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 (Fig. 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 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). This is not surprising as prices in the off season (winter) are heavily dependent on expectations over the next season. Real world markets have more information available to forecast next season allocations than what is present in the model (i.e., dam storage volumes and official forecasts). For example, modelled prices are lower than actuals at the end of the 2018-19 water year, with real world markets better anticipating the drought conditions of the 2019-20 summer.

Modelled prices reach zero during the flood years of 2011 and 2012 due to binding carryover constraints. Actual prices were slightly higher over this period, partly because recently introduced spill rules in northern Victoria were ineffective during this period (see Hughes et al. 2016).

As documented in Hughes et al. (2026), the model generally performs better in the southern MDB than the northern, due to a combination of data quality issues and larger volumes of 'unregulated' water use (i.e., flood-plain harvesting and on-farm dams), see Appendix C.1.

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 full *Historical* (1896–2022) scenario (in terms of southern MDB mean annual

water allocations)[1]. 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 our study, non-stationarity in observational data and related climate ambiguity has important implications for real-world adaptation responses (an issue considered briefly in the Discussion and Conclusions section).

### 3.2 Climate Scenarios

Simulation results for the southern MDB climate scenarios (127-year hydro-climate sequences reflecting 2050 climate projections, see Sect. 2.3.3) are summarised in Figs. 6, 7 and 8. Note that climate projection scenarios are not provided for northern MDB regions at this stage.

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 Fig. 6 by the *Baseline* scenario which is a model simulation based on observed hydro-climate data between 1990 and 91 and 2021-22).

While each climate scenario is subject to unique and subtle changes in rainfall and temperature, including differences in spatial and seasonal patterns, much 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 Fig. 6a and c). This reflects the flexibility of water markets, which allow small changes in spatial or seasonal patterns of supply to be managed through adjustments in trade flows between regions or transfers of water across time via carryover. As shown in Fig. 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 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 (Figs. 6a and 7a). With fixed irrigation development, the driest scenarios result in large increases in simulated water 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 just under $600 per ML in the Murray below zone, compared to the *Historical* scenario mean of $110 (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

[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 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" (Van Dijk et al. 2013) and the "Tinderbox drought" (Devanand et al. 2024).

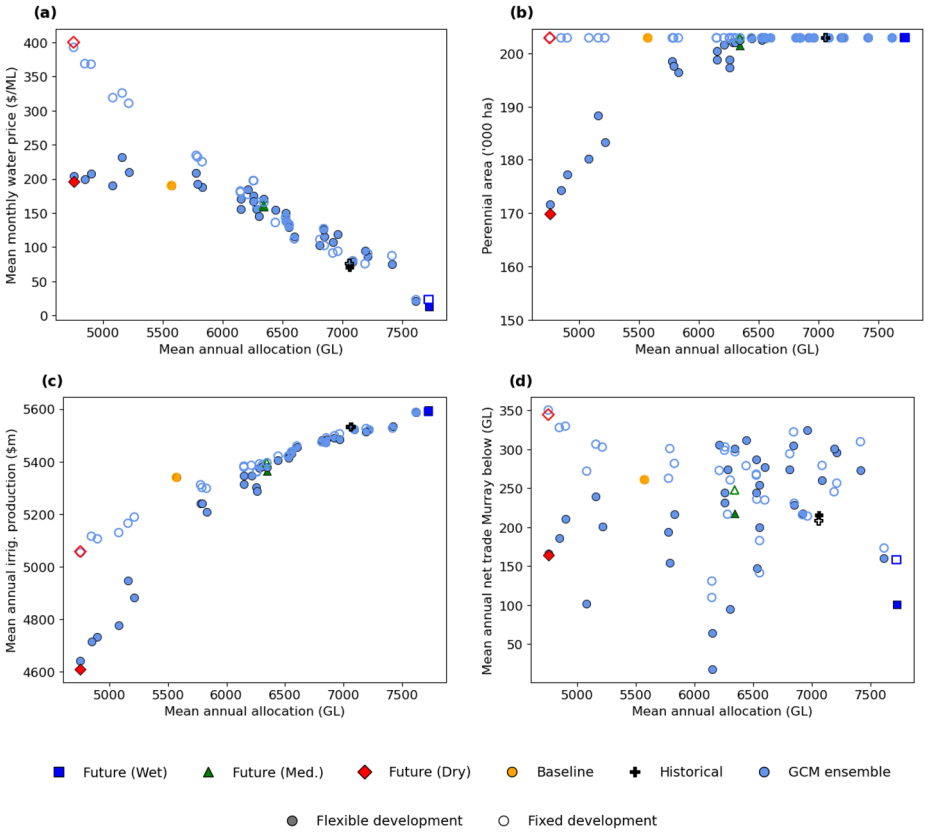



**Fig. 6** Climate scenario long-run mean outcomes versus long-run mean water supply for the total southern MDB, with both fixed and flexible irrigation development. (**a**) Monthly water market prices (**b**) Total perennial crop area (Almonds, Grapes, Other Horticulture and Vegetables) (**c**) Gross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

