Australia's National Science Agency

Groundwater as an adaptation option to current water resources management

Final Summary Report

MD-WERP Deliverable T2.8b.6

Project RQ8b

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Contents

Figures

Tables

Executive summary

Alluvial aquifers are the most extensively developed groundwater resource in the Murray-Darling Basin for irrigation and other purposes. Recent groundwater metering data indicates that approximately 75% of groundwater usage in the MDB is concentrated in eight major alluvial aquifer systems comprising 22 Sustainable Diversion Limit groundwater resource units. This study applied a consistent and comprehensive approach to understand trends, sustainability and resilience characteristics of these alluvial aquifer systems at the basin scale, focusing on these 22 resource units to support more informed groundwater management practices.

Groundwater use varied between 8% and 18% of total water use within the Basin during 2012 to 2019 with larger extractions in years of lesser surface water availability. This pattern can be attributed to several factors, including heightened groundwater irrigation to compensate for reduced rainfall. In areas where both groundwater and surface water allocations are available, surface water tends to be prioritized for economic reasons. This complementary usage pattern between surface and groundwater resources offers potential for adaptive management solutions including Managed Aquifer Recharge (MAR).

To analyse groundwater level trends, data from 910 observation bores spanning 50 years (1971-2021) were utilized, focusing on minimum, mean, and maximum depth to water table. The analysis revealed statistically significant groundwater level declines across the alluvial aquifer systems, averaging 0.11 m/year, with rates ranging from 0.03 m/year to 0.19 m/year. Spatial and temporal trends in groundwater levels were further explored using clustering techniques, which identified six distinct clusters representing variations in groundwater behaviour before, during, and after the Millennium drought (1997-2009). Approximately 50% of bores were part of a cluster that exhibited a consistent increase in DTW, while another significant cluster (26% of bores) showed stable levels before 1996 but experienced declines in groundwater level during and after the drought.

A machine learning (ML) model was used to analyse the causal relationships between climatic and anthropogenic variables—such as rainfall, evapotranspiration, flood events, and groundwater extraction—and observed groundwater level trends. Explainable artificial intelligence (AI) techniques were applied together with the trained and validated ML model to assess the sensitivity of groundwater level to different variables. This approach provided valuable insights into how groundwater levels are influenced by various factors and how these relationships have evolved over time. The causal attribution analysis focused on 14 resource units over a 32-year period (1988-2020). Limitations in groundwater extraction data was overcome by including the number of groundwater extraction bores drilled over time as a proxy for extraction rates. A single feed-forward neural network model was trained and validated using this dataset, successfully predicting both seasonal and long-term groundwater trends.

The sensitivity analysis conducted with explainable AI consistently revealed the importance of flooding information in predicting groundwater level changes. This highlights the importance of groundwater recharge that happens during major flood events. The analysis also revealed that an increase in the number of groundwater bores over the 50-year period is statistically related to long-term changes in average groundwater levels in the resource units. Future modelling efforts could benefit from incorporating additional biophysical variables to further refine the understanding of these influences.

Targeting areas with greater long-term groundwater declines and locally available aquifer storage space through managed aquifer recharge (MAR) could enhance water security. The potential aquifer storage volume estimates for unconfined systems in the Murray-Darling Basin varied significantly across groundwater resource units and confidence intervals. At a 75% confidence interval, about 6500 GL of unconfined storage potential was identified within 5 km of major rivers. However, this capacity was spread over large areas, making it unrealistic to fully realise. Volumetric estimates differed from previous assessments but were within a factor of two. Over 75% of the total potential volumes were identified in four resource units, with significant portions near major rivers. The Lower Namoi, Goulburn-Murray, and Mid-Murrumbidgee had the highest average recharge per unit area, suggesting greater potential for MAR here. The upstream and tributary alluvial resource units had lower volume estimates, with the Upper Condamine Alluvium having the highest volume among them. The sensitivity analysis showed that depth to groundwater was the most sensitive criterion, followed by salinity. No suitable areas were identified in the Upper Namoi Tributary and Upper Gwydir units at the 75% confidence interval.

Across all confined groundwater resource units, approximately 9700 GL of potential storage was identified, with around 4700 GL located within 5 km of major rivers for recharge. However, storage capacity was spread over a large area (>20,000 km^2), making full utilization unrealistic. The Lower Namoi Alluvium showed significant potential storage volumes at a 75% confidence interval (3300 GL) and high robustness (0.76). The Lower Murrumbidgee Deep Alluvium had the second highest potential storage volume at 75% CI (3280 GL) but a lower robustness score (0.13). The Mid-Murrumbidgee Alluvium stands out with a highly robust volume estimate (330 GL) 95% of which was within 5 km of major rivers. Hydrogeological factors significantly influenced the estimated storage volumes, with aquifer thickness, hydraulic conductivity, and transmissivity being key to recharge efficiency. Salinity levels also impacted feasible areas and consequently storage volume potential. These factors influence how effectively each area can receive additional recharge and store water for long-term use.

Assessments of MAR were conducted at Basin scale and results should be considered indicative of regional potential. Results differed from previous work due mainly to the use of different infiltration feasibility criteria (unconfined aquifers) and injection head limitations (confined aquifers). Local scale investigations are required to validate the potential and assess site viability according to Australian risk-based guidelines for MAR project evaluation including technical and socio-economic factors.

An infiltration basin site was conceptualized for the Lower Namoi area, targeting the upper, unconfined aquifer of the Narrabri Formation. The area had high screening confidence and recharge potential, with a total aquifer capacity locally of 32,000-36,000 ML. To achieve this, 8-10 basins of 6.25 ha each would be required. Median allocation trade prices were higher during low flows in the Namoi River, and this was used to set operation rules for targeting higher parts of the hydrograph. The project's median present cost over 50 years was estimated around $18 million, with capital costs of $5 million and operating costs of $13 million. Median levelised cost (LC) of recharge was \$0.09/m^3 and LC of recovered water was \$0.21/m^3 (ranging \$0.12-0.30/m^3). Costs compare favourably against alternative water supply options including recycled water, stormwater harvesting, desalination and unit costs of dam storage. The most sensitive parameter affecting the variability in LC of recovery was the social discount rate, followed by the opportunity cost of water, operational rules based on river flow rates and trade prices, and aquifer storage efficiency. Reducing uncertainty in the assessment could be achieved by conducting investigations to narrow the range of these variables.

An infiltration-based MAR scheme in the Lower Namoi could deliver multiple benefits due to diverse agricultural land uses, regional population centres, and groundwater-dependent ecosystems. The area includes 6,100 km^2 of dryland agriculture, 1,100 km^2 of irrigation, and 0.8 km^2 of horticulture. Key commodities include wheat, cotton, and chickpeas. Severe drought conditions between 2017-2020 highlighted the need for increased water security, with groundwater extraction exceeding limits and declining groundwater levels. Proposed MAR frameworks could supplement supply, improve productivity, support use or trade, and enable conjunctive use of surface and groundwater. The scheme could use surface water during availability to recharge groundwater, providing secure, tradeable entitlements. This model could attract private investment and support environmental outcomes by reducing surface water demand during low-flow periods.

1 Introduction

Climate change is expected to lead to higher temperatures and reduced rainfall in many areas of the Murray-Darling Basin (MDB) (Whetton and Chiew, 2021). Hydrological changes corresponding to these are anticipated to result in reduced availability of water for all users (Robertson et al., 2021). Water resources management in the Basin must adapt to these changes to ensure resilience of the community and environment to impacts.

Surface water systems are more directly impacted by climate variability and change. Often groundwater systems can provide a more robust and resilient supply compared to surface water systems (Kundzewicz and Döll, 2009; Thomas et al., 2017), although aquifers with limited storage or those directly recharged by surface water sources are also vulnerable to climate change.

This study, conducted as part of the Murray-Darling Basin Water and Environment Research Program (MD-WERP), focused on developing an improved understanding of groundwater resources to inform and support adaptation options for water resource management in the MDB.

The study aimed at:

- Analysing long-term records of groundwater levels in key alluvial systems and undertaking causal attribution analyses to investigate plausible relationships with climatic and anthropogenic drivers to temporal trends and patterns observed in groundwater levels.
- Investigating resilience, stress and sustainability characteristics for 22 groundwater Sustainable Diversion Limit (SDL) resources units across eight major alluvial aquifer systems in the MDB.
- Mapping of Managed Aquifer Recharge (MAR) potential based on the assessment of aquifer and physiographic features to identify areas of MAR potential and develop a cost estimate framework for conceptual MAR sites.

The trends and causal attribution analysis provides the evidence base for the status of groundwater in the SDL resource units to investigate its resilience, stress and sustainability together with other confounding characteristics like aquifer properties, groundwater demand and environmental water needs. Similarly, the trend analysis also provides critical evidence base for evaluating aquifer storage for MAR. These three analyses undertaken consistently across all the alluvial SDL resource units at the basin scale enable a relative assessment of groundwater sustainability and management priorities across the basin.

This report summarises key findings from different components of the study. Detailed description of methods, data and results presented for each analysis are provided in the summary reports for the project (Rojas et al., 2021; Rojas et al., 2023c) and journal publications (Fu et al., 2023; Fu et al., 2022; Rojas et al., 2023a). Fu et al. (2023) conducted groundwater level trend analyses and preliminary investigation of explanatory climate variables for resource units within the main alluvial aquifer systems in the MDB. This was followed by a study examining temporal patterns of groundwater levels across those resource units comparing hierarchical clustering and self-organising map methodologies (Fu et al., 2022). A detailed analysis of groundwater resilience, stress and sustainability metrics for these alluvial systems formed the subject of a subsequent study (Rojas et al., 2023a). The methodology and preliminary analysis of causal attribution using machine learning based sensitivity analysis was presented in the second annual summary report (Rojas et al., 2023c). This final report summarises key findings of previous work and presents results from the third year that further explored causal attribution with machine-learning algorithms, assessed MAR potential focusing on resource units with long-term groundwater level decline, and used the results to conceptualise potential MAR sites for preliminary cost estimation and implementation framework in the context of regulated water resources in the MDB.

1.1 Objectives

Addressing the aims stated above, the objectives of the project were to:

1. Develop a basin-scale understanding of the status and trends of groundwater by undertaking groundwater level trend analysis across eight alluvial aquifer systems (22 resource units) and evaluate spatiotemporal patterns in groundwater levels using hierarchical clustering and self-organising map methods.
2. Develop machine learning methods to study causal attribution through covariate analysis considering groundwater extraction, rainfall, evapotranspiration and resource development.
3. Develop and implement a methodology for probabilistic mapping of managed aquifer recharge (MAR) potential in selected alluvial aquifer systems to identify areas with a greater chance of scheme viability (drawing on outputs from 1 and 2).
4. Develop conceptual models of MAR schemes for selected areas (e.g. identified in 3) for preliminary financial assessment by modifying an existing tool developed by CSIRO. Potential implementation frameworks (policy, regulatory, institutional arrangements) for the conceptual MAR schemes will be discussed.

1.2 Description of the study area

The Murray-Darling Basin (MDB) covers an area of over one million square kilometres (ca. 14% of Australia's continental territory), supporting three-quarters of Australia's irrigated agriculture and contributing to over a third of the nation's agricultural production. Being such a large area, the climate varies greatly from sub-tropical in the north to semi-arid in the south and west, and to alpine in the southeast. Rainfall and evaporation vary with a distinct east-west rainfall gradient from high to low (annual averages of around 1500–300 mm) (Crosbie et al., 2012).

There are four main groundwater systems in the MDB; surficial sediments with unconsolidated sedimentary plain and alluvial aquifers (where most extraction occurs), tertiary limestone aquifers of the Murray Basin throughout the western MDB, underlying and outcropping fractured and consolidated rock, and the Mesozoic sediments of the Great Artesian Basin (GAB) (Ross, 2012; Stewardson et al., 2020; Walker et al., 2021).

This study focussed on the MDB's eight main alluvial aquifer systems from which nearly 75% of groundwater extraction in the Basin occurs (MDBA, 2020c). The study was conducted and reported results at the groundwater SDL resource unit scale. These are reporting areas that reflect different aquifer characteristics, levels of management and knowledge of the groundwater resources across the MDB. Of the 80 groundwater resource units in the MDB, 22 representing the main alluvial aquifer systems within the Basin were analysed in this study (Figure 1).

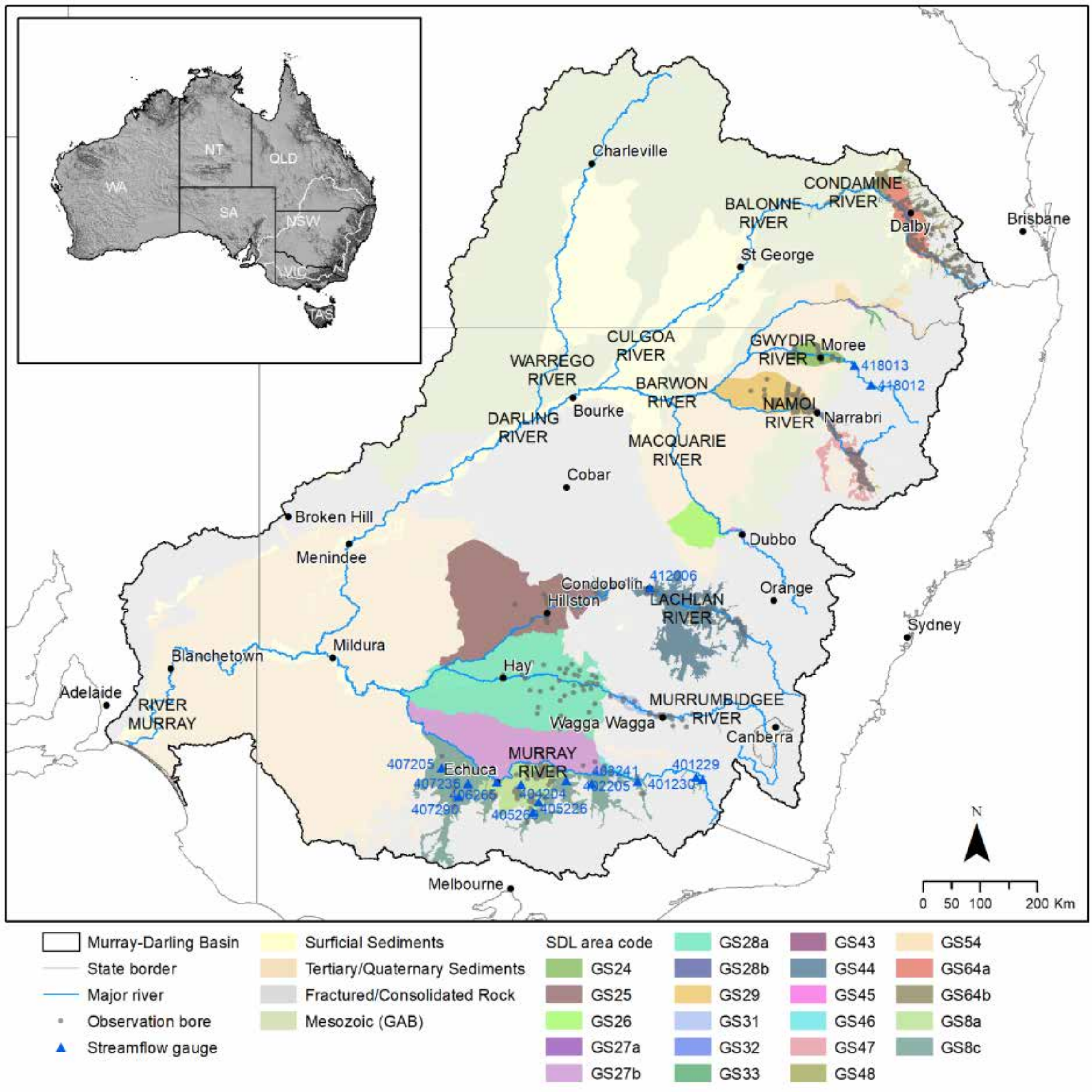

Figure 1 Main alluvial groundwater systems in the Murray-Darling Basin and the corresponding groundwater resource units.

