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Cap and Trade for Water under Seasonal Forecasts: MDB and Po Valley Evidence and a Theoretical Model

Master Thesis

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Abstract

Farmers worldwide face increasing hydrologic variability and water scarcity due to climate change. Two policy tools often considered to enhance adaptation are water markets (to reallocate scarce supplies) and seasonal forecasts (to inform ex-ante decisions). Prior studies typically examine these instruments in isolation, overlooking how expectations about water availability may interact with anticipated trading opportunities in land-use choices.

This thesis studies them jointly. Empirically, using HAC-robust inference, we examine the Murray–Darling Basin—one of the most developed water markets—and show that higher pre-sowing allocations over the prior 12 months are systematically associated with larger acreage of water-intensive opportunistic crops (rice, cotton), conditional on pre-sowing field rainfall. Timing and robustness checks are consistent with a causal interpretation, though we do not separately identify price versus quantity channels of the water-scarcity signal.

Theoretically, we develop a competitive-equilibrium model that links water availability and its forecasts in a joint probabilistic framework with heterogeneous producers and technology-driven price thresholds. Simulations indicate that (i) under scarcity, cap-and-trade delivers the largest efficiency gains by reallocating water to higher-value uses; (ii) forecast information adds benefits when forecast skill is high and variability is pronounced; and (iii) forecasts and trading can be synergistic, with combined welfare gains exceeding the sum of stand-alone effects, particularly for risk-averse producers.

Overall, the results motivate evaluating cap-and-trade and seasonal forecasts together to capture both anticipatory (extensive-margin) and within-season gains. We discuss policy implications for basins with small, risk-averse farms (e.g., the Po Valley) and note key limitations, including the omission of forecast products in the empirical design and stylized assumptions in the model.

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Contents

Chapter 1

Introduction

Global warming is reshaping the spatio–temporal distribution of water resources. Projections consistently indicate more frequent and intense hydroclimatic extremes, larger interannual variability in precipitation, and shifts in the timing and phase of precipitation (rain versus snow). For Europe, high-resolution regional climate simulations point to a marked increase in spring–summer drought frequency and severity over the Mediterranean basin and the Po Valley during the twenty-first century (Spinoni et al., 2018).

The Po basin exemplifies these emerging risks. Although cumulative precipitation from November 2021 to July 2022 was not exceptionally low, the basin experienced a severe hydrological drought in 2022, underscoring the role of non-precipitation drivers in shaping water scarcity (Bonaldo et al., 2023). Using a 216-year discharge record at Pontelagoscuro, Montanari et al. (2023) show that 2022 constitutes the worst hydrological drought in two centuries and is embedded in a rising trend of severe events. They attribute the decline in summer flows primarily to altered seasonality—namely, the shift from solid to liquid precipitation and earlier snowmelt—as well as to increasing evaporation, consumption, and irrigated areas, rather than to precipitation deficits alone (Montanari et al., 2023). Together, these findings suggest that hydrometeorological droughts—driven by the compound effect of climate and human water use—are likely to become more prominent in the basin.

Among demand-side policy responses, two stand out for their potential to curb the welfare costs of scarcity without requiring new large-scale infrastructure developments that, over the twenty-first century, have often entailed serious and unanticipated social, economic, and ecological costs (Gleick, 2003). First, well-designed water markets (cap-and-trade regimes for surface or groundwater) can reallocate scarce water to higher-value uses across time, space, and sectors. Evidence from established markets—such as Australia's Murray–Darling Basin (MDB) and Texas' Rio Grande—indicates that trading facilitates shifts toward higher-value activities and that such reallocations are particularly salient during droughts (Debaere & Li, 2020, 2022). At the same time, effective markets require careful design to reflect the hydrology and institutions of place (property rights, monitoring and enforcement, transaction costs, interactions between surface and groundwater, and ecological constraints) (Bruno & Jessoe, 2024).

Second, seasonal water-availability forecasts (e.g., inflow or allocation outlooks) can improve farmers' input and crop-mix decisions by increasing information at the time of planting. A large literature documents positive farm-level value from seasonal climate forecasts, though magnitudes vary by skill, sector, and evaluation methods (Parton, 2019). In addition, recent advances in drought forecasting using machine learning techniques are creating opportunities to reduce uncertainty in expected water availability, even in basins that lack large reservoirs (Camps-Valls et al., 2025). In systems with large annual storages, by contrast, most inflows occur during the wet season, so the reservoir filling level before planting has long provided farmers with an early and informative signal of likely water availability.

Given the modest effective storage relative to irrigation demand—combined with rising withdrawal pressures (SuWaNu Europe Consortium, 2020) and increasing drought frequency—water markets and seasonal forecasts are of particular interest for the Po Valley.

Empirical motivation and literature gap. We study the MDB because it hosts the world's largest and most valuable water market by trading volume, and because it features both rice cultivation and perennial crops, as in the Po Valley (Rafey, 2023). In Australia's Murray–Darling Basin (MDB), active water markets coexist with pronounced adjustments on the extensive margin: farmers vary the acreage of water-intensive annuals (notably rice and cotton) in response to allocations and prices (Zeleke & Luckett, 2025). During the Millennium Drought, aggregate irrigated output proved remarkably resilient: despite allocations falling to roughly one third of pre-drought levels in 2007–2009, the gross value of irrigated agricultural production (GVIAP), adjusted for price trends, declined by only about 20% (Kirby et al., 2014). By contrast, ex ante modelling exercises that switch off trading typically predict much steeper losses: for example, under a policy-induced 29% reduction in irrigation water use, Mallawaarachchi et al. (2010) estimate a ∼20% fall in GVIAP even allowing for crop-mix changes at fixed crop prices.

Recent causal work quantifies the within-season (intensive-margin) value of market reallocation: using farm-level production functions and observed trades, Rafey (2023) find that annual trading in the MDB raised irrigated output by 4–6% in 2007–2015, equivalent to avoiding an 8–12% uniform reduction in water resources, with convex gains during drought years. Separately, in northeastern Colorado, there is evidence that pre-season expectations about water availability materially shape planting decisions (the extensive margin): in a two-stage model with empirical validation, Manning et al. (2017) show that producers reduce planted area as expected supplies fall. By contrast, for the Murray–Darling Basin we are not aware of a study that causally identifies this pre-season expectations → acreage link; existing MDB work documents associations (e.g., acreage responses to water prices) or broader adaptation patterns during drought, but not a clean causal estimate (Zeleke & Luckett, 2025; Agbola & Evans, 2012). In parallel, meta-analytic syntheses indicate that seasonal climate forecasts can have positive but heterogenous farm-level value, with magnitudes sensitive to forecast skill, activity, and valuation method (Parton et al., 2019).

Taken together, these strands suggest two complementary demand-side channels to mitigate scarcity costs: (i) *ex post* market reallocation once the crop mix is chosen; and (ii) *ex ante* crop and input choices informed by expectations (including SCFs and allocation outlooks). Yet, to our knowledge, prior work has not *jointly* quantified the value of seasonal water-availability information for *crop choice within* a competitive allocation–trading regime that endogenously determines spot prices. Existing market valuations emphasize reallocations *after* planting (Rafey, 2023), while studies on expectations and SCFs typically abstract from equilibrium water prices and trading frictions (Manning et al., 2017; Parton et al., 2019).

The MDB experience shows that trading alone cannot fully account for the modest decline in aggregate value observed under extreme scarcity (Kirby et al., 2014), hinting at important anticipatory adjustments on the extensive margin.

The open questions are therefore: (i) Do expectations about water availability causally affect the acreage of water-demanding crops (the extensive margin) in the Murray–Darling Basin? (ii) In their land-use decisions, do farmers anticipate the option to trade water? (iii) What is the joint effect of water markets and seasonal forecasts on farmers' ability to adapt to interannual fluctuations in water availability?

1.1 Structure of the Thesis

Chapter 2: Cap-and-trade for water — a guide for economists (ch. 2) This chapter starts from hydrological basics, situating water consumption within the water cycle. We then distinguish two policy contexts that need attention: (i) settings where essential Water, Sanitation and Hygiene (WASH) infrastructure is insufficient to deliver water where and when it is needed; and (ii) settings where water resources are over-allocated or over-exploited. Cap-and-trade instruments pertain primarily to the second context, in which agriculture—through irrigation—is typically the dominant consumptive user. We finally examine how climate change affects drought risk, with emphasis on the Mediterranean and on snowmelt-dependent regions, like the Po Valley where several studies report declining early-summer (June–July) flows and increased likelihood of agricultural droughts (Montanari et al., 2023).

In the second section we provide a concise overview of *volumetric* regulation of water use. Because water supports both *public-good* uses (ecosystem services secured via instream/environmental flows) and *common-pool*, consumptive uses (agriculture, industry, municipal), regulation is necessarily bifurcated. A typical sequence is to set environmental flow requirements to safeguard public benefits; the residual volume is then allocated across consumptive uses via (a) quantity controls (licenses/entitlements with annual allocations), (b) price instruments (tariffs, scarcity pricing), or (c) market mechanisms (cap-and-trade of allocations). These instruments aim to prevent the tragedy of the commons.

We then review environmental markets (e.g., emissions trading, tradable fishing quotas) to show how design choices—eligibility rules, spatial trading zones, banking/*carryover*, transfer limits, price collars, monitoring and enforcement—must be tailored to the resource's biophysical and institutional characteristics.

We conclude highlighting features that distinguish water as a common-pool resource—hydrological connectivity, ecological services, limited storage, evaporation losses, and stochastic inflows. We explain how these shape water-market regulation (e.g., carryover rules, zone-based trading). The MDB serves as an illustrative case.

Chapter 3: Adaptation and inertia: crop–choice responses to water allocations in the MDB and the Po Valley (ch. 3) This chapter asks whether, and to what extent, farmers adjust the seasonal crop mix in response to interannual water availability, and why such adaptation may be strong in some settings but weak in others. We first motivate why crop choice is a first-order adaptation margin: irrigation requirements differ markedly *across crops within a location* and, for a given crop, *across locations*. We then contrast the MDB—where storage-backed allocation announcements and active trading provide timely signals—with the Adda–Lario system in the Po Valley. Descriptive evidence indicates robust year-to-year acreage adjustments for water-intensive annuals in the MDB, whereas we do not detect comparably systematic adjustments downstream of Lake Como, plausibly reflecting also the absence of informative pre-summer availability signals.

In the second part of the chapter, we examine whether pre-season water allocations—used as a proxy for farmers' expectations at planting—affect the acreage of the two most water-demanding annuals in the MDB, cotton and rice. We outline an identification strategy based on the timing of allocation announcements relative to land-use decisions and discuss threats to exogeneity. The resulting estimates provide evidence consistent with expectations-driven adjustments on the extensive margin in the MDB, highlighting the role of information for adaptive land use.

Chapter 4: Cap and Trade on water with seasonal forecasts: a theoretical model 4. The final chapter develops a theoretical model to evaluate the economic benefits of a cap-and-trade water market and seasonal water-availability forecasts as adaptation tools under scarcity. The economy features two producer types—high-value perennial growers and flexible seasonal farmers—who face uncertain water availability modeled as a scaled logit–normal distribution. Seasonal farmers choose crops to balance expected returns and risk, and market-clearing water price that is determined endogenously by total availability and crop choices. Using Monte Carlo simulations, the chapter compares expected economic output across four scenarios: (i) neither markets nor forecasts, (ii) markets only, (iii) forecasts only, and (iv) both combined, while varying farmer risk aversion and forecast skill. The results indicate that water markets are the primary driver of gains—especially under scarcity—by reallocating water to higher-value uses. Seasonal forecasts add complementary benefits, particularly for risk-averse farmers and when forecast skill is high, with effects strongest under highly variable supplies (frequent swings between abundance and scarcity). Crucially, the two instruments exhibit complementarities: combined gains can exceed the sum of their standalone effects, especially during severe droughts.

Chapter 2

Cap and Trade on water: a guide for economists

Chapter summary. This chapter introduces the economic and environmental rationale for using cap-and-trade systems to manage water. It begins by establishing freshwater as a scarce, common-pool resource, where agricultural irrigation is the dominant consumptive user. The analysis highlights how over-abstraction and climate change threaten both human water security and ecosystem health, particularly in vulnerable regions like Italy's Po Valley. This context establishes the need for demand-side management that respects ecological limits, primarily by securing environmental flows to define a sustainable 'cap' on withdrawals.

The chapter then presents Australia's Murray-Darling Basin (MDB) as the primary case study of a mature water market. The MDB framework operates under a basin-wide Sustainable Diversion Limit (SDL) and is built upon unbundled, tradable water rights—long-term entitlements and annual allocations. It highlights how the peculiarities of water as a natural resource influence trade restrictions and rules regarding the carryover of allocations from one year to the next.

2.1 Freshwater as a scarce resource

2.1.1 The Hydrological Cycle and Human Water Consumption

While the total mass of water on Earth remains remarkably constant, its distribution and form are continuously altered through the hydrological cycle. This natural process, depicted schematically in Figure 2.1, describes the movement of water between atmospheric, terrestrial, and oceanic reservoirs, transitioning between gaseous, liquid, and solid phases. The time water spends within a particular reservoir, known as its *residence time*, varies dramatically: from approximately 9 days in the atmosphere to decades or millennia in deep groundwater or ice sheets (Pidwirny, 2006; Scanlon et al., 2023). Water vapour, primarily originating from oceanic evaporation (approximately 86% of the global total (NASA Science Mission Directorate, 2018)) and terrestrial evapotranspiration, rises, cools at higher altitudes, condenses, and precipitates as rain, snow, or hail. Precipitation reaching land may infiltrate the soil, flow superficially as runoff towards rivers and lakes, or be stored temporarily as snow and ice. Infiltrated water can evaporate, be transpired by plants, or percolate deeper to recharge groundwater systems. Surface runoff and groundwater eventually discharge into rivers and ultimately flow back to the oceans, completing the cycle. This continuous movement, powered by solar energy, governs the availability of freshwater resources in space and time.

Human activities interact extensively with this cycle, relying on water for numerous purposes. *In-stream uses*, such as navigation, hydropower generation, ecosystem maintenance, and recreation, utilize water within its natural channels without significant removal. Conversely, *off-stream uses* necessitate *water withdrawal* (also termed abstraction or extraction) – the removal of water from its source (rivers, lakes, groundwater) for a specific purpose (Kohli et al., 2012). Due to the high cost of desalination, over 99% of global water withdrawals rely on freshwater sources (Scanlon et al., 2023).

A critical distinction for resource management and economics is between withdrawn water that is consumed and that which is not, based on the state of the water returned to the system. According to the FAO AQUASTAT definitions, *consumptive water use* implies a substantial reduction in the quantity or quality of the water that returns to the system after being withdrawn . This consumption primarily occurs through evaporative losses (including plant transpiration) or by incorporation into products, effectively removing the water from the immediate basin or rendering it unfit for subsequent use without significant treatment. Globally, evapotranspiration in irrigated agriculture represents the largest component of consumptive use, accounting for approximately 90% of water consumption despite representing about 70% of withdrawals . *Non-consumptive water use*, conversely, does not substantially change the withdrawn water volume, with almost all of it returning to the system, although its quality (e.g., temperature, pollutant load) may be altered. The precise definition of a "substantial change" can vary between jurisdictions. A clear example of primarily non-consumptive use is water withdrawn for once-through cooling systems in thermal power plants; the water is returned to the source river or lake in nearly the same quantity, albeit at a higher temperature (Kohli et al., 2012).

It is essential when analysing water use statistics to clarify whether reported figures represent withdrawals or consumption, and how return flows are accounted for. Furthermore, transporting withdrawn water from source to point-of-use inevitably incurs losses (e.g., through leakage or evaporation from canals), which can range from 20-30% on average but may exceed 60% in some systems (Cheong, 1991; McIntosh, 2003).

Globally, agriculture is the dominant sector for water withdrawal and, particularly, consumption. In 2021, agriculture accounted for approximately 72% of total freshwater withdrawals, followed by industry (15%) and municipal/services (12%) (UN Water, 2024). However, due to the significant evapotranspiration losses associated with crop production, agriculture is responsible for an estimated 90% of global freshwater *consumption* (Kohli et al., 2012). Different consumption rates, coupled with varying economic outputs, leads to significant differences in water productivity across sectors. As illustrated in Figure 2.2, the economic value generated per cubic meter of water withdrawn in agriculture (approximately 0.7 USD/m^3 in 2021) is

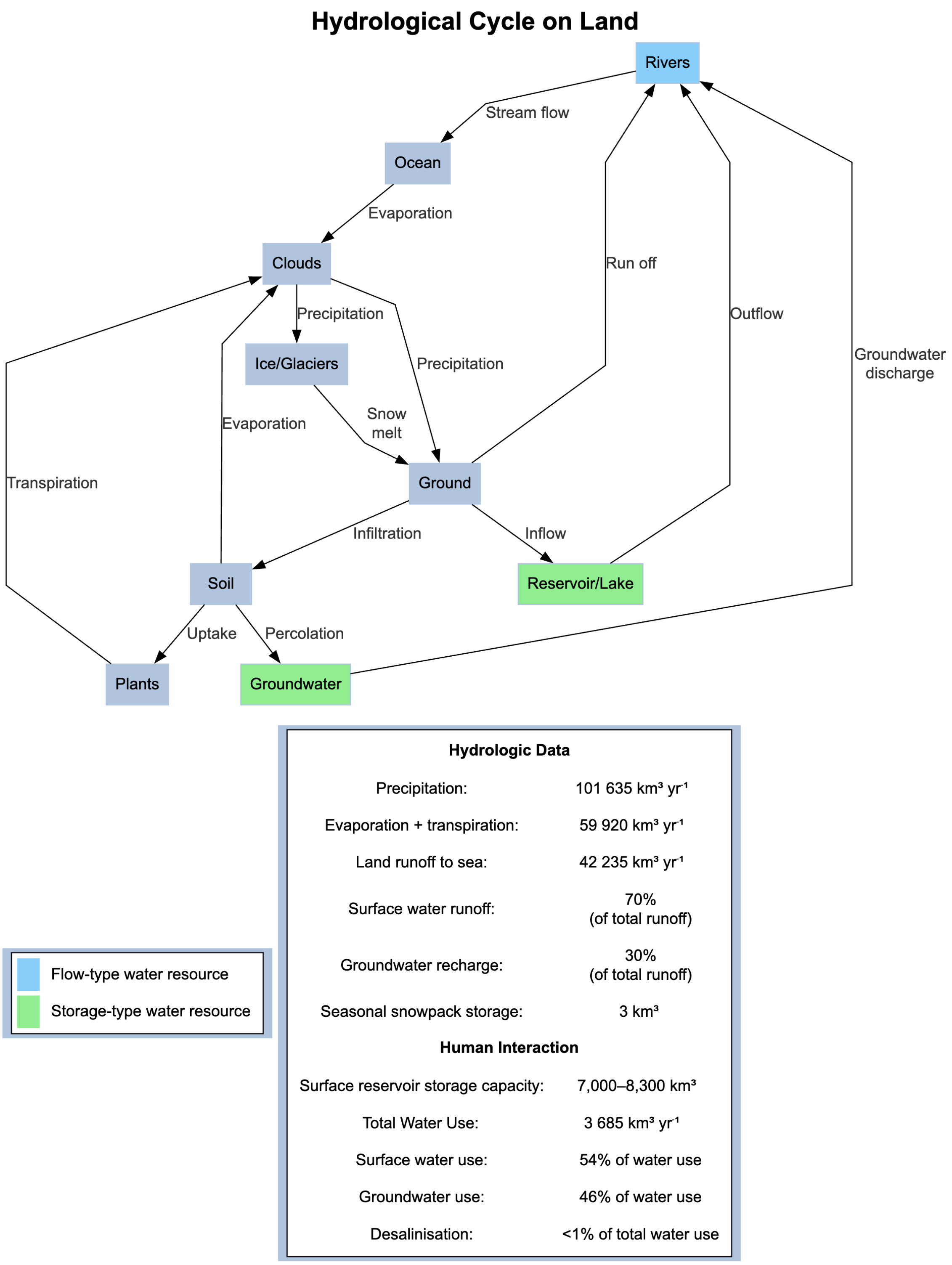


Figure 2.1: Schematic representation of the water cycle without human intervention. Accessible Freshwater resource are Rivers, Reservoir The data for the figure is taken from (Scanlon et al., 2023).

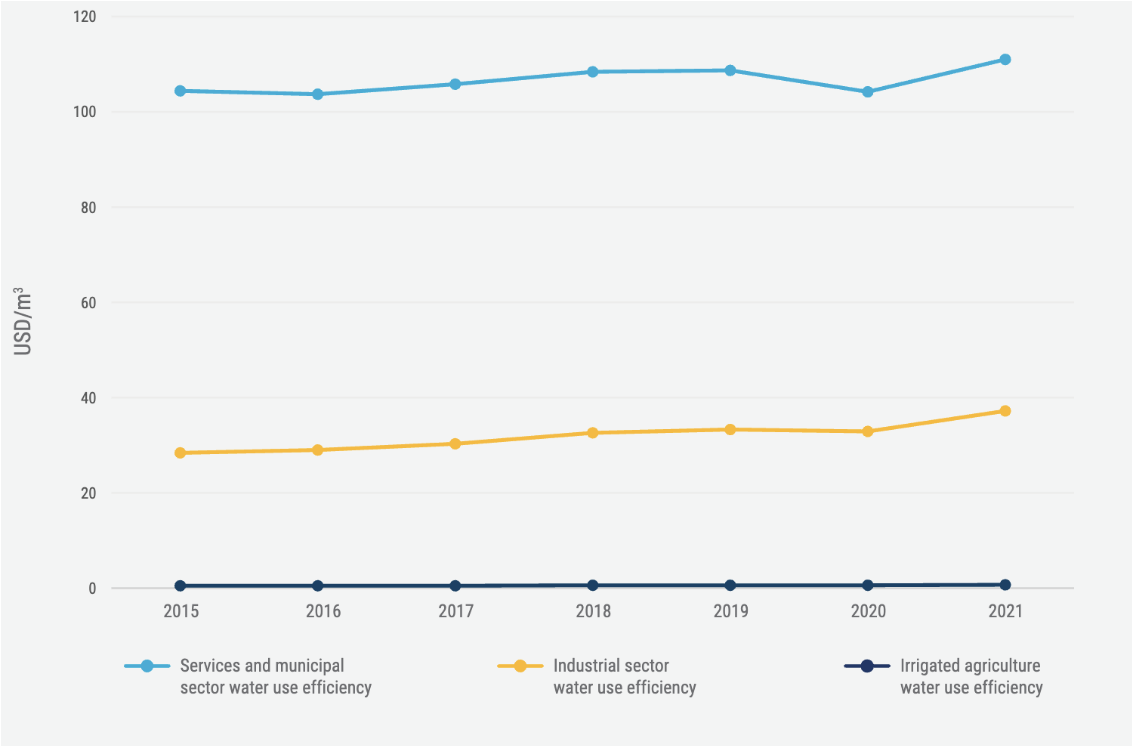


Figure 2.2: Graph of the Water efficiency defined as the ration between the gross added value and the water withdrawal of the sector. The image is taken from (UN Water, 2024).

typically one to two orders of magnitude lower than in the industrial or services sectors (UN Water, 2024).

Alternatives to conventional freshwater sources exist but face significant economic constraints, especially for agriculture. Desalination, while technologically mature and used for domestic and industrial supply in water-scarce regions, generally costs between 1.0 and 1.5 USD/m^3, rendering it largely uneconomical for widespread irrigation (Dhakal et al., 2022). Similarly, long-distance water transport via trucking or shipping is prohibitively expensive for agricultural volumes. Large-scale inter-basin water transfer schemes – man-made conveyances moving water between river basins – while often technically feasible, typically involve substantial capital investment, lengthy construction periods (often spanning decades for major projects), and potentially significant environmental impacts at both source and destination. These factors often make such projects complex and controversial, limiting their applicability as rapid solutions to emerging water stress. Consequently, while historically significant projects exist globally, large-scale new proposals are now primarily concentrated in developing nations seeking to meet growing water demands, whereas many developed countries may have already exploited the most economically viable sites (Seqwater, 2020; Ghassemi & White, 2007). These physical and economic realities underscore the dependence of most water users, particularly agriculture, on locally available, renewable freshwater resources managed within the constraints of the hydrological cycle. These are rivers, reservoirs, lake and groundwater see 2.1.

2.1.2 Water consumption and environmental impacts

Freshwater exhibits key characteristics of a common pool resource: it is *subtractable* (use by one diminishes availability for others) and, while *renewable* through the hydrological cycle (see 2.1), its availability in a specific place and time is often *limited* and highly variable. Beyond direct human needs, freshwater is crucial for ecosystem health. Representing only 2.3% of the Earth's surface, freshwater ecosystems like lakes, reservoirs, and rivers host at least 9.5% of the Earth's described animal species. Yet, these ecosystems face a deepening biodiversity crisis, with population declines outpacing those in marine or terrestrial systems (Reid et al., 2019). A significant portion of global freshwater resources is already under stress; indeed, 65% of continental discharge is considered under moderate to high threat concerning human water security and biodiversity (Vörösmarty et al., 2010). This makes freshwater ecosystems hotspots of endangerment, where high biological richness converges with multiple anthropogenic pressures (Reid et al., 2019).

A primary factor shaping the structure and functioning of aquatic and riparian ecosystems is the river flow regime (Poff et al., 2010). Alterations to natural flow patterns—especially substantial reductions in water volume—undermine the survival of riverine organisms. Maintaining ecosystem health therefore requires securing adequate *environmental flows* (EFs). As defined by the Brisbane Declaration (Declaration, 2007), EFs refer to the quantity, quality, and timing of water flows necessary to sustain freshwater and estuarine ecosystems, as well as the human livelihoods that depend on them. Ecological integrity cannot be preserved by enforcing a fixed minimum flow alone; rather, ecosystems rely on the natural variability of flow regimes, which includes critical periods of low flow, intermediate pulses, and major flood events (Pastor et al., 2014). For example, medium–high flows facilitate sediment transport, while flood flows are essential for floodplain and wetland ecology, supporting processes such as inundation and nutrient cycling (Acreman et al., 2008).

The strong hydrological connection between surface water and groundwater further complicates water resource management. These systems are inextricably linked, intersecting at streambeds, floodplains, wetlands, and springs (Scanlon et al., 2023). This interconnection means that groundwater abstraction can impact surface water bodies. Elevated pumping can capture water that would otherwise discharge to rivers, reducing streamflow, particularly baseflow which is critical during dry periods (Scanlon et al., 2023). In coastal areas, this reduction in freshwater outflow, combined with groundwater depletion, can exacerbate saltwater intrusion, harming both ecosystems and agriculture (Werner et al., 2013; Luo et al., 2024). Furthermore, excessive groundwater withdrawal can lead to irreversible land subsidence due to aquifer system compaction, as documented in California's San Joaquin Valley (Faunt et al., 2016). Conversely, inefficient surface water irrigation can lead to waterlogging and salinization by artificially raising the water table, negatively impacting agriculture in areas like Haryana State, India (Singh et al., 2010).

Therefore, establishing sustainable limits on water withdrawals – the 'cap' in potential water management frameworks like cap-and-trade – necessitates careful consideration of both EFs for surface water bodies and the impacts of abstraction

Table 2.1: The table shows the best fitting hydrological Environmental Flow Requirement calculation Methods for Different Flow Regimes (Tessmann & Variable Monthly Flow). The mean monthly flow (MMF) and the mean annual flow (MAF) are calculated using the dataset from an unaltered condition either before the construction of a dam or simulating the basin flow with natural vegetation without human withdrawals (Pastor et al., 2014). The periods of low flow are considered more critical and therefore smaller percentages of water can be taken.

Hydrological Regime	**Environmental Flow requirement**	
	Tessmann	**Variable Monthly Flow**
Low Flow Regime: MMF $\leq$ 0.4 MAF	MMF	$0.6 \cdot$ MMF
Intermediate Flow Regime Tessmann: 0.4 MAF $\leq$ MMF $\leq$ MAF VMF: 0.4 MAF $\leq$ MMF $\leq$ 0.8 MAF	$0.4 \cdot$ MAF	$0.45 \cdot$ MMF
High Flow Regime Tessmann: MMF $>$ MAF VMF: MMF $>$ 0.8 MAF	$0.4 \cdot$ MMF	$0.3 \cdot$ MMF

on interconnected groundwater systems. Determining appropriate EFs ideally involves mimicking natural flow variability based on local hydrological conditions and ecosystem needs (Pastor et al., 2014). However, quantifying EFs, especially at large scales, remains challenging. Pastor et al. (2014) provided a valuable comparison by evaluating five hydrological methods against 11 locally-derived EF requirements case studies across diverse global settings. This analysis highlighted the Variable Monthly Flow (VMF) and Tessmann (Tessmann, 1980) methods as providing estimates closest to locally-derived requirements (Table 2.1), offering potential tools for larger-scale assessments where detailed ecological data are scarce.

Ultimately, the actual allocation of water reflects societal choices and compromises between direct water use demands, often highest during low flow periods, and the requirements for protecting riverine ecosystems (Poff et al., 2010). These societal priorities and the resulting compromises may evolve, potentially shifting towards greater emphasis on environmental protection in the future (Grafton et al., 2024).

2.1.3 Water Scarcity Globally

On 28 July 2010, the UN General Assembly recognized the human right to water, ensuring access to sufficient, safe, acceptable, physically accessible, and affordable water. Yet, this remains unrealized for billions; as of 2022, 2.2 billion lacked safely managed drinking water, 3.5 billion lacked safely managed sanitation, and 2 billion lacked basic hygiene (United Nations Children's Fund & World Health Organization, 2024). The United Nations Children's Fund & World Health Organization (2024)

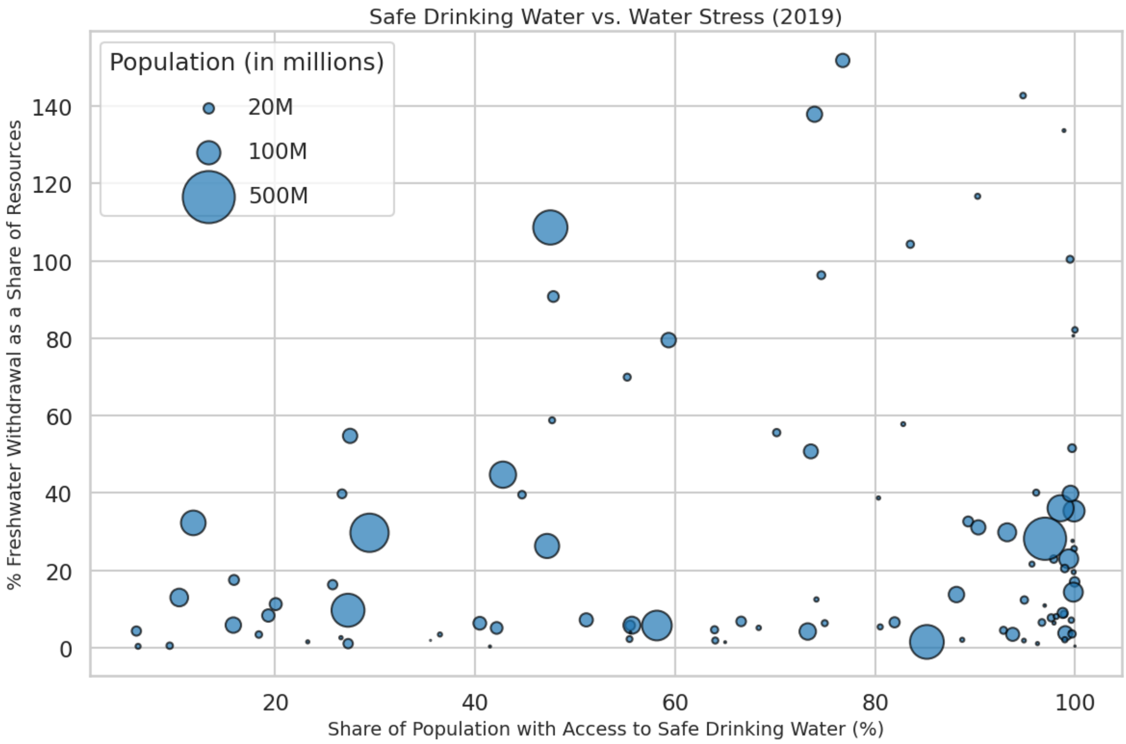


Figure 2.3: Correlation between access to safely drinkable water and the proportion of renewable water resources withdrawn annually per country. Data availability limits the countries shown (Food and Agriculture Organization of the United Nations, 2023; WHO/UNICEF Joint Monitoring Programme (JMP) for Water Supply and Sanitation, 2023). Kuwait and Qatar, which withdraw over 100% of their renewable water primarily through desalination and exhibit high (¿96%) access levels, are outliers not depicted in the chart.

report attributes these gaps primarily to service deficiencies, slow progress, and inequalities, rather than absolute physical water scarcity on a global scale. Indeed, analyses often frame the water crisis in terms of governance failures, policy inertia, and inequitable access rather than solely resource limitations (Grafton et al., 2024). Figure 2.3 supports this perspective, indicating that low access to safe drinking water often correlates with low withdrawal rates from renewable resources, suggesting infrastructural or institutional constraints rather than absolute scarcity.

However, water scarcity emerges as a critical issue when considered at appropriate spatial and temporal scales (see Section 2.1.1). Although less than 4% of global rainfall is directly utilized by humans (Figure 2.1), over 4 billion people reside in areas where, for at least one month per year, water withdrawals exceed 20% of the natural river flow, indicating significant regional and seasonal stress (Figure 2.4) (Mekonnen & Hoekstra, 2016).