below) binding most of the time, leading to persistently higher prices in the Murray below zone compared with the upstream regions (Fig. 8). In the *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 level of irrigation development. Within the model, long-run adjustment involves reductions in the level of development (by region and crop type) which lower mean water prices and return irrigation profits back to *Baseline* levels. As shown in Fig. 6, the level of development declines under drier climate scenarios, with a reduction in southern MDB perennial crops under the *Future (Dry)* scenario of 16% (Fig. 6b), driven 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 (Fig. 7b).

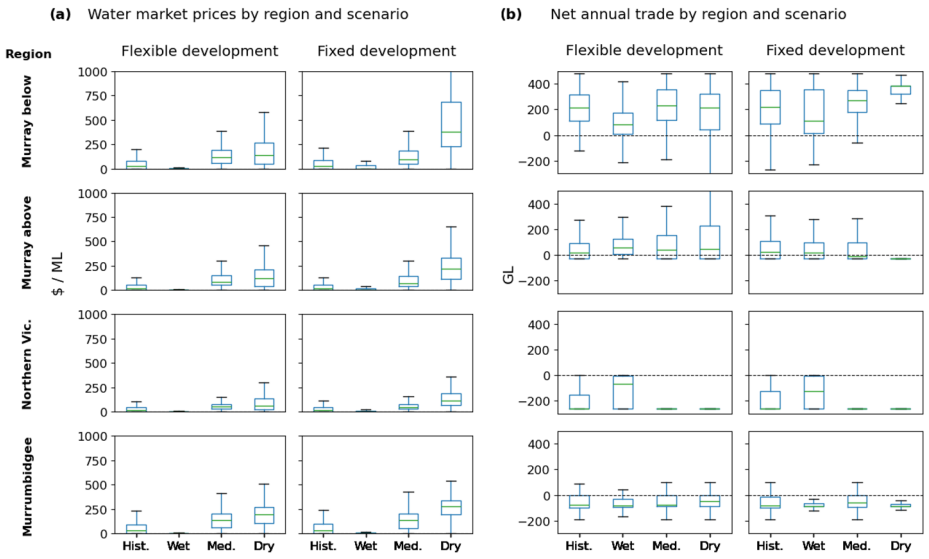



**Fig. 7** (**a**) Distribution of monthly water market prices by trading zone for selected climate scenarios ($ / ML). (**b**) Distribution of annual net trade volumes (GL) by trading zone for selected climate scenarios

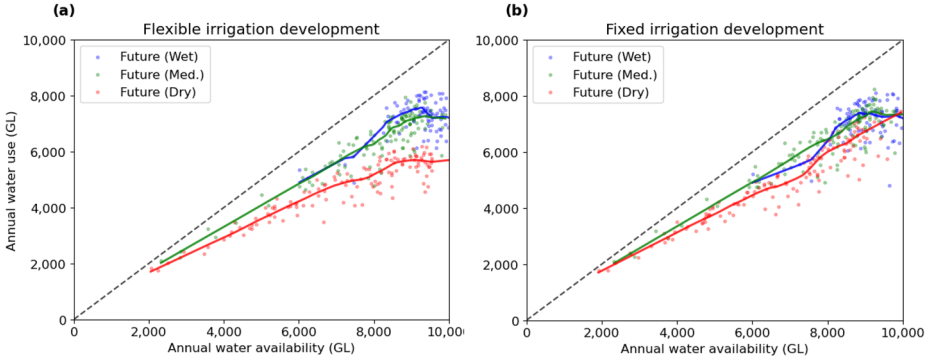



**Fig. 8** Simulated annual water use relative to available annual water supply (opening carryover plus annual allocations plus other water) for the total southern MDB (1896-97 to 2021-22). Scatter points represent individual years within each climate scenario sequence (**a**) Flexible irrigation development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

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

While reductions in supply lead to declines in the value of irrigation production (Fig. 6c), markets limit the impact by allocating water to the most profitable activities across the basin. As such, the changes in production are smaller than the changes in water supply (17%

decline in mean production under the *Future (Dry)* scenario for a 33% decline in water supply). Generally, the results in Fig. 6 highlight the non-linear nature of system responses to changes in water availability.