1.3 Groundwater use across the Murray-Darling Basin

Figure 2 compares the surface and groundwater use in the MDB for the period 2012-13 to 2018-19 reported in the Transition Water Take Reports (MDBA, 2020c). This comprises groundwater use data from the entire MDB and is a more reliable dataset compared to reporting periods prior to 2012. Average groundwater use during this period is $1.482{\times}10^9$ m^3/y and represents about 13% of total water use. Groundwater use ranged between 8% and 18% during this period and was generally found to increase when surface water availability decreased. While surface water use declined between 2012-13 and 2014-15, groundwater actual take increased from 1223 GL to 1543 GL over this period.

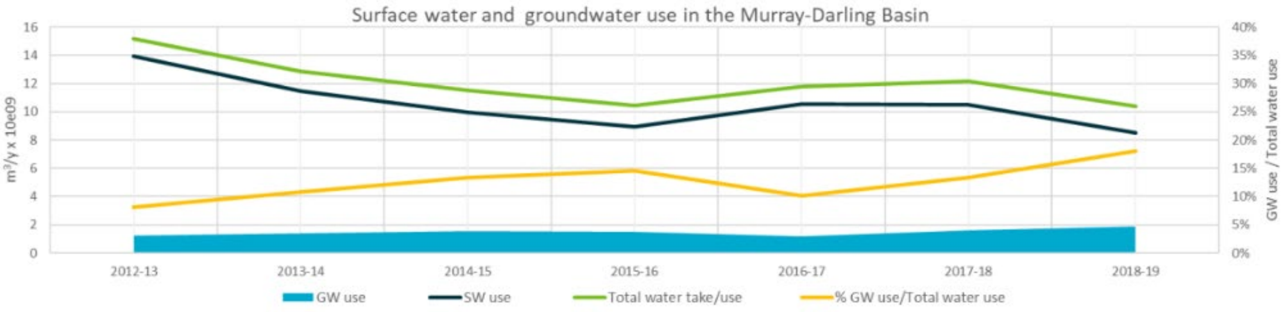

Figure 2 Water use in the Murray–Darling Basin for the period 2012-13 to 2018-19.

The Transition Water Take Reports highlights that 92% of the annual groundwater take (use) was metered for the year 2018-19 representing 12% of the total groundwater take across the Basin (MDBA, 2020c). Metering rates varied by state: 100% in the ACT and New South Wales (although five resource units had no metering), 98% in South Australia, 84% in Victoria, and 45% in Queensland. However, 100% of the groundwater take under basic rights (domestic and stock) is unmetered. Notwithstanding the lack of metering for groundwater take under basic rights, this suggests that recent statistics on groundwater use are more reliable compared to previous estimates. Among the Basin states, NSW uses the largest share of groundwater. For the period 2012-13 to 2018-19, New South Wales (69%), Queensland (14%), and Victoria (13%) account for 96% of the total groundwater use reported in the Basin (Figure 3).

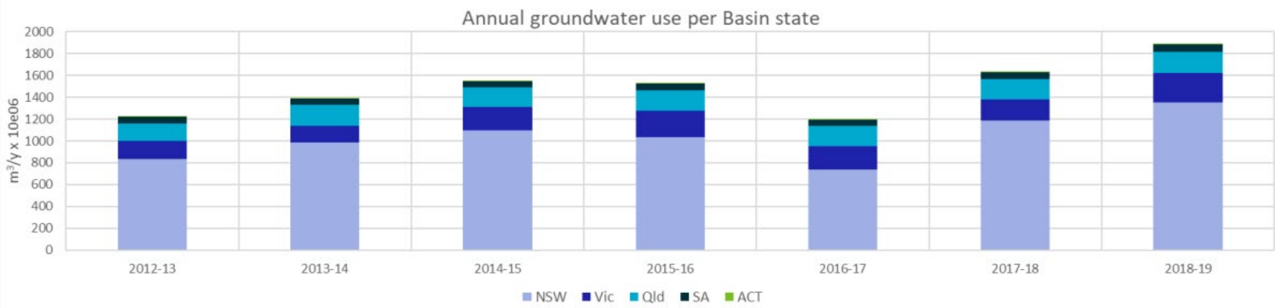

Figure 3 Groundwater use per Basin State for the period 2012-13 to 2018-19

Close to 75% of the groundwater use in the MDB for the period 2012-2019 is concentrated in eight alluvial systems (MDBA, 2020c) (Figure 1). Within each of these systems, specific groundwater resource units show the following patterns in groundwater usage:

- **Condamine** (Upper Condamine Alluvium – Central GS64a[1], – Tributaries GS64b). For the period 2012-13 until 2018-19 this alluvial system concentrates on average 43% of the total groundwater use metered in the MDB portion of Queensland, with the most recent estimate bringing this value close to 50%. If groundwater use in the Upper Condamine Basalts (GS65) is also included, the average use amounts to 80% of groundwater use in the MDB portion of Queensland.
- **Gwydir** (Upper Gwydir, GS43 – Lower Gwydir, GS24). For the period 2012-13 until 2018-19 this alluvial system concentrates on average 4% of the total groundwater use metered in the MDB portion of New South Wales.
- **Namoi** (Upper Namoi, GS47, GS48 – Lower Namoi, GS29). For the period 2012-13 until 2018-19 this alluvial system concentrates on average 18% of the total groundwater use metered in the MDB portion of New South Wales.
- **Macquarie** (Upper Macquarie, GS45 – Lower Macquarie, GS26). For the period 2012-13 until 2018-19 this alluvial system concentrates on average 5% of the total groundwater use metered in the MDB portion of New South Wales.
- **Lachlan** (Upper Lachlan, GS44 – Lower Lachlan, GS25). For the period 2012-13 until 2018-19 this alluvial system concentrates on average 16% of the total groundwater use metered in the MDB portion of New South Wales.
- **Murrumbidgee** (Lower Murrumbidgee Shallow, GS28a – Lower Murrumbidgee Deep, GS28b – Mid-Murrumbidgee, GS31). For the period 2012-13 until 2018-19 this alluvial system concentrates on average 29% of the total groundwater use metered in the MDB portion of New South Wales.
- **Murray** (Lower Murray Shallow, GS27a – Lower Murray Deep, GS27b – Upper Murray, GS46). For the period 2012-13 until 2018-19 this alluvial system concentrates on average 8% of the total groundwater use metered in the MDB portion of New South Wales.
- **Goulburn-Murray** (Shepparton Irrigation Region, GS8a – Sedimentary Plain, GS8c). For the period 2012-13 until 2018-19 this alluvial system concentrates on average 88% of the total groundwater use metered in in the MDB portion of Victoria, with the most recent estimate bringing this value to 90%.

Reported groundwater use in the resource units comprising these resource units and the Border Rivers is presented in the appendix (Table A.1).

1.4 Managed aquifer recharge potential

Managed Aquifer Recharge (MAR) is defined as the purposeful recharge of water to aquifers for subsequent recovery or for environmental benefit (Dillon et al, 2009). MAR is currently practised in only two groundwater resource units in the MDB; one in the Angas Bremer it in South Australia

[1] This nomenclature corresponds to the 80 Groundwater Sustainable Diversion Limits (SDL) Resource Units reported by the Murray-Darling Basin Authority (https://data.gov.au/data/dataset/66e3efa7-fb5c-4bd7-9478-74adb6277955. Accessed on 15-November-2021).

(SA) and another in the Australian Capital Territory (ACT) (MDBA, 2020c). The latter was part of a pilot program by the ACT government to use MAR to store stormwater for future irrigation of urban green spaces in the Sullivans Creek area (ACT Government, 2015).

MAR volumes would need to be accounted for in determining the annual permitted take according to the Basin Plan (MDBA, 2012). In the Angus Bremer, the use of surface water for MAR is accounted for as actual take and later extraction of water from the groundwater storage is accounted for separately from the annual allocations/permitted take/actual take of the groundwater resource unit (DEW, 2019).

Another successful trial to use MAR for environmental benefit was conducted in the Katarapko Floodplain in SA (Martin, 2019). This showed that with relatively small volumes of water injected into the alluvial sediments, the resulting lens of fresh groundwater provided measurable improvements to River Red Gum tree health.

Larger MAR projects have been explored in the MDB in the past. The Broken Hill Managed Aquifer Recharge project investigated groundwater related options including MAR to contribute to water savings in the Basin at the Menindee Lakes Storages located on the lower section of the Darling River in far western NSW and enhance water security for Broken Hill (Lawrie et al, 2012). Other assessments conducted within the MDB have indicated feasibility in the Murrumbidgee River (Khan et al., 2008) and Namoi River regions (Fuentes and Vervoort, 2020). A Basin-wide assessment revealed MAR opportunities of around 2000-4000 GL (Gonzalez et al., 2020).

This study introduces a novel framework for mapping MAR potential across the main alluvial aquifer systems of the MDB, improving upon previous research. Key innovations include the use of groundwater level trend analyses to target areas of depletion, the development of methods for assessing MAR in confined aquifers, and a stochastic approach to account for uncertainty in spatial criteria and feasibility thresholds. These advancements enable more accurate and robust identification of potential areas for MAR implementation.

2 Groundwater level trends and spatiotemporal patterns

2.1 Scope

Assessment of groundwater resources over time is essential for understanding natural and anthropogenic impacts on groundwater resources and informing relevant management options and policies to enable sustainable use. Activities over the past years have developed and applied methods for studying groundwater level trends and spatiotemporal patterns in the main alluvial aquifer systems of the MDB. A brief description of these analyses and key findings are included in this section. More detailed description of the analyses and results are reported in the following journal papers and report:

- Summary of main alluvial aquifers and groundwater use potential in the Murray–Darling Basin (Rojas et al., 2021)
- Trends in Groundwater Levels in Alluvial Aquifers of the Murray–Darling Basin and Their Attributions (Fu et al., 2022)
- Groundwater level trends and aquifer prioritisation in the Murray-Darling Basin (Rojas et al., 2022)
- Spatial and Temporal Patterns of Groundwater Levels: A Case Study of Alluvial Aquifers in the Murray–Darling Basin, Australia (Fu et al., 2023)
- Summary Report – Year 2 Project RQ8b: Groundwater as an adaptation option to current water resources management (Rojas et al., 2023b)

2.2 Groundwater Trend Analysis

Trends in groundwater levels were analysed using three popular trend analysis approaches. These include a) the non-parametric Kendall's test b) Linear trend and c) the Two-Period Comparison and Innovative Trend Analysis Test. These methods were employed to detect long-term trends (1971-2021) in annual mean/minimum/maximum depth to water table (DTW) in 910 bores across the 22 alluvial resource units of MDB. Bore DTW data were accessed using the National Groundwater Information System (NGIS) Version 1.7.0 last updated in July 2021 (BOM, 2022).

There is clearly an overall increasing trend in DTW (or decline of groundwater level) for the MDB alluvial aquifers during the last 50 years (1971–2021), regardless of the groundwater level statistic (mean, minimum, and maximum annual values) or the trend detection methods. About 90–95% of groundwater bores show an increasing trend in depths, of which 84–87% are statistically significant at $\alpha = 0.05$. In contrast, only 7–9% of groundwater bores show a decreasing trend in depths, and 4–5% are statistically significant.

In terms of trend magnitudes, these range from −0.25 to about +1.00 m/year across all three annual groundwater level statistics (mean, minimum, and maximum annual values) and the three analysis techniques for the 50-year period assessed (1971–2021). The median and mean values for the 910 groundwater bores are 0.09 and 0.11–0.13 m/year, respectively. While the maximum trend magnitude can be as high as +1.0 m/year, the 95th percentile is about 0.3–0.4 m/year (Table 1). The 5–10% negative trend magnitudes are consistent with the trend significance results.

The analysis implemented a methodologically consistent and regional trend analysis of groundwater levels in the main alluvial aquifers of the MDB using consistent data for a 50-year time window contained between years 1971-2021. This included data from 910 observation bores, out of nearly 1200 available bores for monitoring in the MDB, with at least two records per year to quantify mean, minimum and maximum DTW per bore. For spatial consistency, we performed the trend analysis for each groundwater resource unit within the main alluvial systems in the MDB. The analysis also attempted to disentangle regional trend patterns by attributing potential drivers to these regionalised trends in groundwater levels.

Table 2 shows the number of bores with statistically significant increasing or decreasing trends across the MDB based on the three different methods. It shows that about 90–95% of groundwater bores show an increasing trend in depths, of which 84–87% are statistically significant at a $\alpha=0.05$ level. In contrast, only 7–9% groundwater bores show a decreasing trend in depths of which only 4–5% are statistically significant.

Table 1 Statistics of groundwater level trend magnitudes in eight alluvial systems of the MDB (m/year)

Methods	Variables	Min	P5	P10	P25	Med	Mean	P75	P90	P95	Max
β	Mean DTW	-0.22	-0.01	0.01	0.04	0.09	0.13	0.20	0.30	0.35	1.01
	Min DTW	-0.22	-0.01	0.01	0.04	0.09	0.12	0.18	0.26	0.29	0.99
	Max DTW	-0.22	-0.01	0.00	0.04	0.09	0.14	0.21	0.33	0.43	1.01
Linear	Mean DTW	-0.23	-0.01	0.01	0.05	0.09	0.13	0.20	0.30	0.37	0.99
	Min DTW	-0.25	-0.01	0.01	0.05	0.09	0.12	0.19	0.26	0.30	0.98
	Max DTW	-0.22	-0.01	0.01	0.04	0.09	0.14	0.22	0.33	0.43	1.01
S-slope	Mean DTW	-0.22	-0.01	0.01	0.04	0.09	0.12	0.20	0.28	0.33	0.83
	Min DTW	-0.25	-0.01	0.01	0.04	0.09	0.11	0.18	0.25	0.29	0.82
	Max DTW	-0.20	-0.01	0.01	0.04	0.09	0.13	0.20	0.31	0.40	0.83

Table 3 shows the mean and maximum trend magnitude for the annual DTW recorded in 14 resource units that fulfilled the data filtering process (40 years with at least two records per year per bore). It shows that mean trend magnitudes vary between 0.03 m/y and 0.19 m/y, with an average across resource units equal to 0.11 m/y. Resource units experiencing above average increasing trends for mean annual DTW corresponds to: Lower Gwydir Alluvium (GS24), Lower Murrumbidgee Deep Alluvium (GS28b), Lower Namoi Alluvium (GS29), Mid-Murrumbidgee Alluvium (GS31), Upper Namoi Alluvium (GS47), Upper Condamine Alluvium-CCA (GS64a) and Goulburn-Murray: Sedimentary Plain (GS8c).

Table 2 Numbers of bores with decreasing and increasing trends in DTW and statistical significance level in eight alluvial systems of the MDB.

Methods	Variables	Sig Decrease	Decrease	Increase	Sig Increase
Kendall test	Mean DTW	39	27	55	789
	Min DTW	37	32	49	792
	Max DTW	40	36	64	770
Linear trend	Mean DTW	41	22	49	798
	Min DTW	42	28	43	797
	Max DTW	44	30	62	774
Two-period comparison	Mean DTW	41	28	55	786
	Min DTW	36	37	51	786
	Max DTW	42	36	74	758

Table 3 Groundwater level trend magnitudes (m/y) per resource unit for the mean and maximum annual DTW, number of bores showing statistically significant decreasing trends adapted from Rojas et al. (2023a).