Historically, the dominant approach to addressing water scarcity and meeting increasing demands has been the "hard path," characterized by the construction of large-scale, centralized infrastructure such as dams, reservoirs, canals, and pipelines (Gleick, 2003; Grafton et al., 2024). This strategy aimed to store water during periods of abundance and transfer it to regions or times of scarcity. The hard path played a fundamental role in providing reliable water access for a large portion of the world's population. However, this supply-oriented approach often continued even

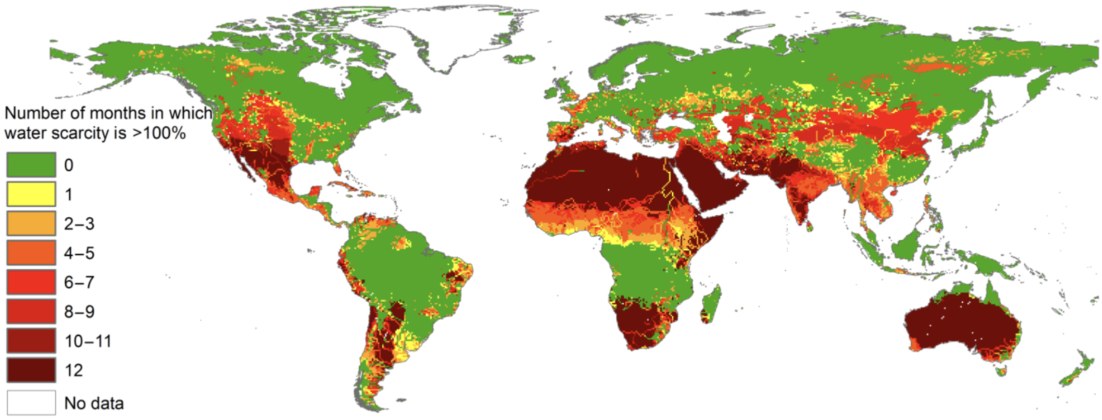


Figure 2.4: Global distribution of monthly water scarcity. The map indicates the number of months per year (1996–2005 average) where water consumption in a 0.5° × 0.5° grid cell exceeded 20% of the natural flow. Figure adapted from (Mekonnen & Hoekstra, 2016).

after basic domestic needs were met, driven by agricultural and industrial demands, leading to significant drawbacks. While often generating substantial economic benefits, the high capital investments required for these megaprojects did not always yield the expected returns (Ansar et al., 2014). Furthermore, the extensive development of supply-side infrastructure frequently resulted in "basin closure," where river discharge to the sea becomes negligible for part or all of the year. This prevents the flushing of sediments and pollutants, impairs salinity control, and severely degrades downstream estuarine and coastal ecosystems (Molle, 2010). Examples include the Colorado River Delta, which received almost no flow for much of the late 20th century, and basins like the Yellow River, Indus, and Murray-Darling. Paradoxically, within closed basins, efforts to increase local water use efficiency (e.g., reducing conveyance losses by lining canals) can exacerbate problems downstream by reducing return flows that previously replenished groundwater or surface water sources (Molle, 2010). Beyond these hydrological consequences, the hard path has significant environmental impacts, contributing, for instance, to the decline of global wetland area by a third since 1970 (Fluet-Chouinard et al., 2023).

These limitations have prompted interest in "soft path" approaches, which emphasize demand-side management, improving water productivity (economic output per unit of water consumed), enhancing water use efficiency at the system level, and utilizing smaller-scale, decentralized water management facilities (Gleick, 2003; Grafton et al., 2024). Water markets represent one potential policy tool within the soft path paradigm, aiming to allocate existing water resources more efficiently rather than solely expanding supply through new infrastructure. The hard and soft path approaches are not mutually exclusive, and their suitability may vary depending on the region and context. For instance, Rosa et al. (2020) demonstrated that while vast areas of rainfed cropland could benefit from irrigation, achieving this sustainably often requires large-scale seasonal reservoirs (characteristic of the hard path) to ensure water availability, particularly under future climate scenarios (Figure 2.5).

Nevertheless, reliance on large-scale infrastructure can create a "vicious cycle" or "reservoir effect": new supply stimulates demand growth, which increases vulnerability during inevitable droughts, leading to calls for yet more infrastructure

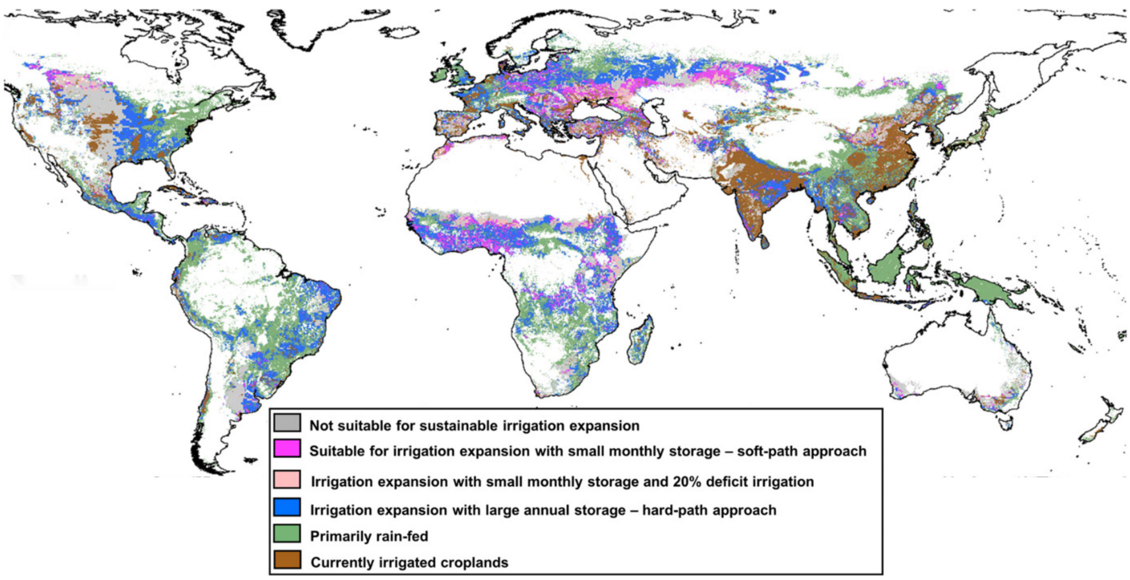


Figure 2.5: Potential for sustainable expansion of irrigated agriculture under the baseline period from 1996 to 2005, assuming a 60% environmental flow requirement. Pink/Red areas indicate suitability for expansion using small-scale monthly storage ("soft path") or with deficit irrigation. Blue areas indicate suitability only with large-scale annual storage ("hard path"). Figure adapted from (Rosa et al., 2020).

until basins effectively close (Di Baldassarre et al., 2018). This dynamic appears to persist, as analysis by Mehta et al. (2024) indicates that over half of the irrigation expansion since the 2000s occurred in regions already experiencing water stress, potentially exacerbating scarcity and highlighting the ongoing importance of evaluating more sustainable, demand-focused management strategies.

2.1.4 Water cycle and Climate change

Increasing global mean temperatures are intensifying the global water cycle. This intensification is driven less by the direct radiative effect of increased CO_2 concentrations and more by the subsequent increase in atmospheric water vapour content, as higher air temperatures increase the air's capacity to hold water vapour. Higher air temperatures also enhance total evaporation. While global mean precipitation is projected to increase, this change will be spatially and temporally heterogeneous. Increased seasonal precipitation variability is expected, leading to a higher frequency and/or intensity of both drought and flooding events (Douville et al., 2021). Observations confirm increases in both dry spell duration and maximum daily rainfall intensity (Caretta et al., 2022a). Changes in the cryosphere significantly impact runoff patterns. Increased snowmelt rates initially boost runoff from basins with high-standing glaciers, but this effect diminishes as glacier mass declines. In regions with lower-standing glaciers or significant snow cover reliance, earlier snowmelt shifts peak runoff towards spring, potentially reducing summer water availability. Surface evaporation from soils, lakes, and rivers is also projected to increase. However, the response of vegetation to elevated atmospheric CO_2 concentrations introduces uncertainty. Plants may exhibit increased water-use efficiency by partially closing their stomata, thereby reducing transpiration. Conversely, enhanced CO_2 can also stimulate plant growth, leading to increased leaf area and potentially higher overall water requirements (Douville et al., 2021).

Understanding projected drought changes requires differentiating between drought types: meteorological (linked to reduced precipitation), hydrological (linked to reduced runoff and streamflow), and agricultural (linked to soil moisture deficits). While these types are often interconnected, they are not always directly sequential. For example, hydrological drought can occur without a preceding meteorological drought due to increased water withdrawals. Similarly, intense rainfall on arid soil may generate high river streamflows (potentially mitigating hydrological drought) without significantly alleviating agricultural drought if soil moisture remains low. Fundamentally, hydrological drought reflects water *availability*, whereas agricultural drought relates more closely to unmet water *demand* for crop growth, often necessitating irrigation. Figure 2.6 illustrates the projected variations in the likelihood of agricultural droughts under different temperature increases. Notably, the likelihood of agricultural drought does not increase uniformly across the globe; for instance, the Mediterranean region shows a projected increase even at lower levels of global warming (e.g., $1.5°C$) (Caretta et al., 2022a).

This suggests that the need for water irrigation is likely to increase in many agricultural areas. Furthermore, climate models show considerable agreement (Figure 2.7) that water availability in streamflows within the north-eastern Mediterranean basin (including Italy, Greece, and Turkey) is projected to decrease during the peak irrigation months of June, July, and August (Douville et al., 2021). This projected increase in water demand coinciding with a decrease in natural supply underscores the need for adaptive water management policies (Caretta et al., 2022a).

2.1.5 Water Scarcity in Italy and the Po Basin

The challenges of water scarcity and variability are acutely felt in Italy. The Po Valley, the country's agricultural heartland, presents a compelling case for studying alternative management approaches. Its high average water consumption (approx. 30% of rainfall) (PoB, 2006; suw, 2021) coupled with declining summer flows (Figure 2.8), especially during peak agricultural demand (June-July), highlights intense resource pressure driven by climate and abstraction trends, causing record breaking saltwater intrusion during the 2022 drought. This has been attributed to reduced snowfall, earlier snowmelt shifting peak flows to spring, increased evaporation due to warming, and rising water abstractions (Montanari et al., 2023). This context strongly favours exploring demand-side management. Conversely, Sicily utilizes a much smaller fraction of average rainfall (approx. 8%) (Autorità di Bacino del Distretto Idrografico della Sicilia, 2021, 2010), yet severe recent droughts triggered acute crises, including domestic rationing in 2024 threatening basic water rights (Tondo, 2024). This suggests Sicily's vulnerability stems more from infrastructural deficits in capture, storage, and distribution (”hard path” limitations) than chronic overuse of average resources. Thus, the immediate focus there rightly centers on supply-side improvements to ensure essential access during scarcity, contrasting with the Po's need for better demand allocation.

Within the Po Basin, agriculture dominates consumptive water use, accounting for 80.3% of total withdrawals, followed by households (12.2%) and industry

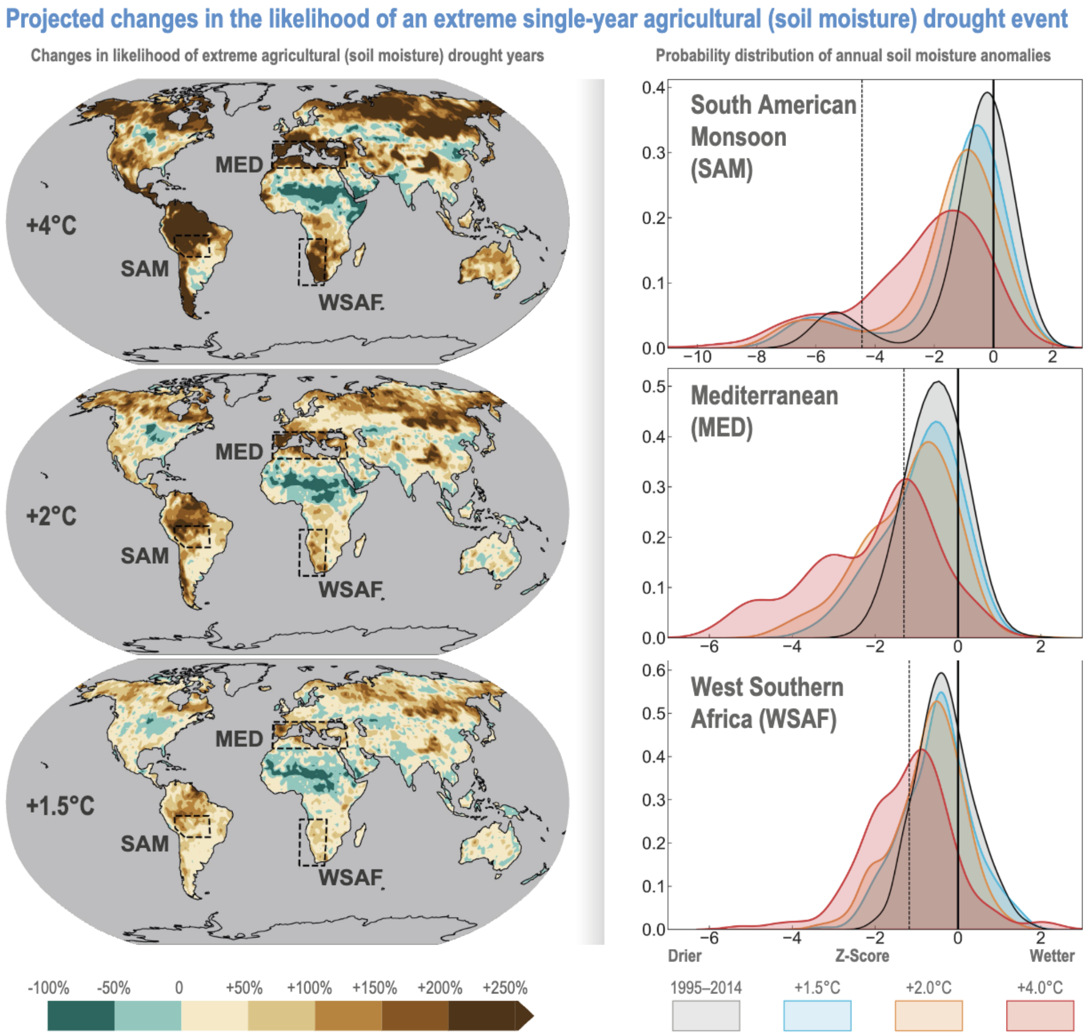


Figure 2.6: Figure and description taken from the IPCC AR6 WGIIs report showing the projected changes in the likelihood of an extreme single-year agricultural (soil moisture) drought event. Extreme drought events are defined as the driest 10% of years from 1995 to 2014 (Cook et al., 2020). Left: Percentage change in the likelihood of extreme drought at Global warming levels for each cell. Right: probability distribution functions of regional mean soil moisture anomalies for the climatic regions Mediterranean (MED), South American Monsoon (SAM) and West Southern Africa (WSAF) (Iturbide et al., 2020), at $1.5°C$, $2°C$ and $4°C$ temperature increases. The solid vertical line shows the baseline soil moisture median. The dashed vertical line shows the 10th percentile for 1995–2014, defining 'extreme drought' at the regional scale.

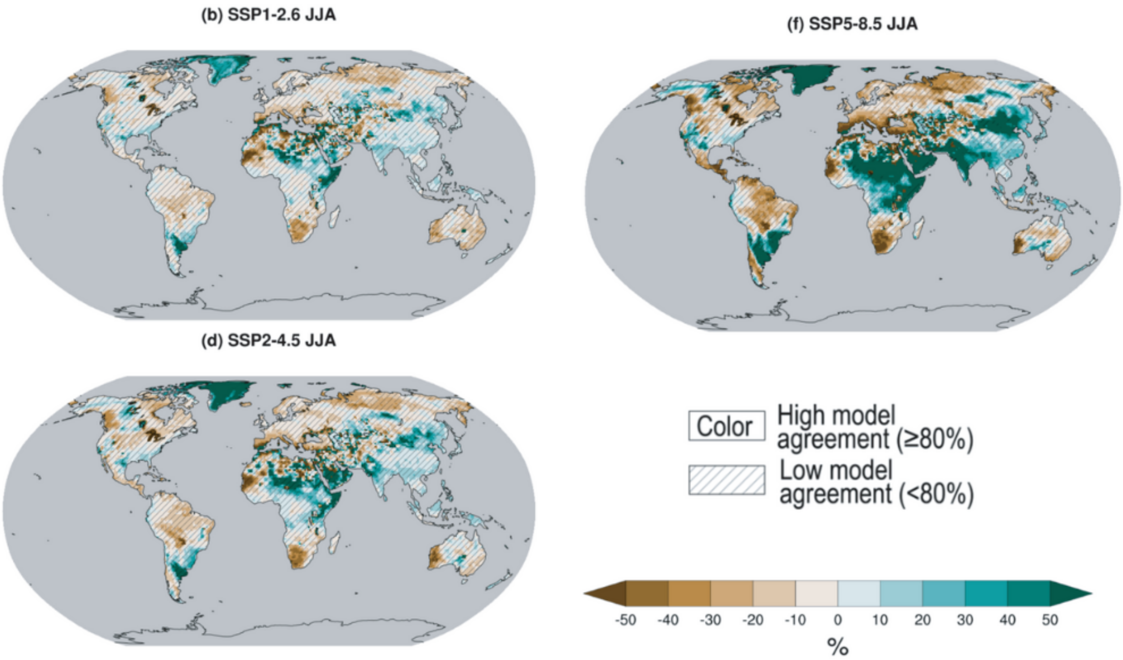


Figure 2.7: Percentage variations in the seasonal mean runoff (June, July and August) in three different Shared Socioeconomic Pathways (SSP): the "sustainability" SSP1-2.6, the "middle-of-the-road" SSP2-4.5 and the "fossil-fuel–intensive" SSP5-8.5. All changes are estimated in 2081–2100 relative to 1995–2014 on a multi-model CMIP6 ensemble. If more than 80% of the models agreed on the predicted sign variation the area is coloured as high agreement. Figure adapted from (Douville et al., 2021) (Specifically, Figure 8.18).

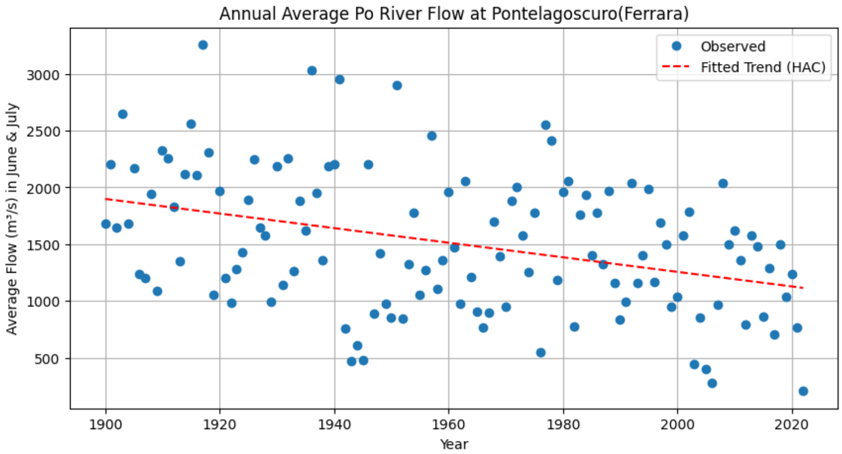


Figure 2.8: Annual average Po River flow (June & July) at Pontelagoscuro (Ferrara) from 1900 to 2022, with a fitted linear trend (red dashed line) using Newey–West (HAC) standard errors. The estimated slope is approximately $-6.41 \pm 1.37\,\mathrm{m}^3/\mathrm{s}$ per year, highly significant ($p < 0.001$), indicating a robust declining trend in summer flows. Model $R^2 \approx 0.138$. Diagnostic tests (Durbin–Watson ≈ 1.896, White test, Breusch–Pagan test) show no major issues.

(7.5%) (Autorità di Bacino del Fiume Po, 2016). However, the current institutional framework in Italy fails to incorporate key principles of efficient water management, providing weak incentives for improving water productivity in agriculture. Italian law generally prohibits the sale of water resources (leg, 1994), preventing informal or formal reallocation among users during shortages, a critical inflexibility witnessed during the 2022 drought. Furthermore, water tariff structures, typically set regionally, often lack a connection to actual consumption. For example, Lombardy's guidelines do not include tariffs based on abstraction volumes, while in Emilia Romagna, consumption-based tariffs are applied only where meters exist, covering a minority of consumption (e.g., 26% in the Consorzio di Bonifica della Romagna Occidentale) (di Bonifica della Romagna Occidentale, 2023). Nationally, indicators based on actual consumption volumes represent only a small fraction (around 16%) of the criteria used for setting irrigation water tariffs (Guerrini et al., 2025). The increasing drought risk in the Mediterranean region due to climate change, combined with the lack of effective water management policies, motivates the exploration of innovative management systems.

2.1.6 The Adda-Lario System

The Adda-Lario system represents a critical sub-basin within the broader Po Valley, encompassing the Alpine catchment of the Adda river, its primary regulator Lake Como (also known as Lario), and the downstream agricultural plain (see Figure 2.9). The river originates in the Rhaetian Alps, flows into Lake Como at its northern end, and exits at the southern Lecco branch, continuing its course southwards across the Lombardy plain to eventually join the Po River (Amaranto et al., 2022). This system is of particular interest due to the intense and often conflicting demands placed upon its water resources, primarily between upstream hydropower generation, flood protection for the lakeside communities, and downstream agricultural irrigation.

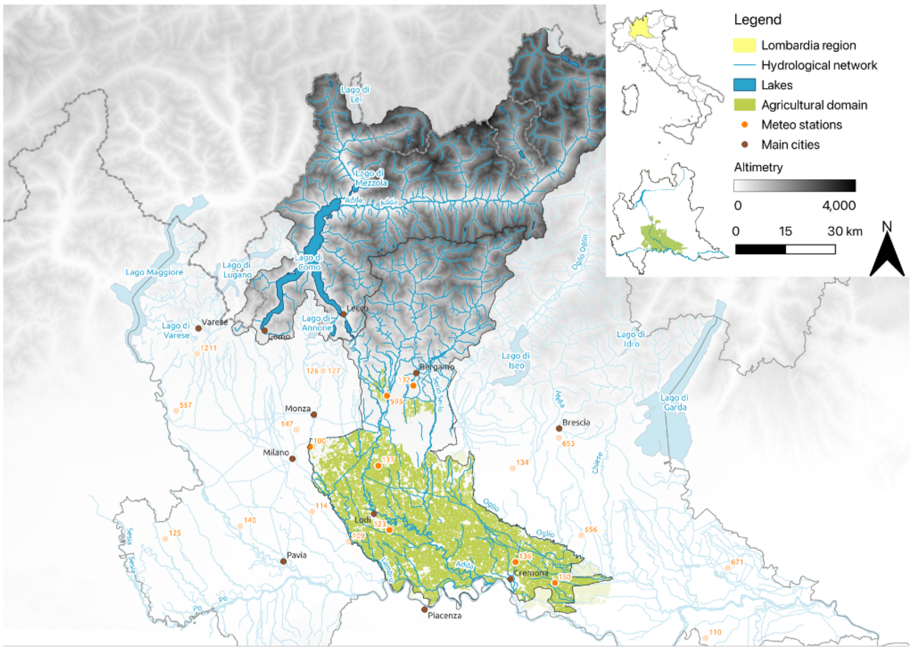


Figure 2.9: Schematic map of the Adda-Lario system, showing the Alpine catchment, Lake Como, and the downstream irrigation district. The image was taken from Gazzotti et al. (2025).

The agricultural plain downstream of the lake is highly productive, with maize being the most widely cultivated crop, followed by permanent meadows which are often used for multiple harvests of fodder. Other significant crops include winter cereals (such as wheat and barley) and soybeans (Micotti et al., 2022). These agricultural activities are almost entirely dependent on irrigation, with the predominant method being gravity-fed surface irrigation, a technique that relies on an extensive network of open channels to flood fields (Amaranto et al., 2022).

The primary water source for this vast agricultural area is Lake Como, which functions as a large, multi-purpose reservoir. The greatest demand for irrigation water occurs during the summer months, peaking sharply in June and July due to high crop water requirements and lower precipitation (Micotti et al., 2022). The lake's regulated storage capacity, the volume available for managed release, is approximately 246.5 million cubic meters (Mm^3). This volume is set against an average summer irrigation demand of around 800 Mm^3. Consequently, the regulated storage of Lake Como can satisfy only about one-third of the total summer agricultural need, covering the equivalent of approximately 35-40 days of peak demand. This significant gap between available storage and demand underscores the system's vulnerability to droughts and highlights the critical importance of inflows from the Alpine catchment during the summer (Amaranto et al., 2022). Water is distributed to farmers through a system of irrigation consortia ("consorzi irrigui"), which manage the secondary channel network. The allocation of water among farmers within these consortia is primarily based on the surface area (hectares) of land they own or cultivate within the district's jurisdiction (Micotti et al., 2022). In the second chapter we will compare the adaptation capacity to changing water availability of farmers from the Murray Darling Basing and the one from the Adda Lario System.

2.2 Water management and Cap and trade

2.2.1 Water Allocation Regimes

Water allocation regimes determine who is permitted to abstract water from a shared resource pool, the conditions of that abstraction (how much, when, quality of return flow), and how the risks associated with water availability fluctuations are distributed among users (OECD, 2015a). Effective allocation is crucial, especially as pressures on water resources intensify due to factors like climate change and increasing demand. Well-designed allocation regimes strive to be robust, performing adequately under both average and extreme hydrological conditions, and adaptively efficient, allowing adjustments to changing circumstances at the least cost (OECD, 2015a).

Water resources possess unique characteristics that complicate their management. As illustrated in Table 2.2, water exhibits features of both public and private goods, depending on the context of its use and valuation (Hanemann, 2005; Griffin et al., 2012). For instance, in-stream flows providing ecosystem services or supporting navigation act as pure public goods (non-rivalrous, non-excludable), whereas water delivered through an irrigation system for consumptive use behaves as a private good (rivalrous, excludable). Shared aquifers often represent common pool resources (rivalrous, non-excludable).

The fundamental difference in how public and private goods are valued is a key prerequisite for such systems: the value of a public good (like environmental flows) derives from the sum of benefits across all potential beneficiaries, whereas the value of a private good (like water abstracted for irrigation) is determined by the marginal utility to the individual user (OECD, 2015a). Consequently, an initial administrative division is commonly made, separating the water needed for in-situ public good uses (e.g., environmental flows) from the remaining 'allocable pool' available for withdrawal as a private or common pool good. This remaining water, generally considered a state-owned resource in most legal frameworks (with exceptions, particularly for groundwater), can then be abstracted by users granted specific rights (OECD, 2015a).

Access to abstract water is typically governed by a system of *water entitlements*, which represent long-term rights to a potential share of the resource. These entitlements usually specify conditions such as maximum flow rates, allowable abstraction volumes per period, points of diversion, and potentially return flow obligations. Complementing these are *water allocations*, which are the short-term rights to withdraw a specific volume of water, granted to entitlement holders based on current resource availability. While critical human and animal needs are often exempt from formal entitlement requirements, most significant water uses require authorisation. However, unregulated access can still pose challenges if cumulative impacts become significant (OECD, 2015a).

In situations of water scarcity, where available supply falls short of demand, rationing becomes necessary. While economic theory advises using water pricing that reflects scarcity value, this approach is rarely implemented comprehensively. Instead, water rationing predominantly relies on quota mechanisms, often preferred due to perceived lower administrative costs, potentially lower income impacts on

Table 2.2: Water as a public and private good

		Rivalry	
		Low	High
Excludability	**High**	**Club good** • Recreational use in water bodies where access can be restricted, such as a private lake.	**Private good** • Water body exclusively on private land. • Drinking water consumed by households. • Irrigation system which allows for exclusion. • Rainwater captured on private land.
	Low	**Pure public good** • In-stream uses, such as navigation, environmental flows supporting ecosystem services, recreational uses (bathing, boating, etc.).	**Common pool resources** • Shared aquifer. • Water provided through a distribution system in an irrigation district (where users cannot be excluded).

Source: Adapted from OECD (2015a), which based its table on Hanemann (2005) and Griffin et al. (2012).

users, and a direct method for limiting consumption. Even where market mechanisms are used for the more effective distribution of the private good component (i.e., the allocated water), the available water is first distributed to entitlement holders before trading occurs (Molle, 2009). The distribution of quotas during scarcity generally follows established principles:

- **Use-based priority:** Legislation defines a hierarchy of uses (e.g., critical human needs, domestic, industrial, national security, agriculture) dictating priority during shortages.
- **Prior appropriation:** Grants senior rights holders priority over junior ones, curtailing newer entitlements first.
- **Priority class:** Entitlements are assigned classes determining the order of curtailment, irrespective of use.

These systems are not static; regions can transition between them, as exemplified by New South Wales moving from prior appropriation to a system prioritizing critical needs and then entitlement class (Davis, 1967; Hanemann & Young, 2020). Rationing methods include volumetric allocation (requiring metering), cease-to-pump orders based on river or water table levels, or time-splitting withdrawal periods for users sharing a resource like an irrigation channel (Molle, 2009; Schmidt et al., 2020).

Effective implementation and enforcement face significant hurdles, particularly in agriculture, which accounts for over 70% of global water withdrawals. The dispersed nature of agricultural abstractions, especially groundwater wells on private property, makes comprehensive control difficult and it is often reliant on other users or NGOs reporting possible misconduct. A critical issue is the prevalence of illegal or unregistered boreholes; estimates suggest that in European Mediterranean countries, illegal wells might outnumber authorized ones (European Academies Science Advisory Council (EASAC), 2010), a problem likely exacerbated in developing countries (Veldwisch et al., 2019; Woodhouse et al., 2017).

Accurate monitoring is fundamental for enforcement. While *telemetry*, which automatically transmits withdrawal data to a central register, offers a powerful tool for checking compliance with allocation regimes, its adoption varies significantly. Victoria, Australia, boasts high telemetry penetration (61%), but this remains an exception globally (Inspector-General of Water Compliance, 2023). The majority of installed meters worldwide do not communicate centrally, and a large proportion of abstraction points, particularly groundwater wells (e.g., only 36% metered in the US), lack any metering device (USDA, 2019). Alternative control methods exist, such as rationing electricity for pumps, that has been successfully applied in Gujarat, India (OECD, 2015b). Even when meters are present, especially in surface gravity systems where timing rather than volume might be the primary regulation method (Molle, 2009), they are often susceptible to breakage or tampering (Molle & Closas, 2017). Farmer resistance to metering, often stemming from fears of stricter future regulations, further complicates implementation (Jakeman et al., 2016; López-Gunn, 2012). Weak penalties, lengthy judicial processes, and potential corruption further strain effective enforcement (Molle, 2009). Satellite remote sensing shows promise for improving enforcement by estimating withdrawals and identifying areas needing in-situ checks, though precision limitations remain for the computation of volumetric charges (Foster et al., 2020).

2.2.2 Cap and trade in general

When individuals have unfettered access to a finite and valuable shared resource, and the benefits of its exploitation accrue directly to them while the costs of depletion are distributed across a larger group, a "tragedy of the commons" can occur if no mechanisms, such as social norms or regulations, prevent overuse, leading to the progressive degradation and potential unusability of the resource for all.

A cap and trade system, which involves creating a limited number of tradable permits to access a common resource, is a potential solution to the tragedy of the commons Hardin (1968); Smith (1982). In this system, the number of allowances created, aiming to maintain resource consumption at a *sustainable* level or to keep societal damages at an acceptable threshold, can be informed by scientific studies but ultimately remains a political decision Schmalensee & Stavins (2017). Theoretically, this limit should ideally be set where the benefits from resource consumption equate to the cost of extraction plus the associated externalities; however, determining these externalities and the damages caused by the consumption of a common resource can be challenging Leonard et al. (2011). The common environmental resources to which cap and trade mechanisms have been applied are various: natural renewable resources like fisheries Schmalensee & Stavins (2017); Stavins (2011), clean air through pollution permits for substances such as SO2 and NOx Stavins (2003), and the allowable stock of CO2 emissions in efforts to meet climate goals Schmalensee & Stavins (2017). The characteristics of each cap and trade market depend significantly on the properties of the environmental resource being managed Stavins (2003). In particular, it is important to consider what constitutes equivalent damage to the common resource. This informs the definition of trading rules. For example, the global stock of CO_2 is considered to be impacted almost equivalently by emissions from different locations due to its global mixing in the atmosphere. Therefore allowances can be traded freely between locations. This contrasts with the RECLAIM program launched in 1994 in southern California to address local air pollution (NO_X and SO_2), where trades from downwind to upwind sources were not permitted Stavins (2003). This restriction acknowledged the differing impacts of emissions based on their geographic location on local air quality. Rules on carryover depend on the nature of the common resource. For example, the carryover limit for individual transferable fishing quotas is generally lower than 50% and varies across different fisheries management systems Wiedenmann & Holland (2020) because allowing excessive carryover could lead to concentrated fishing effort that jeopardizes the long-term sustainability of fish stocks and their reproductive capacity. The total allowable limit of the common resource to be exploited is announced and updated with different frequencies. Differently, in the US SO_2 emissions market under the Clean Air Act Amendment allowances were allocated annually and there was the possibility for banking Berkson & Thorson (2014). Also, given the long residence time of CO_2 in the atmosphere also in the EU ETS carryover is possible. Usually not all sources of depletion of common resources are included in cap and trade mechanisms. For example direct emissions from consumers are beyond the scope of the EU ETS. The reasons for exclusion can be due to the difficulty of enforcing limits or due to political considerations Stavins (2003).

2.3 The Murray Darling Basin Cap and Trade on Water

2.3.1 Water cap and water rights

The Murray-Darling Basin (MDB), see fig. 2.10, spanning five Australian states, is a vital agricultural region, contributing approximately 40% of the nation's irrigated and dryland agriculture gross value (CSIRO, 2008). However, the Basin is characterised by extreme hydro-climatic variability.

Historical records demonstrate significant fluctuations in inflows, with the highest recorded annual inflow exceeding the lowest by more than twentyfold (Figure 2.11) (Murray-Darling Basin Authority, 2012). Furthermore, a pronounced seasonal mismatch exists between water supply and demand; the period of greatest inflow typically occurs during winter and spring, whereas peak demand, primarily for irrigation, occurs in summer (Reynolds, 2020).