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. This further increases the benefits of carryover, effectively creating more storage capacity or 'air space' in dams to retain unused water across years. 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.

## 4 Discussion and Conclusions

In this paper we present a new monthly economic model of the Murray-Darling Basin (MDB) water market. 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 and 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).

Our 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 SSP5-8.5). 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 manage water-supply variability and limit the extent of drought shortages.

Under the most severe dry future scenarios, 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, modelling suggests a reduction in the level of irrigation development would be required to bring water prices and irrigation profits back to baseline levels. Under the worst-case *Future (Dry)* scenario (involving a 33 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 17 per cent.

These results highlight the limits of markets in supporting adaptation to climate change. To be clear, there is no doubt outcomes in the region are significantly better in the presence of water markets under all scenarios. Past research has estimated that inter-regional trading and carryover contribute an average benefit of $172 million per year in the sMDB (around 14% of the market value of water rights Hughes et al. 2023). However, markets are subject to physical limits on the volumes of water that can be reallocated between regions (and across time). Once these limits are reached, the ability of markets to manage periods of short-term scarcity, in a way that preserves existing irrigation development is greatly reduced.

While extending past research in several directions, this study is subject to various limitations and uncertainties. Firstly, the prediction of long-term adjustment in irrigation investment requires strong simplifying assumptions. For example, our analysis 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 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 a wide range of mean supply volumes, due to uncertainty over projected rainfall. Importantly, a majority of the projection ensemble (derived from the 127-year historical record) involve higher mean water supply and lower mean water prices than observed over the recent 1990-91 to 2021-22 period (i.e., many GCM models project higher mean rainfall by mid-century than what has been observed in south-eastern Australia over the last 20–30 years).

Non-stationarity in observational data is a general challenge in hydrological assessments of climate change (see Bayazit 2015; Mondal and Mujumdar 2017). In keeping with standard practice, we measure climate change impact as the difference between two scenarios in which the climate distribution (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 conducive 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. These recent observations remain consistent with the results in this study. While extreme future climates may lead to long-term contraction in development, investors could rightly consider these scenarios unlikely over the current 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) any reduction in irrigation adjustment in response 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 extreme events could have more practical value than predictions of long-term mean outcomes. Recent experience in the MDB has shown that extreme events play a key role in motivating 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 market institutions can be designed to be robust to extremes.

The design of limits on inter-region trade is a key example. Our results show that trade limits have a large bearing on water prices in drought years, particularly for irrigators in downstream regions. In the long term, these trade limits are also likely to influence irrigation development, particularly decisions over investment in perennial crops. Not surprisingly, these limits have been a source of debate in recent years. The current system involves a complex set of rules to determine the volume of allocation trade allowable each season. While these rules are intended to provide clarity to users and river operators, they lack flexibility and are a crude approximation of real-world constraints. For example, in certain cases it might be valuable to allow trade volumes beyond pre-defined limits, if the gains from trade exceed negative externalities (e.g., increased evaporation loss or environmental impacts).

The concept of "smart markets" as applied to electricity, where a centralised algorithm clears markets in real time, offers a useful frame here. In theory, this approach could determine optimal water market and price outcomes in a river system, accounting for both user preferences and system losses and constraints. While research has considered how the concept might extend to water (see Raffensperger and Milke 2017) smart markets have yet to be implemented in any real-world river systems. Regardless, the core principle (i.e., accounting for user preferences and network constraints simultaneously) remains central to future reform of water markets.

While the modelling presented here can highlight the effect of existing trade limits, testing alternative institutions (whether more flexible trade limits or "smart market" approaches) requires the development of 'holistic' hydro-economic models: models with two-way feedback between river systems and water markets (Brouwer and Hofkes 2008). Such models would enable analysis of water policy issues involving complex interactions between hydrology and economics: 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).

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**Author Contributions** Neal Hughes was responsible for conceptualisation, methodology, project administration, software development, validation, data curation and writing of the original draft. April Zhao contributed to software development, data curation (economic data) and review of the draft. Andrew John and Avril Horne contributed to data curation (hydro-climate data) and review of the draft.

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**Data and Code Availability** A complete replication package is available for download via Mendeley Data: https://doi.org/10.17632/2mkwxp7fcc.1. This contains input data, model parameters, climate scenarios, model code, simulation outputs, chart and table artifacts and documentation.

## Declarations

**Competing Interests** The authors have no relevant financial or non-financial interests to disclose.

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