Code	Resource Unit	Area Km²	No. bores	Mean Trend (m/y)	Max Trend (m/y)	Bores showing decreasing trend
GS29	Lower Namoi Alluvium	7115	155	0.19	0.68	98%
GS28b	Lower Murrumbidgee Deep Alluvium	32438	36	0.18	0.50	81%
GS47	Upper Namoi Alluvium	3573	174	0.16	0.53	95%
GS8c	Goulburn-Murray: SP	21929	55	0.15	0.59	100%
GS64a	Upper Condamine Alluvium (CCA)	4346	74	0.12	0.48	91%
GS24	Lower Gwydir Alluvium	2340	48	0.12	0.35	73%
GS31	Mid-Murrumbidgee Alluvium	1473	90	0.12	0.35	100%
GS44	Upper Lachlan Alluvium	12963	56	0.11	0.42	100%
GS27b	Lower Murray Deep Alluvium	17803	4	0.11	0.36	75%
GS25	Lower Lachlan Alluvium	25283	31	0.10	0.33	84%
GS64b	Upper Condamine Alluvium (Tributaries)	3778	73	0.06	1.01	93%
GS28a	Lower Murrumbidgee Shallow Alluvium	32438	12	0.03	0.09	67%
GS46	Upper Murray Alluvium	489	6	0.05	0.16	83%
GS8a	Goulburn-Murray: SIR	6580	96	0.04	0.21	89%

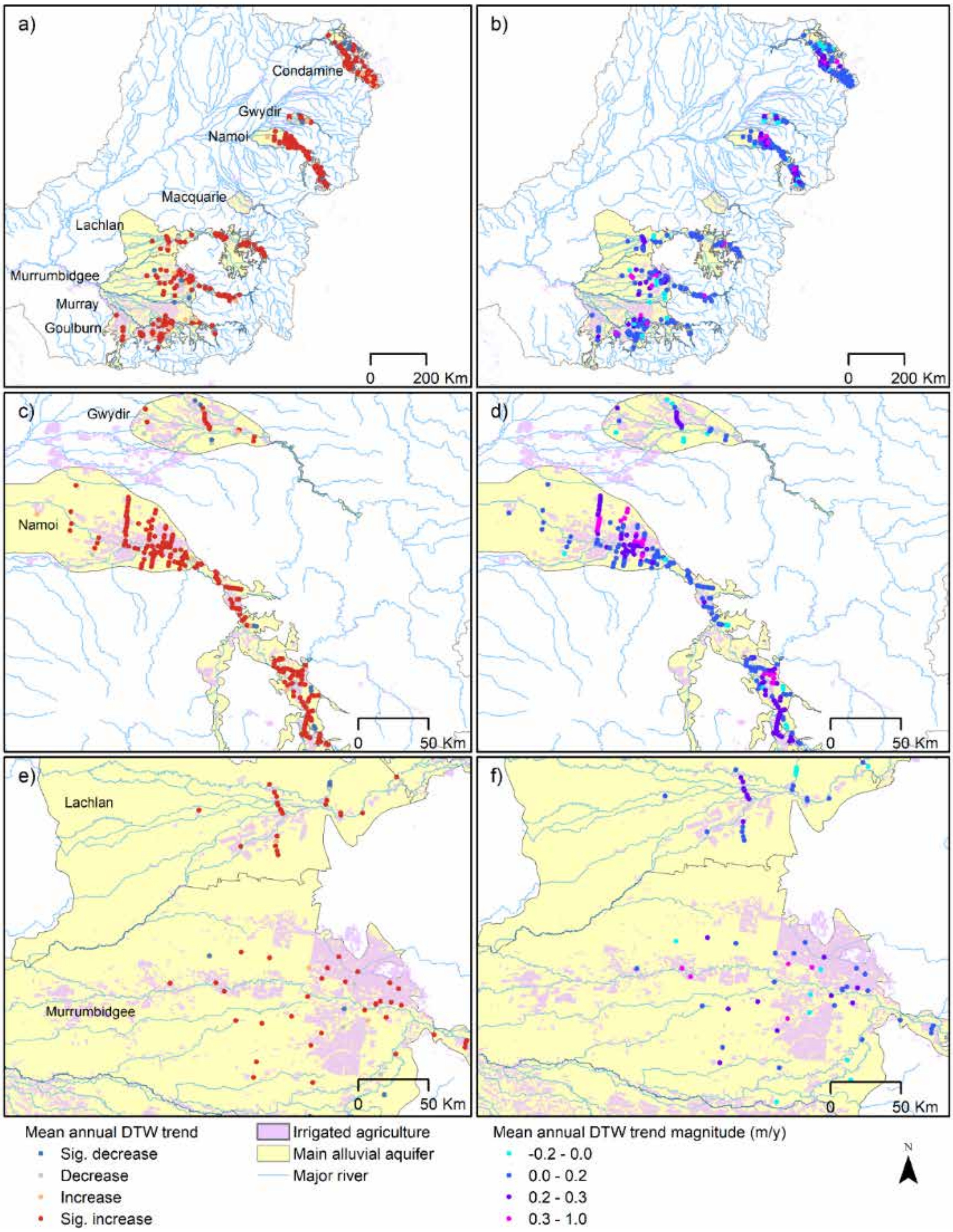

Figure 4 Spatial distribution of groundwater level trend magnitude and trend significance obtained from the Kendall test across the study area (a, b), Namoi and Gwydir region (c, d) and Lachlan and Murrumbidgee region (e, f).

A statistically significant increasing trend obtained from the Kendall test can be observed across the MDB in Figure 4. Most groundwater bores with increasing DTW have a magnitude in the range of 0–0.3 m/year. There were far fewer bores with decreasing DTW (increasing water levels). While trends were statistically significant, magnitudes for these bores were generally in the lower -0.2–0 m/year range.

2.3 Clustering Analysis

A subsequent analysis investigated spatial patterns of groundwater level trends using two clustering methods. Clustering analysis was used to answer questions including: What are the dominant patterns in groundwater level trends? How robust are these patterns to different clustering techniques? What is the performance of these clustering techniques? Is there a spatial configuration for these patterns? What is the impact of the Millennium Drought on these patterns? By answering these questions, the clustering analysis helps to interpret the observed trends and its relationship with potential causal factors.

Two popular clustering analysis methods in the literature, hierarchical clustering analysis (HCA) and the self-organizing map (SOM), were used in this study to investigate the temporal patterns of groundwater levels. Hierarchical cluster analysis (HCA) is an algorithm that seeks to build a hierarchy of groups or clusters so that each cluster is distinctive from other clusters but the elements within the same cluster are broadly similar. The results of hierarchical clustering can be presented as a dendrogram, which is a diagram with a tree structure representing the hierarchical relationship between elements. Figure 5 shows the dendrogram of DTW level with 910 bores used in this study. The six clusters/groups are chosen for this study based on the distances among them and their temporal patterns.

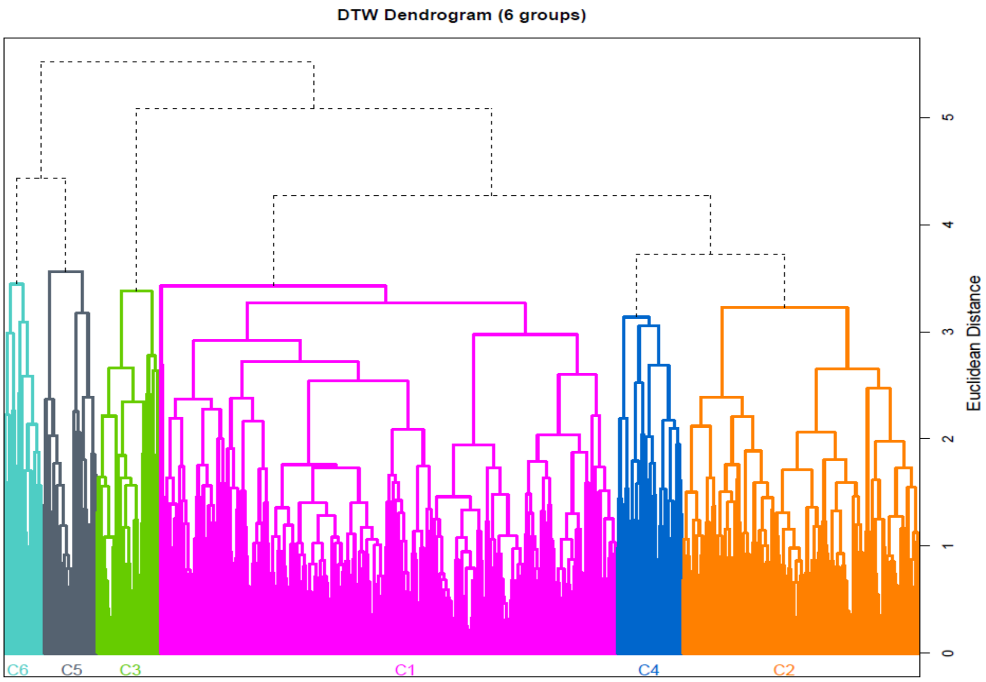

Figure 5 Dendrogram of groundwater levels from 910 bores, separated into six clusters (C1-C6) with the hierarchical clustering algorithm.

Distinct temporal patterns in mean values of the standardized DTW for the six clusters are shown in Figure 6. The vertical blue dashed lines represent the Millennium Drought period in 1997–2009, a severe and prolonged dry period in southeast Australia. The rainfall, streamflow, groundwater level and storage, wetland, lakes and their relationships have changed significantly, before, during and after the Millennium Drought (Fu et al., 2023). The geographic locations of the cluster members are shown in Figure 7.

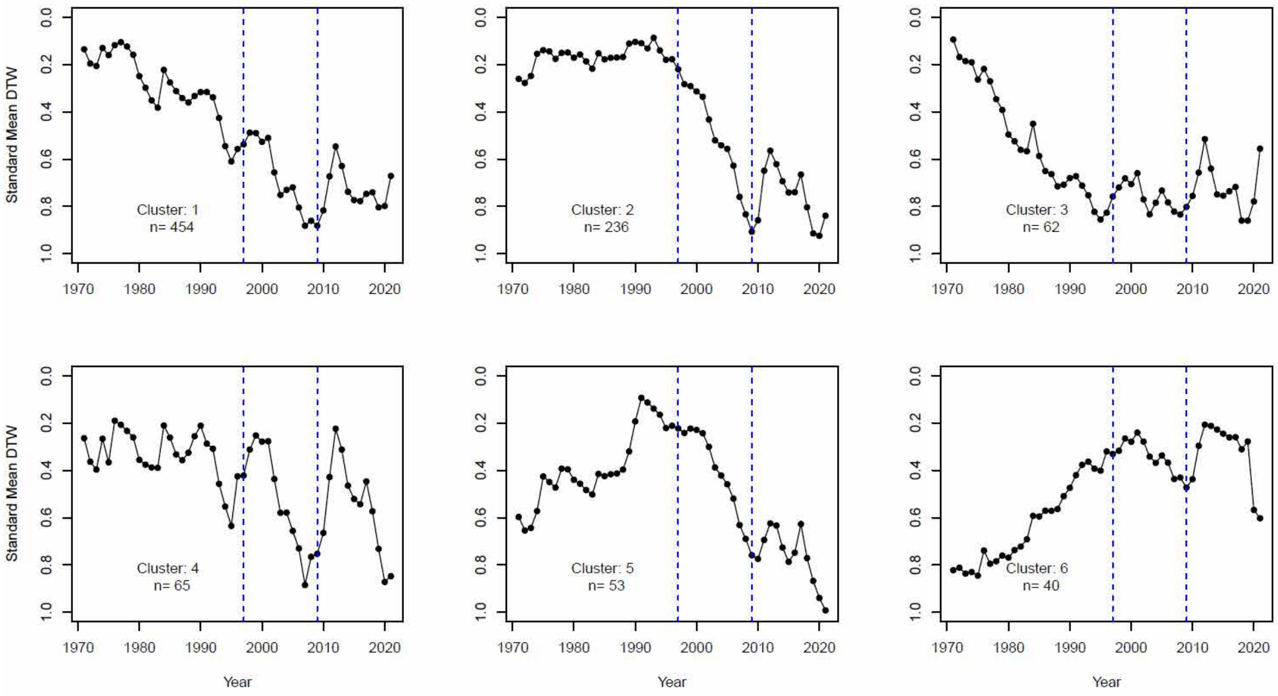

Figure 6 Time series of annual mean standardized groundwater level (depth to water level, DTW) from six clusters based on hierarchical cluster analysis (Fu et al., 2023). The vertical blue dashed lines represent the Millennium Drought period from 1997–2009.

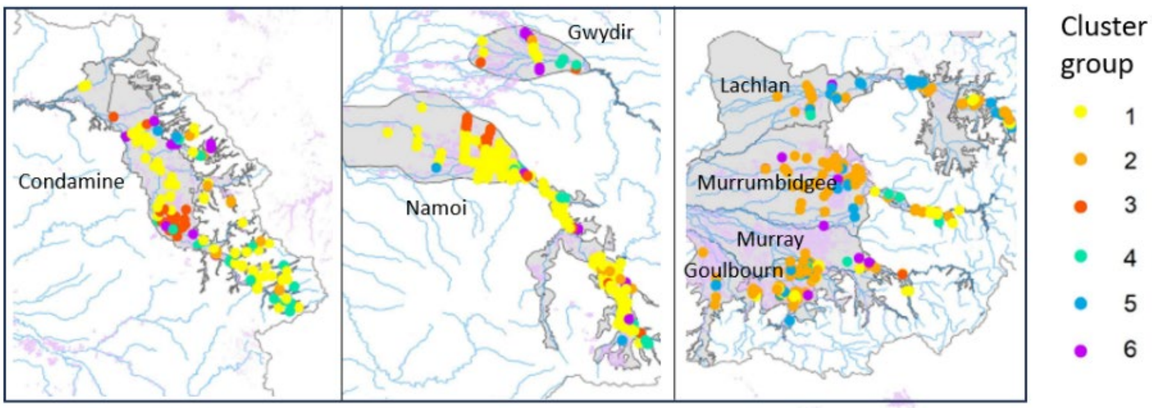

Figure 7 Spatial distribution of hierarchical clusters.

The SOM analysis resulted in six similar clusters, corresponding well to the patterns found in the hierarchical analysis. This implies a robust identification of the main temporal patterns of groundwater levels in the study area.

2.4 Key findings

The results of the groundwater level trend analysis showed an overarching declining trend across all alluvial aquifers analysed. The analysis showed:

1. An overall declining groundwater level trend across alluvial aquifers attributable to changes in recharge from rainfall, potential evaporation, and groundwater extraction. The

trend was consistent regardless of the trend detection method and indicators used (mean, minimum, maximum annual values).

2. The methods employed show similar statistical significances and magnitudes, but differences were observed.
3. The annual minimum DTW had a smaller trend magnitude than annual mean DTW, and the annual maximum DTW had a larger trend magnitude than mean DTW.
4. Irrigation with surface water is responsible for some of the rising trends in groundwater level, most likely due to localized processes in shallow aquifers through irrigation induced recharge.

The clustering analysis showed that:

1. Six dominant clusters were found that could explain the groundwater level trends in the Murray-Darling Basin. Interpretation of each of these patterns indicates how the groundwater time series in each cluster behaved before, during and after the Millennium Drought.
    a) There are 454 groundwater bores (about 50% of the total 910) in Cluster 1 (C1 in Figure 6), which show continuous declines in groundwater levels from 1971–2019, i.e., before and during the Millennium Drought (MD) periods. However, the groundwater level is relatively stable after the MD. Partial recovery of groundwater level during the 2011–2012 wet years is also observed.
    b) There are 236 groundwater bores (~26%) in Cluster 2, which show a stable groundwater level in 1971–1996 before the MD period, followed by a declining trend during and after the MD periods.
    c) There are 62 groundwater bores (~7%) in Cluster 3, which show significant groundwater level declines in 1971–1996 before the MD period but are relatively stable during and after the MD periods.
    d) There are 65 groundwater bores (~7%) in Cluster 4, which show overall groundwater level declines for the entire study period. However, this time series shows the greatest fluctuation, implying stronger sensitivity of groundwater level to rainfall anomalies. The 2011–2012 wet years lead to the biggest rises in groundwater levels for this cluster.
    e) There are 53 groundwater bores (~6%) in Cluster 5, which show rising groundwater levels in 1971–1996 before the MD period and declines during and after the MD periods. The rising trends in 1971–1996 could be due to irrigation, followed by the declines due to reduced recharge and increased pumping during the MD.
    f) There are 40 groundwater bores (~4%) in Cluster 6, which show similar groundwater level rise as seen in Cluster 5 but a relatively stable levels during and after the MD. The underlying physical processes could be due to additional irrigation-induced recharge before the MD and reduced irrigation and recharge due to lower surface water availability and rainfall.