Historically, water management in the MDB followed a 'hard path' approach,

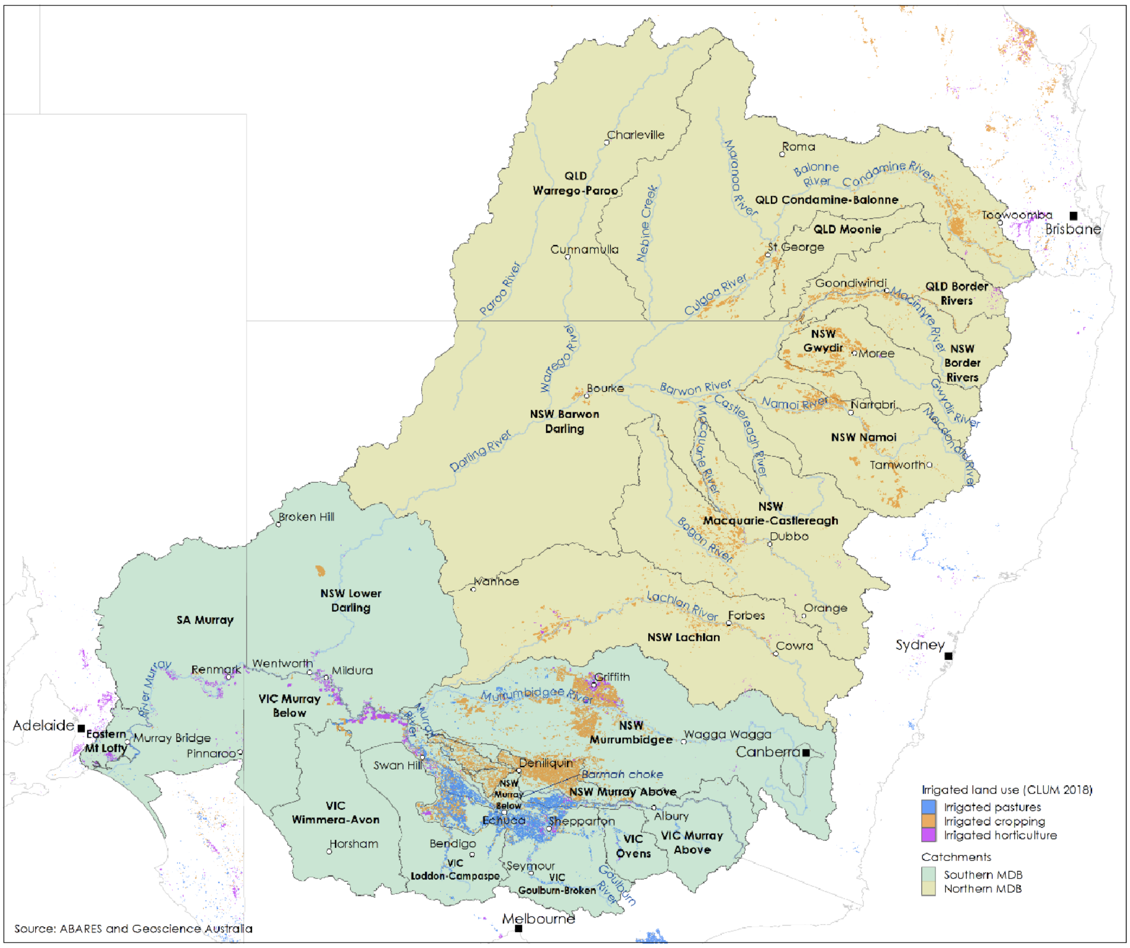


Figure 2.10: Map of rivers, irrigated areas and the division in sustainable diversion units of the Murray Darling Basin. The different basin states are indicated with an abbreviation: SA is Saouth Asutralia, VIC is Victoria, NSW is New South Wales and QLd is Queensland, The image has been taken from Goesch et al. (2020).

focusing on increasing supply through infrastructure development, such as large reservoirs, to mitigate this variability and support agricultural expansion. This led to significant storage capacity being constructed throughout the 20th century. However, this supply-driven approach resulted in the over-allocation of the water resources and contributed to significant environmental degradation, including increased salinity and frequency of algal blooms. Consequently, a policy shift towards demand-side management occurred, capping water consumption and establishing water markets to facilitate the reallocation of water resources to higher-value uses. Despite the informal or formal existence of water trading since World War II, significant market development primarily occurred from the 1980s onwards (Wheeler, 2014).

The current water management framework in the MDB operates under a basin-wide cap known as the Sustainable Diversion Limit (SDL), established under the Commonwealth *Water Act 2007* and the *Basin Plan 2012*. The SDL framework applies to all forms of consumptive water take, including surface water diversion, groundwater extraction, floodplain harvesting, commercial plantation interception, and runoff capture in farm dams (Murray–Darling Basin Authority, 2025). The

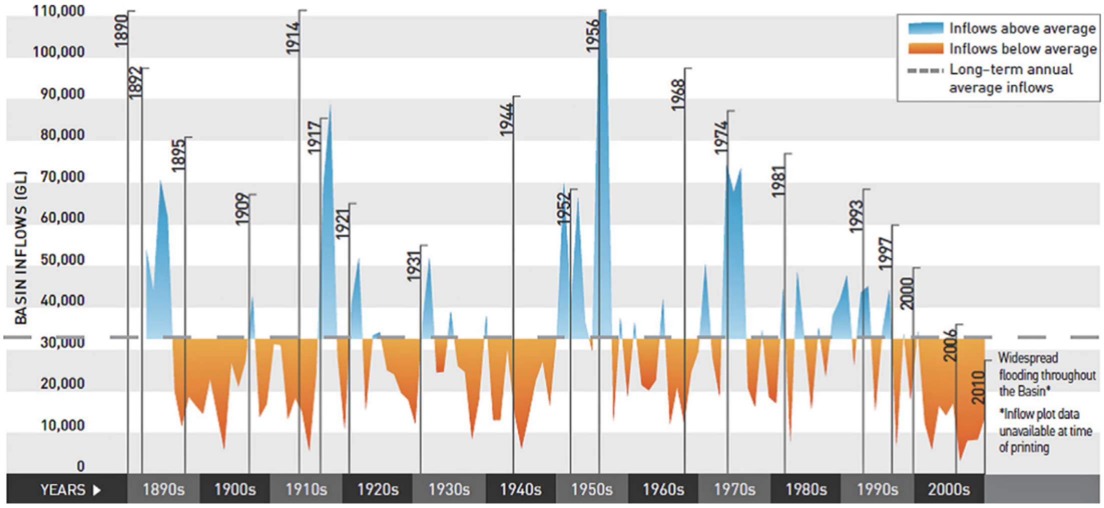


Figure 2.11: Total Murray Darling basin system inflows (Gigalitres per year) from 1890–2010, illustrating high inter-annual variability. Data from (Murray-Darling Basin Authority, 2012).

Basin is divided into 29 surface water and 80 groundwater SDL resource units (see Figure 2.10), each with a specific SDL. The SDL represents a long-term average limit on consumptive use, not a strict annual cap. Compliance is assessed based on state-proposed Water Resource Plans (WRPs). These plans detail the rules for water management within each SDL resource unit. To assess compliance, the average Permitted Take (PT) over a historical climate sequence (typically 1895-2009) is simulated based on the WRP rules and compared to the SDL:

$$\frac{(PT_{1895\text{–}96} + PT_{1896\text{–}97} + \ldots + PT_{2007\text{–}08} + PT_{2008\text{–}09})}{114 \text{ years}} \leq SDL$$

Only WRPs demonstrating compliance with the SDL are accredited by the relevant Commonwealth Minister. To track compliance dynamically, a cumulative balance is maintained for each SDL resource unit, recording the difference between the annual Permitted Take (the modelled allowable take under the year's conditions) and the Annual Actual Take (AAT):

$$\text{Cumulative Balance}_n = \text{Cumulative Balance}_{n-1} + (\text{Permitted Take}_n - \text{Actual Take}_n)$$

If the cumulative balance indicates a debit (use exceeding permitted take) greater than 20% of the SDL, the Basin state must implement an action plan to return the balance to an acceptable level, failing which the Commonwealth government may intervene (Murray–Darling Basin Authority, 2025).

Various forms of water abstraction exist within the MDB. A fundamental distinction is made between rights that can be traded and those that cannot. Non-tradable rights include take under basic landholder rights (domestic, livestock, native title) and harvestable rights (allowing collection of rainfall runoff), which generally do not require formal licensing (NSW Department of Planning and Environment, 2023). Tradable abstractions fall into two broad categories based on their temporal characteristics:

- **Storage type resources:** These rights pertain to water stored in reservoirs (regulated rivers) or groundwater aquifers, allowing consumption to be delayed, potentially across water years if allowed by carryover rules. Access is governed by Water Entitlements, which are typically perpetual or long-term rights representing a share of the available resource. Entitlements vary by security level (e.g., High Security entitlements generally receive a higher proportion of their share compared to General Security entitlements, see Figure 2.14). The actual volume available for use in a given year is determined by Water Allocations (expressed in megalitres, ML), which are distributed periodically based on water availability assessments to entitlement holders according to the share of the total entitlements on that storage they own (NSW Department of Planning and Environment, 2023, 2019).
- **Flow type resources:** Abstraction is contingent on specific flow conditions and cannot typically be delayed. This includes take from unregulated rivers, floodplain harvesting, and forestry interception (relevant in some jurisdictions like South Australia, see Regan et al. (2023)). Regulated rivers also feature supplementary entitlements, permitting abstraction during announced high flow events. For these flow-dependent types, water allocations are often implicitly linked to the occurrence of specific flow events rather than volumetric announcements based on storage assessments. Rules governing these takes often include specific river flow thresholds or conditions that must be met to permit abstraction (NSW Department of Climate Change, Energy, the Environment and Water, 2025; NSW Department of Planning and Environment, 2019).

	Reg. rivers (GL)	Water-courses (GL)	Runoff dams (GL)	Plantation take (GL)	Groundwater (GL)	**Total** (GL)
Queensland	n.a.	87.3	514.4	2.0	165.3	1545.3
New South Wales	3294.6	387.4	1593.9	219.0	540.1	5545.1
Australian Capital Territory	n.a.	5.8	4.6	7.2	0.5	17.6
Victoria	1653.7	47.7	193.1	116.8	75.3	2038.8
South Australia	n.a.	477.2	29.6	3.3	53.5	516.1
Total Basin	**4948.3**	**1266.3**	**2335.6**	**348.3**	**834.7**	**9733.2**

Table 2.3: Annual actual water take (GL) by Basin State and forms of take in 2022–23. Regulated rivers data is available only for New South Wales and Victoria; not applicable (n.a.) for other states in this context. 'Watercourses' refers to unregulated river abstractions for NSW and VIC and all water takes from rivers for the other basin states. 'Runoff dams' includes floodplain harvesting and on-farm rainfall capture. Data sourced from (Murray–Darling Basin Authority, 2024)

In the Murray-Darling Basin (MDB), rights to water, specifically water allocations (temporary water) and water entitlements (ongoing rights), can be traded. Trading also involves related products like carry-over (storing allocated water between seasons) and delivery rights. There is no single central market exchange, but several privately run exchanges and water brokers operate within the basin. While irrigators often utilize water brokers for assistance, participants can also arrange trades privately. However, for a trade to be effective, it must be registered with and approved by the relevant Basin state authority, which verifies compliance with various trading rules and constraints (see 2.3.4). The most active markets are for surface water, which also accounts for the majority of water extracted in the MDB (see 2.3). Market participants are not restricted to water users; non-landholders,

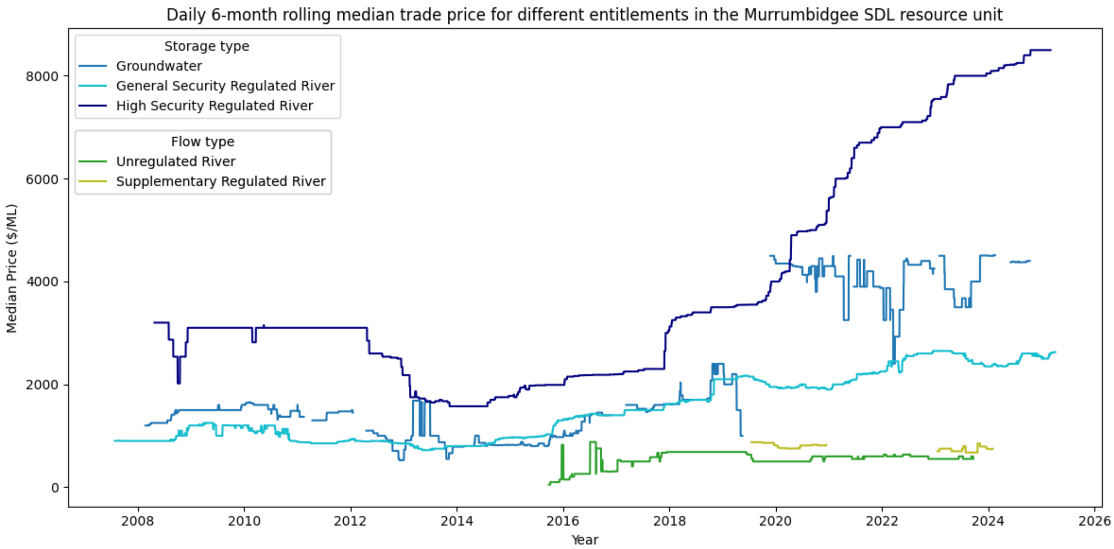


Figure 2.12: 6-month rolling average price for five different entitlement classes in the Murrumbidgee SDL resource unit, distinguishing storage and flow types. Groundwater data represents the Lower Murrumbidgee Deep Groundwater source. Unregulated river data aggregates all available trades within the relevant SDL unit. Data sourced from Australian Bureau of Meteorology (Australian Bureau of Meteorology). Price reporting became compulsory in 2014, though enforcement challenges still exist (de Bonviller et al., 2020). Prices are filtered in the range between 50 and 20 000 AUD/ML as per Bureau of Meteorology methodology.

including financial investors and environmental water holders, are permitted to participate (Wheeler et al., 2020).

2.3.2 Distribution of allocations and delivery

This subsection focuses on New South Wales (NSW) as an illustrative case for allocation distribution and delivery, specifically using the Murrumbidgee region, which accounts for over 22% of total MDB surface water diversion. While allocation rules differ between states, NSW provides a representative example. The Murrumbidgee system includes major storage infrastructure and is influenced by transfers from the Snowy Mountains Hydro-electric Scheme (Figure 2.13).

In NSW, the water year commences on July 1st with an Available Water Determination (AWD) that distributes water allocations to accounts of entitlement owners based on resource availability and entitlement category. High Security (HS) entitlements receive priority allocation, followed by General Security (GS) entitlements. Domestic, stock, and Aboriginal cultural licences also receive high priority (NSW Department of Planning and Environment, 2023). The available water for water allocations are distributed according to the formula:

$$Available\ Water = Current\ Resource + Future\ Inflow - Commitments - Overheads \tag{2.1}$$

where 'Current Resource' is water in storage; 'Future Inflow' is a conservative estimate based on historical low-flow sequences; 'Commitments' include environmental water requirements, already allocated water and reserves for next year high-security entitlements; and 'Overheads' represent system losses like evaporation and transmission (Department of Planning & (NSW), 2022a,b,c,d).

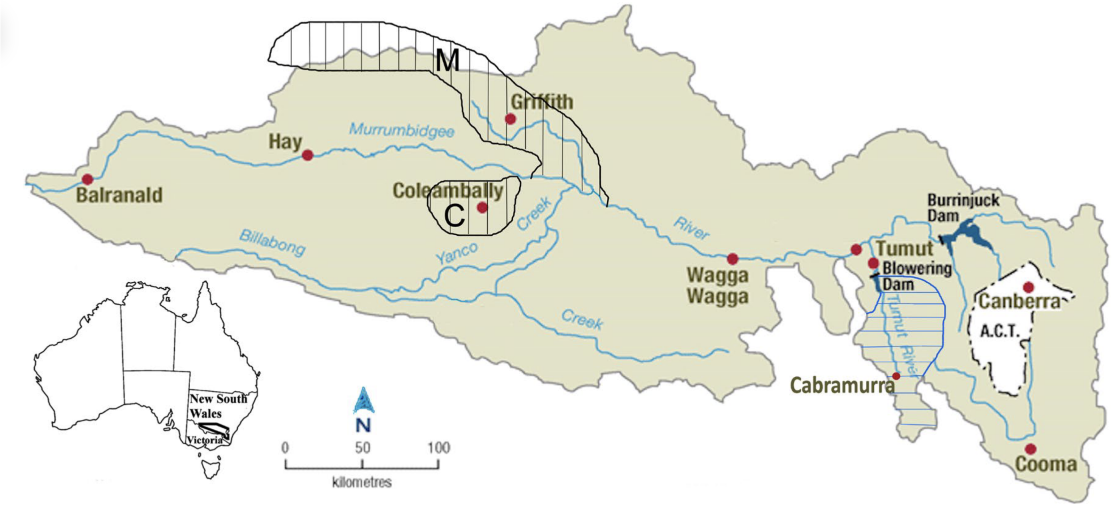


Figure 2.13: The Murrumbidgee River catchment area. Major Irrigation Operator areas are indicated: Murrumbidgee Irrigation (M) and Coleambally Irrigation (C). Also shown are the Snowy Mountains Hydro-electric Scheme transfer (blue hatching) and major storages (Blowering and Burrinjuck Dams). Source: Speer et al. (2021).

In the Murrumbidgee regulated river system (capacity approx. 2659 GL, supplemented by Snowy Scheme transfers of approx. 1026 GL/year), HS entitlements (approx. 400 GL) generally receive full or near-full allocation, while GS entitlements (approx. 1900 GL) experience significant variability (Figure

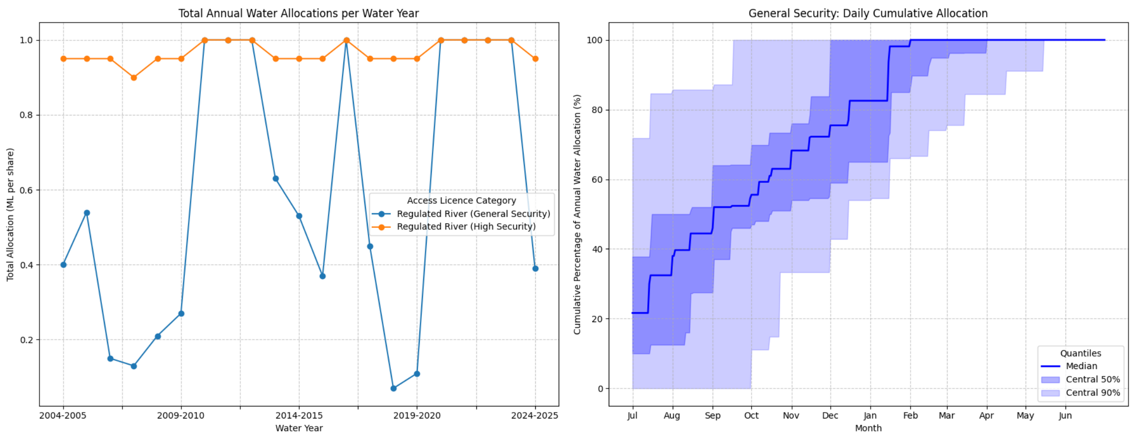


Figure 2.14: Left: Daily announced allocation percentage for General Security entitlements in the Murrumbidgee regulated river. Right: Total annual water allocation distributed to High Security and General Security (1 ML entitlement equivalent) owners. Data sourced from the NSW Water Register (WaterNSW, 2025a).

2.14) (Department of Planning & (NSW), 2022d). GS allocations are distributed only after HS allocations reach 95% of their entitlement[1]. This often results in GS

[1]The authors were not able to explain why in the 2007-08 water year just 90% (see 2.14) of the

allocations commencing lower and increasing through the water year. Consequently, HS entitlements command higher market prices than GS entitlements (Figure 2.12). Groundwater allocation distribution is based on the average extractions over the previous five-year period, assessed against the Sustainable Diversion Limit (SDL). If growth in extractions causes the five-year average to exceed the SDL by more than 5% or 10% (depending on the SDL resource unit), the volume of water that can be extracted—even if allocations from the previous year remain—is reduced(NSW Department of Planning, Industry and Environment, 2020a).

Since 2016, when data became available, groundwater entitlement holders have consistently received their full share of water allocation in the Lower Murrumbidgee Deep Groundwater Source.

Groundwater is usually extracted using private bores on privately owned land, allowing irrigators to extract water whenever needed. It is the irrigator's responsibility to ensure that sufficient allocations are available and that there are no local withdrawal restrictions in place due to emerging impacts from water extraction (New South Wales Department of Industry – Water, 2019).

Instead, surface water delivery from dams requires lead time for water to travel to the user. Private diverters place orders via the WaterNSW platform, which manages releases considering travel time (e.g., approx. 7 days to Coleambally area) (WaterNSW, 2025b; mur, 2021). In contrast, irrigators within Irrigation Infrastructure Operators (IIO) schemes (like Murrumbidgee Irrigation or Coleambally Irrigation) benefit from internal delivery systems often incorporating surge reservoirs, allowing much faster delivery (e.g., within 2-48 hours) after ordering via the IIO's platform (acc, 2020; Coleambally Irrigation Co-operative Limited, 2025).

2.3.3 Carryover and Volatility of Allocation Prices

Unlike cap-and-trade systems for emissions (e.g., the EU ETS) where the timing of emission release has less immediate impact relative to the long atmospheric lifetime of greenhouse gases (Stavins, 2003), water under a cap-and-trade system requires physical storage if consumption is to be deferred. Water storage capacity in dams and reservoirs is finite, and dam operators must also manage storage levels to mitigate flood risks, creating inherent limitations on the total volume of water that can be held (Hughes et al., 2013). Consequently, water markets implement 'carryover' rules, allowing entitlement holders to save just a portion of their unused water allocation from one water year to the next.

Typically, rules define a maximum percentage of an entitlement that can be carried over and a maximum limit on the volume an account can hold (the 'account limit'). For example, in the NSW Murrumbidgee, general security (GS) users could carry over up to 30% of their entitlement, with an account limit of 100% of entitlement volume; exceeding this limit meant foregoing further allocations (Commonwealth Environmental Water Office, 2013). High Security (HS) entitlements in this system often had 0% carryover, because their water for the next year is already taken in to account in the commitments. Some systems, like Victoria's, utilize 'spillable water accounts' (SWA). Water exceeding entitlement limits might

allocations had been distributed to High Security Entitelment owners before the distribution to General Security ones started.

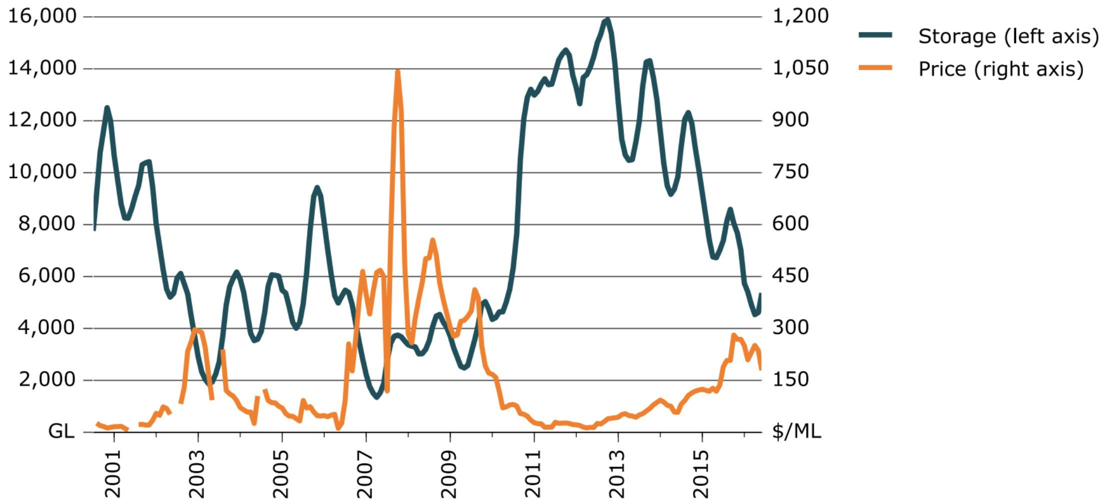


Figure 2.15: The graph shows southern MDB storage volumes excluding the inter basin transfers and Lake Victoria and monthly water allocation prices for the Murray trading zones. Source:Hughes et al. (2016).

enter an SWA, becoming accessible only after dam authorities declare a low risk of storage spill (Hughes et al., 2016). Furthermore, carried-over water is often subject to deductions to account for losses, such as evaporation (e.g., a 5% deduction in Victoria) (Plummer & Schreider, 2015).

These storage and carryover dynamics make allocation prices highly sensitive to the volume of water available in storage. As storages deplete, especially during droughts, prices can increase dramatically, often oscillating between near-zero in wet periods and over 1000 AUD/ML during severe scarcity, as shown in Figure 2.15. In systems or periods where carryover was disallowed, entitlement holders faced a 'use-it-or-lose-it' situation at the end of the water year. This could incentivise using water on low-value activities simply to avoid forfeiture (Plummer & Schreider, 2015).

This end-of-season pressure contributed to distinct seasonal price trends, often with declining prices late in the water year, and significant price jumps between the end of one season and the start of the next, as illustrated in Figure 2.16. The introduction and refinement of rules allowing for carryover have been crucial in mitigating this inter-seasonal volatility and the associated price jumps, allowing for smoother water use patterns and more stable price signals across years (Plummer & Schreider, 2015). It has also be shown that greater carryover limits reduce price volatility in general (Whittle, 2021). Indeed, the Lower Murrumbidgee Deep Groundwater Source that allows up to 2 ML of carryover per 1 ML of entitlement exhibits fewer price spikes and drops compared to the corresponding surface water source. Groundwater can be used as a substitute during surface water shortages, although it entails higher extraction costs due to the energy required for pumping. Groundwater prices tend to follow surface water prices in a lead-lag relationship (Wheeler et al., 2021).

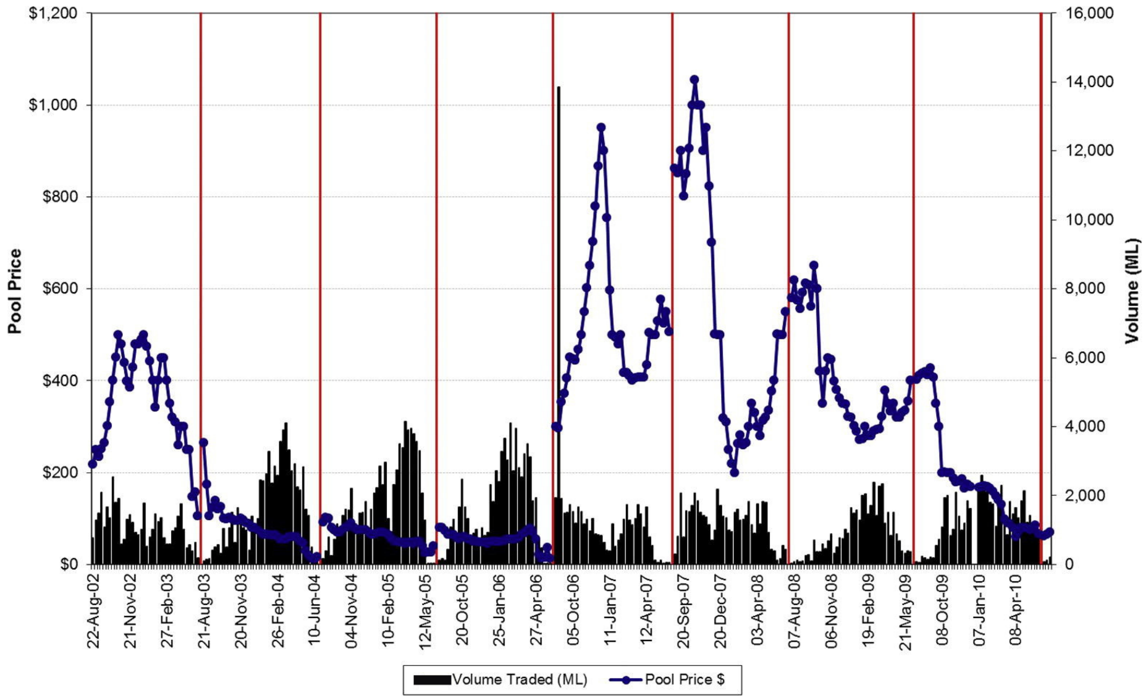


Figure 2.16: Water allocation prices for the greater Gouldburn and volumes of traded water. The lines in red show the beginning of the water year with the initial distribution of allocations. Carryover was initially not allowed. In March 2007, the possibility to carryover 30% of allocations was announced, but preparations were difficult late in the season. In 2008, 50% carryover became possible. Source: Plummer & Schreider (2015).

2.3.4 Environmental protection and trade restrictions

The first step in the MDB Environmental Water Management System under the 2012 Basin Plan is to identify environmental assets and set quantifiable objectives for each SDL resource unit. These include targets related to native fish, vegetation, waterbirds, frogs, ecosystem functions, and connectivity with floodplains and wetlands. These objectives are detailed in the long-term water plans (NSW Department of Planning, Industry and Environment, 2020b). Based on these objectives, environmental water requirements (EWRs) are calculated for specific flow components, including base flows in upland catchments, small freshes, wetland connectivity flows, larger freshes, bankfull flows, and floodplain connection flows (see Figure 2.17). For each flow component, required frequencies and volumes are estimated.

To meet EWRs, environmental water rules are implemented: variable minimum-flow requirements, cease-to-pump rules on unregulated rivers, and physical constraints such as flow limits through narrow channels. A key example is the Barmah Choke the reach of the Murray River with the lowest channel capacity (10.6 GL day^{-1})—above which flows spill into the adjacent Barmah Millewa Forest, a natural winter spring inundation area. Unseasonal summer or autumn flooding can damage red-gum stands (Ladson & Chong, 2005). Therefore, a maximum flow limit is imposed through the Choke.

To achieve higher-flow objectives—such as wetland or floodplain inundation, large freshes, and bankfull flows—environmental water holders (Commonwealth or

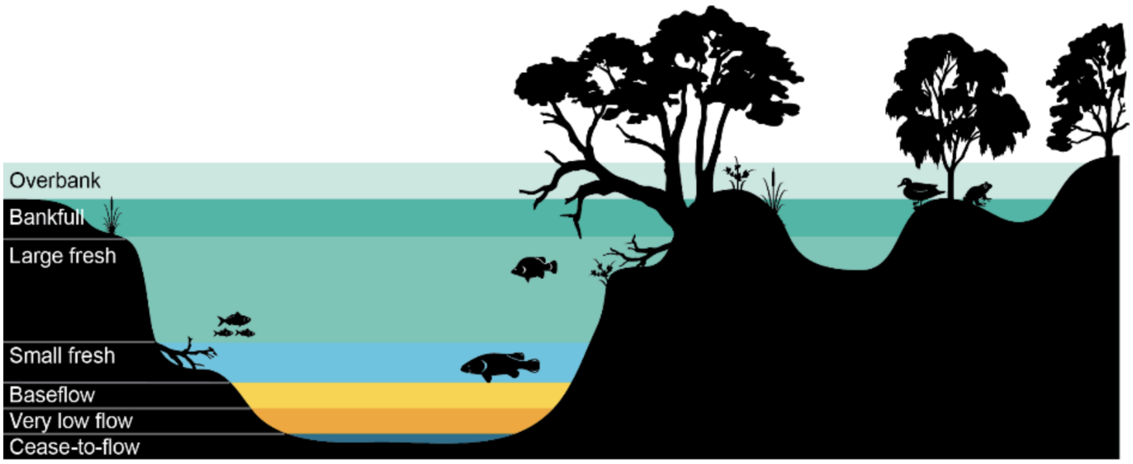


Figure 2.17: Illustration of different flow events. A sequence of these events with a certain frequency over time forms a flow regime. Flow and inundation regimes are essential for maintaining the ecological characteristics of rivers, wetlands, and floodplains (Poff et al., 2010). Source: NSW Department of Planning, Industry and Environment (2020b).

state agencies) purchase water entitlements across the basin. The Commonwealth Environmental Water Holder (CEWH) is the largest entitlement holder in the MDB; for example, in the Murrumbidgee SDL resource unit it owns 3.6% of High-security, 15.1% of General-security, and 45.3% of Supplementary entitlements, which permit abstraction during dam spills (Department of Planning & (NSW), 2022d; Department of Climate Change, Energy, the Environment and Water, 2024). Each year, the ecological condition of each SDL unit is assessed, and environmental water holders may request releases, trade allocations to fund acquisitions elsewhere, or transfer water between SDL units to meet ecological needs.

For instance, the Fivebough and Tuckerbil wetlands in the Murrumbidgee Irrigation Area support diverse waterbird populations, including internationally significant migratory species. They require between 300 ML and 1 000 ML, and 450 ML to 550 ML per annum, respectively, drawn from irrigation channels. The exact volumes depend on local conditions but are guaranteed by CEWH allocations and delivered via its entitlements (NSW Department of Planning, Industry and Environment, 2020b).

When operating in the market, the CEWH maintains market neutrality; its allocation trades are generally too small to influence prices. The legacy water buyback program, valued at AUD 3.1 billion and concluded in 2019, has a debated impact on entitlement prices (Wheeler et al., 2020). In 2023, the Commonwealth Government announced a new buyback of up to 49 GL of entitlements (Donnellan, 2023).

Water trading in the MDB is more constrained than in many other environmental markets. Trades can only occur between abstraction points connected to a common hydrological source; for instance, transfers between the northern and southern MDB are not possible because the two regions are hydrologically isolated. Delivery and trade constraints due to environmental safeguards include the Barmah Choke and modified Goulburn–Murray Inter-Valley Trade limits, introduced to prevent excessive summer flows that suppressed riparian vegetation growth (Victoria State Government, 2021). Instead, the Murrumbidgee Inter-Valley regulation limits downstream trade to the Murray River aiming to avoid overfilling Murrumbidgee

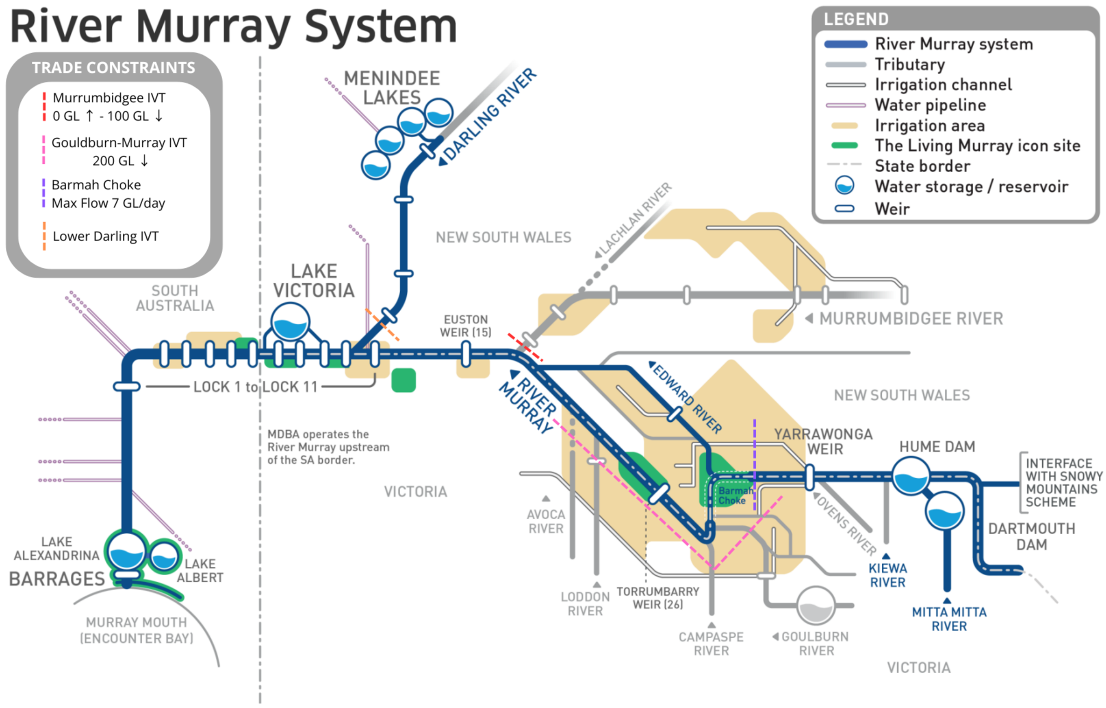


Figure 2.18: Simplified schematic of the Murray system. Trade constraints are indicated by ↑ (upstream limit) and ↓ (downstream limit). Water from Menindee can be traded to South Australia only when the MDBA manages the lakes and storage exceeds 640 GL (Wheeler et al., 2020). Source: Reynolds (2020).

storages with external water, reducing spill risk. Local water needs may also impose additional constraints, such as the Lower Darling IVT. As of 2014, over 1 500 trading restrictions were registered, many of which have since been lifted (Wheeler et al., 2020).

When trade constraints are binding, price differentials emerge between zones, as shown in Figure 2.19.

Water allocations traded out of an SDL unit are still accounted as consumptive use in the origin region for SDL accounting. Groundwater trading between different zones is generally not permitted due to limited connectivity (Murray–Darling Basin Authority, 2025; Consulting, 2020).

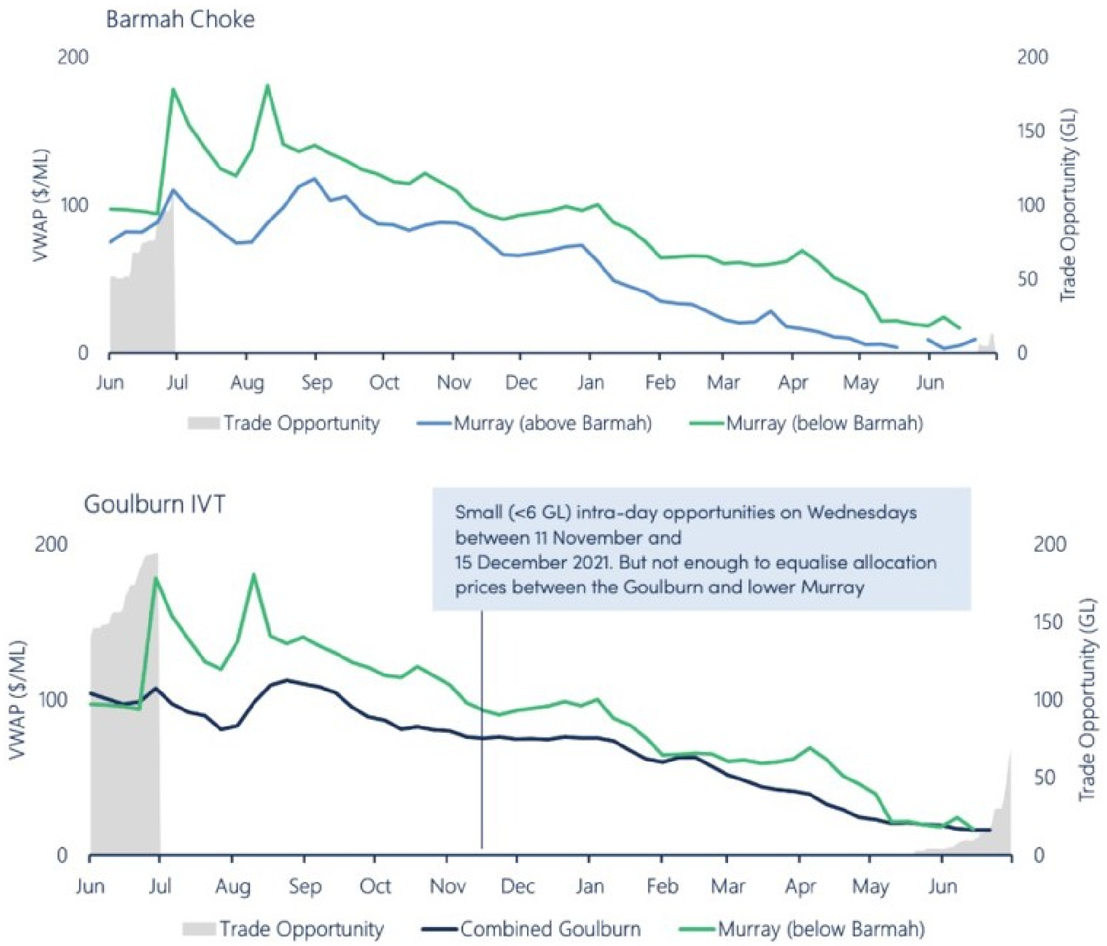


Figure 2.19: Price differentials generated by trade constraints. Source: Ricardo Energy & Environment (2022).

Chapter 3

Adaptation and inertia: crop-choice responses to water allocations in the MDB and the Po Valley

Chapter summary. This chapter examines how differences in crop water requirements and economic water productivity shape farmers' incentives to trade water and adjust land use in the Murray–Darling Basin (MDB) and Italy's Po Valley. Producers with perennials (inflexible water demand) behave differently under scarcity from those growing flexible seasonal crops. Empirically, we construct a composite "opportunistic" area—rice and cotton weighted by water intensity—and regress it on pre-season allocations (water allocated in the 12 months before planting) and pre-sowing rainfall for NSW Sustainable Diversion Limit (SDL) units. We use heteroskedasticity- and autocorrelation-robust inference and extend the model with lagged allocations to reflect carryover. Opportunistic acreage responds positively, and often significantly, to allocations. In the Adda–Lario system, limited storage capacity makes pre-summer inflows poor predictors of later availability and, combined with the absence of market signals, yields little year-to-year acreage adjustment. We conclude that pre-season quantity signals facilitate adaptive crop choice and outline next steps on incorporating seasonal forecasts and disentangling price- versus quantity-driven channels.

3.1 Changing crop choice and water availability

3.1.1 Crops, Irrigation Needs and Adaptation Flexibility

Agriculture represents the largest consumptive user of freshwater globally, responsible for 50–90% of all water use (Jiménez Cisneros et al., 2022). This global reality is reflected in the two basins central to this study: the Po Valley in Italy and the Murray-Darling Basin (MDB) in Australia, where agricultural withdrawals account for approximately 80% and over 90% of total water use, respectively (Autorità di Bacino del Fiume Po, 2016; Hughes et al., 2023).

The primary driver of this water consumption is evapotranspiration (ET), a composite process comprising direct soil moisture evaporation and plant transpiration. The rate of ET is governed by a combination of climatic variables—such as temperature, humidity, solar radiation, and wind speed—and crop-specific factors, including the type of plant, its growth stage, and canopy cover. For example, ET rates are highest during hot, dry, sunny, and windy conditions, which are characteristic of the summer growing season in both the MDB (December-February) and the Po Valley (June-August). During these periods, high atmospheric evaporative demand accelerates water loss from both soil and plants. Furthermore, ET peaks during specific crop development stages, such as the flowering and grain-filling stages of maize, when the leaf area is at its maximum and physiological activity is highest (Chiarelli et al., 2020b). Conversely, ET rates are significantly lower during cool, humid, and overcast conditions, typical of the winter months in these temperate regions, or during the initial and late stages of a crop's life cycle when canopy cover is minimal.

The need for supplemental irrigation arises only when soil moisture depletes below a critical threshold beyond which plants experience water stress, a point often related to the readily available water (RAW) in the root zone. Consequently, the irrigation water requirement (IWR) for a specific crop exhibits significant spatial and temporal variability. Maize, for instance, demonstrates this variability on a global scale (Figure 3.1). Its consumptive irrigation needs range from negligible in temperate, rain-fed systems to over 10 ML/ha/yr in arid and semi-arid regions (see 3.1). Globally, approximately 80% of maize cultivation is rain-fed (Chiarelli et al., 2020b).

Within a given region, different crops display markedly different water intensities. This distinction is crucial for understanding agricultural adaptation possibilities.

Seasonal crops, such as cereals, cotton, and vegetables, offer farmers the flexibility to alter cultivation choices on a year-to-year basis. This allows possibly for adaptation to forecasted or actual water availability. In both the Po Valley and the MDB, rice cultivation is by far the most water-intensive seasonal crop, primarily due to its cultivation in flooded paddies which requires substantial water withdrawals (Figures 3.2 and 3.3) (Chiarelli et al., 2020b). Other significant seasonal crops requiring substantial irrigation include cotton and maize. Conversely, winter cereals such as wheat and barley often require only supplemental or emergency irrigation, with many cultivations being entirely rain-fed.

Perennial crops, such as almonds in the MDB and orchards or grapevines in the Po Valley, present different characteristics. These crops require a multi-year investment before reaching full productivity, making them an inflexible component of a farmer's portfolio in the face of short-term water scarcity. While their water needs vary—with almonds in the MDB consuming over 9 ML/ha (Figure 3.3) and fruits in the Po Valley requiring less than 3 ML/ha (Figure 3.2)—their long-term nature precludes their use as an adaptive strategy to annual fluctuations in water supply.

Climate change is intensifying the global water cycle, leading to greater variability in water availability and more frequent and severe droughts (see Section 2.1.4; (Caretta et al., 2022b)). Consequently, shifting cultivation from water-intensive to less water-intensive seasonal crops is a primary adaptation strategy for farmers to

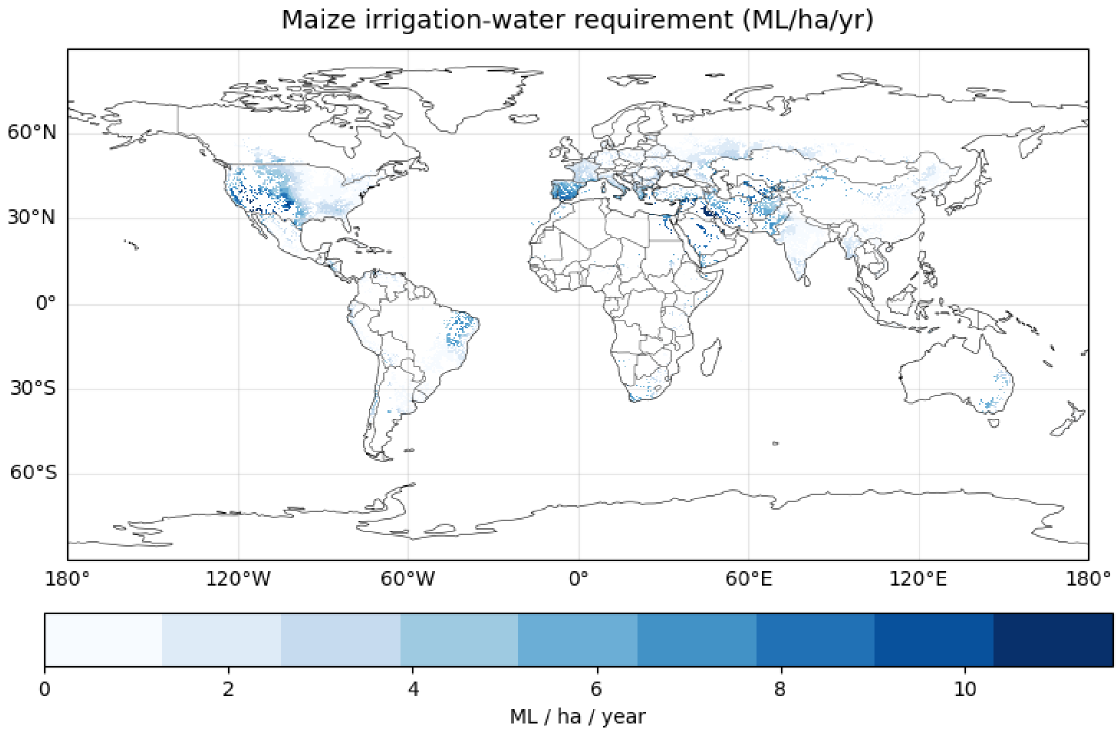


Figure 3.1: Global consumptive irrigation water requirement (blue water) for maize (ML/ha/yr), based on 2016 data. The map illustrates the significant climatic influence on irrigation needs. Note: These values represent the consumptive water requirement (ET deficit) and do not account for irrigation efficiency or conveyance losses; thus, they are not equivalent to applied water volumes or withdrawals. Data sourced from Chiarelli et al. (2020b)

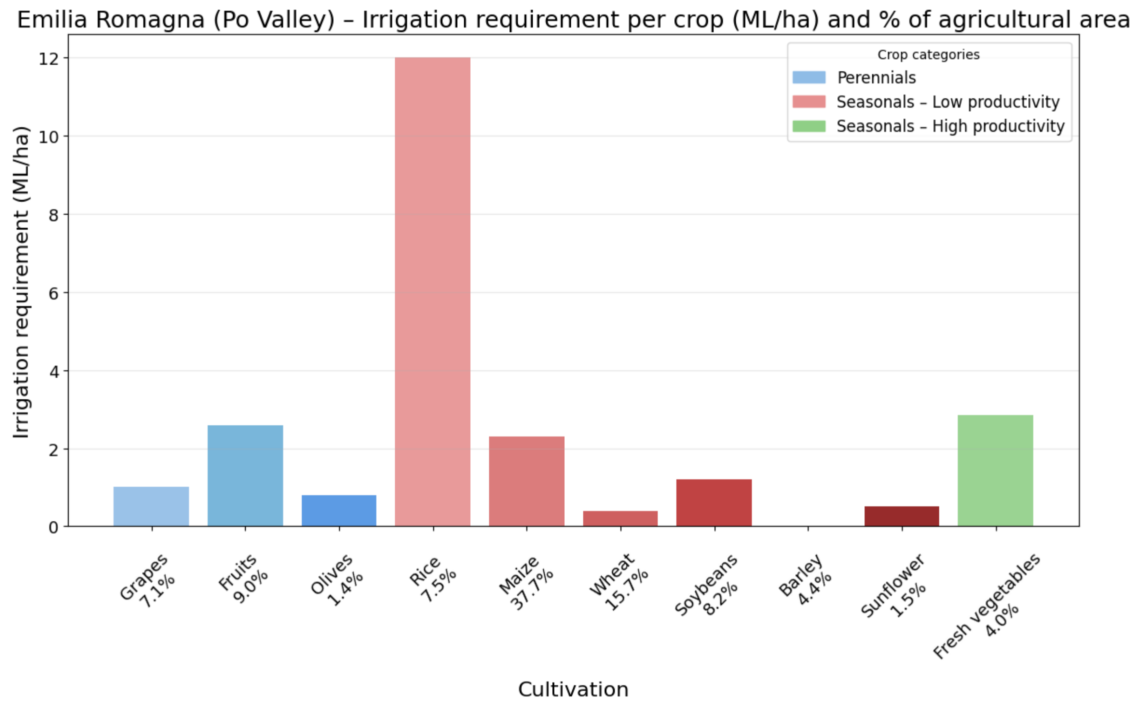


Figure 3.2: Irrigation water requirement per crop (ML/ha) in Emilia Romagna and share of total agricultural area (%) in Northern Italy. Bar heights represent the net seasonal irrigation requirement at the field level, excluding conveyance and application losses. Percentages below bars indicate the crop's share of the region's agricultural land. Data adapted from Regione Emilia-Romagna & ARPAE Emilia-Romagna (2021) and land use data from Copernicus Land Monitoring Service (2020).

enhance resilience and mitigate the risks associated with increasing water scarcity.

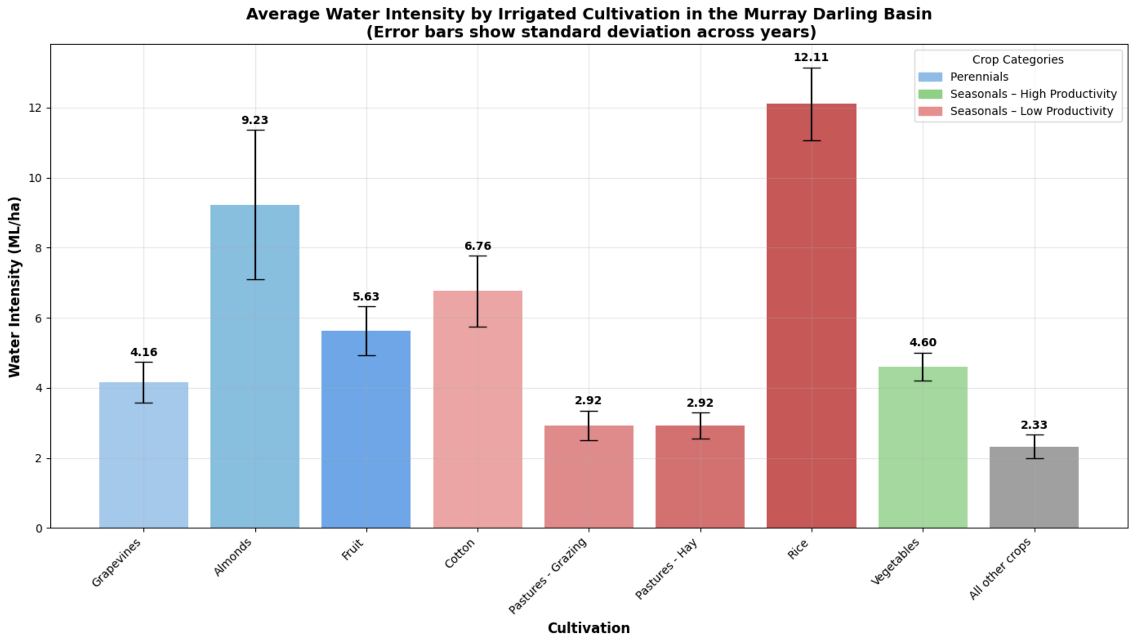


Figure 3.3: Average volumetric water intensity for key irrigated cultivations in the Murray-Darling Basin (ML/ha). Values are calculated by dividing the total annual water application for each crop by its respective irrigated area across the basin. Error bars represent the standard deviation across the years of the dataset, indicating inter-annual variability in water application rates. Crop categories (perennial, seasonal high/low productivity) are distinguished by color. Data sourced from Walsh et al. (2021).

Beyond volumetric water intensity, the economic productivity of water—defined as the economic output per unit of water applied—is a crucial driver of crop choice, particularly in regions with established water markets.

For example, while vegetables are relatively water-intensive (over 4 ML/ha in the MDB), they exhibit high economic water productivity (Figure 3.4). This high economic return incentivizes their cultivation, especially during periods of scarcity. Indeed, studies from other water-market systems, such as the Rio Grande basin, have demonstrated that the cultivation area for high-value vegetables increases during droughts, as water is reallocated from less profitable crops (Debaere & Li, 2020). This dynamic illustrates how water markets can facilitate a shift not just to crops that use less water, but to those that generate the most economic value from each megalitre applied.

3.1.2 Reasons to Trade in the Murray Darling Basin

The preceding discussion highlighted how crops differ widely in both their irrigation requirements and their economic water productivity. These differences translate directly into distinct strategies for coping with water scarcity. Accordingly, the trading behaviour of water allocation holders in the southern Murray–Darling Basin (sMDB) is strongly shaped by the type of agricultural enterprise they operate. Market par-

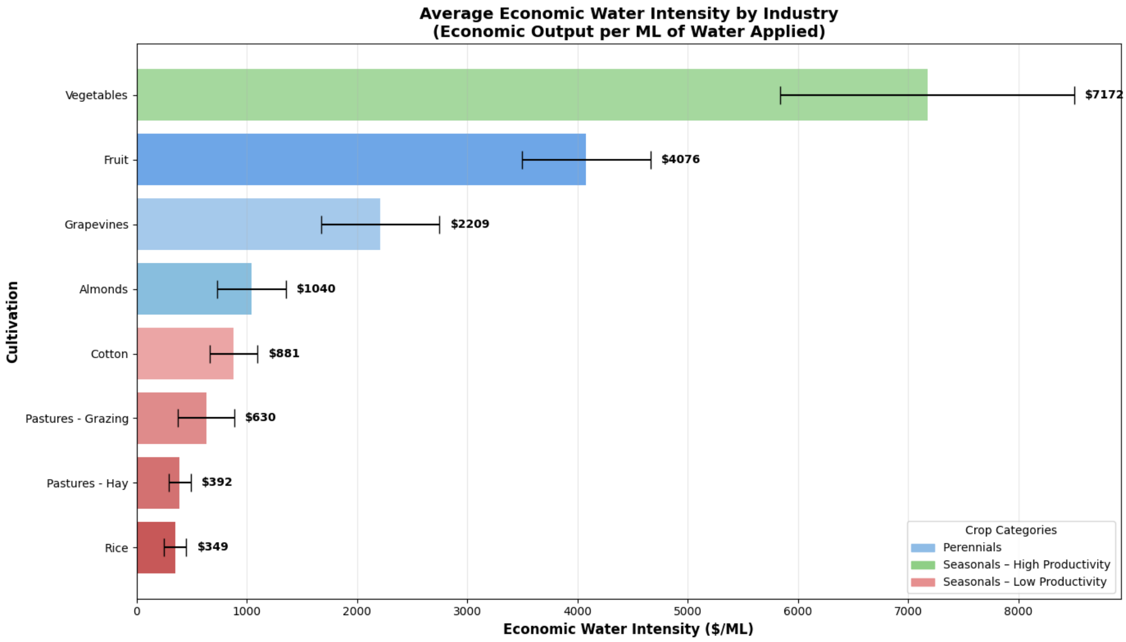


Figure 3.4: Average economic water intensity by industry in the Murray-Darling Basin ($/ML). The chart displays the economic output in Australian dollars generated per megalitre of water applied. Error bars indicate the standard deviation across the years of the dataset. Vegetables, a high-productivity seasonal crop, generate the highest economic return per unit of water. Data sourced from Walsh et al. (2021).

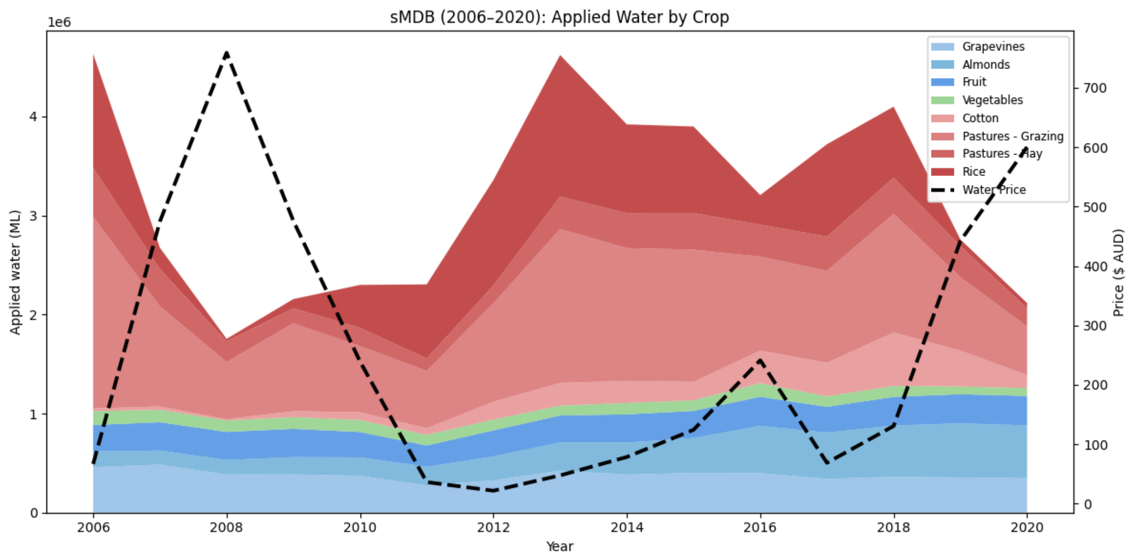


Figure 3.5: Applied water by crop in the sMDB for water years 2005–2006 to 2019–2020, excluding the NSW Lower Darling, shown as a stacked area chart. Each year label y on the horizontal axis refers to the water year $y-1$–y. The dashed black line indicates the water-weighted average price (WWAP) for the sMDB, computed by weighting each region-year price by the corresponding volume of water applied. Data sourced from Walsh et al. (2021).

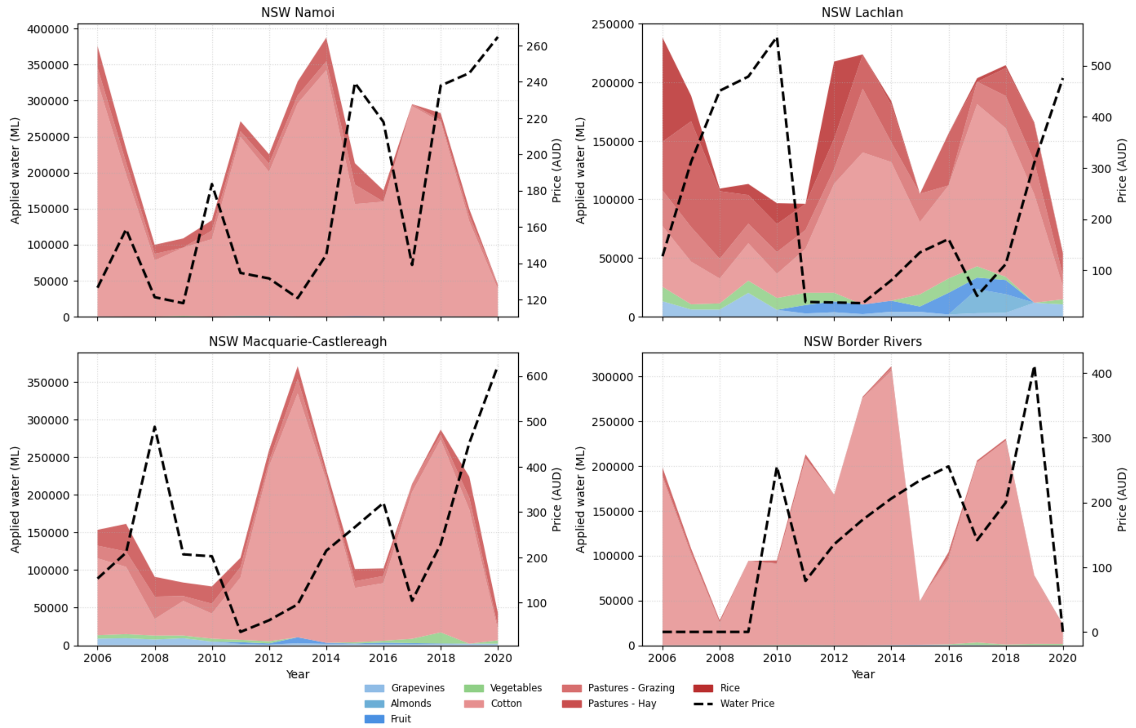


Figure 3.6: Applied water by crop in the northern MDB of New South Wales for water years 2005–2006 to 2019–2020. Each year label y on the horizontal axis refers to the water year $y-1$–y. The dashed black line indicates the water-weighted average price for each region. Data sourced from Walsh et al. (2021).

ticipants can be broadly categorised based on their response to water prices, which is largely dictated by their production systems and the economic water intensity of their crops.

- Broadacre farmers, such as rice and cotton producers, demonstrate high sensitivity to water prices. During periods of water scarcity and high prices, these farmers often sell their water allocations and choose to fallow their land or switch to dryland crops like wheat, barley, canola, or oats (Wheeler et al., 2020). Conversely, when water is abundant and prices are low, they significantly increase both the acreage and the volume of water applied to their crops (see Figure 3.5). This behaviour is a response to the low economic water intensity of their crops compared to other agricultural sectors.
- Dairy producers, who primarily use water for pasture, also cultivate a commodity with relatively low economic water intensity (see Figure 3.4). In response to high water prices, they typically reduce water application on pastures. However, their primary asset is the cattle herd, which requires a consistent feed supply. Consequently, they often switch from irrigated pasture to purchasing feed from external sources (Competition & (ACCC), 2021). This strategy can be challenging due to the correlation between high water prices and high feed prices during drought periods.
- Vegetable growers cultivate crops that are often water-intensive. Although their annual production cycle could allow for adjustments in water consumption, the high-value nature of their produce results in very high water productivity. As a result, their demand for water is relatively inelastic, and the volume of water they

apply remains quite insensitive to fluctuations in water prices (Wheeler et al., 2020).

- Perennial horticulture, including orchards and vineyards, represents a long-term capital investment, with several years required before plants reach full productivity. While there are significant differences in economic water intensity within this category, farmers are generally willing to pay very high prices for water to ensure the survival of their trees and protect their initial investment (Competition & (ACCC), 2021). In recent years, high commodity prices for crops like almonds have driven a notable expansion in the acreage dedicated to perennial horticulture, further increasing water demand from this sector (Ricardo, 2019).

In contrast, the water market in the northern Murray-Darling Basin (nMDB) is less liquid and developed than in the south, primarily due to hydrological constraints that lead to greater price disparities between different Sustainable Diversion Limit (SDL) resource units (Competition & (ACCC), 2021). The dominant irrigated crop in the nMDB is cotton, and historical data shows a strong negative correlation between the volume of water applied and the allocation price (see Figure 3.6) (Associates, 2020). While cotton was traditionally concentrated in the nMDB, new varieties have enabled its expansion into the sMDB, where it now competes with rice as a major broadacre summer crop (Marsden Jacob Associates, 2020a).

3.1.3 MDB and the Po Valley two different tales

Given the increasing variability of water availability, the ability to adapt the acreage of seasonal crops based on reliable forecasts can be particularly beneficial for mitigating the economic damages caused by water scarcity. In Australia's Murray-Darling Basin (MDB), this flexibility has proven crucial. Kirby et al. (2014) found that during the Millennium Drought (from 2000 to 2011), a two-thirds reduction in water availability was associated with only a 20% decline in the gross value of irrigated production (adjusted for price trends). This resilience was significantly aided by a sharp decrease in the acreage of annual crops like cotton and rice, alongside the substitution of irrigated pastures with imported feed. Improvements in crop yields and irrigation efficiency also played a vital role.

The adaptive capacity of MDB farmers is demonstrated by the strong correlation between water supply and planting decisions. Zeleke & Luckett (2025) identified a significant positive correlation between the total volume of General Security (GS) allocations announced during a water year and the corresponding rice acreage in the southern MDB (see Figure 3.7). Farmers in the southern MDB did not just reduce rice cultivation during the drought; they expanded it again once water availability recovered, treating it as an opportunistic crop. This behaviour is facilitated by the water rights structure, where broadacre farmers, who cultivate annual crops, predominantly hold GS entitlements. These entitlements have lower reliability than High Security (HS) ones but offer greater flexibility, whereas farmers with perennial crops favour HS entitlements to guarantee water supply and protect their long-term investments (Downham & Gupta, 2021).

In contrast, the Adda-Lario system in Italy's Po Valley exhibits a markedly different dynamic. This area is dominated by the cultivation of maize, one of the most water-intensive seasonal crops in the region, primarily grown as animal feed

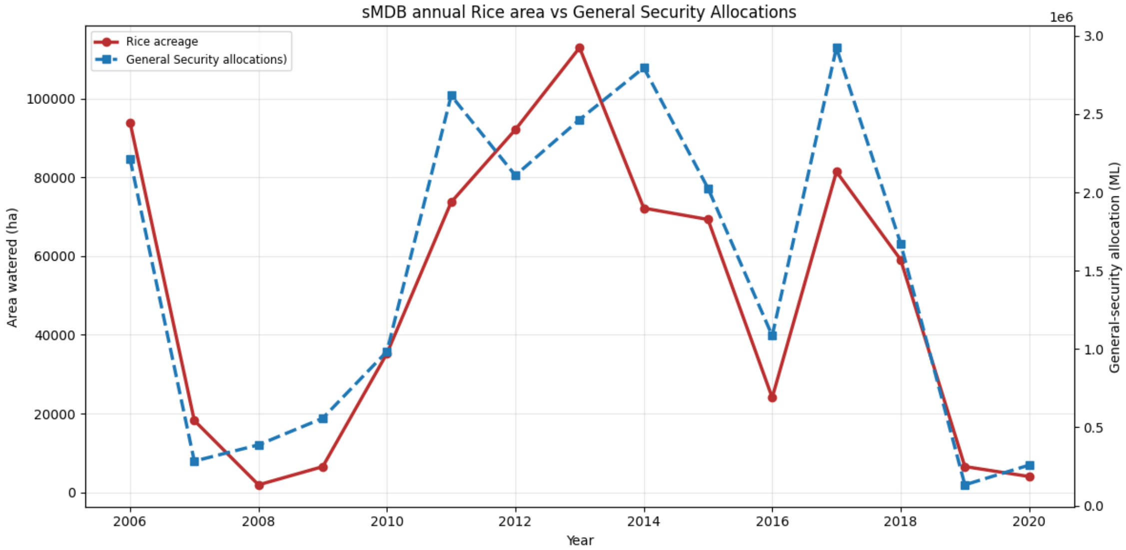


Figure 3.7: The figure plots (i) rice area watered (left axis, ha) as the sum across the sMDB catchments and (ii) general-security allocations (right axis, ML) summed across the same catchments. We get the same results as Zeleke & Luckett (2025), we first aggregate to annual sMDB series and then compute the Pearson correlation across years between the two series. Over 2006–2020 ($n = 15$) the correlation is $r = 0.917$, with a 95% confidence interval of $[0.762, 0.972]$ with Fisher's method and a two–sided p–value $p = 1.56 \times 10^{-6}$.

(Legambiente Lombardia, 2023). Over the last decade, a decline in the land share dedicated to maize has been observed. This trend is driven not only by a strategy to mitigate drought risk but also by economic pressures from low crop prices (Coldiretti Lombardia, 2025). However, unlike in the MDB, this shift does not appear to be an adaptive, year-to-year response to water availability. As shown in Table 3.1 and Figure 3.8, there is no significant annual correlation between the water available for irrigation during the critical summer period (June-July) and the planting decisions for the most water-demanding crops.

Table 3.1: Pearson correlation between crop land share and mean water availability (15 June–31 July) in the Adda-Lario system. Two-sided tests; 95% confidence intervals via Fisher's z transform; t-tests use $df = 18$.

Crop	r	95% CI	$t(18)$	p	Significance
Maize	0.140	$[-0.323,\ 0.548]$	0.598	0.557	n.s.
Rice	0.209	$[-0.257,\ 0.596]$	0.908	0.376	n.s.
Soy	0.118	$[-0.343,\ 0.532]$	0.503	0.621	n.s.