2. The two clustering methods produced similar patterns, indicating the robustness of the six dominant patterns that have been identified.
3. The patterns that are predominantly found in each geographical area were identified. In the Condamine region all patterns are represented, in the Gwydir/Namoi region Clusters 1, 3, and 4 are most common, and in the Lachlan, Murrumbidgee, Murray and Goulburn region Clusters 2, 5 and 6 dominate.
4. The six patterns identified in this study transcend resource unit boundaries. Conversely, bores in proximity could exhibit different temporal variability.
5. The MD from 1997 to 2009 had a clear impact on groundwater level temporal variability and trends. Diverse post-drought responses were found in bores with similar groundwater patterns before and during the drought.
6. The spatial distribution of the temporal patterns shows that different areas had varying responses to severe drought and to post-drought recharge and recovery.

3 Causal attribution analysis

3.1 Scope

A causal attribution analysis has been undertaken to explore factors that contribute to the observed trends in groundwater levels. This analysis investigates covariates such as rainfall, potential evapotranspiration, flood events and groundwater extractions, and evaluates whether trends in groundwater levels could be dominantly attributed to changes in any of the covariates.

A machine learning model is trained to predict groundwater levels based on the set of climate and anthropogenic predictors. The model is then queried for the most influential inputs in generating accurate predictions at certain times or locations. An explainable artificial intelligence (AI) algorithm (SHAP) is used to determine which variables cause a greater response in groundwater level predictions across the resource units for the entire study period. This analysis is then examined at higher resolution to identify the contribution of each predictor to each monthly prediction, revealing varying patterns of influence across space and time.

To compromise between the objectives of 1) investigating long-term trends and 2) distinguishing the influences from both climate and groundwater extractions, two models are built here:

- A longer-term model (32 years) simulates groundwater levels from 1988-2020 at 14 resource units, investigating changes in groundwater influences over the periods before, during and after the Millenium Drought. This model uses the number of groundwater extraction bores as a proxy for the volume of groundwater extracted, since historical extraction data are not readily available everywhere and for the full period.
- A shorter-term model (14 years, 2007-2021) includes measured groundwater extraction data instead of the proxy of number of bores. However, due to the restricted amount of data available in this time series, this model is only able to represent six bores from near the end of the Millenium Drought onwards. It will therefore not be useful for assessing long-term changes or variations over all resource units.

Although the shorter-term model is limited both temporally and spatially compared to the longer-term model, it provides some insights on potential direct analysis with groundwater extraction data and the relative efficacy of the number of groundwater bores as a proxy for extraction data.

3.2 Methods

3.2.1 Data

Depth to groundwater level data is gathered into a collection of monthly time series for bores within each resource unit, from January 1971 to October 2021. The time series are scaled to a range of [0,1] by individual bore before averaging within each resource unit to provide one monthly value per resource unit. The values are then inverted to provide groundwater levels rather than depths – a more intuitive variable to work with, where a positive increase in the variable corresponds to a vertical increase in groundwater level. Trends and fluctuations for all resource units are evident in Figure 8.

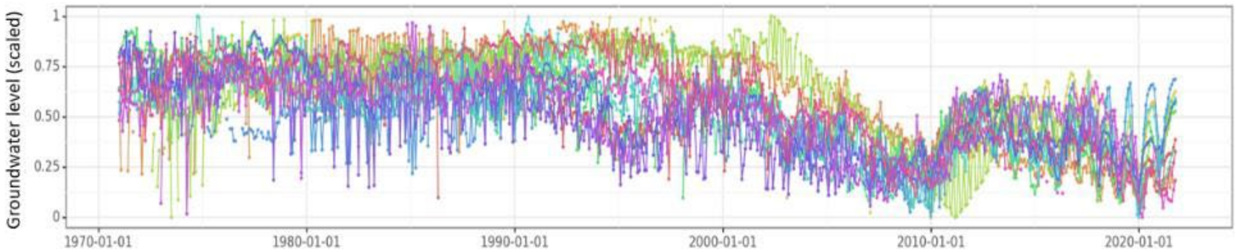

Figure 8 Groundwater level data 1971-2021 for 14 resource units comparing time series trends and magnitudes highlighting level declines during the Millenium Drought and partial recovery after 2010.

Climate data for precipitation and potential evapotranspiration (PET) were also aggregated by resource unit and month. In addition to rainfall at the current month, aggregations of rainfall data were included in the input data set to represent antecedent soil moisture conditions (3-month rainfall average) and longer-term climate conditions (12-month average). Overbank flooding events were represented by a monthly time series of percentage flood inundation for each resource unit based on Landsat data, beginning in January 1988.

Groundwater extraction data were obtained from relevant state government agencies (NSW, Qld and Vic). The original data have an extraction site ID, longitude, latitude and extraction volume. The monthly time series of groundwater extraction data used in this study are sums of all groundwater extraction volumes from all extraction locations within a specific resource unit during a specific month. Groundwater extraction data was available from November 2006 for four resource units only, increasing to 12 resource units by October 2012.

The cumulative number of extraction bores drilled in each aquifer (1971-2020) was calculated from National Groundwater Information System data (BOM, 2023). Due to the longer period available, it was used in this study as a proxy for the increase in groundwater pumping over time as the resource is developed. The number of production bores has increased in the last 50 years across all studied alluvial aquifers, with a marked increase in the 2000s coinciding with a cap on surface diversions and the Millennium Drought when surface water became very scarce (Fu et al., 2022).

Data for variables with particularly skewed distributions – the flood extent percentage and groundwater extractions - were log-transformed before being used in the model. One large spike in the extraction measurements was removed. All numerical input data were scaled into the range [0,1] by resource unit (except year, for which the scale is common across all resource units). The month variable was converted into a seasonal variable with four categories.

3.2.2 Machine learning models

A machine learning (ML) model is used for the main causal attribution analysis. A feed-forward neural network model is trained and tested to relate groundwater levels to climatic and anthropogenic drivers at a monthly timestep. One ML model covers the multiple resource units, sharing information between the regions whilst making predictions for groundwater levels on a resource unit scale. The scalability of including any number of resource units in a single model is a benefit of ML models, as is the ability to easily add or remove predictors or aggregations of variables for model testing.

The predictor data consists of monthly values for each resource unit of current and past precipitation (current month's rainfall, 1 month lagged, average of past 3 months, average of past 12 months rainfall), potential evapotranspiration, year, season, resource unit, percentage flood extent and the number of extraction bores. The output data (target variable) is the average groundwater level at each resource unit (averaged over potentially multiple bores per resource unit and multiple measurements per month). Model validation is undertaken to optimise the network architecture, followed by model training to optimise the network weights. This data set consists of 4754 data points – between 184 and 393 per resource unit.

For comparison, a shorter-term model is also created that includes actual groundwater extraction observations. The measured extraction data is included as a predictor, replacing the 'number of extraction bores' proxy variable used in the model above. As measured extraction data is currently available only in certain regions, with the earliest bores beginning in 2006, this restricts the scope considerably if this data is to be included.

Six resource units have groundwater extraction data beginning by June 2007: GS24, GS27b, GS28a, GS28b, GS29, and GS47. The second, shorter-term model is created using the method described above but including only these six resource units, which have consistent extraction data for the 15-year period June 2007 – June 2022. This data set consists of 885 observations - between 122 and 163 data points per resource unit. The extraction volume at the current month, as well as a sum over the previous 12-months, are used as predictors at each time step, with these two variables replacing the 'number of extraction bores' variable. Otherwise, all predictor and target variables are as described above for the main causal analysis model. The results of this model are presented in the Appendix.

3.2.3 Causal analysis with explainable ML

The trained neural network model is used in a causal analysis framework to investigate the impact of each input variable on the production of groundwater level predictions. This sensitivity analysis is conducted over the complete data set, as well as at specific locations and times. Sub-periods (decades) and locations (resource units) are investigated to determine if the dominating causes of groundwater level trends have changed over time or differ between regions. The machine learning techniques of permutation feature importance, partial dependence plots and SHapley Additive exPlanations (SHAP) are used.

Permutation feature importance determines the decrease in model prediction performance when a single input variable is randomly shuffled or is no longer included in the model. This indicates which variables are most important overall for producing accurate groundwater level predictions. A single ranking represents the data relationships over all regions and times.

Partial dependence plots show the marginal effect each feature has on the predicted outcome of an ML model. The individual effects of each observation, as well as the average effect of each feature, are shown. These plots are used to determine if the relationships between input and output are linear, monotonic, or potentially more complex. Flatter lines indicate less impact of the feature on the predictions. Interactions between predictors are not considered.

SHAP is a post-hoc explainable machine learning analysis based on concepts from game theory. The contributions of each input to the overall result are quantified, indicating the impact of each feature on the model predictions. The summarised relevance of each variable on predicting the groundwater levels (global impact), as well as the impact of individual measurements on the model's predictions (local impact), are given. Both the permutation feature importance and SHAP methods consider interactions between the input variables in producing the predictions.

3.3 Results

3.3.1 Neural network predictions

The neural network predictions for the longer-term analysis are shown in Figure 9 for each of the 14 resource units. These predictions are produced from a single model trained on climate and anthropogenic data from all resource units combined. With the inclusion of a resource unit identifier as an input variable, the model can produce unique predictions for each region.

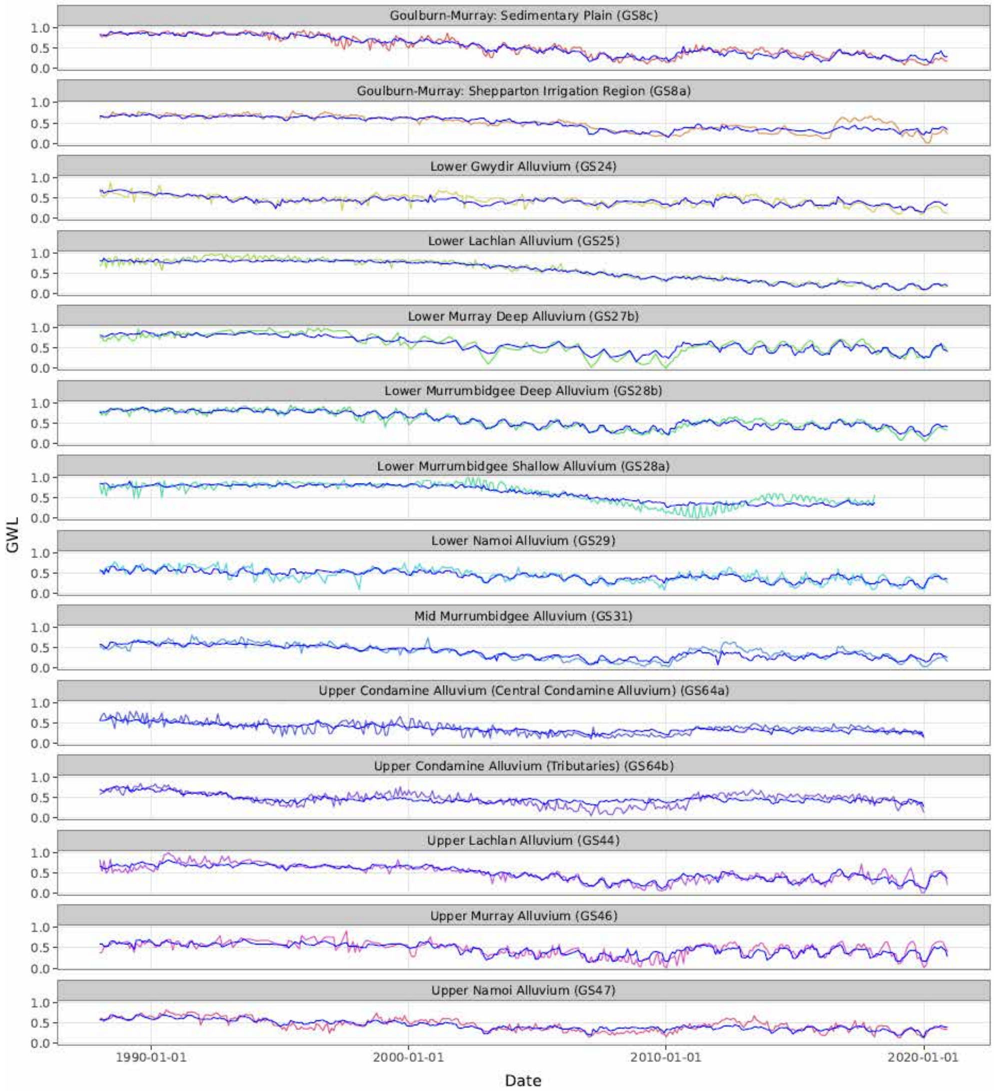

Figure 9 Predicted groundwater levels from the ML model (blue) in comparison with monthly averaged observed groundwater levels (coloured lines) for 14 resource units. A separate prediction is made by the model for each

resource unit. Groundwater levels have been scaled into the range [0,1] to eliminate differences in vertical scale between the regions.

On Figure 9, the predictions (blue lines) generally follow the observed groundwater level trends and fluctuations (coloured lines), although in some cases they do not accurately follow the peaks, troughs or higher resolution groundwater fluctuations. These inaccuracies indicate the model is not capturing all the influences on groundwater levels, either because the aggregations of data used are removing important information or because influential factors are not entirely represented by the input variables. One of these omitted factors is groundwater extraction data, which is not available for the timescale or geographical coverage of this model.

3.3.2 Permutation feature importance

The importance of the input variables for making accurate predictions are ranked by measuring the decline in model performance when each variable is randomly shuffled. The results, shown in Figure 10, indicate overall importance over the entire period of data and geographical coverage of the study. It was found that the number of extraction bores (proxy for groundwater development) was the most influential variable for groundwater level predictions in this model.

The next two highest-ranked variables are resource unit and Year, which represent spatial and temporal distinctions amongst the time series, potentially reflecting spatial or temporal variations not captured by other variables. For example, geology may be the most important factor distinguishing resource units from each other, yet as this variable is not included in the model and the importance of it would be attributed to the resource unit variable.

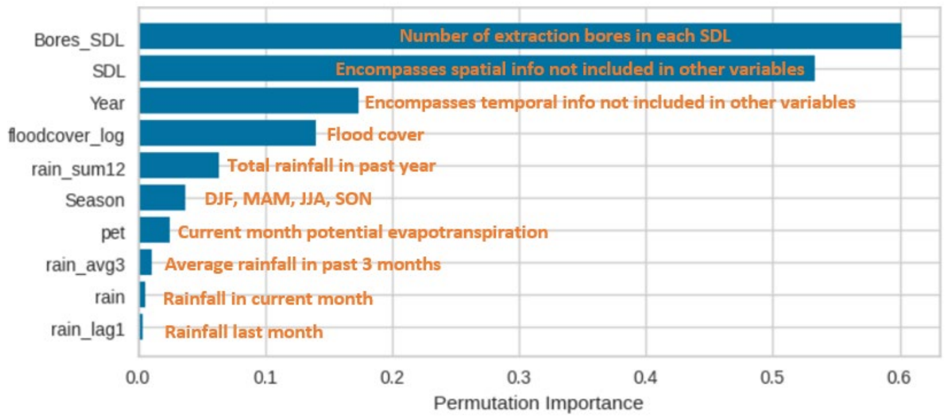

Figure 10 Permutation feature importance results – higher inputs on the y-axis are deemed more important overall for accurate groundwater level predictions across the entire region and period of the study.