This fundamental difference in adaptive capacity can be attributed to two key institutional and infrastructural factors. First, in the MDB, farmers have a higher degree of certainty about water availability for the upcoming irrigation season. The basin's total active storage capacity is more than double the sustainable diversion limit (the long-term mean of withdrawals) (Competition & (ACCC), 2021). This means that at the time of planting, a significant share of the water for the next summer has already been captured in reservoirs and distributed to farmers as formal

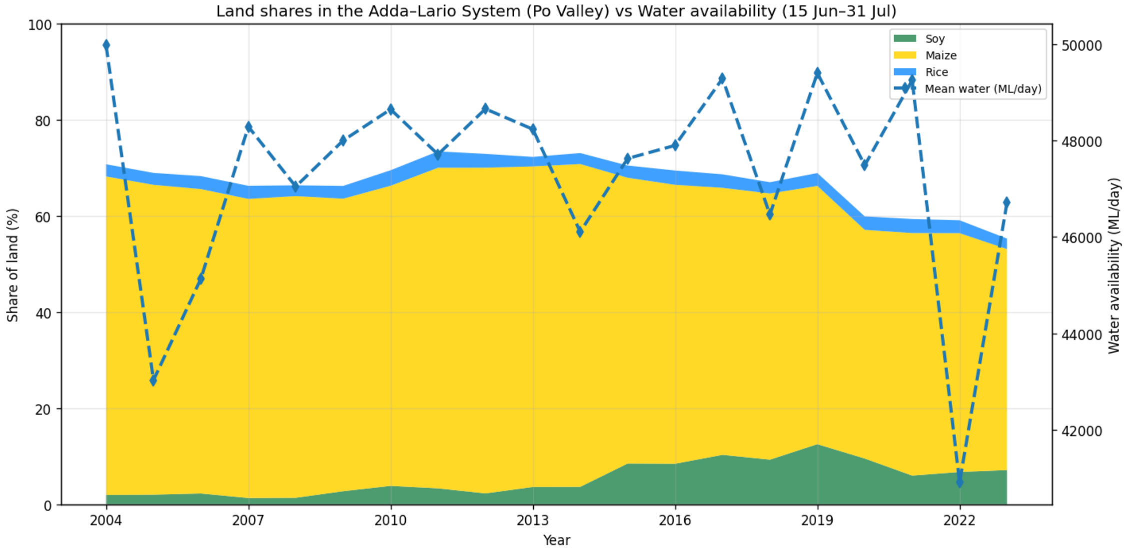


Figure 3.8: Share of agricultural land occupied by major crops in the Adda-Lario System (Po Valley, see subsection 2.1.6) and mean available water for irrigation during the period of major water stress (15th of June to the 31st of July). Data sourced from Amaranto et al. (2022).

water allocations. The initial allocation levels thus provide a reliable forecast of seasonal water availability, informing farmers' planting decisions well in advance. Second, the cap-and-trade mechanism provides a direct economic incentive to adapt: in dry years, high water allocation prices encourage farmers to plant dry land crops and then to sell their water for profit.

In the Adda-Lario system, both of these factors are absent. Farmers lack advance knowledge of summer water availability because the system relies heavily on contemporaneous inflows from Alpine snowmelt. The active storage of Lake Como is only about 246 GL, approximately one-third of the peak season crop water demand, and could be emptied by withdrawals in a matter of days (Amaranto et al., 2022). Furthermore, without a market mechanism, there is no price signal to incentivize water conservation. This combination of hydrological uncertainty and a lack of economic incentives makes the Italian system far more rigid and less resilient to annual fluctuations in water availability.

The following section of this chapter will focus on statistically analyzing whether inflows in the months preceding crop choice influence planting decisions in the MDB. Specifically, we will look for evidence of a causal relationship between water allocations in the year before planting and the crop choices for rice and cotton across the SDL resource units of New South Wales.

3.2 Water Allocation cause Rice and Cotton acreage?

In the MDB, rice and cotton are two of the most water-intensive seasonal crops and are often treated as opportunistic summer crops, with their planted areas varying significantly each year depending on water availability (Zeleke & Luckett, 2025) (see Figures 3.10 and 3.11). The cultivation of these crops is geographically distinct and subject to different agronomic and economic considerations.

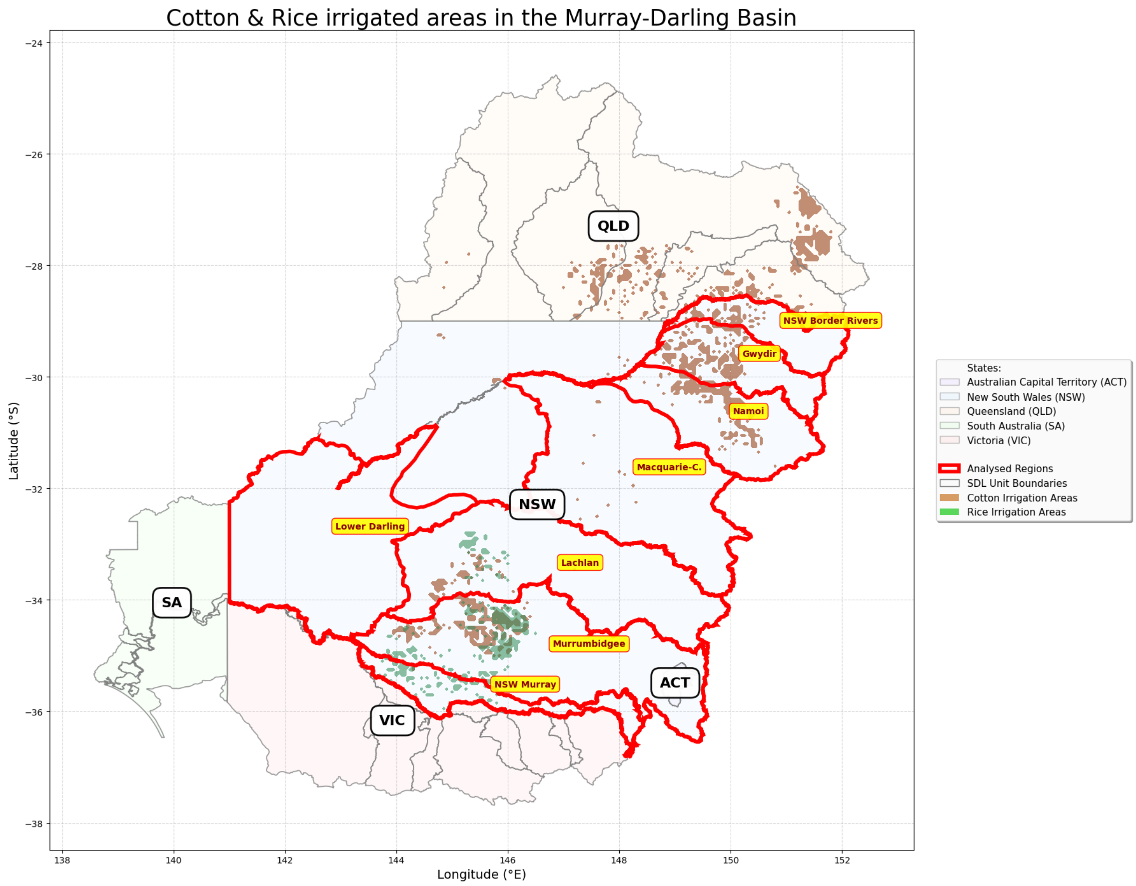


Figure 3.9: Map showing areas where irrigated cotton and rice are present. The map uses a 5 km^2 grid; a cell is colored if, in at least one of the three years (2010–11, 2015–16, 2020–21), at least 5% of its area was occupied by the corresponding irrigated crop. Surface Water SDL resource units with red contours indicate the regions selected for further analysis. Data sources: Murray–Darling Basin Authority (2018) and Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) (2023).

The vast majority of Australian rice production is concentrated in the Riverina region of southern New South Wales (NSW), encompassing the NSW Murray, Murrumbidgee, and Lachlan SDL resource units (see Figure 3.9). In years of high water availability, this area accounts for approximately 98% of the national total. However, the higher financial returns offered by cotton have led to it increasingly substituting rice as the dominant opportunistic summer crop in this region, a trend aided by the development of new cotton varieties suited to the southern climate (Zeleke & Luckett, 2025; Associates, 2020).

The decision to plant rice is multifactorial. Key drivers include the price offered by Sunrice (which operates as a near-monopsony buyer), the relative profitability of alternative crops, and, crucially, the price and availability of water, given the crop's substantial irrigation requirements (Marsden Jacob Associates, 2020b). Rice in Australia is grown in flooded paddy fields, which serve to protect the plants from high temperature fluctuations. This cultivation method requires significant preparation; the contour banks that contain the water must be formed at least three months before sowing. Consequently, farmers typically make preliminary decisions on which fields to potentially allocate to rice during the winter months of July and August. These banks are a costly and long-term investment and are often left intact during rotations with other crops like wheat or barley. The final sowing occurs between late October and early November, after which an initial "flush" irrigation is applied. Favourable pre-sowing rainfall, which moistens the soil without causing waterlogging, is therefore highly beneficial (Troldahl, 2018).

Australia is a major cotton exporter, typically accounting for 10 to 15 percent of world exports, which exposes its producers to the volatility of global commodity markets, particularly the Intercontinental Exchange (ICE) for Cotton Futures. Cotton is grown primarily in NSW and Queensland (see Figure 3.9). While 10–15% of the national crop is rain-fed, this practice is largely confined to the northern regions; irrigated production is dominant in NSW. In the southern parts of NSW, growers are almost entirely dependent on water allocations from public storages. In contrast, northern NSW and Queensland growers supplement these allocations with water captured in private, on-farm storages, a practice known as "water harvesting" (United States Department of Agriculture, Foreign Agricultural Service, 2025).

As a summer crop, soil preparation for cotton occurs between July and September, with planting from October through December and harvesting from March to June . Good soil moisture is critical for successful crop establishment, so favourable rainfall during the pre-planting and sowing period is highly beneficial (CRDC and CottonInfo, 2022). The primary factors influencing a farmer's decision to plant cotton are water availability and price. Water availability includes both the volume already held in public and private storages and the expected contribution from future rainfall. The expected price is influenced by futures market trends and the AUD/USD exchange rate (United States Department of Agriculture, Foreign Agricultural Service, 2025). To aid farmers in these assessments, the Australian Bureau of Meteorology has been publishing three-month seasonal rainfall outlooks since 1989, providing farmers with probabilistic forecasts (Bureau of Meteorology, 2014).

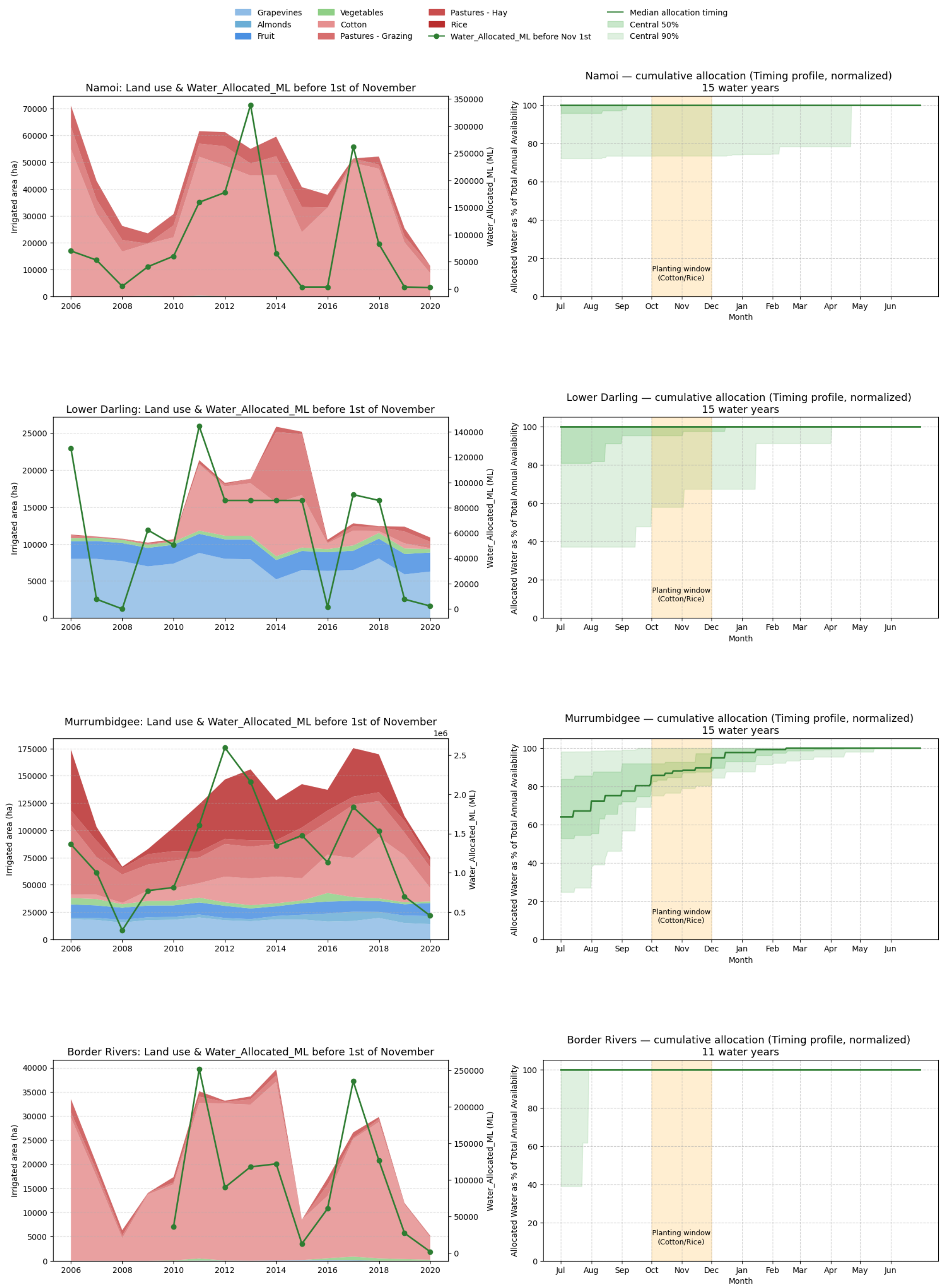


Figure 3.10: **Left panel:** yearly irrigated area by crop for each region, together with the total volume of water allocated in the 12 months preceding the land-use decision date (chosen as 1 November). **Right panel:** cumulative allocation profiles showing, for each day of the water year, the percentage of the total annual volume that had been allocated up to that date. Curves cover water years 2005–2006 to 2019–2020; the median profile is shown together with shaded bands for the central 50% and 90% ranges. Carry-over volumes are counted as if they were allocated on 1 July. Data sources: Walsh et al. (2021); WaterNSW (2025a); New South Wales Government (2020a,b, 2019, 2020c).

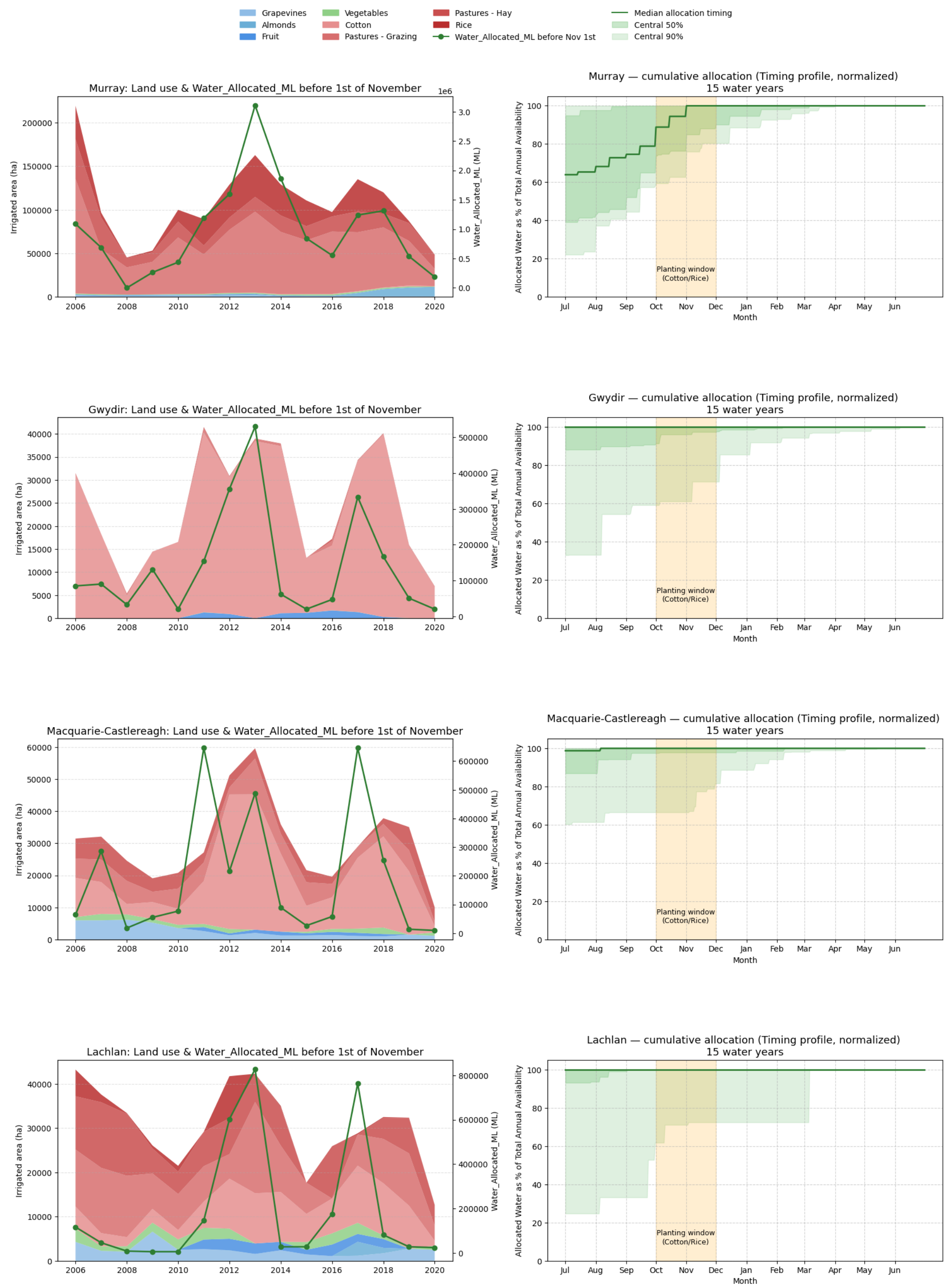


Figure 3.11: Left panel: yearly irrigated area by crop for each region, together with the total volume of water allocated in the 12 months preceding the land-use decision date (chosen as 1 November). **Right panel:** cumulative allocation profiles showing, for each day of the water year, the percentage of the total annual volume that had been allocated up to that date. Curves cover water years 2005–2006 to 2019–2020; the median profile is shown together with shaded bands for the central 50% and 90% ranges. Carry-over volumes are counted as if they were allocated on 1 July. Data sources: Walsh et al. (2021); WaterNSW (2025a); New South Wales Government (2020d,e,f,g).

3.2.1 Identification strategy: pre-season allocations and threats to exogeneity

Zeleke & Luckett (2025) identified a significant correlation between the total General Security allocations announced over a water year (July to June) and the acreage of rice sown in the preceding October or November. While this result highlights a strong association, a causal relationship cannot be established directly from it, as planting decisions are made before the total water year allocations are known. To rigorously assess the causal impact of water availability on farmers' land use decisions, it is crucial to select an explanatory variable that is determined prior to the decision-making period and to address potential threats to exogeneity.

Two potential regressors to assess farmers' reactions would be (i) water allocation prices just before planting and (ii) the volume of water available at that time (the sum of carryover and allocations made since the start of the water year). However, both present econometric challenges. To establish a causal relationship and ensure the consistency of the Ordinary Least Squares (OLS) estimator, the explanatory variable must be exogenous to the error term. According to Verbeek (2017), several factors can violate this condition:

- **Simultaneity (Reverse Causality).** A primary concern is that water prices and the acreage of opportunistic, water-intensive crops are jointly determined. While lower water prices can induce more planting, a larger aggregate planted area can increase water demand, thereby driving prices up. To circumvent this endogeneity, this analysis focuses on a predetermined measure of water availability—specifically, water allocations realized before the land-use decision—rather than relying on contemporaneous water prices which are determined within the market.
  Furthermore, the acreage response to additional water is not uniform across regions due to differing crop mixes. For instance, in the NSW Murray, cotton cultivation is minimal, and rice constitutes a small share of irrigated land (see Fig. 3.11). Consequently, the marginal effect of additional water on annual plantings is expected to be smaller than in SDL units where cotton is the main summer crop. Therefore, estimating a single common slope for all regions would be inappropriate. The model must account for this heterogeneity, for instance by estimating separate regressions for each SDL unit or by using interactive terms.
- **Omitted Variable Bias (OVB)**. OVB arises when a relevant variable is omitted that (i) affects the outcome y and (ii) is correlated with at least one included regressor x; then $\hat{\beta}$ is biased because x picks up part of the omitted effect. By contrast, if the omitted variable lies on the causal path from x to y (i.e., it is a mediator), omitting it is not an error when the goal is the total effect of x on y—including the indirect pathway. For example, if allocations x partly influence a local basis price Z which in turn affects acreage y, then Z is a mediator; controlling for Z would remove that indirect channel and identify only the direct effect. If we used as a regressor the available water defined as the sum of carryover and allocations in the first month of the water year, we would introduce crop prices as a confounding factor: higher commodity prices can lead farmers to save more water for the following season, increasing carryover and thus biasing our regressor. To avoid this problem, we use the total water allocations in the 12 months

preceding the land-use decision as our main explanatory variable. Given the fixed allocation rules, this variable is driven primarily by climatic and meteorological factors. In the MDB, inflows to the major storages are strongly influenced by the El Niño–Southern Oscillation (ENSO): El Niño events typically reduce rainfall across south-eastern Australia, while La Niña events increase it. As a result, the same meteorological phenomenon affects both inflows (hence allocations) and local rainfall. Since both higher rainfall and higher allocations expand the acreage of opportunistic crops such as rice and cotton, we include rainfall as a control variable to isolate the causal effect of water availability. Conversely, local wet conditions could depress local commodity prices, reducing land allocation; any bias from ENSO through local price effects would therefore attenuate our estimated coefficient, making our results conservative. Local expected prices of commodities are difficult to observe, but given the direction of the potential bias, finding a significant positive effect strengthens confidence in the results. The possible persistence of La Niña events, which can generate above-average expected rainfall over multiple seasons, should be explicitly considered in further causal analyses through the seasonal climate outlooks published by the Bureau of Meteorology.

- **Autocorrelation with a lagged dependent Variable.** A common dynamic model in econometrics includes a lagged dependent variable as a regressor, such as the Autoregressive Distributed Lag (ARDL) model. Consider the simple ARDL(1,1) model:

$$y_t = \alpha + \theta y_{t-1} + \beta_0 x_t + \beta_1 x_{t-1} + \varepsilon_t \tag{3.1}$$

where ε_t is an error term.
A key assumption for the Ordinary Least Squares (OLS) estimator to be unbiased and consistent is that the regressors are uncorrelated with the error term. However, if the error term ε_t is serially correlated, this assumption is violated. Suppose the errors follow a first-order autoregressive, AR(1), process:

$$\varepsilon_t = \rho \varepsilon_{t-1} + v_t \tag{3.2}$$

where v_t is a white noise process. The regressor y_{t-1} is determined by variables up to period $t-1$, including the error term ε_{t-1}. Because ε_t is a function of ε_{t-1} (when $\rho \neq 0$), it follows that y_{t-1} and ε_t will be correlated.

$$\mathrm{Cov}(y_{t-1}, \varepsilon_t) \neq 0 \tag{3.3}$$

This correlation renders the OLS estimator for θ (and other coefficients) both biased and inconsistent. By not including cotton prices it is plausible that there could be autocorrelation in the in the error terms due to a certain persistence in commodity prices. In the Lachlan and Murrumbidgee regions, a transition has occurred from rice being the main opportunistic crop to cotton. This transition is gradual and the capital of the farm needs to be reallocated from one production to another (ex. the field preparation is different and for cotton the leeves are not needed). Therefore this transition would need to be modeled with a lagged variable process. To avoid the presence of Autocorrelation with a lagged dependent Variable the acreage of cotton and rice have been aggregated (see Figure 3.12).
Defining $\kappa^C_{r,t}$ as the water applied per hectare for cotton in the SDL resource unit r in the year t. $\kappa^R_{r,t}$ is the equivalent for rice. As in the data construction, use

region-level averages (across years) for the weights:

$$\bar{\kappa}_r^C = \frac{1}{T}\sum_{t=1}^{T}\kappa_{r,t}^C, \qquad \bar{\kappa}_r^R = \frac{1}{T}\sum_{t=1}^{T}\kappa_{r,t}^R. \tag{3.4}$$

The aggregated (composite) area used in the regressions is the water–intensity–weighted average of cotton and rice areas:

$$\text{land\_opp}_{r,t} \equiv \frac{\bar{\kappa}_r^C\,\text{land\_cotton}_{r,t} + \bar{\kappa}_r^R\,\text{land\_rice}_{r,t}}{\bar{\kappa}_r^C + \bar{\kappa}_r^R}. \tag{3.5}$$

If in a certain region there is no land allocated to a certain crop, the intensity of water application is set to 0 for that crop. $\text{land\_opp}_{r,t}$ is the area of a single "composite" seasonal crop with the same average water use per hectare as the cotton–rice mix, so that changes in $\text{land\_opp}_{r,t}$ map proportionally to changes in seasonal water demand.

- **Measurement Error.** The aggregation proposed in eq. 3.5 does not account for differences in economic water productivity between cotton and rice or in the marginal profit of an additional unit of irrigation. This simplification could introduce measurement error. For instance, a shift from rice to the more water-intensive and economically valuable cotton could appear as a change in the composite irrigated area, even if the total amount of available water remains unchanged because farmers purchase additional allocations from other producers. Nevertheless, a graphical inspection of the resulting time series does not suggest that this is a major empirical concern (see Figure 3.12).

Based on this framework, the regression model is specified as follows:

$$\text{land\_opp}_{r,t} = \beta_{0,r} + \beta_{1,r}\,\text{Water\_allocated}_{r,t} + \beta_{2,r}\,\text{Rainfall}_{r,t} + \epsilon_{r,t} \tag{3.6}$$

where, for each SDL resource unit r and year t: $\text{land\_opp}_{r,t}$ is the composite opportunistic crop area; $\text{Water\_allocated}_{r,t}$ is the total water allocated in the 12 months prior to the land-use decision (1 November); $\text{Rainfall}_{r,t}$ is the rainfall over irrigated areas in the 3 months prior to the decision; the β coefficients are parameters to be estimated; and $\epsilon_{r,t}$ are the error terms.

3.2.2 Dataset construction

The data for the construction of $\text{land\_opp}_{r,t}$ is taken from Walsh et al. (2021). This dataset divides the SDL resource unit NSW Murray in NSW Murray Above the Barmah Choke and NSW Murray Below. For our analysis we added the carryover, land allocations and the applied water of Murray Below and Above together. The NSW Barwon Darling is present in the dataset but it doesn't have water allocations because all of its surface water resources are of flow type, therefore it was not considered. In figure 3.9) it can be seen that it is the only region from NSW not included in the analysis. The daily allocated water is taken from the General Purpose Water Accounting Report (GPWAR) (New South Wales Government, 2020d,e,f,g,a,b, 2019, 2020c). When they were not available the data has been taken from WaterNSW (2025a). The GPWAR from Lachlan of the water year of 2011-2012 has not been

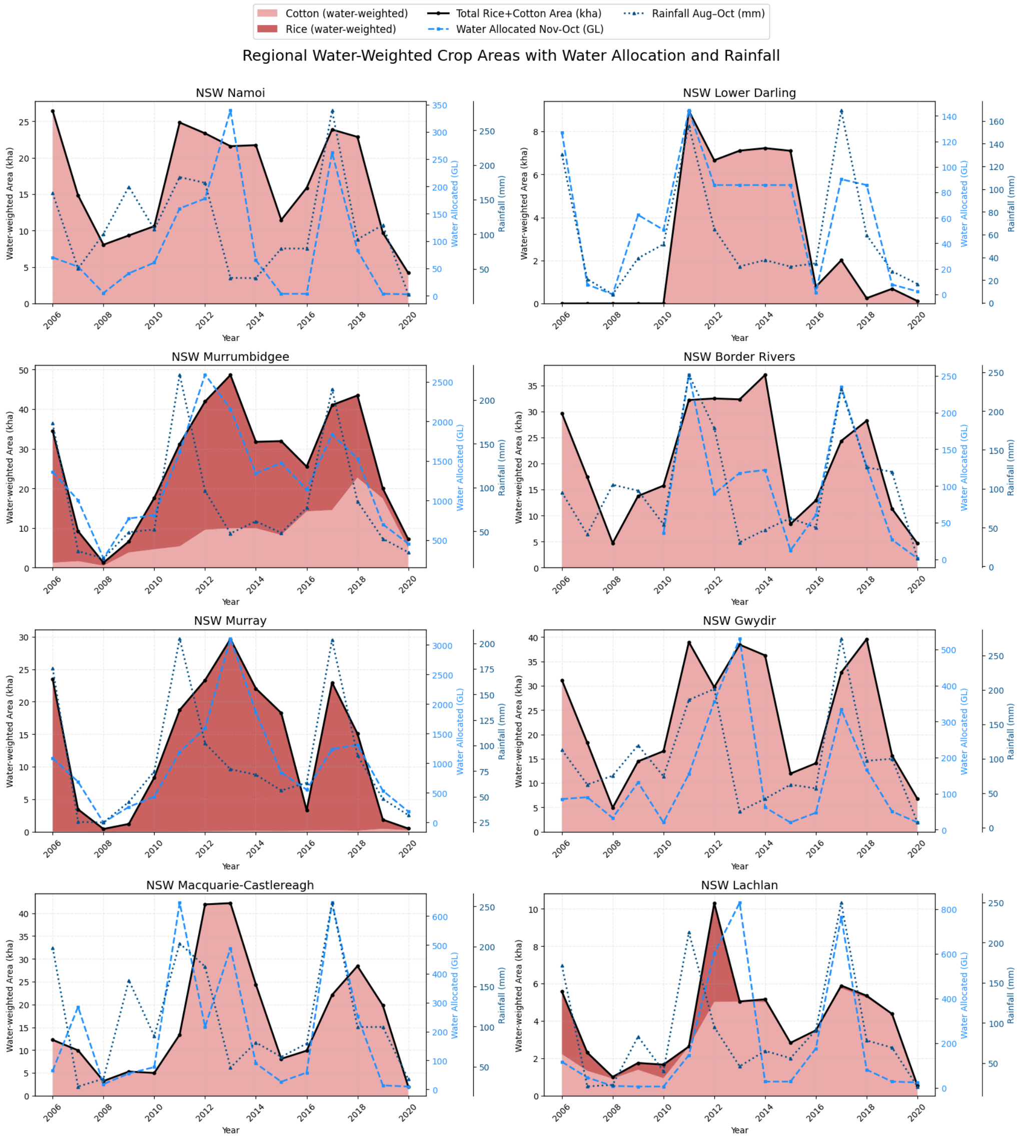


Figure 3.12: Yearly irrigated area by crop, weighted by its water intensity for each region (computed with Eq. 3.5), together with the total volume of water allocated in the 12 months preceding the land-use decision date (chosen as 1 November) and the rainfall in August–September–October preceding the land-use decision. Data sources: Walsh et al. (2021); WaterNSW (2025a); New South Wales Government (2020d,e,f,g,a,b, 2019, 2020c).

found and in the Water register 0 allocation where displayed but in the supply file in Walsh et al. (2021) a 134% GS allocation is indicated. Between the february and march 2012 a flood has been reported by abc (2012) therefore it has been decided that to insert a 134% GS allocation at the beginning of march.

In cases where an SDL resource unit included more than one regulated river, we assigned the allocations based on the dominant regulated system, i.e., the river with the largest combined number of High Security (HS) and General Security (GS) entitlements. This choice reflects the fact that the vast majority of water allocations in such units are tied to a single major river, making it a reliable proxy for the unit's allocation dynamics. For instance, in the Namoi (SS21), the Lower Namoi Regulated River Water Source holds a total of 248,979 unit shares, compared to 11,534 in the Upper Namoi and 30,439 in the Peel (New South Wales Government, 2020c). Similarly, in the Lachlan (SS16), the Lachlan Regulated River accounts for 666,439 ML of entitlement volume, while the Belubula Regulated River contributes only 24,094 ML(New South Wales Government, 2020d). Given these strong imbalances, using the largest regulated river as the reference system does not materially affect the representativeness of allocations at the SDL resource unit level.

For finding the average rainfall over irrigated fields we first build a binary irrigation mask over the Murray–Darling Basin on the SILO rainfall grid that is coarser. To build the mask for each epoch of the National Land Use Map (NLUM) at 250 m resolution (2010–11, 2015–16, 2020–21), we classify pixels as irrigated using the `IRGN` field in the raster attribute table. Each NLUM is clipped to the Basin, reprojected and areally averaged to the SILO grid.

A cell is marked as irrigated if at least one epoch reports $\geq 5\%$ irrigated area within that cell. Next, we use the SILO gridded monthly rainfall product (SIL, 2021) and compute, for each SDL resource unit defined by the Murray–Darling Basin Authority (SDL, 2013), the spatial mean rainfall over the irrigated cells:

$$\overline{R}^{(u)}_{y,m} = \frac{\sum_{\mathbf{s}\in\mathcal{S}_u} M(\mathbf{s})\, R_{y,m}(\mathbf{s})}{\sum_{\mathbf{s}\in\mathcal{S}_u} M(\mathbf{s})},$$

where $M(\mathbf{s})$ is the irrigation mask and $R_{y,m}(\mathbf{s})$ is the SILO rainfall (mm) at grid cell $\mathbf{s}$, year y, month m. We use in the regression the sum of $\overline{R}^{(u)}_{y,m}$ for August, September, and October, an example of the rainfall is the Figure 3.13.

3.2.3 Results and Discussion

Baseline OLS Model

For each region r, we first estimate the linear specification detailed in Equation (3.6), restated here for convenience:

$$\text{land\_opp}_{r,t} = \beta_{0,r} + \beta_{1,r}\,\text{Water\_allocated}_{r,t} + \beta_{2,r}\,\text{Rainfall}_{r,t} + \epsilon_{r,t}. \tag{3.7}$$

The Ordinary Least Squares (OLS) estimates are denoted with hats, and the corresponding residuals are defined as $\hat{\epsilon}_{r,t} = \text{land\_opp}_{r,t} - \widehat{\text{land\_opp}}_{r,t}$. In this model, the coefficient $\hat{\beta}_{1,r}$ measures the change in the composite area of opportunistic irrigated crops (in hectares) per additional gigalitre (GL) of water allocated, while $\hat{\beta}_{2,r}$ represents the change per millimetre (mm) of pre-season rainfall.

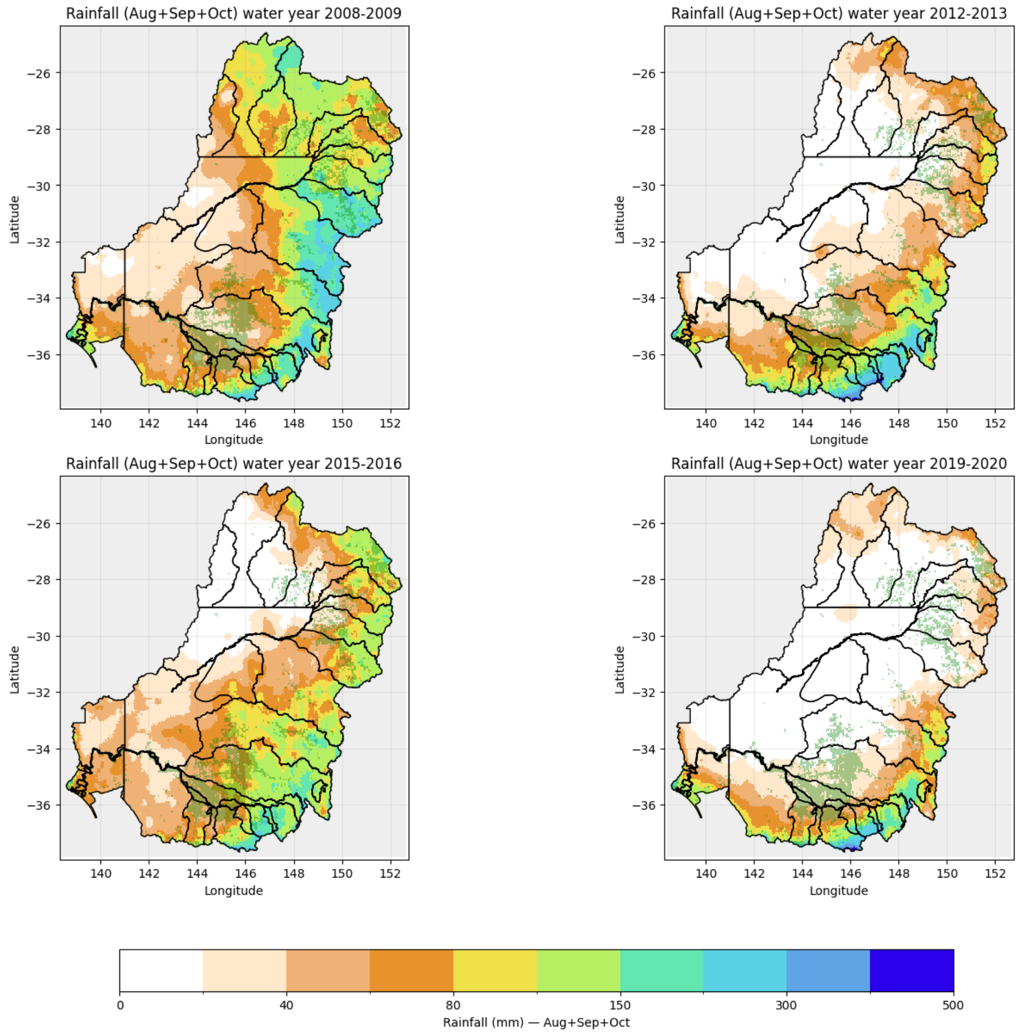


Figure 3.13: Cumulative rainfall in the months of August, September and October in the MDB for the years 2008, 2012, 2015 and 2019. The green areas in the maps show the location of the irrigated areas Data sources: SIL (2021); NLU (2022); SDL (2013).

The results of this regression are presented in Table 3.2. Under the initial assumption that the error terms are independent and identically distributed (i.i.d.) from a Gaussian distribution, statistical significance is assessed using a Student's t-distribution. As shown in the table, the estimated coefficients for water allocation, $\hat{\beta}_{1,r}$, are positive across all regions. They are statistically significant at conventional levels for all regions except Macquarie–Castlereagh. This finding supports the hypothesis of a positive relationship between pre-season water availability and the planted area of opportunistic crops. The magnitude of these coefficients is plausible; all estimated values are below 148 ha/GL, a theoretical maximum derived from the inverse water intensity of cotton (see Figure 3.3).

Table 3.2: Per-region OLS estimates for Eq. (3.6). Values are rounded to three significant digits.

Region	T	R^2_{adj}	$\hat{\beta}_{0,r}$ [kHa]	$\hat{\beta}_{1,r}$ [ha/GL]	$\hat{\beta}_{2,r}$ [ha/mm]
Border Rivers	11	0.432	13.7* (4.44)	129* (50.3)	-44.0 (52.0)
Gwydir	15	0.318	14.0* (4.75)	45.7* (19.5)	29.6 (40.9)
Lachlan	15	0.314	2.44* (0.888)	4.95* (2.11)	5.32 (8.67)
Lower Darling	11	0.571	0.220 (1.33)	81.3** (21.6)	-30.1 (18.9)
Macquarie–Castlereagh	15	0.0742	11.6 (6.11)	26.7 (17.1)	-2.63 (54.3)
Murray	15	0.863	-2.55 (1.96)	9.55*** (1.39)	68.4** (18.1)
Murrumbidgee	15	0.777	-1.41 (4.29)	20.1*** (3.44)	24.0 (32.4)
Namoi	15	0.372	10.5** (2.91)	40.7* (16.2)	22.3 (23.5)

Notes: T indicates the number of annual observations. R^2_{adj} is the adjusted coefficient of determination. Standard errors are in parentheses. Significance levels: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Units: $\hat{\beta}_{0,r}$ in kilohectares (kHa); $\hat{\beta}_{1,r}$ in hectares per gigalitre (ha/GL); $\hat{\beta}_{2,r}$ in hectares per millimetre (ha/mm).

The estimated coefficients $\hat{\beta}_{1,r}$ exhibit considerable variation across regions, which can be attributed to several factors:

- Regional Crop Composition: The marginal response of opportunistic area to water allocations depends on the regional mix of irrigated agriculture. In regions like Murray, where irrigated pasture is prevalent and opportunistic crops form a smaller share of land use, the response is more muted compared to regions such as Border Rivers and Gwydir, where cotton dominates irrigated agriculture (see Figures 3.10 and 3.11).
- Dependent Variable Construction: The definition of the dependent variable, $\text{land\_opp}_{r,t}$ (Equation (3.5)), is sensitive to the regional presence of rice and cotton. In regions without rice cultivation (e.g., Border Rivers, Gwydir, Lower Darling), the variable simplifies to represent cotton area, leading to larger coefficient estimates

($\hat{\beta}_{1,r} \geq 45.7$ ha/GL). Conversely, in regions with a diverse crop mix, the water-intensity weighting in Equation (3.5) yields smaller coefficients.

- Water Market Integration: The degree of connectivity to inter-regional water markets varies. The Murrumbidgee and Murray regions are well-integrated with markets in Victoria and South Australia, whereas trade in the northern MDB is more constrained (Competition & (ACCC), 2021; NSW Natural Resources Commission, 2024; Australian Competition and Consumer Commission, 2020). These differences can influence how local water allocations translate into planting decisions.
- Climatic Conditions: Regional differences in climate affect crop water intensity, influencing how much land can be irrigated with a given volume of water and thus affecting the magnitude of $\hat{\beta}_{1,r}$.

The model's explanatory power, measured by the adjusted R^2, is highest in the Murray (0.863) and Murrumbidgee (0.777) regions. The fit is particularly weak for Macquarie–Castlereagh ($R^2_{\text{adj}} = 0.074$), as illustrated by the divergence between actual and predicted values in Figure 3.14. The intercept terms, $\hat{\beta}_{0,r}$, are of limited interpretative interest. The coefficient for pre-season rainfall, $\hat{\beta}_{2,r}$, is positive in five regions and negative in three, but is statistically significant in only one case (Murray).

Robustness to Serial Correlation and Heteroskedasticity

We next examine the residuals for violations of the i.i.d. assumption. Table 3.3 reports results from standard tests for autocorrelation and heteroskedasticity. The p-values from the Durbin-Watson (DW), Breusch-Godfrey (BG), and Ljung-Box tests uniformly fail to reject the null hypothesis of no serial correlation at the 5% significance level. The only exception is a borderline signal for Gwydir from the BG test at lag 2 ($p = 0.0915$). Similarly, the Breusch-Pagan and White tests show no statistically significant evidence of heteroskedasticity, with all p-values exceeding 0.12.

Table 3.3: Residual diagnostics by region (p-values). H_0: no autocorrelation / homoskedasticity.

Region	T	DW	BG(1)	BG(2)	Ljung–Box(2)	BP	White
Border Rivers	11	0.254	0.557	0.799	0.842	0.690	0.759
Gwydir	15	0.493	0.711	0.0915	0.139	0.738	0.267
Lachlan	15	0.831	0.115	0.269	0.359	0.254	0.165
Lower Darling	11	0.298	0.960	0.825	0.790	0.784	0.538
Macquarie–Castlereagh	15	0.129	0.209	0.278	0.436	0.484	0.120
Murray	15	0.829	0.179	0.404	0.328	0.984	0.578
Murrumbidgee	15	0.165	0.464	0.738	0.673	0.216	0.472
Namoi	15	0.293	0.800	0.843	0.877	0.731	0.396

While the formal diagnostic tests do not provide strong evidence against the i.i.d. assumption, it is well-established that such tests can have low power in small

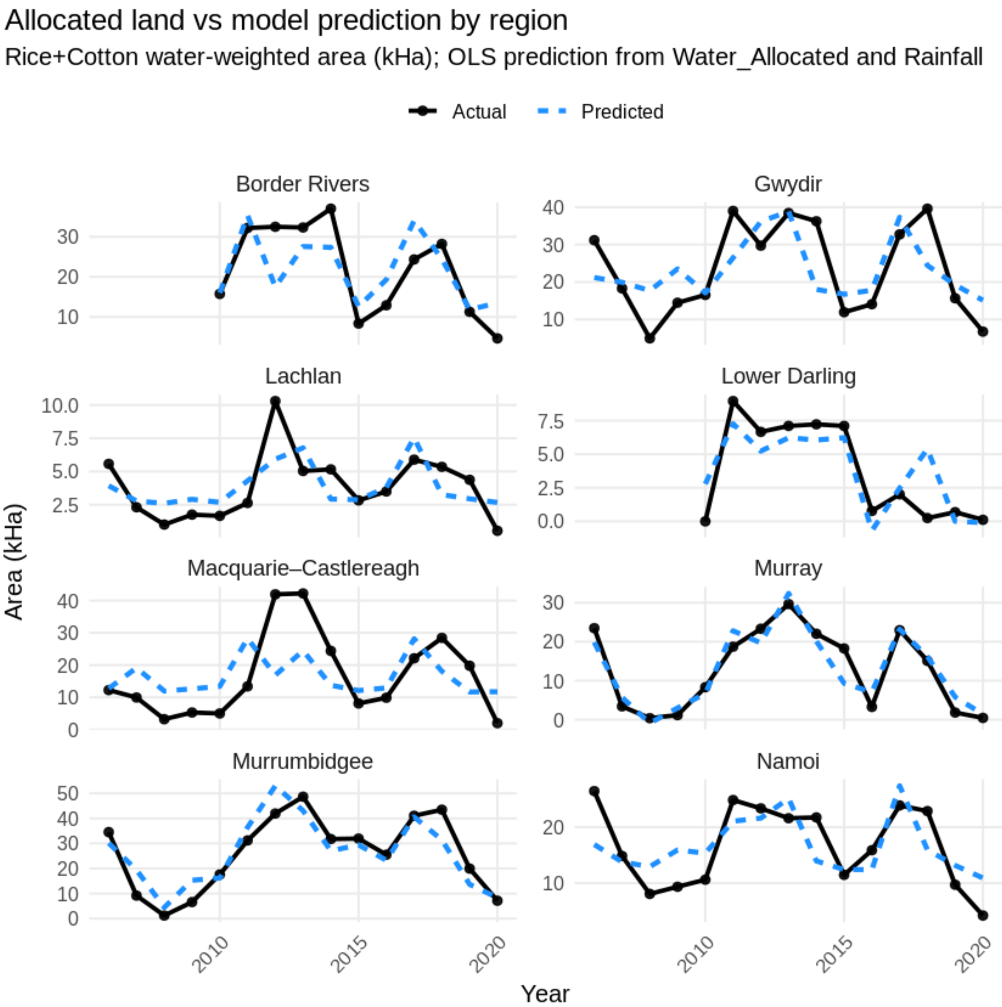


Figure 3.14: Actual opportunistic acreage ($\text{land\_opp}_{r,t}$) versus predicted opportunistic acreage ($\widehat{\text{land\_opp}}_{r,t}$) from the baseline OLS regression without lagged variables.

samples ($T \in \{11, \ldots, 15\}$). Given the time-series nature of the data, where unobserved factors (such as commodity price cycles or multi-year climate patterns) could introduce serial dependence, adopting a conservative approach is prudent. Therefore, to ensure the robustness of our inferences, we complement the OLS results with standard errors that are robust to both heteroskedasticity and autocorrelation (HAC).

We complement the i.i.d. OLS results for Eq.3.7 with the Equal-Weighted Cosine (EWC) heteroskedasticity-and-autocorrelation–robust test of Lazarus et al. (2018). Following their recommendations, we use the fixed-b EWC procedure with degrees of freedom

$$\nu = \lfloor 0.4\, T^{2/3} \rfloor$$

and Student-t_ν reference critical values. In line with the paper's practical advice, we do not report a "Newey–West hack" (ad-hoc truncation and conventional normal/t critical values), which can suffer size distortions at small T. Implementation. For each region r and the coefficient on water, $\beta_{1,r}$, we proceed in four steps following the Frisch–Waugh–Lovell construction:

1. Estimate the unrestricted OLS regression

$$\text{land\_opp}_{r,t} = \beta_{0,r} + \beta_{1,r}\, \text{Water\_allocated}_{r,t} + \beta_{2,r}\, \text{Rainfall}_{r,t} + \epsilon_{r,t}, \tag{3.8}$$

   and collect the residuals $\hat{\epsilon}_{r,t}$.

2. Regress Water_allocated$_{r,t}$ on Rainfall$_{r,t}$ and an intercept, obtaining the residuals $r_{r,t}$.

3. Form the scalar series using the residuals from (3.8):

$$z_{r,t} = r_{r,t}\, \hat{\epsilon}_{r,t}, \tag{3.9}$$

   demeaned over t.

4. Compute the EWC long-run variance (LRV) via the Type-II discrete cosine transform (DCT-II):

$$\widehat{\phi}_j = \sqrt{\tfrac{2}{T}} \sum_{t=1}^{T} z_{r,t}\, \cos\!\Big(\pi j\, \tfrac{t-\frac{1}{2}}{T}\Big), \tag{3.10}$$

$$\widehat{\mathrm{LRV}}_{\mathrm{EWC}} = \frac{1}{\nu} \sum_{j=1}^{\nu} \widehat{\phi}_j^2. \tag{3.11}$$

Let $S_r = \sum_{t=1}^{T} r_{r,t}^2$. The EWC standard error and test statistic for $\hat{\beta}_{1,r}$ are then given by

$$\widehat{\mathrm{SE}}_{\mathrm{EWC}}(\hat{\beta}_{1,r}) = \frac{\sqrt{T\, \widehat{\mathrm{LRV}}_{\mathrm{EWC}}}}{S_r}, \qquad t_{\mathrm{EWC},r} = \frac{\hat{\beta}_{1,r}}{\widehat{\mathrm{SE}}_{\mathrm{EWC}}} \text{ with reference } t_\nu.$$

Table 3.4 reports $\hat{\beta}_{1,r}$ together with $\mathrm{SE}_{\mathrm{EWC}}$, t_{EWC}, the degrees of freedom ν, and the corresponding p-values under t_ν. Relative to the standard OLS estimates, the EWC

Table 3.4: EWC HAC-robust estimates for $\hat{\beta}_{1,r}$ (water) in Eq. (3.6).

Region	$\hat{\beta}_{1,r}$ [ha/GL]	$\mathrm{SE}_{\mathrm{EWC}}$ [ha/GL]	t_{EWC}	df_{EWC}	p_{EWC}
Border Rivers	129	25.0	5.17	1	0.122
Gwydir	45.7**	9.46	4.83	2	0.040
Lachlan	4.95*	1.51	3.27	2	0.082
Lower Darling	81.3	28.1	2.89	1	0.212
Macquarie–Castlereagh	26.7*	6.35	4.20	2	0.052
Murray	9.55***	0.432	22.1	2	0.0020
Murrumbidgee	20.1***	1.20	16.7	2	0.0036
Namoi	40.7**	8.09	5.04	2	0.037

Notes: Coefficients and standard errors are in hectares per gigalitre (ha/GL). Values are rounded to three significant digits. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

procedure widens the standard errors, particularly for regions with smaller sample sizes (e.g., Border Rivers, Lower Darling).

Nevertheless, the qualitative conclusion remains unchanged: water allocations are positively associated with opportunistic acreage in every region. The association remains highly significant ($p < 0.01$) for Murray and Murrumbidgee and is significant at the 5% level for Gwydir and Namoi. Furthermore, the coefficients for Macquarie–Castlereagh and Lachlan become significant at the 10% level. These EWC results provide a more conservative and reliable basis for inference than standard OLS given the data limitations.

Extended Model with Lagged Water Allocations

In half of the regions studied, the total volume of carryover water during the observation period exceeds the total volume of new allocations (Figure 3.15, left panel). This high carryover ratio suggests that a substantial volume of water is held in storage for more than one season, influencing decisions over longer time horizons. This motivates extending the model to include a lagged term for water allocations:

$$\widehat{\text{land\_opp}}_{r,t} = \hat{\beta}_{0,r} + \hat{\beta}_{1,r}\,\text{Water\_allocated}_{r,t} + \hat{\beta}^{\text{lag}}_{1,r}\,\text{Water\_allocated}_{r,t-1} + \hat{\beta}_{2,r}\,\text{Rainfall}_{r,t}. \tag{3.12}$$

Table 3.5 presents the OLS results for this extended specification. All estimated coefficients for both contemporaneous ($\hat{\beta}_{1,r}$) and lagged ($\hat{\beta}^{\text{lag}}_{1,r}$) water allocations are positive. At the 5% significance level, the contemporaneous term is significant in six regions, and the lagged term is significant in five.

A key finding is that in regions with a carryover ratio greater than one (Gwydir, Macquarie-Castlereagh, Namoi), the coefficient on lagged water allocations ($\hat{\beta}^{\text{lag}}_{1,r}$) is larger than the contemporaneous one ($\hat{\beta}_{1,r}$). This indicates that in these systems, water allocated 12-24 months prior has a stronger influence on planting decisions than water allocated in the most recent 12-month period. Lachlan is a notable exception, where neither water allocation coefficient is significant. This may reflect the region's complex agricultural system, which involves significant variations in irrigated pasture not fully considered in our model.

Table 3.5: Per-region OLS estimates with contemporaneous and lagged water allocations.

Region	R^2_{adj}	ΔR^2_{adj}	Carryover Ratio	$\hat{\beta}_{0,r}$ [kHa]	$\hat{\beta}_{1,r}$ [ha/GL]	$\hat{\beta}^{\text{lag}}_{1,r}$ [ha/GL]	$\hat{\beta}_{2,r}$ [ha/mm]
Border Rivers	0.777	0.345	0.648	5.02 (3.95)	174** (35.3)	88.8* (24.7)	-93.5* (36.5)
Gwydir	0.668	0.350	1.310	3.60 (4.45)	25.1 (15.6)	52.5** (15.4)	78.3* (33.2)
Lachlan	0.377	0.0637	1.445	1.90 (0.968)	4.52 (2.20)	2.73 (1.99)	4.65 (9.36)
Lower Darling	0.535	0.209	0.447	0.153 (2.32)	75.3* (25.9)	6.65 (24.5)	-25.8 (24.7)
Macquarie–Castlereagh	0.607	0.533	1.012	3.23 (4.63)	30.3* (12.7)	41.9** (10.3)	-14.0 (42.2)
Murray	0.876	0.0133	0.570	-4.40 (2.37)	8.03** (1.76)	2.54 (1.74)	73.7** (21.3)
Murrumbidgee	0.874	0.0974	0.293	-9.62* (4.23)	12.3** (3.80)	10.8* (3.53)	68.2 (32.4)
Namoi	0.708	0.336	1.025	5.39 (2.47)	29.8* (11.6)	38.1** (11.7)	38.9 (17.7)

Notes: Values are rounded to three significant digits. ΔR^2_{adj} is the absolute improvement over the baseline model. Significance levels: $^{**}p < 0.01$, $^{*}p < 0.05$. Intercepts are in kHa; water coefficients in ha/GL; rainfall effects in ha/mm. The carryover ratio is the total water carried over divided by total water allocated between 2005–06 and 2019–20.

The improvement in model fit from including the lagged term, measured by ΔR^2_{adj}, is systematically related to regional water management characteristics. As illustrated in Figure 3.15, the increase in explanatory power is generally larger in regions with higher carryover ratios and lower serial correlation between contemporaneous and lagged water allocations. The water allocation time series for Murrumbidgee and Murray exhibit significant positive autocorrelation ($p < 0.1$, circular permutation test). The significance of the lagged term for Murrumbidgee in the extended model might raise concerns about omitted variable bias in the baseline specification. However, this is expected when an omitted variable (the lag) is correlated with an included regressor. The stability of the contemporaneous coefficient across both models for this region provides some reassurance regarding the robustness of the primary finding.

3.2.4 Conclusion

Adapting seasonal crop cultivation to variable water availability is a key strategy for enhancing agricultural resilience to climate change, given the markedly different irrigation requirements of seasonal crops within the same region. As climate change is projected to increase both water scarcity and inter-annual fluctuations in supply, the capacity of farmers to adjust their land use choices becomes critical. This study contrasts the adaptive capacity of two major irrigated systems: Australia's Murray-Darling Basin (MDB) and Italy's Adda-Lario system. In the MDB, this flexibility has been observed. During the Millennium Drought, a two-thirds reduction in water availability resulted in only a 20% decline in the gross value of irrigated production (price adjusted). Kirby et al. (2014) suggested that one of the major contributing factors was the shift away from water-intensive annual crops. Conversely, in the

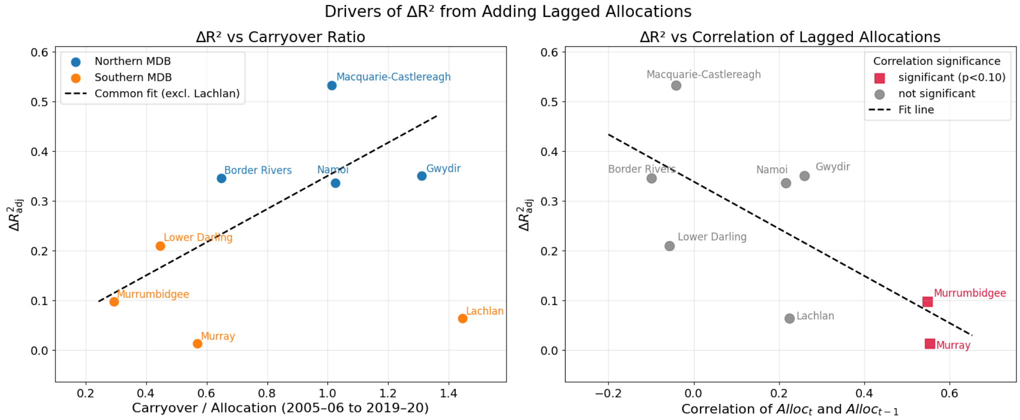


Figure 3.15: **Left Panel:** Relationship between the increase in adjusted R^2 (ΔR^2_{adj}) from including lagged water allocations and the carryover ratio. The line is fitted excluding Lachlan. **Right Panel:** Relationship between ΔR^2_{adj} and the Pearson correlation between $\text{Water\_allocated}_{r,t}$ and $\text{Water\_allocated}_{r,t-1}$. Significance of the correlation is assessed with a circular permutation test.

Adda-Lario system, no significant adaptation in the acreage of major water-intensive crops like rice and maize is observed in response to annual water availability. While previous research has established a strong correlation between annual water allocations and rice acreage in the sMDB (Zeleke & Luckett, 2025), this analysis seeks to establish a more rigorous causal relationship.

To establish causality, this study regressed the composite acreage of opportunistic crops (rice and cotton) on water allocations from the 12 months preceding the land-use decision, controlling for pre-sowing rainfall. Unlike Zeleke & Luckett (2025), who relied on total annual allocations that are only fully known after the cropping decisions have been made, this approach uses information available to farmers ex-ante. The Ordinary Least Squares (OLS) analysis revealed a positive and statistically significant effect of water allocations on opportunistic crop acreage in seven of the eight NSW Sustainable Diversion Limit (SDL) resource units studied (5% significance level), even with limited time series data. Even if no evidence of autocorrelation or heteroskedasticity was found in the residuals, the standard errors were recomputed using EWC heteroskedasticity- and autocorrelation-robust estimators. Under this specification, a significant positive effect was still observed in six of the eight regions, albeit at the 10% significance level.

In regions where carryover volumes were substantial, incorporating lagged water allocations into the model significantly improved its explanatory power (R^2_{adj}). The estimated coefficients for both contemporaneous and lagged allocations were positive and, in most cases, statistically significant (5% significance level). This confirms that farmers' decisions are influenced not only by recent water availability but also by the accumulated supply from previous seasons.

These results provide evidence for a causal relationship between pre-season water availability and land use decisions in Australia's Murray-Darling Basin (MDB), moving beyond the correlational findings of Zeleke & Luckett (2025). Given that a large portion of the water year's supply is allocated before planting decisions are finalized, these pre-decision allocations serve as a proxy for farmers' expectations of seasonal water availability, allowing them to adapt the acreage of opportunistic crops like rice and cotton.

The significance of this finding extends beyond the MDB. In the context of climate change, which is intensifying the variability of annual water supplies globally, the ability to facilitate yearly crop adaptation could become a key policy goal. While the MDB's large storage capacity has historically provided the certainty needed for such adaptation, recent advancements in the forecast of droughts through machine learning techniques are creating new possibilities. As noted by Camps-Valls et al. (2025), these tools can reduce uncertainty in expected water availability even in basins lacking large reservoirs. Therefore, understanding the institutional and economic conditions that support this adaptive capacity is important for agricultural systems worldwide that face increasing uncertainty in water availability.

Future directions

Based on this study, several avenues for further research can be identified to improve our understanding of this adaptive mechanism. The next steps include:

1. Incorporating forward-looking forecasts: Future empirical analysis should move beyond using past allocations as a proxy for expectations. A more refined analysis could directly include forward-looking variables, such as the Seasonal Climate Outlooks published by the Australian Bureau of Meteorology. For instance, in October the Outlook reports the probability of exceeding median rainfall for the following three months.

2. Developing a theoretical framework: A formal framework would help to model how farmers make land-use decisions under different degrees of uncertainty regarding future water availability and prices, both with and without water markets.

3. Identifying the transmission channel: An important question for the MDB is whether scarcity is transmitted primarily through market prices or directly through the volume of water allocations distributed to farmers. If the price channel plays the dominant role, then annual economic valuations of water markets, such as those in Rafey (2023), may need to be updated to incorporate the benefits of adaptive land-use responses. One possible approach would be to use, as an instrumental variable, inflows into a dam that do not increase allocations in a given SDL resource unit but do affect prices in that region because trade is possible between the area where the new allocations occur and the region of interest.

4. Assessing structural preconditions: Replicability warrants attention. In the MDB, the average irrigated farm operates 563 hectares (296 irrigated) Rafey (2023), and access to diverse machinery may enable flexible crop choices. It is unclear whether similar adaptation is feasible where farms are smaller and structures differ. In Lombardy—the region that contains the Adda–Lario system—the average utilized agricultural area is 21.4 hectares (ISTAT, 2020), and crop diversification requires machinery suited to different crops and operations. Recent progress by Giulio Palcic (personal communication, 2025) in forecasting six-month average inflows to Lake Como (the main agricultural

reservoir of the Adda–Lario system) makes the question more compelling, as seasonal water-availability signals could still support adaptive land-use choices in the Po Valley, albeit under different structural constraints.

The next chapter develops a simple theoretical framework to analyze land-use choices under uncertain water supply, comparing scenarios with and without water markets. This model, centered on a cap-and-trade mechanism for water combined with seasonal forecasts, clarifies the conditions under which pre-season water signals (quantities and/or prices) can generate observable adjustments in opportunistic crop area.

Chapter 4

Cap and Trade on water with seasonal forecasts: a theoretical model

Chapter summary. This chapter develops a theoretical model to evaluate the economic benefits of a cap-and-trade water market and seasonal water availability forecasts as tools for adapting to water scarcity. The model features two types of agricultural producers—high-value perennial growers and flexible seasonal farmers—who face uncertain water availability, which is modeled using a scaled logit normal distribution. It solves for the optimal crop choice for seasonal farmers, who must balance profit potential with risk, and determines the market-clearing equilibrium price for water based on total availability and crop choice.

Using Monte Carlo simulations, the chapter compares the expected economic output across four scenarios: a baseline with neither markets nor forecasts, a scenario with each mechanism in isolation, and a scenario with both combined, while also considering varying levels of farmer risk aversion and forecast skill. The results demonstrate that water markets are the primary driver of economic gains, especially under scarce conditions, by reallocating water to high-value uses. Seasonal forecasts provide additional, complementary benefits, particularly for risk-averse farmers, when forecast skill is high, and especially when the water supply is highly variable, with frequent years of both abundance and scarcity. Crucially, the model reveals a synergy between the two mechanisms, showing their combined value during severe droughts can exceed the sum of their individual effects.

4.1 Model Setup

We consider an economy with a fixed land endowment, normalized to 1, which is divided between

$$\omega_o \quad \text{(perennial producers)}, \qquad \omega_s = 1 - \omega_o \quad \text{(seasonal producers)}.$$

The revenue function $Q(\theta, c)$[1] (measured in dollars, which can be read as \$/ha given the land normalization) is modeled as a linearly increasing function of con-

[1] More generally, revenue can be written as $Q(\theta, c) = Y(\theta, c)\, p$, where $Y(\theta, c)$ denotes yield per hectare and p the (exogenous) output price. In partial-equilibrium settings one might allow p to fall with aggregate output (so $\partial Y/\partial\theta > 0$ and $p'(\cdot) < 0$). Here we treat the basin as a small open

sumed water[2] with a saturation point normalized at 1. Here, θ denotes the crop typology, and $c \in \mathbb{R}^+$ is the normalized amount of water consumed per hectare. While the saturation level typically varies across crop types, we assume a common normalized value for simplicity.

The generic production function[3] of a cultivation occupying a share of land ω is:

$$Q(\theta, c) = \theta \left(1 - \theta + \theta \frac{\min\{c, \omega\}}{\omega}\right) \omega, \tag{4.1}$$

Figure 4.1 illustrates the behavior of $Q(\theta, c)$ for different crop choices.

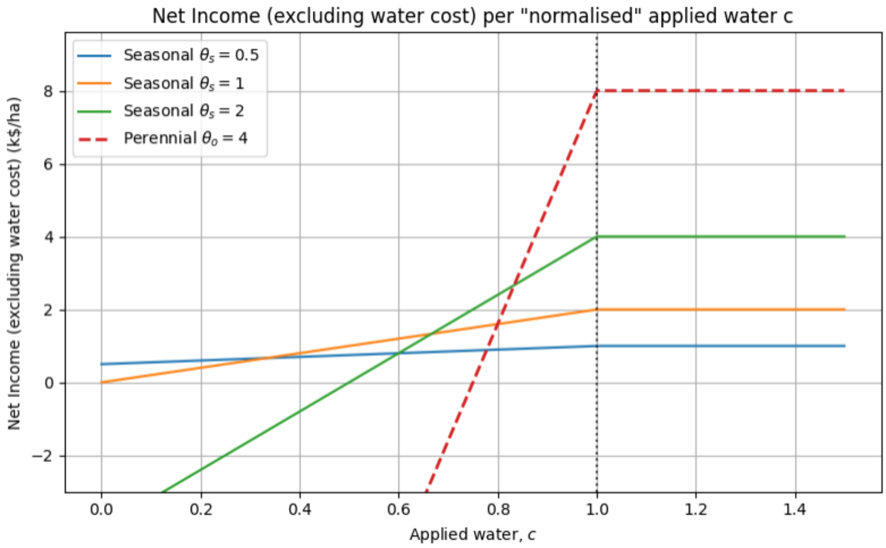


Figure 4.1: Revenue per unit of water $Q(\theta, c)$ as a function of the normalized water input c, shown for seasonal crops with $\theta \in \{0.5, 1, 2\}$ (solid lines), and for perennials with $\theta = 4$ (dashed). The vertical dotted line indicates the water saturation point at $c = 1$.

Perennial crops—such as vineyards, almonds, or peaches—generate revenues between two and five times greater than seasonal crops (Hughes, 2011). However, these crops require substantial upfront investment: trees must be irrigated for several years before bearing fruit. A failure to irrigate in any year results in plant death and significant losses. Therefore, for perennial producers, we fix $\theta_o = 4$, which reflects this high-stakes behavior in Equation 4.1 and in Figure 4.1.

In contrast, seasonal farmers make planting decisions each year, choosing $\theta_s \in [0,\ 2]$. As Figure 4.1 shows, they face a trade-off: higher θ leads to greater potential profits but also to greater risk in low water years, while lower θ provides safer but less profitable outcomes.

economy: local production does not affect world prices. Without loss of generality we therefore set $p = 1$ and omit it.

[2]Consumed water typically includes both irrigation and effective rainfall. For tractability, we assume that consumption occurs solely via irrigation. We also assume that the provided water is equal water used for evapotranspiration. This is generally not true but we assume is to keep the model simple (Varzi, 2016).

[3]When the production function is plotted, the values are multiplied by 2000 k$, to match the scale of estimates in Hughes (2011).

4.1.1 Distribution of Available Water and Forecast Structure

We model available water in a resource unit by a *scaled logit–normal* random variable $W \in (0, s)$. Let

$$Z \sim \mathcal{N}(\mu, \sigma^2), \qquad \ell(z) := \frac{1}{1+e^{-z}} \ \text{(logistic function)},$$

and define

$$W \;=\; s\,\ell(Z) \;=\; \frac{s}{1+e^{-Z}}, \tag{4.2}$$

which we denote by $W \sim \mathrm{SLN}(s; \mu, \sigma^2)$. Here $s > 0$ is a scale parameter that sets the support $(0, s)$ (allowing $s > 1$ accommodates years with allocations above the long–run mean).