Flood extent and annual precipitation are the next most important variables universally. These are followed by season and potential evapotranspiration, both of which provide information for seasonal fluctuations. Interestingly, the current and recent rainfall were of least overall value for predicting groundwater levels in this model. This may be because flood extent and annual precipitation are already capturing the rainfall effect, or it may be an artifact of averaging over time periods and regions, or the time lag that naturally occurs between rainfall and recharge processes.

3.3.3 Partial dependence plots

The partial dependence plots in Figure 11 show the marginal relationships between observed features and observed groundwater levels. A negative or downward trend (dependent variable decreasing as independent variable increases) suggests that higher values of the predictor feature reduce the predicted outcome; for example when the number of bores is higher, the groundwater level would be lower. A flat line on the plot indicates that the feature has little or no overall impact on the prediction, that is the prediction would not be expected to change significantly if this variable were to increase or decrease.

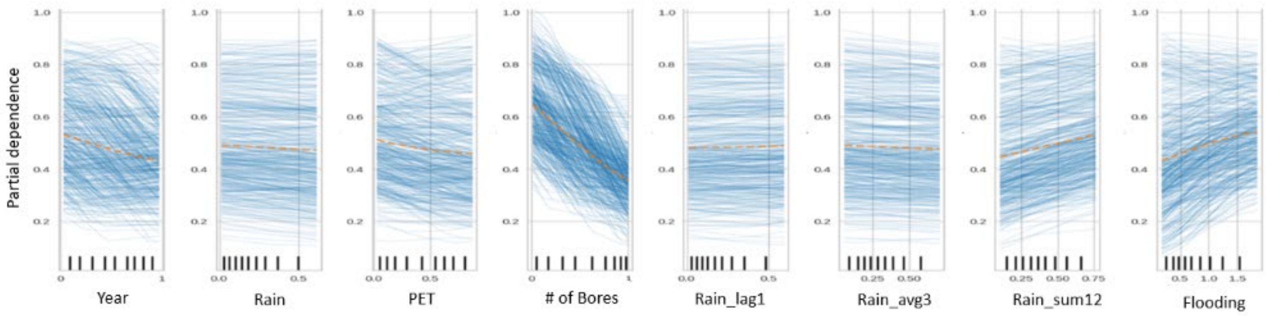

Figure 11 Partial dependence plots. Blue lines indicate the individual effects of each observation, orange lines show the average effect over all observations.

The blue lines represent individual observations, and the orange is the average of all observations. Where the blue lines are relatively parallel, the feature appears to have a similar impact on groundwater level predictions at all times and locations. On the contrary, in some cases the blue lines cross and bend – indicating that the same feature has differing impacts on groundwater levels for different observation locations and times. For example, on the right-hand panel of Figure 11, when flood extent is low (but non-zero) the groundwater level continues to decline at some locations, though for other observations (perhaps at other places or times) even a small amount of flood extent appears to raise the groundwater level. It is these complexities that can be investigated with the SHAP analysis.

3.3.4 Variable influences on predictions

The SHAP analysis investigates the contribution of each input variable to each individual prediction. Larger SHAP values indicate a greater influence of the input variable on the prediction, while the sign of the SHAP values (+/-) shows the direction in which the predictor affects the outcome.

Figure 12 displays the SHAP values for all input variables and all predictions split into three time periods. Observations from 1988-1998 are shown on the left panel, from 1999-2009 in the middle, and 2010-2020 on the right panel.

Each line represents an individual observation (set of input values) and the prediction the model makes based on this input. Beginning at the bottom of the plot and moving upwards, the prediction changes by a certain amount (the SHAP value) as it passes each predictor. The cumulative influence of all predictors, and therefore the final model output, is reflected by the point where each line crosses the bar at the top of the plot.

The model predictions in the first period (left panel of Figure 12) tend to be higher groundwater levels than the predictions on the right panel. Moving upward on the plot, noticeable differences in predictions begin with the impact of PET and annual precipitation. These differences continue to grow with the effects of time (year), flood inundation, location (resource unit), and groundwater development (number of extraction bores).

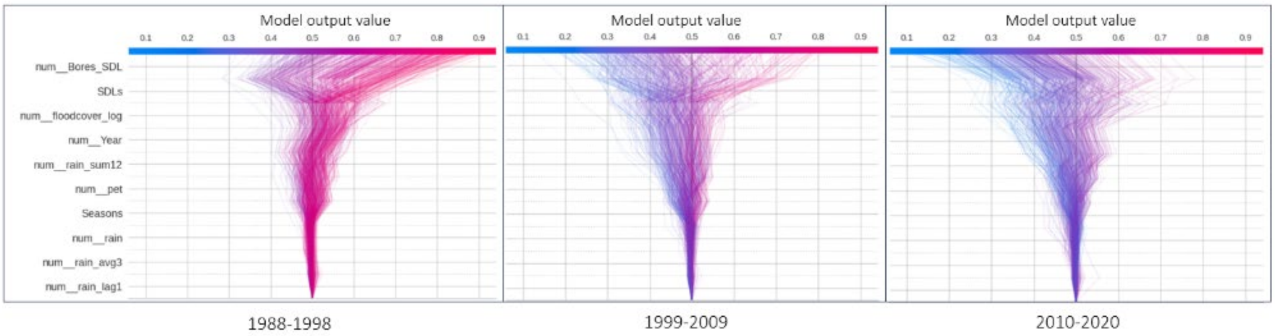

Figure 12 SHAP results showing the influence of each predictor on individual predictions. The y-axis is ordered by the global influence of predictors.

The changing influence of the variables throughout the study period can be seen by plotting SHAP values over time, as shown in Figure 13. Results are separated by resource unit on the left panel. The SHAP values tend to follow similar trends for all resource units, but it is evident that some variables are more influential at certain resource units. Over time, changes in the whole region are evident.

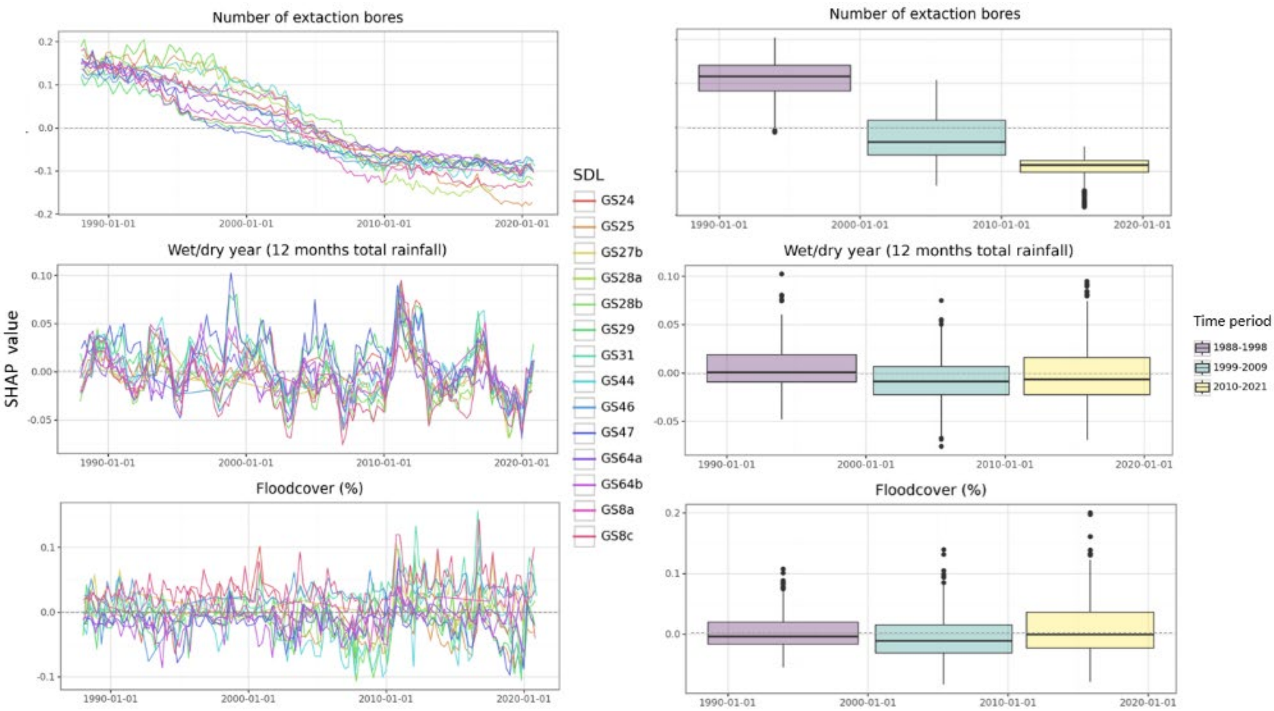

Figure 13 SHAP values plotted over time, left panel shows SHAP values for individual resource units, right panel shows SHAP values across all units for three periods (before, during and after the Millenium Drought).

On the right panel of Figure 13, SHAP values are combined across all resource units for three time periods. The time segments correspond to before (purple), during (green) and after (yellow) the Millenium Drought. The influence of each variable across all regions is shown to change over time.

As time proceeds, the number of extraction bores has an increasingly negative influence on groundwater levels. During the Millenium Drought (green boxes), the low annual precipitation and few flooding events were more influential on groundwater level predictions than these variables were before or after the drought (mean is further from the zero line). After the drought, flooding played more of a role in increasing groundwater level predictions than it did before the drought.

Changes over time in the impact of a single variable, in relation to the magnitude of the variable, are indicated with a scatterplot of SHAP values. In Figure 14, all SHAP values for annual precipitation, flood extent and PET are plotted against the actual values of the same variable and coloured by year. Both high and low values of annual precipitation have greater impact on groundwater level predictions than less extreme values, as expected. Both the highest and lowest impacts have occurred in recent years (pink data points), indicating the increased variations in antecedent rainfall conditions, as well as the increased response of groundwater levels to these conditions, in recent years compared to the 1980s and 90s. The same patterns are seen for flood extent and PET – more extreme values occurred in recent years, and these had greater influence on the groundwater level predictions. At the end of the study, both very wet years and very dry years have more influence (in opposite directions) on groundwater levels than at the start of the study. The same pattern holds for overbank flow and PET.

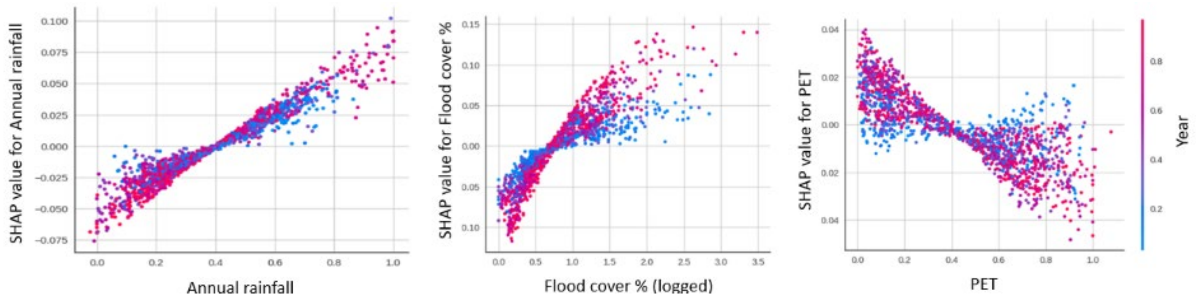

Figure 14 SHAP values for annual precipitation, flood extent and PET against actual values and coloured by year (early to recent = blue to pink). In recent years, the influence of these variables on predicted groundwater levels is stronger.

In summary, the longer-term SHAP analysis indicates:

- The monotonically decreasing SHAP values for the 'number of extraction bores' variable show that this variable dominates in influencing the long-term trend component of groundwater level predictions in this model, and that the influence is strengthening over time.
- The cyclical SHAP values of climate variables such as precipitation and potential evapotranspiration indicate their role on the seasonal dynamics of groundwater level predictions.
- Values of climate variables (annual rainfall, PET, flooding) are becoming more extreme over time (higher and lower values), and the SHAP values indicate the magnitude of influence (both +/-) of these variables on groundwater levels also increases over time.
- SHAP values for climate variables such as annual rainfall and flooding became more negative during the Millenium Drought indicating the expected influence on lowering groundwater levels, before their positive impact increases following the drought.

Results of the shorter-term analysis are given in the Appendix.

3.4 Limitations

The causal analysis assessment comes with certain limitations in the data and model:

- The monthly datasets are aggregations over several observations within each month. If the values were highly variable during the month, the average will not represent either the high or the low points.
- There is no indication of the alignment of the data sets with each other - for example, in any given month the rainfall measurements may occur after the groundwater level measurements and therefore no correlation will exist.
- The resource unit aggregations are averages of measurements at multiple bores across a geographic region. We have seen from the cluster investigation in Chapter 2 that a defined cluster structure exists in the data. This means that within most resource units groundwater levels will be increasing or decreasing at different rates at various bores. By aggregating the data to the resource unit level, these distinctions of cluster trends are lost. The climate and groundwater extraction information (also aggregated) are assumed to apply across the region.
- There are two major challenges with the groundwater extraction data for this causal attribution investigation: 1) the earliest available metered groundwater extraction volumes are 2006, which limits the long-term analysis, and 2) there are unmetered and unreported groundwater extractions in these regions meaning that the uncertainty in the extraction data is unknown.
- In the longer-term model, the ‘Year’ and ‘Number of bores’ variables are correlated. The main difference is that ‘Number of bores’ is different for each resource unit, so whilst it is generally monotonically increasing as ‘Year’ is, some resource units will be increasing at a more rapid rate, and some may be steady over multiple years.
- As this is a time-series based analysis, a dynamic ML model such as the long-short term memory model (LSTM) would generally be preferred. This is a deep learning model specifically designed for time series analysis that can capture short and long-term trends in the data by cycling sequentially over long series of inputs. However, the LSTM requires continuous time series for all variables (no missing data) which were not available in this study. The LSTM is also not compatible with explainable AI frameworks such as SHAP used for post-hoc causal analysis, hence the use of the feed-forward neural network in this study. The creation of lagged and long-term averaged input variables attempts to bring a dynamic component to this model, allowing predictions to be based on past conditions.

3.5 Key findings

The input variables are found to influence groundwater level predictions with different timing, direction and magnitude at each resource unit. Specific findings of the causal analysis are:

- Overall, ‘the number of extraction bores’ – a proxy for the development of groundwater resources – was found to be the most influential input variable for predicting groundwater levels over the long term.
- The high importance of the resource unit variable in both short and long-term models indicates strong regional differences in groundwater responses to the predictor variables.
- In the short-term model, the annual extractions and flooding information became the most influential inputs (along with resource unit), when the number of bores variable was not used.
- Climate variables influence groundwater predictions more at some resource units than others, and this influence varies over time. The magnitude of influence of climate variables such as PET and wet/dry years, has increased over time (both +/-) across all areas.
- Overbank flooding has more impact than precipitation on groundwater level predictions, indicating flood events are a more influential source of recharge than rainfall. Annual precipitation is more influential than shorter term precipitation values.
- The number of extraction bores is shown to have an increasingly negative influence on the prediction of groundwater levels over the study period. SHAP values for the number of extraction bores continued to decline following the drought, suggesting that the impact of groundwater development did not recover afterward. However, this is likely an artifact of the variable type – a cumulative sum of the number of bores. As bores are not often removed (or not recorded if they are), then this number will remain stable or increase even if actual extraction volumes fluctuate year to year.

Although the shorter-term model including actual groundwater measurements has temporal and spatial limitations compared to the longer-term model, it foreshadows the insights that could emerge if groundwater extraction data were more widely available. With this model, it was shown that each bore has a differing relationship between groundwater extractions and groundwater levels, and these relationships vary over time – unlike the relationships in the longer-term model between number of bores and groundwater levels which showed similar patterns across all bores and a constantly increasing influence over time.