Estimation. The parameters (μ, σ, s) are obtained by maximum likelihood using the series of water available for irrigation in the SDL resource units (NSW Border Rivers, Gwydir, Lachlan, Lower Darling, Macquarie–Castlereagh, Murray, Murrumbidgee, and Namoi), divided by the surface-water Baseline Diversion Limit (BDL) (Murray–Darling Basin Authority, 2025), which represents the long-term average water consumption for each unit; see Walsh et al. (2021). In this normalization, the random variable W represents the share of usual (BDL) water consumption that can be met in a given year.

Forecast variable and skill. When farmers observe a seasonal forecast before choosing the annual crop, we denote the forecast by F, obtained from another latent normal variable Z_f through the same scaling:

$$Z_f \sim \mathcal{N}(\mu, \tau_1^2), \qquad F \;=\; s\,\ell(Z_f).$$

Forecast skill is modeled on the logit scale by

$$r \;:=\; \mathrm{Corr}(Z_f, Z) \in [0, 1].$$

A convenient parametrization that achieves this correlation is

$$Z \;=\; Z_f \;+\; \varepsilon, \qquad \varepsilon \sim \mathcal{N}(0, \tau_2^2), \quad Z_f \perp\!\!\!\perp \varepsilon, \tag{4.3}$$

with

$$\tau_1 \;=\; r\,\sigma, \qquad \tau_2 \;=\; \sigma\sqrt{1-r^2}. \tag{4.4}$$

Indeed, independence in (4.3) implies $\mathrm{Var}(Z) = \tau_1^2 + \tau_2^2 = \sigma^2$ and $\mathrm{Corr}(Z_f, Z) = \tau_1/\sigma = r$.

Posterior given a forecast. Observing $F = f \in (0, s)$ is equivalent to observing $Z_f = \mathrm{logit}(f/s) := \ln\!\left(\frac{f/s}{1-f/s}\right)$. From (4.3)–(4.4),

$$Z \,\big|\, F = f \;\sim\; \mathcal{N}\big(\mathrm{logit}(f/s),\; \tau_2^2\big)\,,$$

and therefore, by (4.2),

$$W \,\big|\, F = f \;\sim\; \mathrm{SLN}\big(s;\; \mu_{\text{post}} = \mathrm{logit}(f/s),\; \tau_2^2\big)\,. \tag{4.5}$$

The posterior distributions of W given a certain forecast F are plotted in the figure 4.5.

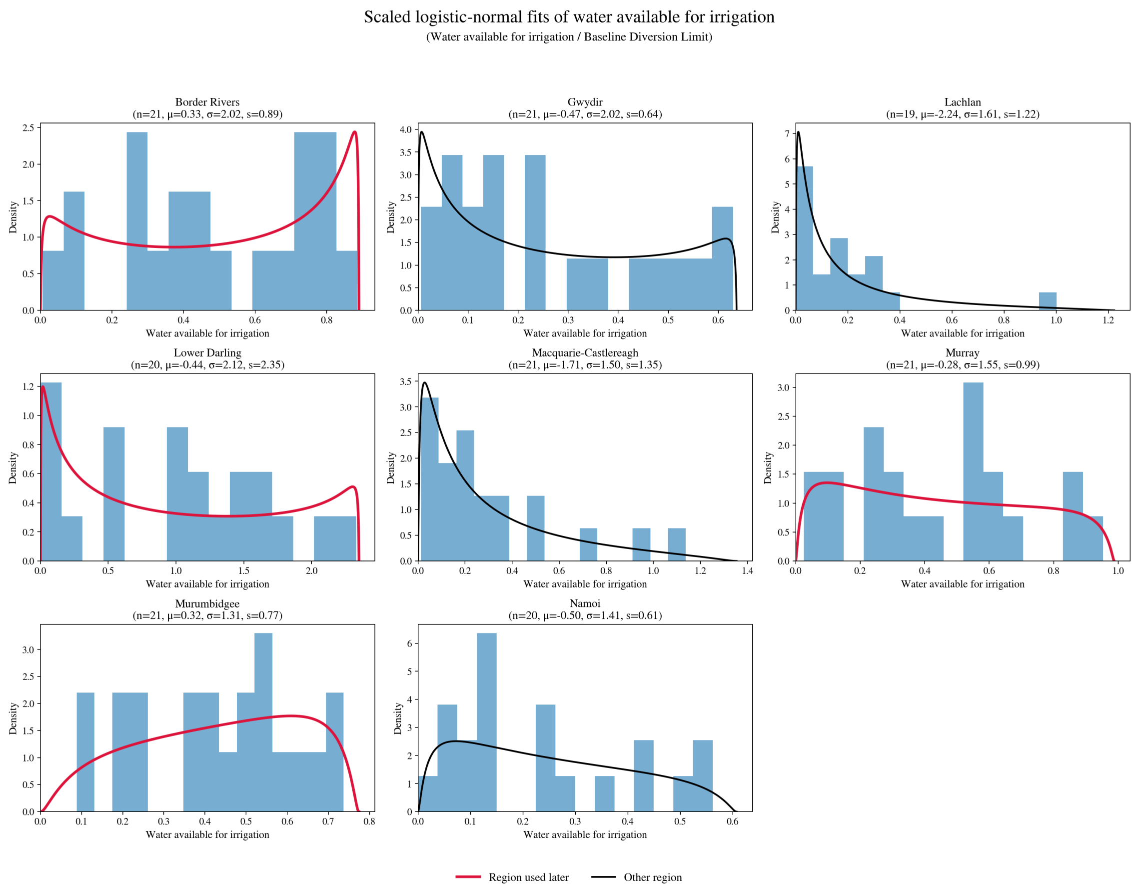


Figure 4.2: Histograms of the annual share W of usual water consumption that can be met, together with fitted scaled logit–normal densities $\mathrm{SLN}(s; \mu, \sigma^2)$. In the subsequent analysis we focus on four units that illustrate distinct shapes: Border Rivers (U–shaped with no mass above $s = 0.89$), Lower Darling (U–shaped with mass above 1, $s = 2.35$), Murray (left–skewed, relatively flat), and Murrumbidgee (right–skewed, relatively flat).

4.1.2 Decision Timeline

Each farmer with a land endowment of ω holds a water portfolio X and receives a water allocation ωW. After discovering the allocation the farmer may buy or sell an amount b of water at price P. The total amount c is then consumed for irrigation. Since no overconsumption is permitted, the water balance constraint is:

$$X = W\omega + b - c\ 0. \tag{4.6}$$

In the following sections, we solve the farmer's optimization problem in three steps. First, we identify the optimal irrigation and trading strategy given a realized water allocation and a fixed price P. Second, we derive the equilibrium market price as a function of total water availability. Third, we analyze the optimal crop choice under uncertainty about future water availability.

4.2 Best Consumption and Trading Strategy

At time $T/2$, after the crop type θ has been fixed and the amount of available water is realized, a farmer who owns a land share ω and cannot influence the price with

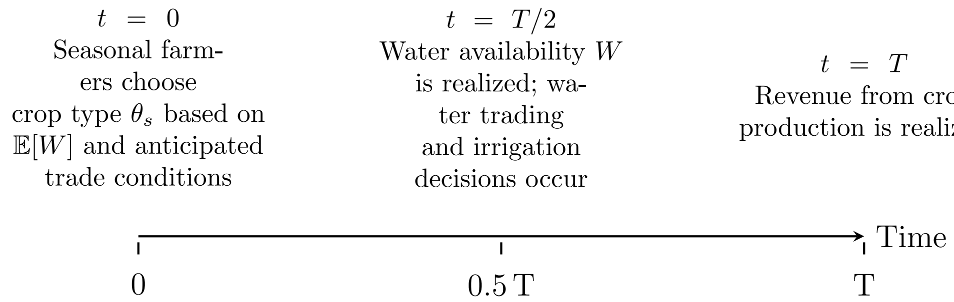


Figure 4.3: Timeline of crop selection, water allocation, and trading decisions.

his trading behavior aims to maximize profit π, which depends on the output (see Equation 4.1) and the cost incurred from purchasing water b at price $P \geq 0$. The farmer solves:

$$\max_{b,\,c} \pi(b, c, \omega, \theta, P) = \max_{b,\,c} \left\{ -\,bP + \theta\left(1 - \theta + \theta\,\frac{\min\{c,\,\omega\}}{\omega}\right)\omega \right\}. \tag{4.7}$$

$$\text{s.t.} \quad W\,\omega + b - c \geq 0. \tag{4.8}$$

If $P = 0$, then the objective function depends only on the production term, and that has a plateau for $c^* \geq \omega$. Therefore, in this case, the optimal irrigation level satisfies $c^* \geq \omega$, and the corresponding water purchase is

$$b^* \geq c - W\,\omega \geq (1 - W)\,\omega.$$

This implies that if the initial water allocation is insufficient, the farmer will buy additional water until full saturation is reached. Conversely, if the allocation exceeds the saturation level, it becomes irrelevant whether the surplus water is used or sold, as it does not affect profit.

Since the objective is linear and decreasing in b, the constraint binds:

$$b^* = c - W\,\omega$$

Substituting this into the profit function gives:

$$\pi(c) = P\,W\,\omega + g(c), \quad \text{where} \quad g(c) = \begin{cases} -\,c\,P + \theta(1-\theta)\omega + \theta^2\,c, & \text{if } c \leq \omega, \\ -\,c\,P + \theta\,\omega, & \text{if } c > \omega. \end{cases}$$

Define the critical price:

$$P_{\text{crit},\,\theta} := \theta^2.$$

Taking the derivative of $\pi(c)$:

$$\frac{\partial \pi(c)}{\partial c} = \begin{cases} -P + P_{\text{crit},\,\theta}, & \text{if } c \leq \omega, \\ -P, & \text{if } c > \omega. \end{cases}$$

We study the sign of $\frac{\partial \pi(c)}{\partial c}$:

- If $P > P_{\text{crit},\,\theta}$, then $\pi(c)$ is strictly decreasing on $[0, \omega]$, so $c^* = 0$.
- If $P < P_{\text{crit},\,\theta}$, then $\pi(c)$ increases on $[0, \omega]$ and decreases thereafter, so $c^* = \omega$.

- If $P = P_{\text{crit},\theta}$, then $\pi(c)$ is constant on $[0, \omega]$, so any $c \in [0, \omega]$ is optimal.

The case $c > \omega$ can only occur if $P = 0$, but in that case $\pi(c) = \pi(\omega)$, so this case can be absorbed into the optimum at ω.

Thus, the single-farmer optimum is:

$$(c^*, b^*) = \begin{cases} (0, \ -\omega W), & \text{if } P > P_{\text{crit},\theta}, \\ (c, \ c - \omega W), \quad c \in [0, \omega], & \text{if } P = P_{\text{crit},\theta}. \\ (\omega, \ \omega (1 - W)), & \text{if } P < P_{\text{crit},\theta}, \\ (c, \ b), \quad c \geq \omega, \ b \geq c - \omega W, & \text{if } P = 0, \end{cases} \tag{4.9}$$

Given the linear structure of the production function and the absence of trading frictions, the optimal strategy is binary: if $P > P_{\text{crit},\theta}$, the farmer sells all received water allocations; if $P < P_{\text{crit},\theta}$, the farmer purchases the additional water needed to fully saturate crop production. When $P = P_{\text{crit},\theta}$, any convex combination of these two strategies yields the same profit and is therefore equally optimal. The resulting profit is:

$$\frac{\pi(b^*, c^*, \omega, \theta, P)}{\omega} = \begin{cases} \theta(1 - \theta) + PW, & \text{if } P > P_{\text{crit},\theta}, \\ \theta - (1 - W)\, P, & \text{if } P \leq P_{\text{crit},\theta}. \end{cases} \tag{4.10}$$

4.3 Equilibrium Price with Two Farmer Types

We aim to determine the equilibrium price P_e such that the total amount of water sold equals the total amount purchased. Given that all seasonal farmers and all perennial farmers are homogeneous within their respective groups, the market-clearing condition simplifies to:

$$b_s^*(P_e) + b_o^*(P_e) = 0. \tag{4.11}$$

Since $\theta_o \geq \theta_s$, it follows that $P_{\text{crit},\theta_o} > P_{\text{crit},\theta_s}$. According to the trading behavior derived in Equation 4.9, the water demand or supply of each group depends on both the realized water availability W and the market price P. An equilibrium can exist only if one group is a net buyer and the other is a net seller (or indifferent).

$b_s \backslash b_o$	0	$0 < P < P_{\text{crit},s}$	$P = P_{\text{crit},s}$	$P_{\text{crit},s} < P < P_{\text{crit},o}$	$P = P_{\text{crit},o}$	$P > P_{\text{crit},o}$
$W < \omega_o$	B/B	B/B	I/B	S/B	S/I	S/S
$W = \omega_o$	B/B	B/B	I/B	S/B	S/I	S/S
$\omega_o < W < 1$	B/B	B/B	I/B	S/B	S/I	S/S
$W \geq 1$	I/I	S/S	S/S	S/S	S/S	S/S

Table 4.1: Net positions of seasonal (b_s) and perennial (b_o) farmers. B = net buyer, S = net seller, I = indifferent. Blue-shaded cells denote the equilibrium price(s) for each rainfall regime (proof below).

We analyze four water availability regimes:

(i) Extreme scarcity ($W < \omega_o$). In this case, equilibrium can occur only in the interval $P \in \left[P_{\text{crit},\theta_s}, P_{\text{crit},\theta_o}\right]$. Seasonal farmers are potential sellers in this price range and can supply at most $\omega_s W$ units of water. Meanwhile, perennial farmers need $\omega_o(1 - W)$ to reach full saturation.

Focusing on prices strictly between the two thresholds,

$$P \in \left]P_{\text{crit},\theta_s},\, P_{\text{crit},\theta_o}\right[,$$

we apply the individual trading rules:

$$c_s^*(P) = 0, \quad b_s^*(P) = -\omega_s W, \qquad c_o^*(P) = \omega_o, \quad b_o^*(P) = \omega_o(1 - W).$$

Hence the net aggregate demand is:

$$B(P) = b_o^*(P) + b_s^*(P) = \left[\omega_o(1 - W) - \omega_s W\right].$$

To determine whether this net demand is positive:

$$\omega_o(1 - W) > \omega_s W \iff \frac{\omega_s}{\omega_o} W < 1 - W \iff \left(1 + \frac{\omega_s}{\omega_o}\right) W < 1 \iff W < \omega_o, \tag{4.12}$$

which holds by assumption. Thus, $B(P) > 0$ (excess demand), and the price must rise. The unique equilibrium is:

$$P_e = P_{\text{crit},\theta_o}.$$

(ii) Exact balance, $W = \omega_o$. Seasonal farmers can supply exactly the quantity perennials need (insert ($W = \omega_o$ in 4.12). Any price in the open interval $\left(P_{\text{crit},\theta_s}, P_{\text{crit},\theta_o}\right)$ clears the market, while the two end-points make both groups indifferent, hence the whole closed interval is an equilibrium set.

(iii) Moderate scarcity, $\omega_o < W < 1$. Even after perennials are fully saturated, the residual water $(W - \omega_o)$ can only be absorbed if the price falls to P_{crit,θ_s}, where seasonal farmers turn from sellers into indifferent traders and can keep (or dump) the surplus.

(iv) Full abundance, $W \geq 1$. All land can be saturated without trade; any strictly positive price would create excess supply, so the unique competitive equilibrium is $P_e = 0$.

Figure 4.4 illustrates how the equilibrium price P_e evolves with the share of available water W, given the saturation requirements of different crop types.

4.4 Optimal Crop Coefficient for Seasonal Farmers

At the beginning of each water year, seasonal farmers choose the crop type $\theta \in [0, 2]$ to maximize expected profits. Formally, they solve

$$\max_{\theta \in [0,2]} \mathbb{E}\left[\pi(\theta, b^*, c^*, \omega, P^*, W)\right].$$

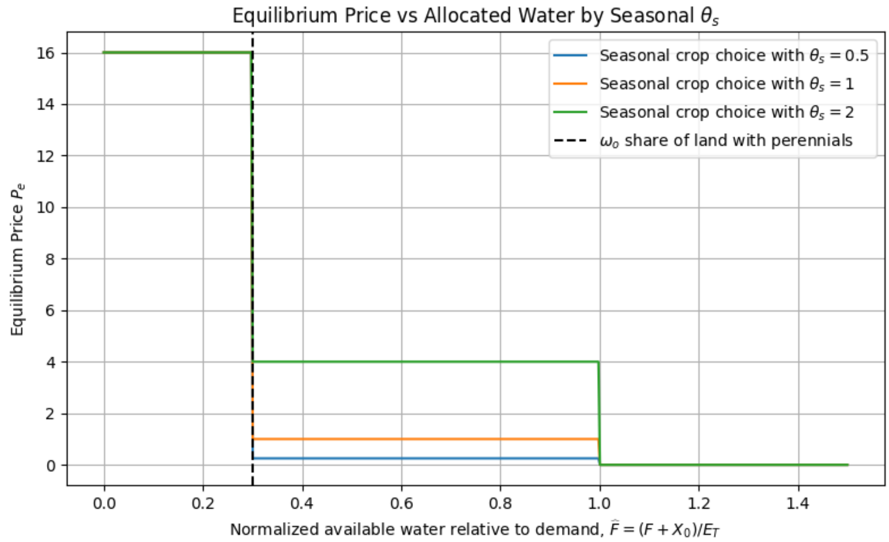


Figure 4.4: Equilibrium price P_e versus normalized water availability W, shown for each seasonal crop choice $\theta_s \in \{0.5, 1, 2\}$. The vertical dashed line marks the perennial land share ω_o.

4.4.1 Risk-neutral with trade

In the individual farmer's problem we treat the competitive price as parametric, i.e. determined by the *aggregate* seasonal choice θ_s. Conditional on realized water W, profit per unit land is

$$\frac{\pi(\theta, W)}{\omega} = \begin{cases} \theta, & W \geq 1, \\ \theta_s^2 W \; + \; \theta(1-\theta), & \omega_o < W < 1, \\ \theta_o^2 W \; + \; \theta(1-\theta), & W \leq \omega_o, \end{cases}$$

where θ is the individual choice and θ_s is the aggregate seasonal choice (held fixed when differentiating). At the symmetric equilibrium we set $\theta = \theta_s = \theta_s^*$.

Let $D := \Pr(W < 1)$. Taking expectations,

$$\frac{\pi(\theta)}{\omega} = \theta\,(1-D) \; + \; \theta(1-\theta)\,D \; + \; \theta_s^2\,\mathbb{E}\big[W\,\mathbf{1}_{\{\omega_o < W < 1\}}\big] \; + \; \theta_o^2\,\mathbb{E}\big[W\,\mathbf{1}_{\{W \leq \omega_o\}}\big].$$

Only the first two terms depend on θ. Differentiating w.r.t. θ (holding θ_s fixed) gives

$$\frac{\partial}{\partial\theta}\frac{\pi(\theta)}{\omega} = (1-D) \; + \; D\,(1-2\theta) = 1 \; - \; 2D\,\theta.$$

Setting this to zero yields the risk–neutral optimum

$$\boxed{\theta_s^* \; = \; \frac{1}{2D}} \qquad \text{clipped to } [0, 2].$$

If $D = 0$ (always abundant), there is no interior solution and the upper bound $\theta_s^* = 2$ is optimal. If $D = 1$ (always scarce), $\theta_s^* = \frac{1}{2}$. Both cases can be seen in the top-left panel of Figure 4.5.

In addition, higher water forecasts lead to riskier seasonal crop choices, since they increase expected profits due to expected water abundance. When forecast skill is low (blue lines, $r = 0.1$), the optimal choice reacts only mildly to different realizations of the forecast, reflecting the limited informational content. By contrast, for intermediate (orange, $r = 0.5$) and high skill (green, $r = 0.9$), the optimal choice varies substantially across quantiles of the realized forecast, showing that informative forecasts generate greater responsiveness in land-use decisions.

The bottom row of the figure confirms this mechanism: while the prior distribution of water availability (black) is fixed, better-skilled forecasts (from left to right) yield sharper conditional posteriors, leading to more dispersed and differentiated optimal choices across realizations of F.

4.4.2 Extension: risk-averse seasonal farmers

We now relax risk neutrality and assume mean–variance preferences. The objective is

$$U(\theta) := \mathbb{E}[Y(\theta, W)] - \frac{\rho}{2}\operatorname{Var}[Y(\theta, W)] = A(\theta) + \frac{\rho}{2}\big(A(\theta)^2 - M(\theta)\big),$$

where $Y(\theta, W) := \pi(\theta, W)/\omega$,

$$A(\theta) := \mathbb{E}[Y(\theta, W)], \qquad M(\theta) := \mathbb{E}[Y(\theta, W)^2],$$

and $\rho \geq 0$ is the risk-aversion parameter. We keep the price-taking convention in derivatives: the middle-regime price term uses the *aggregate* choice θ_s (held fixed when differentiating), and symmetry is imposed ex post.

Introduce

$$D := \Pr(W < 1), \quad \bar{W}_s := \mathbb{E}[W\,\mathbf{1}_{\{W \leq \omega_o\}}], \quad \bar{W}_m := \mathbb{E}[W\,\mathbf{1}_{\{\omega_o < W < 1\}}],$$

$$\overline{W_s^2} := \mathbb{E}[W^2\mathbf{1}_{\{W \leq \omega_o\}}], \quad \overline{W_m^2} := \mathbb{E}[W^2\mathbf{1}_{\{\omega_o < W < 1\}}],$$

and

$$K_0 \;:=\; \theta_s^2\,\bar{W}_m \;+\; \theta_o^2\,\bar{W}_s \qquad \text{(constant in } \theta \text{ when differentiating).}$$

Moments. With

$$Y(\theta, W) = \begin{cases} \theta, & W \geq 1, \\ \theta_s^2 W + \theta(1-\theta), & \omega_o < W < 1, \\ \theta_o^2 W + \theta(1-\theta), & W \leq \omega_o, \end{cases}$$

we obtain

$$A(\theta) = \mathbb{E}[Y(\theta, W)] = \theta \;-\; D\,\theta^2 \;+\; K_0, \qquad A'(\theta) = 1 - 2D\,\theta.$$

For the second moment,

$$M(\theta) = \theta^2 \;+\; D\big(\theta^4 - 2\theta^3\big) \;+\; 2\theta(1-\theta)\,K_0 \;+\; \theta_s^4\,\overline{W_m^2} \;+\; \theta_o^4\,\overline{W_s^2},$$
$$M'(\theta) = 2\theta \;+\; 4D\,\theta^3 \;-\; 6D\,\theta^2 \;+\; 2K_0(1-2\theta).$$

FOC. The first–order condition

$$\frac{\partial U}{\partial \theta} = A'(\theta) + \frac{\rho}{2}\big(2A(\theta)A'(\theta) - M'(\theta)\big) = 0$$

simplifies to the compact cubic

$$\boxed{0 \;=\; 1 - 2D\,\theta \;+\; 2\rho\,(1-D)\,\theta\big[\,K_0 - D\,\theta^2\,\big]\;.}$$

Symmetry (fixed point). At the symmetric competitive outcome set $\theta = \theta_s = \theta_s^*$, so $K_0(\theta_s^*) = (\theta_s^*)^2\bar{W}_m + \theta_o^2\bar{W}_s$. The FOC becomes

$$\boxed{0 \;=\; 1 - 2D\,\theta_s^* \;+\; 2\rho\,(1-D)\,\theta_s^*\big[\theta_o^2\bar{W}_s + (\bar{W}_m - D)\,(\theta_s^*)^2\big]\,, \quad \theta_s^* \in [0,2].}$$

Setting $\rho = 0$ recovers the risk-neutral solution $\theta_s^* = 1/(2D)$;

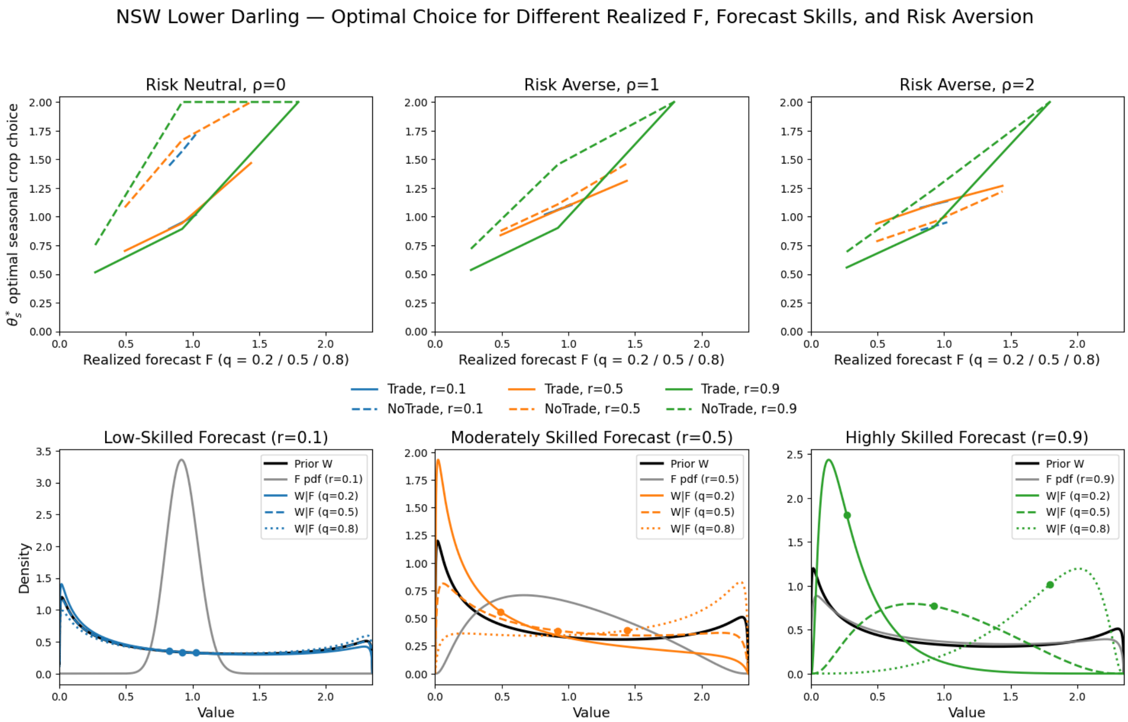


Figure 4.5: Optimal seasonal crop choice θ_s^* in the NSW Lower Darling under different levels of risk aversion ($\rho = 0, 1, 2$) and forecast skill ($r = 0.1, 0.5, 0.9$). The top row shows θ^* as a function of realized forecast values F at three quantiles ($q = 0.2, 0.5, 0.8$), distinguishing between the case with trade (solid lines) and without trade (dashed lines). The bottom row illustrates the underlying probabilistic structure: the prior distribution of water availability W (black), the distribution of the forecast F (gray), and the conditional posteriors $W|F$ for the different quantiles (colored curves with dots at the realized forecast values). Higher forecast skill sharpens posterior beliefs, resulting in more variable and responsive crop choices, while increasing risk aversion dampens the responsiveness of θ^* to forecast realizations.

Figure 4.5 shows that ρ increases, the optimal seasonal choice θ_s^* if farmers do not have access to highly skilled forecasts becomes less sensitive to the realized forecast F: the slope of the θ_s^*–F relation flattens.

4.5 Total Output

The total economic output, denoted by Π, is defined as the sum of the revenues generated in each state of the world. Water exchanged through trading does not directly contribute to aggregate output, as its economic value cancels out across buyer and seller: it enters with opposite sign in the profit functions of the two farmers involved in the transaction.

To compute total output across different water availability scenarios, we must still determine the water consumption of seasonal farmers under moderate scarcity and that of perennial farmers under extreme scarcity.

Reminding that moderate scarcity is defined as:

$$\omega_o \le W < 1$$

Under this regime, the market-clearing condition (see Equation 4.9) yields:

$$\omega_o(1-W) + c_s = \omega_s W$$

Solving for the seasonal farmers' consumption:

$$c_s = \omega_s W - \omega_o(1-W) = \omega_s \left(W - \frac{\omega_o}{\omega_s}(1-W) \right)$$

Extreme scarcity is defined as:

$$W < \omega_o$$

In this case, only perennial farmers consume water. The market-clearing condition gives:

$$c_o = (\omega_o + \omega_s)W = W$$

Let θ_s^* be the optimal crop choice for seasonal farmers. Then total profit across all land is:

$$\Pi = \omega_s\, \pi_s(c_s) + \omega_o\, \pi_o(c_o) = \omega_s\; Q(\theta_s^*, c_s) + \omega_o\, Q(\theta_o^*, c_o)$$

$$\Pi(\theta_s^*, W) = \begin{cases} \omega_o\theta_o + \omega_s\theta_s^*, & W \ge 1, \\ \omega_o\theta_o + \omega_s\theta_s^* \left(1 - \theta_s^* + \theta_s^* \left(W - \frac{\omega_o}{\omega_s}(1-W)\right)\right), & \omega_o \le W < 1, \\ \omega_o\theta_o \left(1 - \theta_o + \theta_o \frac{W}{\omega_o}\right) + \omega_s\theta_s^*(1-\theta_s^*), & W < \omega_o. \end{cases}$$

Taking expectations:

$$\begin{aligned} \mathbb{E}[\Pi(\theta_s^*, W)] = {} & \bar{H}(\omega_s\theta_s^* + \omega_o\theta_o) \\ & + (1-\bar{H})(\omega_o\theta_o + \omega_s\theta_s^* - \omega_s\theta_s^{*2}) - \omega_o\theta_o^2\, \mathbb{E}[\mathbf{1}_{\{W<\omega_o\}}] \\ & + \theta_o^2\, \mathbb{E}[W\mathbf{1}_{\{W<\omega_o\}}] + \omega_s\theta_s^{*2} \left(1 + \frac{\omega_o}{\omega_s}\right) \mathbb{E}[W\mathbf{1}_{\{\omega_o<W<1\}}] \\ & - \omega_o\theta_s^{*2}\mathbb{E}[\mathbf{1}_{\{\omega_o<W<1\}}] - \omega_s\theta_s^{*2}\mathbb{E}[\mathbf{1}_{\{W<1\}}]. \end{aligned}$$

4.5.1 Expected Total Profit Without Water Markets

To compare a scenario with water trading to one without, we first determine the optimal crop choice for seasonal farmers in the absence of markets. This allows us to compute the corresponding total economic output.

In the absence of trade, no water is bought or sold, so the water consumed by a farmer is entirely determined by their initial allocation:

$$b = 0 \quad \Rightarrow \quad c = (X_0 + F)\,\omega = W\,\omega.$$

Substituting this into the revenue function (Equation 4.1) yields

$$\pi(\theta) = \theta\left(1 - \theta + \theta\,\frac{\min\{W\omega,\,\omega\}}{\omega}\right)\omega = \theta\,(1 - \theta + \theta\,\min\{W, 1\})\,\omega.$$

Hence, the profit per unit of land is

$$\frac{\pi(\theta)}{\omega} = \begin{cases} \theta(1 - \theta + \theta\,W), & W \leq 1, \\ \theta, & W > 1. \end{cases}$$

Optimal crop choice. Introduce the shorthand

$$D := \Pr(W \leq 1), \qquad \bar{W}_D := \mathbb{E}[W\,\mathbf{1}_{\{W \leq 1\}}].$$

The expected profit is

$$\mathbb{E}\left[\tfrac{\pi(\theta)}{\omega}\right] = \theta - \theta^2 D + \theta^2 \bar{W}_D = \theta + \theta^2(\bar{W}_D - D).$$

Differentiating gives

$$\frac{\partial}{\partial\theta}\,\mathbb{E}\left[\tfrac{\pi(\theta)}{\omega}\right] = 1 - 2\theta(D - \bar{W}_D).$$

Since the second derivative is $-2(D - \bar{W}_D) \leq 0$, the problem is concave whenever scarcity has positive probability. The optimal crop choice is therefore

$$\theta^* = \frac{1}{2(D - \bar{W}_D)} = \frac{1}{2\,\mathbb{E}\big[(1 - W)_+\big]},$$

provided this value lies in $[0, 2]$; otherwise the optimum is at the boundary ($\theta^* = 0$ or $\theta^* = 2$).

Figure 4.5 shows that, in the absence of trade, risk–neutral farmers always choose riskier crops, since they know that any water conserved by planting less risky, more "water–efficient" crops cannot be sold.

Extension: risk-averse seasonal farmers. Suppose now that seasonal farmers have mean–variance preferences with weight $\rho \geq 0$:

$$U(\theta) = \mathbb{E}[Y(\theta)] - \frac{\rho}{2}\operatorname{Var}(Y(\theta)) = \mathbb{E}[Y(\theta)] + \frac{\rho}{2}\Big(\mathbb{E}[Y(\theta)]^2 - \mathbb{E}[Y(\theta)^2]\Big),$$

where

$$Y(\theta) = \frac{\pi(\theta)}{\omega} = \theta - \theta^2 \mathbf{1}_{\{W\leq 1\}} + \theta^2 W\, \mathbf{1}_{\{W\leq 1\}}.$$

The second moment is

$$\mathbb{E}[Y(\theta)^2] = \theta^2 + 2\theta^3(\overline{W}_D - D) + \theta^4\big(\overline{W_D^2} - 2\overline{W}_D + D\big)$$

with

$$\overline{W_0^2} := \mathbb{E}[W^2\, \mathbf{1}_{\{W\leq 1\}}].$$

The first-order condition for the optimal choice is

$$1 - 2\theta(D - \bar{W}_D) + 2\rho\,\theta^3\Big[(D - \bar{W}_D)^2 - D + 2\bar{W}_D - \overline{W_D^2}\Big] = 0,$$

which reduces to the risk-neutral solution when $\rho = 0$.

Risk-averse seasonal farmers tilt toward less water-intensive crops, and this effect is markedly stronger when water cannot be traded. Without trade, the payoff in low-water years is entirely borne through lower yields, so the variance of income increases steeply with the crop index θ; hence, mean–variance preferences push θ downward.

With trade, adverse realizations of W can be partially hedged by selling water at the spot price $P_e(W)$. In scarcity, our market-clearing conditions imply

$$P_e(W) = \begin{cases} \theta_o^2, & W < \omega_o \quad \text{(extreme scarcity)},\\ \theta_s^2, & \omega_o < W < 1 \quad \text{(moderate scarcity)},\\ \text{any } P \in [\theta_s^2, \theta_o^2], & W = \omega_o, \end{cases}$$

so drought years generate high prices (at least θ_s^2, and up to θ_o^2 under extreme scarcity). If drought is *unexpected* (low forecast skill), farmers may still have planted relatively high θ_s ex ante; the ensuing high P_e in scarcity further strengthens the hedge by raising the revenue from selling water. This insurance channel is absent without trade, so to reduce risk exposure seasonal farmers optimally choose lower θ_s in the no-market benchmark.