4 Groundwater resilience, stress and sustainability analysis

4.1 Scope

This section reports an integrated assessment of three characteristics of alluvial aquifers in the MDB namely resilience, stress and sustainability as defined below:

- **Groundwater resilience** is the ability of a groundwater system to maintain reserves and its essential functions despite major anthropogenic disturbances.
- **Groundwater stress** is the ratio between the use and availability of groundwater resources.
- **Groundwater sustainability** is the beneficial use of groundwater that supports present and future demands while ensuring that unacceptable environmental, economic and social consequences do not occur.

Groundwater resilience, stress and sustainability characteristics were quantitatively evaluated by combining three lines of evidence as described in the following section. Detailed description of the methods are results are documented in a previous report and a journal article (Rojas et al., 2022; Rojas et al., 2023a).

4.2 Methods

Figure 15 shows the conceptual framework implemented for the analyses of resilience, stress and sustainability characteristics to support opportunities for the improvement of groundwater management. The concepts of groundwater resilience, stress and sustainability were evaluated using: a) long-term trend analysis of groundwater levels; (b) calculation of groundwater footprint indices considering volume and quality; and (c) an explicit comparison of groundwater management areas in terms of groundwater usage, sustainable use, storage volumes, presence and diversity of groundwater-dependent ecosystems (GDEs), and buffering capacity to absorb changes in recharge rates. Each line of evidence used a series of groundwater indicators as proxies for resilience, stress, and sustainability, noting that the main objective was to obtain a basin-scale perspective.

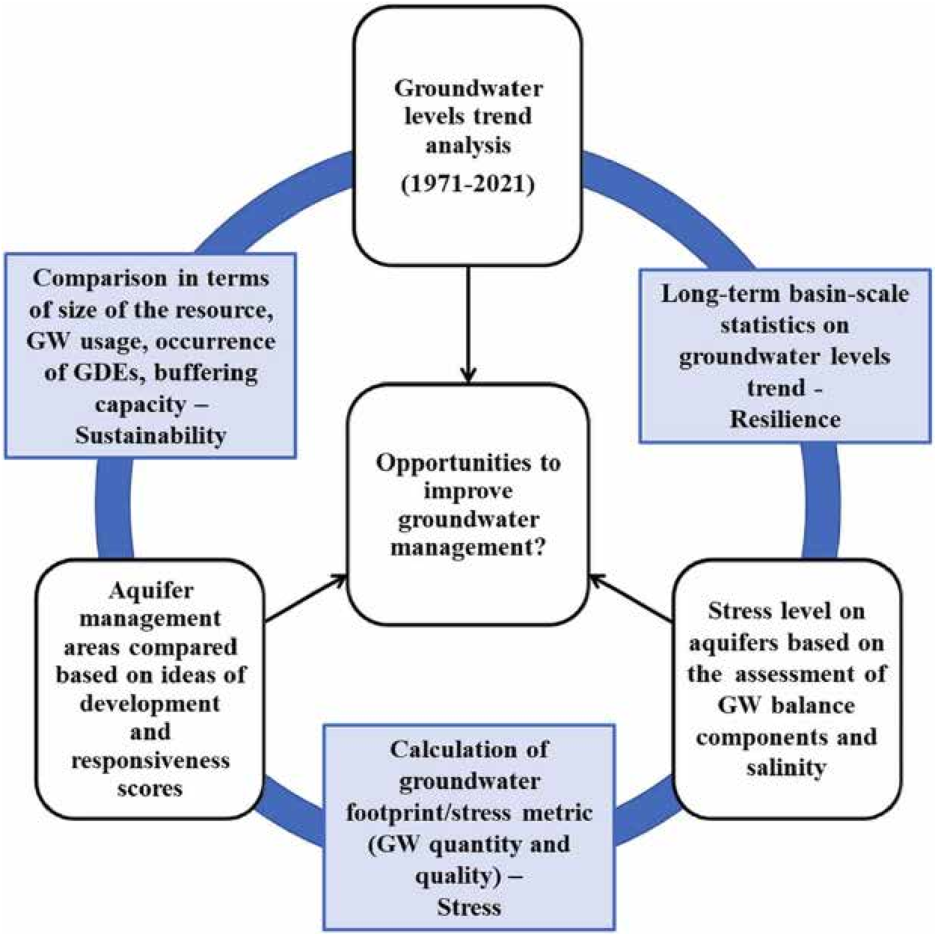

Figure 15 Conceptual framework to identify opportunities to improve groundwater management in the alluvial aquifers of the MDB. White boxes represent the lines of evidence used to explore the concepts of resilience, stress, and sustainability through their corresponding proxies (blue boxes).

Groundwater trend analysis described in the previous section underpinned the analysis of the metrics relevant for resilience analysis. Groundwater footprint was calculated as the ratio of annual groundwater abstraction to net annual recharge (recharge minus groundwater contribution to environmental streamflow) multiplied by areal extent of the aquifer. Effect of groundwater quality on stress was accounted by including different salinity classes in the computation of stress.

Indicators of aquifer development and responsiveness were used to inform aquifer sustainability. Aquifer development and responsiveness indicators modified from past studies (Barron et al, 2011 and Currie et al., 2010) were used to evaluate sustainability considering both aquifer performance and management perspectives. Aquifer development score was used to implement a consistent approach to quantify the relative development status of different resource units in the MDB by considering actual groundwater use and the long-term average sustainable diversion limit of each resource unit in relation to the maximum use and maximum limit across all units. The aquifer development score also weighed in the occurrence and diversity of groundwater-dependent ecosystems in the resource unit. Two widely used diversity indices, namely, Shannon and Simpson Diversity Indices (Gorelick, 2006; Spellerberg & Fedor, 2003) were adapted to use class areas instead of species counts within each groundwater resource unit.

Similarly, the aquifer responsiveness score considered actual groundwater use in a resource unit in comparison with the long-term average sustainable diversion limit of that unit while weighing in the recharge buffering capacity of the aquifer. Recharge buffering capacity represents the capacity of the aquifer to buffer potential changes in recharge rates.

Both indicators can be combined to obtain a numerical ranking following the standardisation process described in Barron et al. (2011). Additionally, an ordination approach was employed (Barron et al., 2011) to rank groundwater resource units as follows: developed aquifer systems (low responsiveness and high development scores); responsive aquifer systems (low development and high responsiveness scores); and relevant aquifer systems (high development and high responsiveness scores).

4.3 Key findings

Long-term trend analysis indicated that nine groundwater resource units show above-average declining trends in groundwater levels (Table 3), with a high number of observation bores showing statistically significant declining trends and high depletion rates, thus pointing towards groundwater resilience issues. Groundwater footprint assessment indicated that three groundwater resource units are under stress, mainly driven by groundwater extraction and contributions to environmental streamflow (Figure 16). Including data on groundwater salinity in the assessment adds substantial pressure to the groundwater resource units.

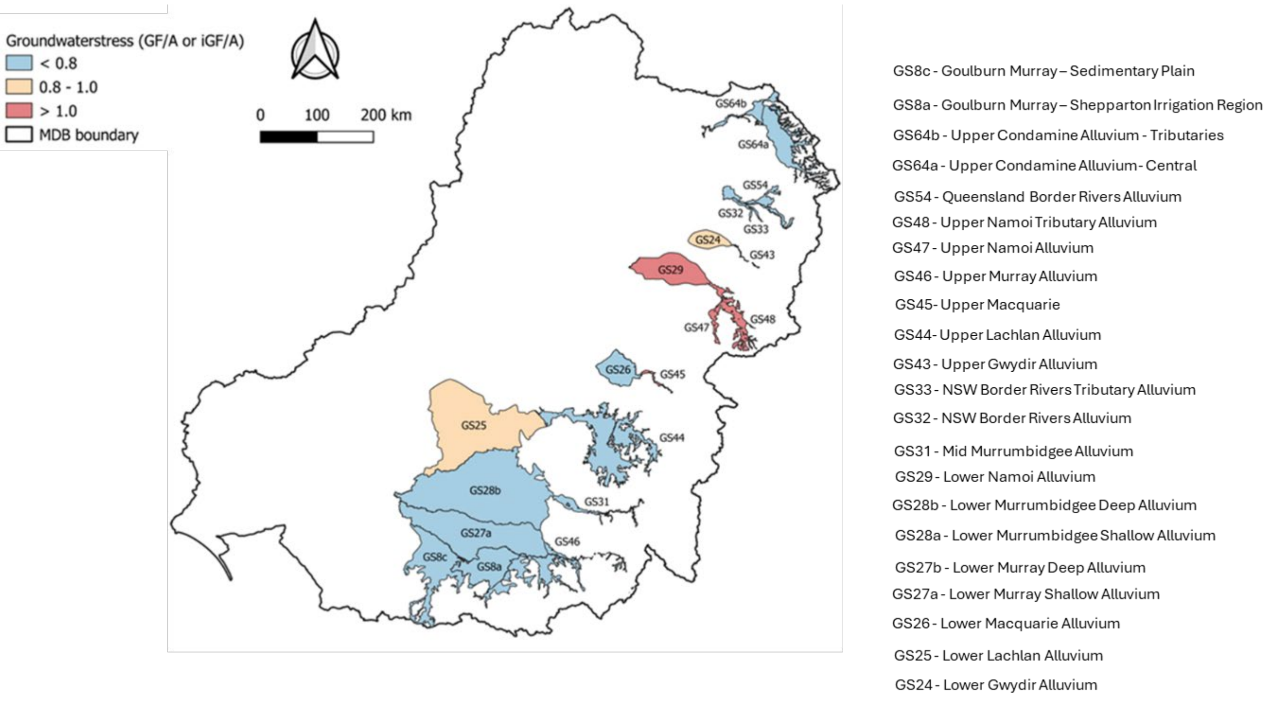

Figure 16 Groundwater stress indices for groundwater resource units while considering groundwater use without considering salinity classes.

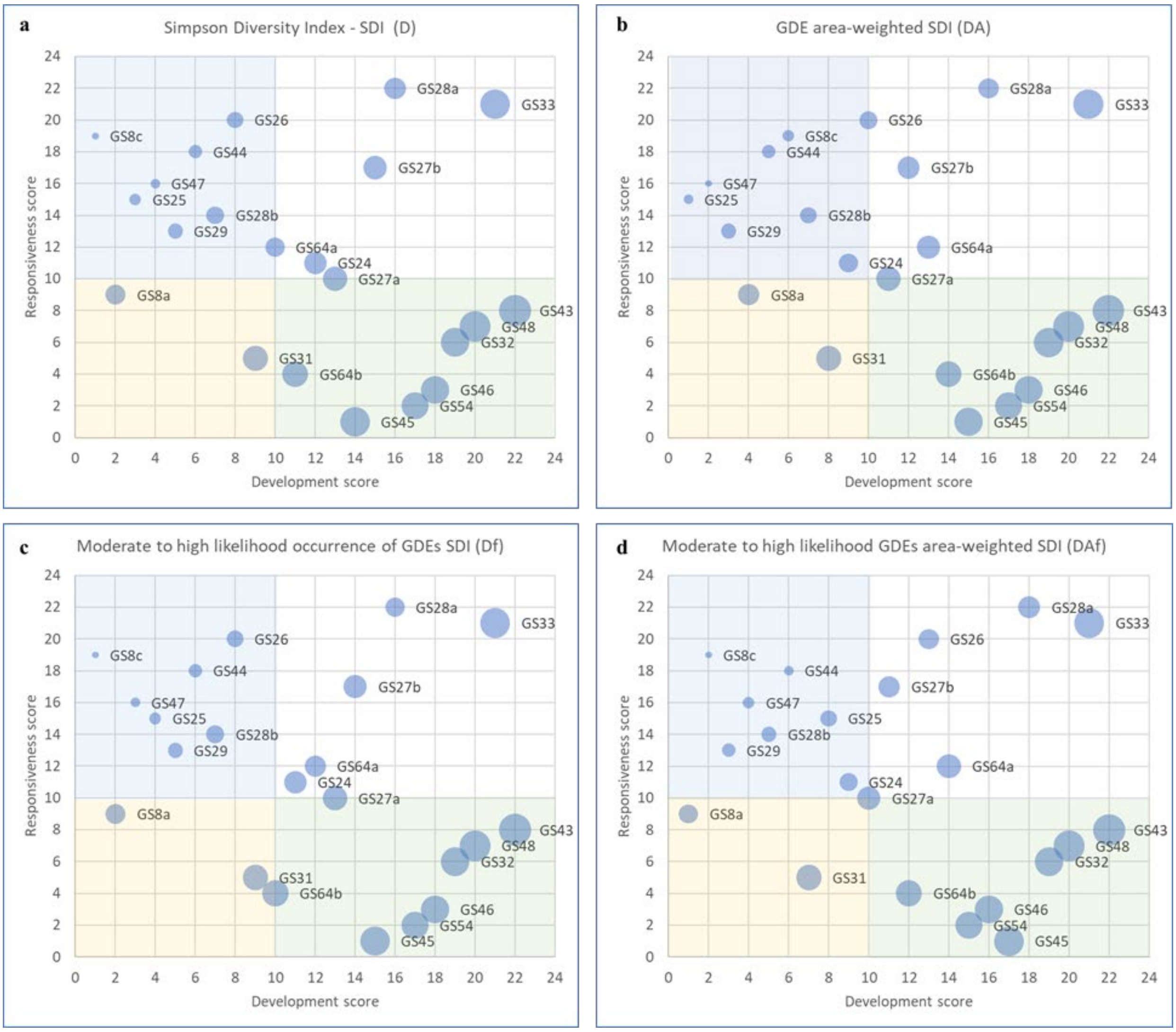

Figure 17 Development, responsiveness and numerical relevance scores of groundwater resource units using (a) Simpson Diversity Index (SDI), (b) area-weighted SDI, (c) SDI using moderate to high GDE potential area, (d) area-weighted SDI using moderate-to-high GDE potential areas.

The size of the bubble reflects numerical relevance with small size bubbles reflecting high numerical scores and vice versa (from Rojas et al. (2023a)).

Aquifer development and responsiveness ranked scores, and numerical relevance obtained using different weighting schemes are shown in Figure 17. The coloured regions in the panels of Figure 17 represent the ranking approach. The blue region represents resource units with high-ranking development scores and low-ranking responsiveness scores, while the green region represents high-ranking responsiveness and low-ranking development scores. The yellow region reflects both high-ranking development and responsiveness scores. Based on this approach, two groundwater resource units (Shepparton Irrigation Region GS8a and Mid-Murrumbidgee Alluvium GS31) consistently displayed high-ranking development and responsiveness scores across various weighting schemes as demonstrated in Figure 17.

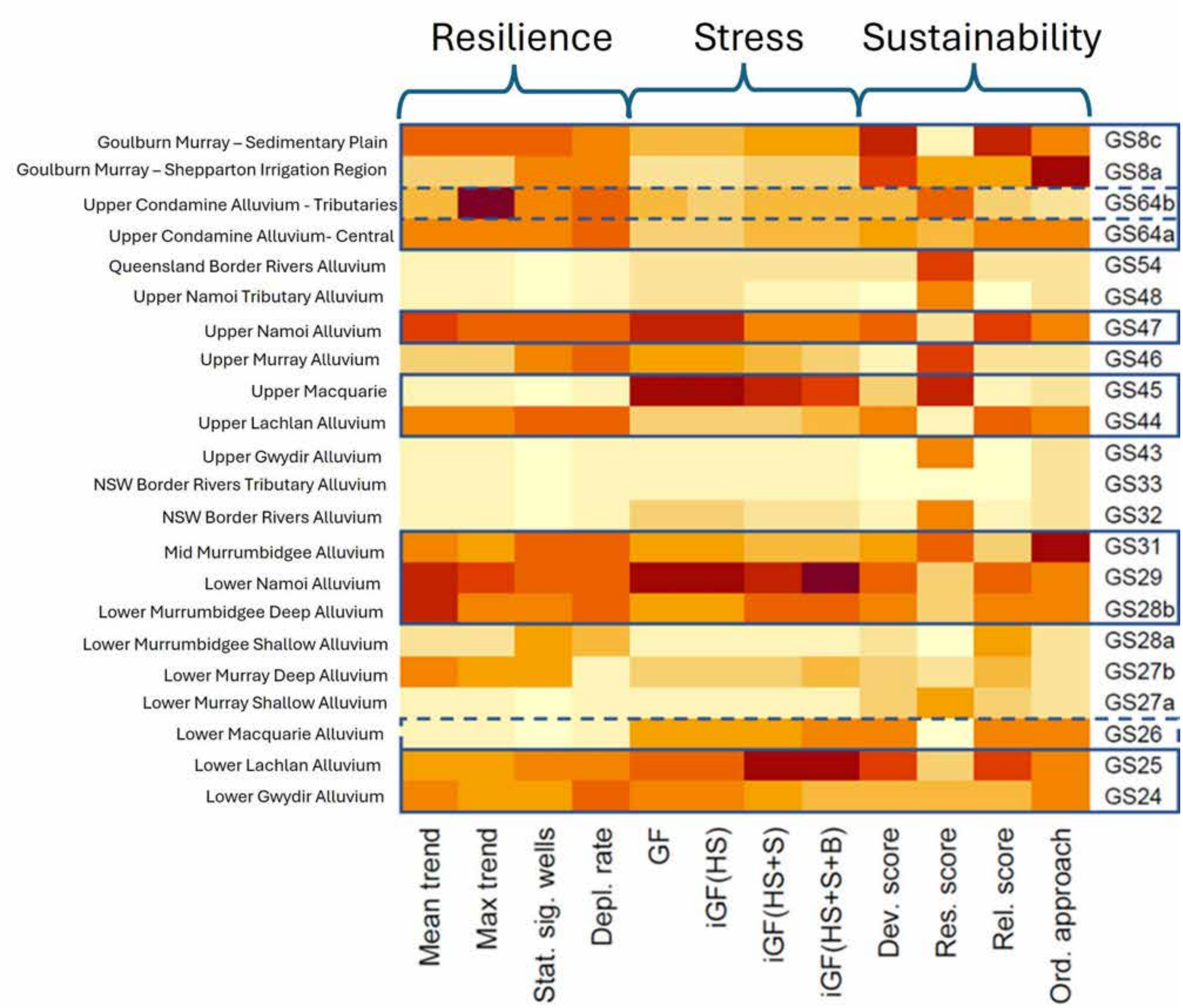

Figure 18 Heatmap representing standardised groundwater indicators of resilience, stress and sustainability for groundwater resource units used to manage the main alluvial aquifer systems in the MDB.

iGF(HS): highly saline areas; iGF(HS+S): highly saline and saline areas; iGF(HS+S+B): highly saline, saline and brackish areas. Solid line boxes identify resource units where normalised groundwater indicators for resilience, stress or sustainability are above-average. Dashed line boxes identify two resource units where groundwater indicators indicate emergent issues.

Figure 18 summarises all indicators used for assessing resilience, stress and sustainability characteristics for all 22 resource units considered in this study.

Overall, the analysis showed that:

1. Eleven (out of 22, Figure 18) groundwater resource units were identified as having resilience, stress or sustainability issues across the main alluvial aquifers of the MDB.
2. The Namoi Alluvium (GS29 and GS47) shows signs of resilience, stress, and potential sustainability issues, whereas Mid-Murrumbidgee (GS31) shows resilience and sustainability issues.
3. The Upper Condamine Alluvium (GS64a), Lower Murrumbidgee Deep (GS28b) and Goulburn-Murray: Sedimentary Plains (GS8c) show signs of resilience issues, potential stress issues when considering groundwater salinity, and potential sustainability issues due to the presence and diversity of GDEs.

4. Upper Macquarie (GS45) shows stress driven mainly by significant groundwater discharge to streams compared to recharge. In contrast, Upper Lachlan (GS44) shows resilience issues driven by declining trends and high depletion rates, and potential sustainability issues driven by the high proportion of groundwater use compared to diversion limits.
5. A similar pattern is observed for Goulburn-Murray: Shepparton Irrigation Region (GS8a), with stronger evidence indicating sustainability issues. Despite having above-average values across all indicators, the Lower Gwydir (GS24) and Lower Lachlan (GS25) show no clear evidence of specific resilience, stress or sustainability issues at the resource unit scale.
6. The exception is for Lower Lachlan (GS25) when considering groundwater salinity. Two other specific groundwater management units show signs of emergent resilience (GS64b) or sustainability issues (GS26) due to localised maximum declining trends and the presence and diversity of GDEs.

The findings showed the value of simultaneously examining various aspects related to groundwater resilience, stress and sustainability to gain broader insights into overall resource conditions and identify a wide range of potential issues that can occur to varying extents in different areas. This framework can be used to prioritise and focus efforts to address specific resilience, stress and sustainability issues in different regions to generate more efficient and effective planning and management outcomes. Similar assessments conducted at finer spatial scales could identify potential local issues that are not captured at resource unit scale.

5 Assessment of managed aquifer recharge potential and conceptual site costs

5.1 Scope

This section presents a framework for mapping managed aquifer recharge (MAR) potential based on a desktop analysis of aquifer and physiographic features to identify areas with a high likelihood of feasibility across the main alluvial aquifer systems of the MDB. It builds upon the work by Gonzalez et al. (2020) and a subsequent study that covered other regions around Australia (Page et al., 2021). The framework used a similar approach to a recent study of NSW groundwater resources, but differed in several aspects including assessment scale, reporting units and grid resolution, input data, and calculations of potential recharge volumes (Gonzalez and Page, 2024). Groundwater level trend analyses, following the work of Fu et al. (2022), rather than static, point in time groundwater levels, were incorporated that enabled the potential for MAR to be assessed in areas of groundwater depletion. Methods for assessing MAR potential in confined aquifer conditions, in addition to unconfined, were developed and applied. A stochastic approach to the spatial screening component of the assessment was applied to capture uncertainty in input spatial criteria and assumed technical feasibility thresholds. The key assumption for estimating potential storage volumes in unconfined aquifers was that the available aquifer space was limited by historical water levels (circa 1970s) in areas of long-term declines, and effective porosity. In confined aquifers, injection volumes were assumed to be limited by overburden pressure as a function of injection rate and aquifer properties (storativity, conductivity and transmissivity) calculated through pumping equations. Methods are summarised in this report for brevity, for further details refer to the technical metadata report (Gonzalez, 2024).

A financial cost assessment methodology that accounts for uncertainty was deployed to estimate costs of MAR. The spatial assessment of MAR potential in combination with the resilience, stress and sustainability assessment (Rojas et al., 2023a) and groundwater level trend work (Fu et al., 2023; Fu et al., 2022) was used to develop a conceptual MAR scheme for cost estimation. Capital, operating and levelized costs were estimated including a summary of the most important and sensitive factors influencing costs and uncertainties. To outline the governance arrangements for implementation, institutional, policy and regulatory principles are explored (Page et al., 2022).

5.2 Methods

5.2.1 Assessment area

The eight main alluvial aquifer systems in the MDB comprise 22 resource units that together account for >75% of average annual groundwater extraction in the Basin (Fu et al., 2022) were assessed for unconfined and/or confined storage potential. The aquifers, confinement and approximate depths of formations within the resource units were taken from resource descriptions (MDBA, 2020a; NSW Government, 2024a), see Appendix Table A.2.

5.2.2 Spatial screening method

Stochastic iterations of spatial criteria thresholds were generated by converting spatial input data into uniform, 1 km resolution grids. Binary screening arrays were created for each spatial criterion, evaluating the input grids against each threshold iteration. These criteria related to the presence and extent of suitable aquifers for MAR, predictors of infiltration or permeability potential, groundwater salinity and levels and aquifer properties (Gonzalez, 2024). The proportion of iterations meeting all criteria at each grid cell provided a metric of screening confidence, e.g. where 25, 50 and 75% of iterations meet all criteria, the screening confidence intervals are 25, 50 and 75% respectively. The total area meeting all criteria was calculated across various screening confidence intervals for resource units. Gridded estimates of potential storage volumes were derived from aquifer properties, summing these estimates for assessment units based on different confidence levels. A local sensitivity analysis identified the most influential factors affecting the screening assessment by systematically omitting each spatial criterion and observing the resulting changes. This iterative process helped pinpoint which criteria had the greatest impact on overall results.

5.2.3 Unconfined spatial criteria

The lateral extent of suitable aquifers for infiltration-based MAR was assumed to coincide with corresponding groundwater resource unit boundaries with unconfined aquifers. Five other spatial criteria were used to screen feasible areas for infiltration-based MAR in unconfined aquifer conditions across the resource units assessed. These criteria related to the vertical extent of suitable aquifer material, vertical soil hydraulic conductivity, groundwater salinity and available storage space in the aquifer as a function of groundwater levels. Plausible ranges for each criterion were set within which stochastic realisations were generated based on random uniform distributions (Appendix Table A.3).

5.2.4 Confined assessment criteria

The lateral extent of suitable aquifers for well injection-based MAR was assumed to coincide with corresponding groundwater resource unit boundaries with confined aquifers. As the assessment of MAR potential relied on an analytical solution for calculating head responses to well injection, two other spatial criteria, groundwater salinity and groundwater head trend, were used to screen feasible areas (Appendix Table A.4).

5.2.5 Groundwater level trend interpolation

Bore standing water level (SWL) data were sourced from the National Groundwater Information System (BOM, 2023). SWL measures the distance from the top of the well casing to the water level. Bores were categorized into resource units based on intersecting areas and classified as confined or unconfined according to their drilled depths and reported depths of upper and lower aquifer formations from resource descriptions (MDBA, 2020a; NSW Government, 2024a). Only records with at least two SWL observations per bore each year for 20 of the 50 years from 1971 to 2021 were included to ensure adequate data for interpolation, particularly in areas with limited records. Annual minimum SWL values were used for trend analysis. Groundwater level trends from 1971 to 2021 were analysed using Sen's Slope estimator, revealing trends grouped by aquifer systems like Shepparton and Lachlan. Trends exhibited a normal distribution with filtered outliers, resulting in specific ranges for unconfined (-0.28 to 0.27 m/y) and confined systems (-0.08 to 0.47 m/y). Interpolation was performed using Empirical Bayesian Kriging, generating mean predictions and standard errors.

5.2.6 Groundwater salinity interpolation

Bore salinities were obtained from the National Groundwater Information System (NGIS) (BOM, 2023). Bores were categorized into resource units based on their areal extents and assigned to confined or unconfined aquifer systems according to drilled depths as aquifer attribution and depths of screened intervals were not recorded. Only records with a minimum of four salinity observations per bore were included. Salinity data exhibited a positive skew and included outliers beyond reasonable groundwater values (electrical conductivity (EC) <1 - >500,000 µS/cm), which were filtered to yield an EC range of 131 – 51,260 µS/cm. The 75th percentile salinity values for each bore were summarized by aquifer system (Appendix Table A.6). Spatial distribution issues prevented interpolation for the Border Rivers deep alluvial aquifer system. For other systems, the 75th percentile salinity values were interpolated using Empirical Bayesian Kriging with K-Bessel variogram models, and mean predictions and standard errors were exported as gridded layers. Stochastic realizations of salinity interpolations were created by adjusting predictions within ±1 standard error, maintaining spatial autocorrelation.

5.2.7 Potential storage volume calculations

Potential infiltration volumes for unconfined aquifers were estimated using groundwater level decline over 50 years (1971-2021) and specific yield (Sy). Stochastic models provided quantiles of groundwater level change based on interpolated mean predictions and standard error. Sy was modelled by scaling the minimum and maximum Sy values from the uppermost layers of corresponding NSW groundwater models on soil porosity estimates derived from gridded bulk density estimates, and regolith thickness estimates (Grundy et al., 2015), reflecting coarser materials in thicker aquifers typical of paleochannels (Bates and Jackson, 1980) and deposition processes(Dixon, 2015).

The recharge potential for confined aquifers via well injection was calculated using an inverse form of the Theis solution (Theis, 1935), injecting 1 GL over a 100-day cycle. Four injection wells, spaced 250 m apart, were placed in each 1 km^2 grid cell, each injecting 2500 m^3/d for 100 days. Confined aquifer thickness was derived by subtracting the average thickness of the overlying unconfined aquifer from the regolith thickness grid (Table A.2). Upper and lower hydraulic conductivity (K) values from regional groundwater models were used to rescale a combined aquifer thickness and inverse clay content grid (Bates and Jackson, 1980; Dixon, 2015; Freeze and Cherry, 1979). Specific storage (Ss) was assumed to be 3.3×10^{-7}/m (Woessner and Poeter, 2020), with storativity being the product of Ss and confined aquifer thickness. Effective saturated thickness was assumed to be 50% of total aquifer thickness. Transmissivity (T) was calculated by multiplying K and effective saturated thickness grids. Injection pressure (hydraulic head, m) should not exceed 1.5 times the overburden thickness (NRMMC-EPHC-NHMRC, 2009), which was assumed to be the average thickness of the overlying unconfined aquifer (Table A.2). The injection head pressure limit was calculated for each grid cell. Injection heads were calculated for each well in the cell including the additional heads from neighbouring injection wells 250 m away. The total computed head increase values for each cell were set to zero where the overburden head limit was exceeded.

5.2.8 Cost estimation framework for conceptual MAR sites

This study employs a framework for water balance and financial assessment adapted from Gonzalez et al. (2024), that outputs cost distributions and performs sensitivity analyses. It focuses on levelised cost, considering capital and operating expenses for economic sustainability and full-cost recovery following international pricing principles. The 50-year project horizon aligns with similar water infrastructure assessments (OECD, 2020). Monetary values are reported in inflation-adjusted Australian dollars as present values. A social discount factor range of 3-7% is applied. A global sensitivity analysis, using the SALib package in Python 3 (Herman and Usher, 2017), evaluates variable impacts on water recovery costs through 10,000 Latin hypercube sampling iterations. First order Sobol sensitivity indices are calculated using the Delta-moment independence measure (Borgonovo, 2007).

The scheme conceptualisation was based on MAR potential mapping that identified areas within which an area of recharge was assumed giving an upper limit to local storage capacity. Recharge rates were parameterised from gridded input data, e.g. vertical soil hydraulic conductivity. The design capacity was based on reaching the local storage capacity within five years of recharge. It was assumed a practical duration for annual recharge would occur over 90-120 days in a recharge year which was used to calculate the infrastructure requirements needed to reach the storage capacity. Storage efficiency, or recovery efficiency (i.e. the proportion of water able to be recovered at suitable quality for intended application) was determined based on end use water quality requirements and groundwater salinity and considered hydraulic connectivity with other aquifers or the surface. The distance and elevation difference between the water source (e.g. river channel) and point of recharge was calculated from the mapped area and DEM.

An analysis of surface hydrology and water market data was conducted to determine operating rules (when to recharge and recover) (BOM, 2024a) and opportunity costs of water (based on allocation trade prices) (BOM, 2024b) for each site. This analyses water allocation trade prices and river flow data filtering out zero-dollar trades and calculating median monthly and annual prices for a specific water system. River flow and allocation price data are converted to annual time series and flow exceedance probabilities are calculated. Statistical tests compare water prices during low and high flow periods based on exceedance probabilities, using Monte Carlo simulations to generate price distributions and tests for normality and significance. The allocation price distributions (e.g. interquartile range) for high and low flows at given exceedance probabilities are used as bounds for opportunity costs of water in the cost estimation model.