Total output. Given the optimal seasonal choice, total economic output is

$$\Pi_{\text{no trade}}(W) = \omega_s\theta_s^*\big(1 - \theta_s^* + \theta_s^* \min\{W,1\}\big) + \omega_o\theta_o\big(1 - \theta_o + \theta_o \min\{W,1\}\big).$$

Taking expectations yields

$$\mathbb{E}[\Pi_{\text{no trade}}] = \omega_s\theta_s^*(1 - \theta_s^*) + \omega_o\theta_o(1 - \theta_o) + (\omega_s\theta_s^{*2} + \omega_o\theta_o^2)\,\mathbb{E}[\min\{W,1\}].$$

4.6 Results

In this section we evaluate the gains from water availability forecasts (F) and water markets (Tr), both individually (NoF–Tr and F–NoTr) and in combination (F–Tr), relative to a baseline scenario with neither. Expected profits are computed for different levels of risk aversion $\rho \in [0, 2]$ and forecast skill $r \in [0, 1]$. For each scenario and each (ρ, r) combination, expected profits are estimated by Monte Carlo simulation with $n_{\text{sims}} = 10\,000$. Simulations are run under two alternative distributions of available water: (i) the fitted distribution based on historical data of water availability for irrigation (Figure 4.2), where in most years water is insufficient to fully meet crop water requirements; and (ii) a counterfactual distribution where available water is doubled more similar to the Po Valley. The latter represents a situation in which water is sufficient in most years for regions such as Lower Darling, and sufficient in almost half of the years in the other regions. The updated distribution can be seen in the left column of Figure 4.7.

Figure 4.6 shows that, in the absence of trade and forecasts, expected profits are negative in all regions where the scale factor $s < 1$. This is the case for Border Rivers, Murray, and Murrumbidgee under the fitted water availability distribution. By contrast, in regions where the scale factor $s > 1$, expected profits remain positive even without trade and forecasts.

When water trade is introduced (with or without forecasts), expected profits become positive in all scenarios. The magnitude of the gains is larger the smaller the expected profit was in the absence of trade, meaning that gains are significantly higher when the fitted water availability distributions are used. Gains from trade tend to be slightly lower for more risk–averse farmers when water is scarce, but this effect reverses when available water is doubled.

The additional gains from forecasts appear only at moderately high levels of forecast skill, and are larger when there is a possibility of having enough water to satisfy all demands. They also increase with the degree of farmers' risk aversion.

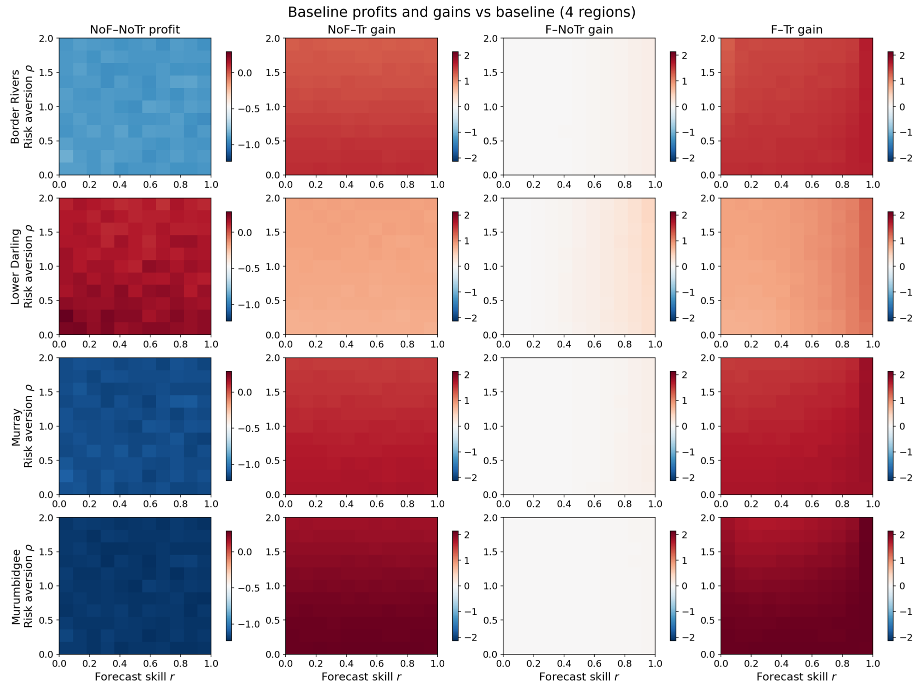
Figure 4.8 shows that the largest share of profit gains in the combined scenario with water markets and forecasts is explained by trade. This share decreases as forecast skill improves and as the likelihood of having enough water to satisfy all demand increases. The share of gains explained by access to forecasts is complementary. It reaches around 50% when the water availability distribution is U–shaped with spikes near zero and above one (as in the case of Lower Darling under the doubled water availability scenario).

In most cases, the gains from forecasts and trade taken separately explain the gains observed in the combined scenario. However, when farmers are highly risk–averse and water availability is expected to fall in intermediate drought or abundance conditions, there is an additional gain from the interaction of trade and forecasts that cannot be explained by the sum of the two effects.[4]

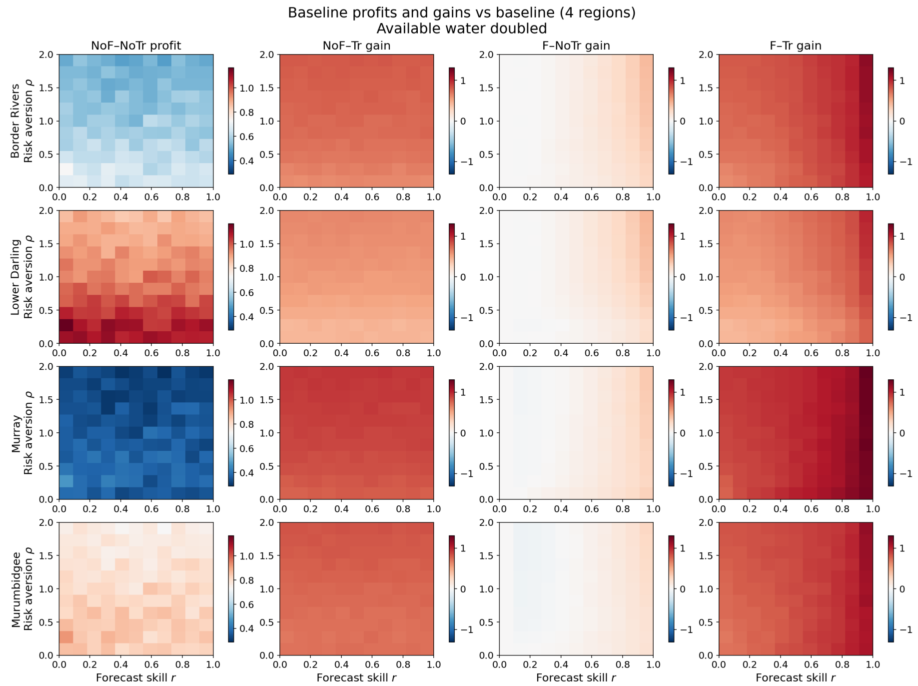
We now analyse the results considering only drought years, defined as those

[4]The explained fraction is computed as

$$\frac{\mathbb{E}[\Pi_{\text{F-Tr}}] - \mathbb{E}[\Pi_{\text{NoF-NoTr}}]}{\left(\mathbb{E}[\Pi_{\text{NoF-Tr}}] - \mathbb{E}[\Pi_{\text{NoF-NoTr}}]\right) + \left(\mathbb{E}[\Pi_{\text{F-NoTr}}] - \mathbb{E}[\Pi_{\text{NoF-NoTr}}]\right)}.$$

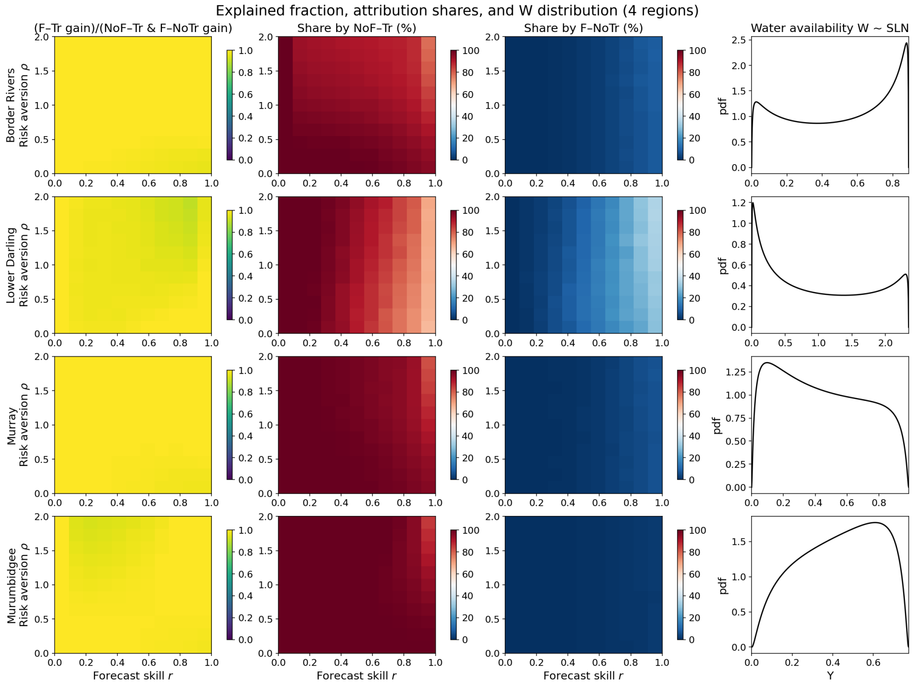


(a) Fitted Water availability

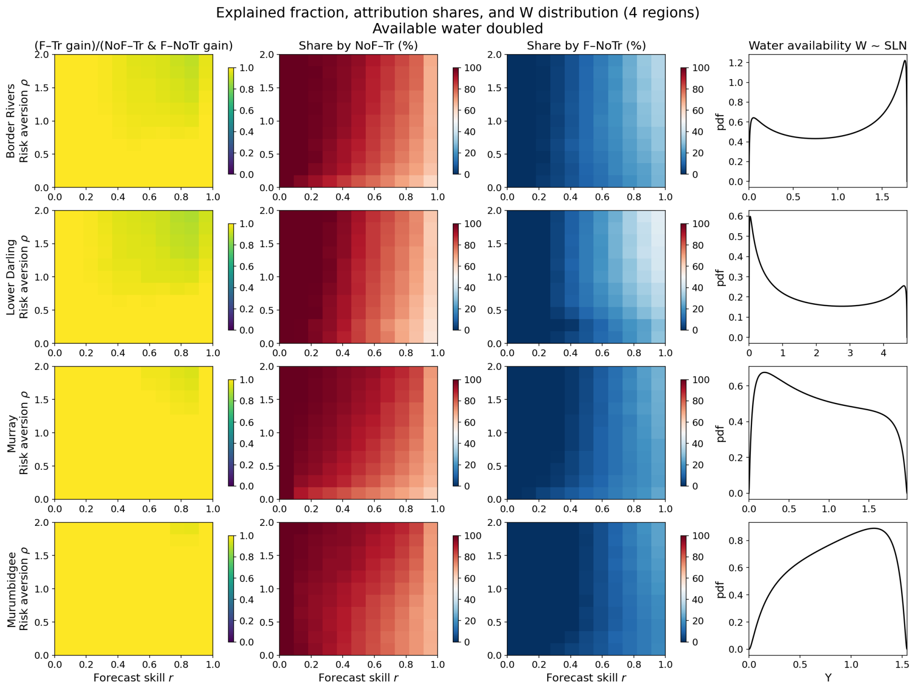


(b) Available water doubled with respect to fitted distributions

Figure 4.6: Composite 4×4 heatmaps by region (rows) over risk aversion ρ (y) and forecast skill r (x). Columns show baseline profits (NoF–NoTr) and average gains from NoF–Tr, F–NoTr, and F–Tr relative to baseline. Scenarios: NoF means the farmer chooses θ without using the forecast (prior moments only); F means θ is chosen using the forecast (posterior, per-draw). NoTr disallows trading; Tr allows trading. For each grid cell (ρ, r) and region, we simulate $n_{\text{sims}} = 10000$ draws of water availability W and the forecast X and compute the average.

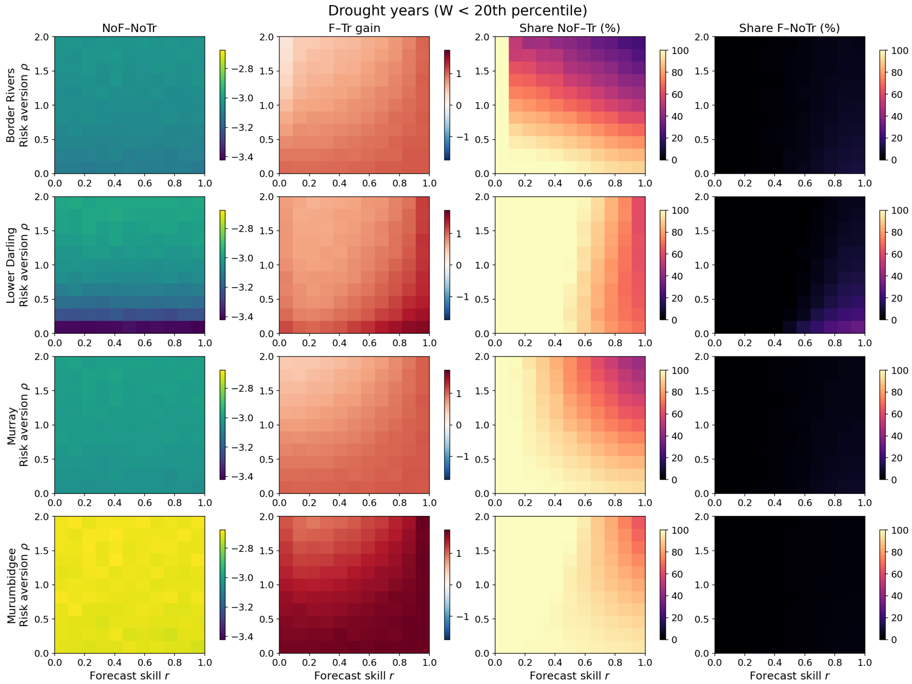


(a) Fitted Water availability

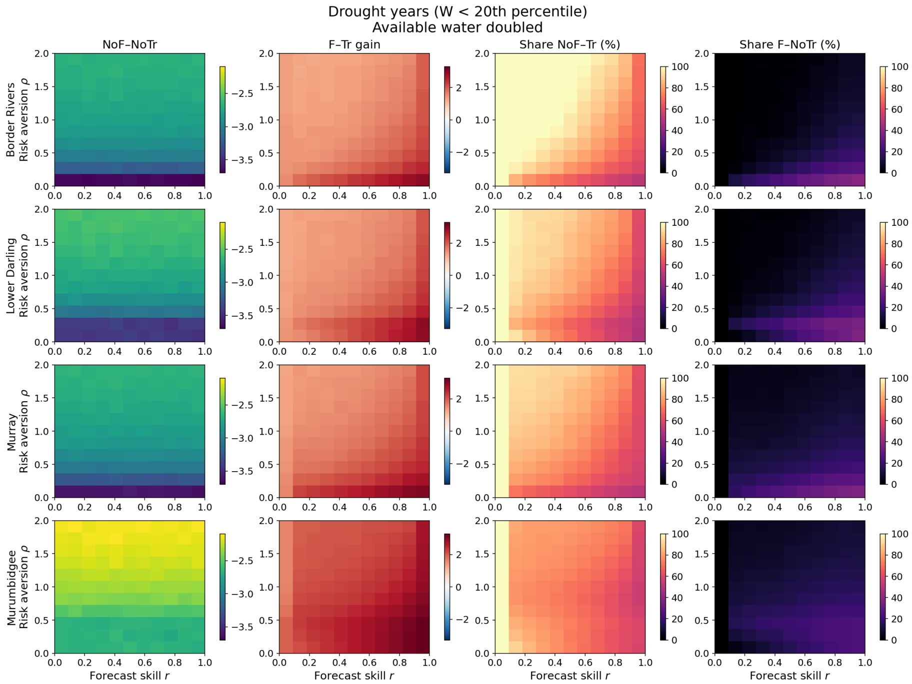


(b) Available water doubled with respect to fitted distributions

Figure 4.7: Composite 4×4 heatmaps by region (rows) over risk aversion ρ (y) and forecast skill r (x). Columns show baseline profits (NoF–NoTr) and average gains from NoF–Tr, F–NoTr, and F–Tr relative to baseline. Scenario definitions: NoF $= \theta$ chosen without using the forecast (prior only); F $= \theta$ chosen using the forecast (posterior, per-draw); NoTr = trading not allowed; Tr = trading allowed. For each grid cell (ρ, r) and region, $n_{\text{sims}} = 10000$ draws of water availability W and the forecast X are simulated and averaged.



(a) Fitted Water availability



(b) Available water doubled with respect to fitted distributions

Figure 4.8: Drought subset (conditioning on W below its 20th percentile). Rows are regions; axes are ρ (y) and r (x). Columns show baseline (NoF–NoTr) profits, F–Tr gains with respect to (NoF–NoTr) profits, and the percentage of F–Tr gain explained by gains of NoF–Tr and F–NoTr. Scenario definitions: NoF = θ chosen without using the forecast (prior only); F = θ chosen using the forecast (posterior, per-draw); NoTr = trading not allowed; Tr = trading allowed. Values computed as in Fig. 4.6, restricted to drought draws.

with W below the 20th percentile, see Figure 4.8. In this subset of simulations, expected profits under the fitted water availability distribution are always negative, regardless of the scenario. A similar pattern is observed when available water is doubled, except that in the Murrumbidgee region, under very good forecasts and with water markets, expected profits approach zero.

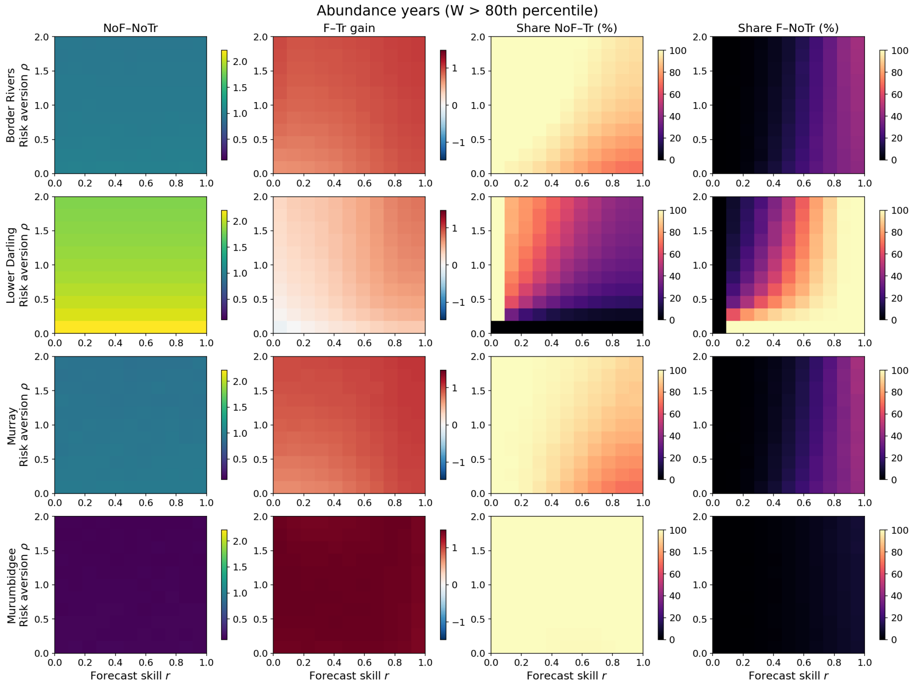
During drought years, risk–neutral farmers face the largest losses, since they are willing to accept negative outcomes as long as the expected return increases. Importantly, the share of gains in the combined scenario (forecasts and trade) that can be explained by trade alone is lower than in the average case across all simulations. This indicates that, under severe water stress, their combination provides an additional source of flexibility that cannot be explained by either mechanism in isolation. The contribution of forecasts alone remains very limited under the fitted water availability distribution, but becomes more relevant when water is doubled.

We now analyse the results considering only years of water abundance, defined as those with W above the 80th percentile (Figure 4.9). In this subset of simulations, expected profits are always positive, regardless of the scenario or the water availability distribution. The highest profits are realised by risk–neutral farmers, whose utility function does not penalise high income variance.

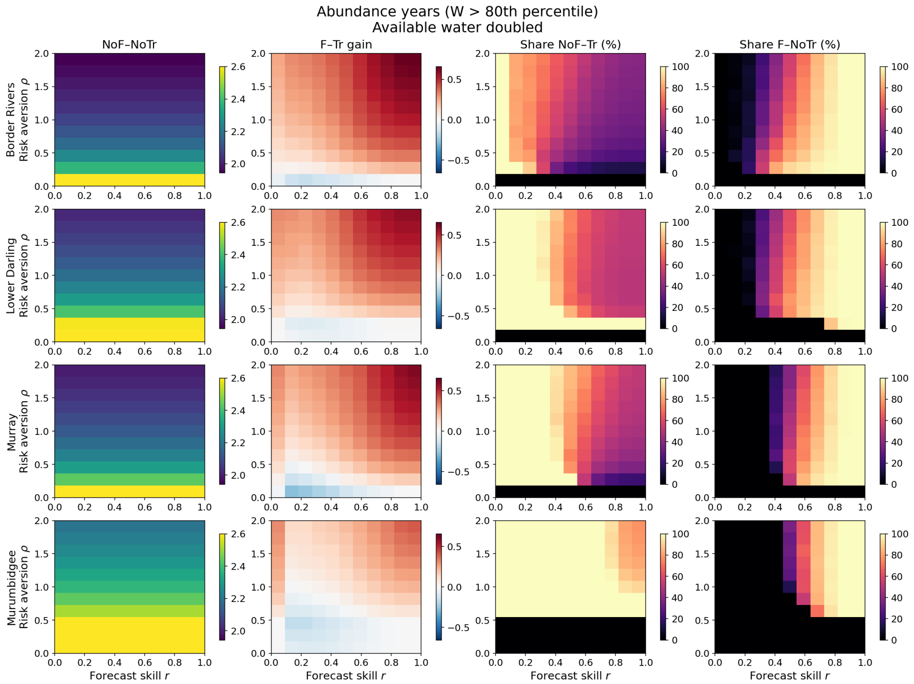
In wet years under the doubled water availability scenario, the more conservative crop choice induced by the presence of water markets for risk–neutral farmers (see Figure 4.5) actually lowers expected profits. In regions where water needs are never fully satisfied, trade still generates benefits also in abundant years; however, when distributed water quotas already meet everyone's needs, reallocation through markets does not produce additional gains. By contrast, good forecasts remain valuable in water–abundant scenarios, as they help optimise crop choices even when water is plentiful.

4.7 Discussion

In the first section, we found that the water available for irrigation, W, and its forecast, F, can be modeled with two scaled logit-normal (SLN) functions, keeping the conditional distribution of W—F a scaled logit-normal distribution. The SLN distribution has a lower bound of 0 and an upper bound, s, which is very natural for water available in an irrigation system with capacity constraints. Comparing expected profits across scenarios—baseline (NoF–NoTr), each mechanism individually (NoF–Tr and F–NoTr), and both combined (F–Tr)—shows that water markets are the dominant driver of gains under scarcity, when consumer needs are often not fully satisfied. Forecasts, by contrast, become more valuable in distributions that feature both drought and abundance years, and their contribution on average is more important for risk–averse farmers. The combination of forecasts and markets provides additional flexibility, particularly under drought years, where complementarities arise that cannot be explained by either mechanism in isolation.



(a) Fitted Water availability



(b) Available water doubled with respect to fitted distributions

Figure 4.9: Abundance subset (conditioning on W above its 80th percentile). Rows are regions; axes are ρ (y) and r (x). Columns show baseline (NoF–NoTr) profits, F–Tr gains with respect to (NoF–NoTr) profits, and the percentage of F–Tr gain explained by gains of NoF–Tr and F–NoTr. Scenario definitions: NoF $= \theta$ chosen without using the forecast (prior only); F $= \theta$ chosen using the forecast (posterior, per-draw); NoTr $=$ trading not allowed; Tr $=$ trading allowed. Same computation and settings as Fig. 4.6, restricted to abundance draws.

4.7.1 Limitations and directions for future work

Rainfall on fields (non–tradable water). In the current model rainfall at the plot is omitted. Operationally, effective rainfall R would reduce the irrigation need to $(1-R)_+$ (per ha), shifting the scarcity thresholds from $\{\omega_o, 1\}$ to $\{\omega_o(1-R)_+, (1-R)_+\}$. If R were *independent*, *mean–zero* (anomaly) and *unforecastable*, then—under risk neutrality—the first–order effect on decisions is negligible and also on expected outputs; nevertheless, second–order (curvature) effects remain and can change scarcity probabilities and thus optimal θ. A clean extension is to integrate R out (if unforecastable) or to condition on a rainfall forecast (if available).

Calibration window and dry-sample bias. Available-water data are fit over 2001–2021, a period including persistent the dry years of the Millenium Drought. This lowers the fitted scale parameter s, making $W < 1$ frequent and, in turn, preventing prices from reaching $P_e = 0$ in most simulations. We partially stress-test this by a counterfactual "×2 water" scenario. Future work should: (i) re-estimate on longer baselines; (ii) explore climate-adjusted scenarios.

Revenue (production) function. The gross-revenue function in (4.1) is stylized: linear in irrigation up to a common, normalized plateau at 1. This unified saturation ignores crop-specific absolute water needs and cannot generate $P_e = 0$ in regions where W seldom exceeds 1 under the fitted distribution (e.g. Murray, Murrumbidgee). The form was chosen as a one-parameter analog to FAO's linear yield–water relation (Varzi, 2016). Priority improvements include (i) crop-specific saturation $c_{\max}(\theta)$, (ii) concavity in water (diminishing marginal returns), and (iii) calibration to agronomic response curves.

Other inputs and costs. Land is plausibly non-scarce at basin scale, but labor, fertiliser, energy, and fixed/overhead costs are omitted. This simplification aids tractability, and considering only water as the input for crop choice is a reasonable first approximation, given that water availability alone reaches $R^2_{\text{adj}} > 0.7$ in explaining opportunistic crop choice in the SDL resource units of the MDB (see Table 3.5). A natural extension is a multi-input technology (e.g. Cobb–Douglas or translog) with water-specific curvature and explicit variable and fixed costs.

Output-price dynamics. Crop prices are treated as exogenous and effectively independent of W. While this may be reasonable for highly traded crops (e.g. export cotton), it is less so for more insulated markets (tariffs, storage/transport frictions) where p may co-move with local water. Extending the model to allow $p = p(\text{market conditions}, W)$ and to include future crop price would refine welfare and θ^* predictions.

Adjustment costs and dynamics. Seasonal farmers can change θ costlessly year-to-year. This likely overstates the value of forecasts and the responsiveness of θ. Adding convex adjustment costs (e.g. $\kappa(\theta_t - \theta_{t-1})^2$), discrete switching costs, rotational constraints, or lead times, within a dynamic program, would yield more realistic inertia.

Homogeneity of seasonal farmers. The baseline assumes a common θ_s for all seasonal farmers. Heterogeneity in risk preferences, technology, and water access is omitted. An appealing extension is to allow acreage shares across two (or more) seasonal "crop archetypes" and model θ_s as a convex combination, $\theta_s = \alpha\,\theta_{\text{risky}} + (1-\alpha)\,\theta_{\text{safe}}$, enabling calibration to observed acreage (currently infeasible under the single-parameter revenue curve).

Frictionless trading and hydrological constraints. Trading has no transaction costs, no delivery losses, no conveyance capacity limits, no carryover losses, and no institutional caps (e.g. inter-valley transfer limits). Ignoring these frictions likely *overstates* gains from trade. Introducing per-unit costs/spreads, capacity constraints, and storage/carryover dynamics would produce more conservative and spatially differentiated price signals.

4.7.2 Implication and contribution

Prior work has assessed the value of seasonal climate/streamflow forecasts for agriculture *outside* price-forming water markets (e.g. Meza et al., 2008; Shafiee-Jood et al., 2014; Kaune et al., 2020a), and has studied welfare and pricing effects of water trading *without* explicitly modeling how forecasts shape farmers' ex-ante crop choices (e.g. Rafey, 2023). We fill this gap by jointly valuing seasonal water-availability forecasts within a *competitive* cap-and-trade market that endogenously determines spot prices.

Methodologically, we model water availability W and its forecast F with a Gaussian copula (meta-Gaussian dependence) and logit–normal margins, which is appropriate for bounded shares $(0, s)$. We then embed this probabilistic structure into a market with two farmer types (perennial and seasonal) and technology-driven price thresholds. This integration delivers (i) closed-form pricing regimes $P_e(W)$, (ii) tractable optimal crop-choice rules (including risk aversion), and (iii) an internally consistent, ex-ante valuation of forecast information based on competitive market clearing.

Our simulation results are broadly consistent with prior evidence. In scarcity regimes, competitive water trading delivers the main share of its gains by reallocating scarce water to higher–value uses (e.g., Kirby et al., 2014; Debaere & Li, 2020; Rafey, 2023). The incremental value of seasonal forecasts emerges when forecast skill is moderate to high and when the hydrologic regime features both drought and abundance years, in line with prior valuations of seasonal climate and streamflow forecasts (e.g., Baethgen et al., 2008; Parton, 2019; Kaune et al., 2020b). Consistent with standard value–of–information results, risk aversion increases the payoff to forecasts (e.g., Hansen et al., 2011; Cabrera et al., 2007; Mushtaq et al., 2013).

Ongoing improvements in water-availability forecasting (Camps-Valls et al., 2025) and renewed interest in water-market design (Bruno & Jessoe, 2024), driven by rising hydroclimatic variability and scarcity, make their joint evaluation particularly relevant. The combined value tends to exceed the sum of the individual components for more risk-averse farmers and for U-shaped distributions of available water. In the Murray–Darling Basin (MDB), the average irrigated farm is relatively large (about 563 ha; Rafey, 2023). By contrast, smaller and less-wealthy farmers—who are typically more risk-averse (Sckokai & Moro, 2006)—are prevalent in other basins. Hence, when assessing water markets and seasonal forecasts in regions with smaller farm sizes—such as the Po Valley, where irrigation water is sufficient in most years but shortfalls occur and are likely to become more frequent (Montanari et al., 2023), and where farms are comparatively small (ISTAT, 2020)—it is especially important to evaluate these measures in combination rather than in isolation.

Chapter 5

Conclusion

This thesis asked whether and under what institutional and informational conditions farmers adapt on the extensive margin to hydroclimatic variability. Empirically, it contrasted Italy's Po Valley with Australia's Murray–Darling Basin (MDB). Theoretically, it developed a competitive cap-and-trade model that embeds seasonal forecasts to quantify the joint value of information and reallocation.

Empirical synthesis. In the Po Valley, we do not detect robust year-to-year comovement between expected pre-summer water availability and seasonal crop acreage, a pattern consistent with weak pre-season quantity signals and the absence of allocation trading. In the MDB, by contrast, higher pre-sowing allocations are *systematically associated* with larger acreage in water-intensive opportunistic crops (rice, cotton). Identification checks in Chapter 3 (timing, controls, and lags) are consistent with a causal interpretation, though residual endogeneity cannot be fully excluded. We cannot separately identify price from quantity channels; establishing their relative importance remains a priority for future work.

Theoretical contributions. The model couples a Gaussian-copula structure for available water and its forecast with heterogeneous producers and technology-driven price thresholds. It yields closed-form pricing regimes and tractable ex-ante crop-choice rules (with risk aversion) under market clearing. Simulations show: (i) in scarcity regimes, competitive trading delivers the largest share of gains by reallocating water to higher-value uses; (ii) forecast information adds complementary value when skill is moderate-to-high and variability is pronounced; (iii) information and markets are *synergistic*, with combined welfare gains that exceed stand-alone effects, especially for more risk-averse producers.

Policy implications. We model a setting with both seasonal and perennial producers, as in the Po Valley. The simulations indicate that most of the welfare gains from water trading materialize in drought years. This suggests that enabling trading of allocation quotas in the Po Valley could facilitate efficient reallocation during increasingly frequent hydrological droughts.

Developing and using seasonal water-availability forecasts should likewise be encouraged, since their marginal value rises with interannual variability—precisely the conditions under which the Po Valley is increasingly operating.

Finally, for basins characterized by small, risk-averse farms—such as the Po Valley—the model indicates that combining informative pre-season forecasts with well-governed water trading yields gains that exceed those of either instrument used in isolation.

Limitations. The main limitation of the empirical analysis is the omission of the Bureau of Meteorology's seasonal climate outlooks. Because pre-season allocations are positively correlated with rainfall, omitting these outlooks risks attributing part of the forecasts' effect to allocations (omitted-variable bias). Our focus on expected water availability as the driver of acreage decisions mitigates—but does not eliminate—this concern. Future work should explicitly incorporate these outlooks (and their skill metrics).

On the modeling side, we abstract from crop-switching costs, assume frictionless trade and a stylized revenue function, and treat output prices as exogenous. Finally, we adopt a mean–variance utility specification, which penalizes positive and negative deviations from the mean symmetrically; given farmers' likely downside-risk aversion and skewed profit distributions, this is unlikely to be realistic. Impeoving the revenue function and extending the model to CRRA/CARA preferences or to downside-risk measures (e.g., semi-variance or expected shortfall) is a natural next step.

Open questions. Two questions structure the agenda: (i) *Through which channel does scarcity transmit to land use—prices or quantities?* An event–study design exploiting exogenous storage shocks that shift expected prices while leaving allocations unchanged for a subset of farmers could serve as an instrument for price expectations. (ii) *Replicability under small-farm constraints.* Can the MDB's extensive-margin responsiveness be matched in the Po Valley via reallocation and probabilistic pre-season allocation bands? The much larger average farm size in Australia cautions against direct extrapolation: smaller, land- and machinery-constrained farms may face higher adjustment costs and stronger downside risk aversion.

Our results motivate—rather than prove—the hypothesis that credible pre-season signals and well-governed reallocation operate as complements: when both are present, farmers appear more able to adapt *before* scarcity materializes. Testing this interaction directly (prices vs. quantities; with and without forecast information) is an important task for future work.

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