5.3 Results

5.3.1 Unconfined MAR potential

The storage volume estimates for unconfined aquifers within the Murray-Darling Basin varied significantly across groundwater resource units and confidence intervals (Figure 19). At a 75% screening confidence interval, more than 9500 GL of storage potential over the resource units assessed was identified with about 60% (6500 GL) of this capacity located within 5 km of major rivers (Table 4). The estimates made at resource unit scale are indicative of the empty pore space in aquifers due to long-term drawdown that underlie areas that have favourable characteristics for infiltration. However, it is not realistic to assume that this capacity would be fully realisable through managed aquifer recharge as the capacity is spread over very large areas (>10,000 km^2). There is potential to target areas of greater long-term decline that have locally available storage space. These commonly coincide with areas of higher groundwater extraction and future demand where additional water security offered through MAR could benefit a wider range of potential users.

The estimates of MAR potential made in this study differ from a previous regional scale assessment of potential storage in unconfined aquifers in the MDB but are within a factor of 2 in comparison (Gonzalez et al., 2020). The figures are not directly comparable as different regions were used to summarise results (river regions instead of groundwater resource units) and some areas were not included due to data paucity. However, at MDB scale 2000-4000 GL was previously identified within 5 km of major rivers (depending on salinity constraint) compared to about 6500 GL within the resource units assessed in this study. The differences can be attributed to the use of different data sources to indicate infiltration potential, mainly from using gridded vertical hydraulic conductivity estimates rather than clay content grids as a proxy for soil permeability, the use of spatially variable gridded specific yield (porosity) values rather than a uniform assumption of 10%, and the use of interpolated groundwater level trends to estimate storage heights as a function of long-term groundwater level decline rather an uniform, nominal recharge height of 0.1 m. The estimates presented in this study are more precise than earlier estimates, are based on improved datasets, and capture uncertainty in screening criteria and spatial interpolation error.

There are significant differences in potential infiltration volumes compared with a recent study across NSW groundwater management areas (Gonzalez and Page, 2024). This is mainly due to the different input data related to predicting soil permeability, and the use of groundwater level trends to estimate available recharge heights as opposed to assuming recharge to a set height below ground level. The most influential factor was the difference between using recently produced estimates of soil vertical hydraulic conductivity based on the ROSETTA pedological transfer function (PTF) (Crosbie et al., 2025) instead of gridded estimates of clay content and the associated empirical relationship with conductivity from limited data (Alakayleh et al., 2018) used in other studies (Gonzalez et al., 2020; Gonzalez and Page, 2024; Page et al., 2021). The ROSETTA PTF is a neural network approach to determine soil hydraulic properties and offers hierarchical functions that accommodate different levels of data availability (Schaap et al., 2001; Stumpp et al., 2009). The function used here relied on six parameters: sand, silt and clay fractions, soil bulk density, and drained upper and lower limit volumetric water contents from gridded national datasets (Crosbie et al., 2025; Grundy et al., 2015). More details on its implementation in the MDB are provided by Crosbie et al. (2025). Using these data, much greater areas where acceptable infiltration rates are identified compared to eliminating areas where clay content is above a threshold of around 40%. If this clay content threshold is also applied, the total potential storage volume reduces from 9500 GL to about 2000 GL at the 75% screening confidence interval. This is comparable to the total estimate of 2200 GL for the 14 highest potential NSW Groundwater Sources within the MDB made previously (Gonzalez and Page, 2024). The six parameter ROSETTA model is observed to yield high accuracy, particularly in sandy soils but in high clay soils, errors are larger (Stumpp et al., 2009). This reinforces the need for field validation and site-specific investigations to verify the feasibility of MAR in areas identified from regional scale maps.

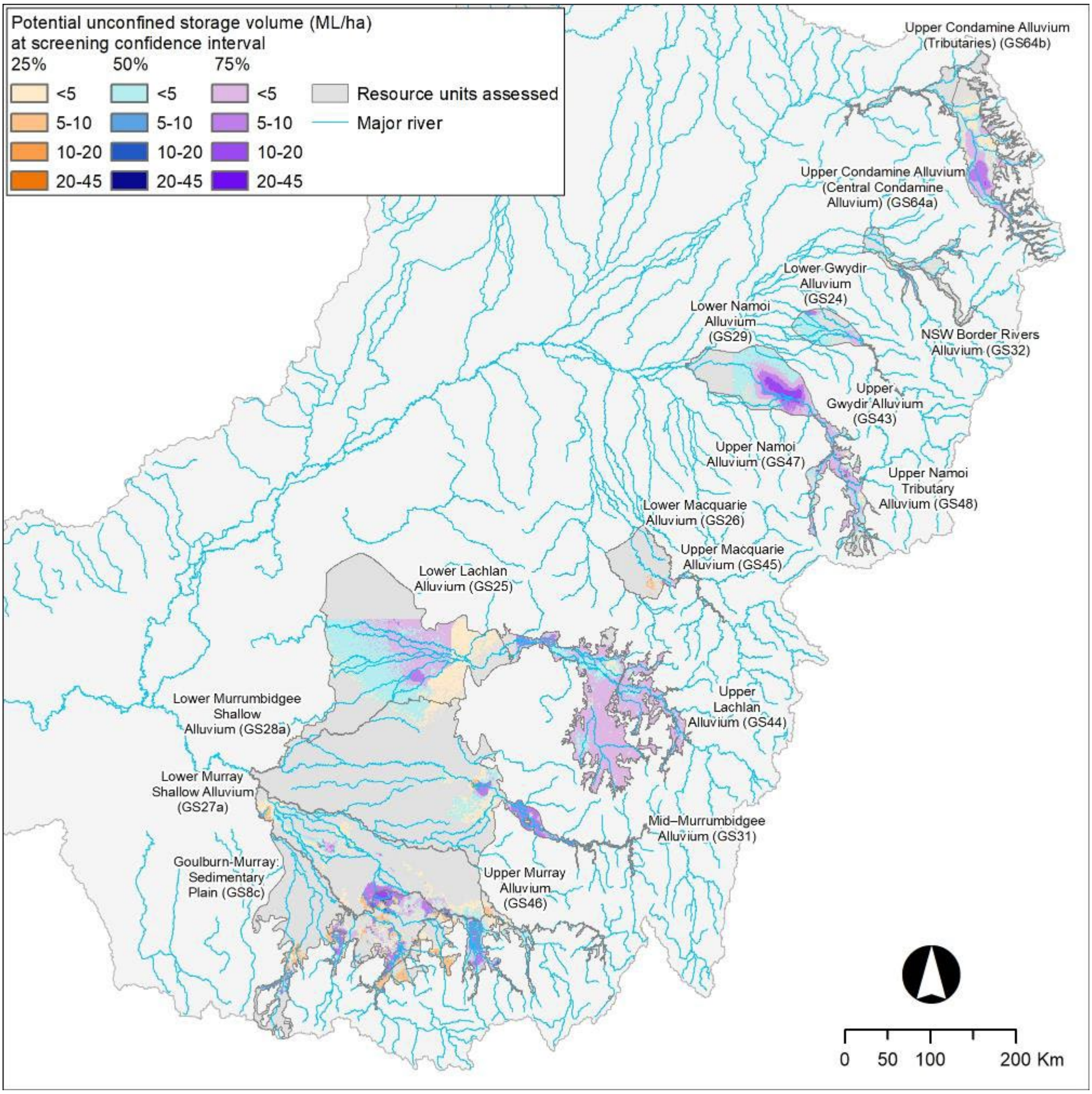

Figure 19 Potential storage volumes in unconfined aquifer areas at 25%, 50% and 75% screening confidence levels across the main alluvial resource units in the Murray-Darling Basin.

Over 75% (7500 GL) of the total potential volumes estimated were identified within four resource units: the Upper Lachlan, Lower Lachlan, Lower Namoi and Goulburn-Murray Sedimentary Plain (Table 4 and Figure 20). On average, about 60% of this potential capacity (4600 GL), was located within 5 km of major rivers (Figure 21). The proportional difference between estimates made at 25% and 75% confidence intervals reflected screening assessment robustness. The Lower Lachlan and Goulburn-Murray Sedimentary Plain showed the lowest values (0.43 and 0.29, respectively) indicating higher sensitivities to screening criteria bounds and less reliable data. In contrast, the Upper Lachlan and Lower Namoi had high values (0.82 and 0.80, respectively) indicating robustness to variations in screening criteria thresholds and more reliable data. These differences are visualised in the stacked bar chart showing the potential capacities at 25, 50 and 75% confidence intervals for the resource units assessed (Figure 20).

The Lower Namoi, Goulburn-Murray: Sedimentary Plain and Mid-Murrumbidgee had the highest average recharge heights of the resource units with high storage potential, suggesting a greater potential for water to infiltrate and recharge the aquifer at MAR site scales (Table 4). In contrast, the Upper Lachlan, despite having the highest estimated potential storage volumes at 75% confidence interval, had a lower average recharge height (0.27 m) meaning that the potential capacity is distributed across wide areas. This is evident in the map that shows the Upper Lachlan generally had <5 ML/ha available across a large part of the resource unit (Figure 19). Conversely, the Lower Namoi, Goulburn-Murray and other areas where higher volumes are concentrated in certain areas offer potential to target smaller areas that could accept greater recharge rates (Figure 19).

Table 4 Summary of storage potential at different screening confidence intervals (CI) in the unconfined aquifers of the main alluvial resource units in the Murray-Darling Basin.

Resource unit	Potential storage volume at 25% CI (GL)	Potential storage volume at 50% CI (GL)	Potential storage volume at 75% CI (GL)	Average potential recharge height at 75% CI (m)	Screening criteria robustness	Percent volume at 75% CI within 5 km of major rivers	Average water level decline (m)
Upper Lachlan Alluvium (GS44)	3360	3260	2745	0.27	0.82	58	3.37
Lower Lachlan Alluvium (GS25)	4300	3390	1828.9	0.40	0.43	69	2.12
Lower Namoi Alluvium (GS29)	2090	2090	1677.4	0.61	0.80	46	2.82
Goulburn-Murray: Sedimentary Plain (GS8c)	4490	2660	1286.3	0.57	0.29	77	3.84
Upper Condamine Alluvium (Central Condamine Alluvium) (GS64a)	940	750	671.7	0.37	0.72	66	2.81
Mid–Murrumbidgee Alluvium (GS31)	700	680	604.9	0.52	0.86	91	2.58
Lower Murray Shallow Alluvium (GS27a)	1170	690	399.5	0.47	0.34	62	-1.48
Upper Namoi Alluvium (GS47)	510	480	361.6.	0.20	0.70	74	2.51
Lower Murrumbidgee Shallow Alluvium (GS28a)	610	370	126.1	0.54	0.21	52	-2.24

Resource unit	Potential storage volume at 25% CI (GL)	Potential storage volume at 50% CI (GL)	Potential storage volume at 75% CI (GL)	Average potential recharge height at 75% CI (m)	Screening criteria robustness	Percent volume at 75% CI within 5 km of major rivers	Average water level decline (m)
Upper Condamine Alluvium (Tributaries) (GS64b)	180	140	105.1	0.16	0.60	82	1.32
Lower Gwydir Alluvium (GS24)	390	370	93.8	0.29	0.24	77	0.02
Lower Macquarie Alluvium (GS26)	130	40	23.1	0.28	0.18	100	2.67
NSW Border Rivers Tributary Alluvium (GS33)	30	20	13.7	0.11	0.51	100	2.04
Upper Macquarie Alluvium (GS45)	30	20	9.8	0.18	0.35	100	0.99
Upper Murray Alluvium (GS46)	120	20	5.8	0.32	0.05	100	2.32
Queensland Border Rivers Alluvium (GS54)	30	30	5.4	0.07	0.16	100.00	0.47
Goulburn-Murray: Shepparton Irrigation Region (GS8a)	10	10	5	0.15	0.57	84.00	3.01
NSW Border Rivers Alluvium (GS32)	20	20	3.6	0.05	0.15	100.00	1.05
Upper Namoi Tributary Alluvium (GS48)	0	0	0	-	0.00	-	1.99
Upper Gwydir Alluvium (GS43)	20	10	0	-	0.00	-	1.73

The upstream and tributary alluvial resource units generally had lower volume estimates compared to the first four resource units. The Upper Condamine Alluvium (Central Condamine Alluvium) (GS64a) has the highest volume among these units but were significantly lower than the volumes of the first four units. No potential storage was identified at the 75% confidence interval for the Upper Namoi Tributary Alluvium (GS48) or the Upper Gwydir Alluvium (GS43). These results are due to the limited lateral extent of aquifers in narrow river valleys that are generally thinner, comprised of finer sediments with higher bulk densities and lower porosities, and generally have shallow groundwater. Consequently, these units had much lower average recharge heights compared to the first four units. Where potential was identified, a higher percentage of their volume was within 5 km of corresponding rivers e.g. Upper Condamine Alluvium (Tributaries) (82%).

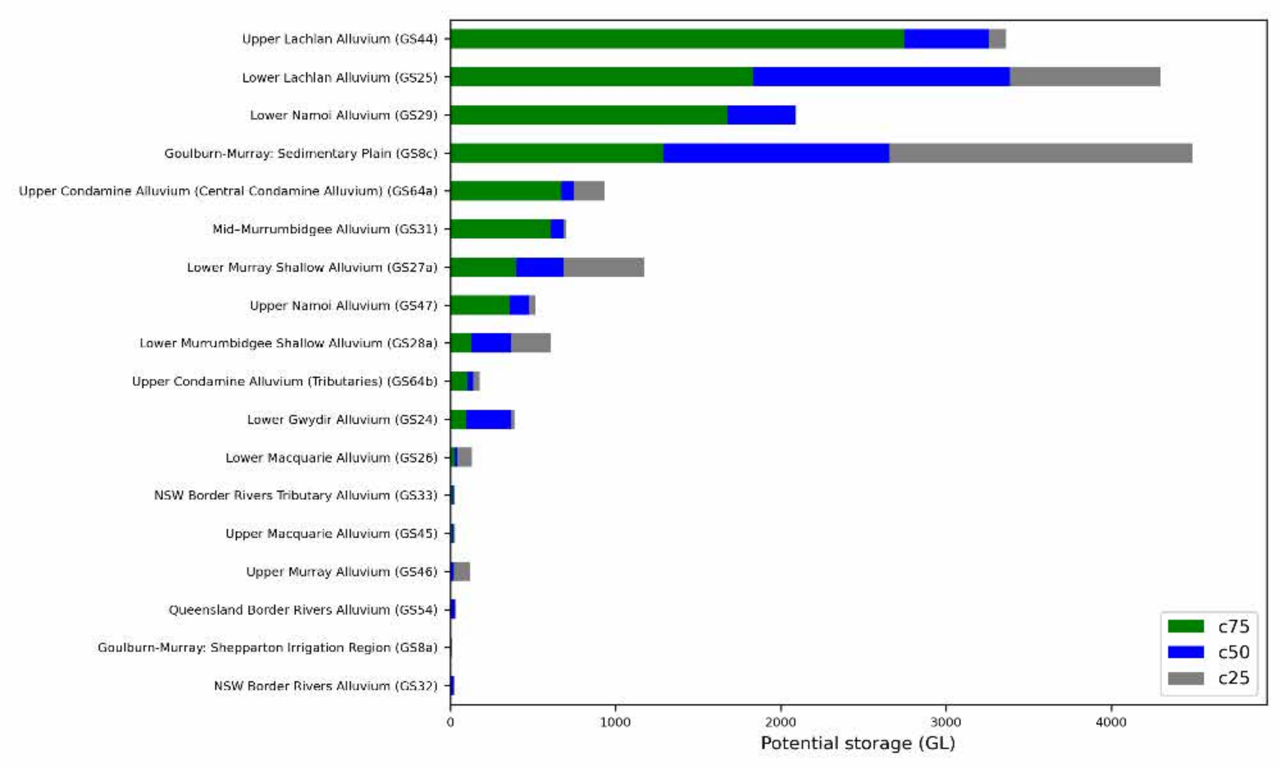

Figure 20 Potential storage volume estimates for unconfined areas of resource units made at 25%, 50% and 75% screening confidence intervals.

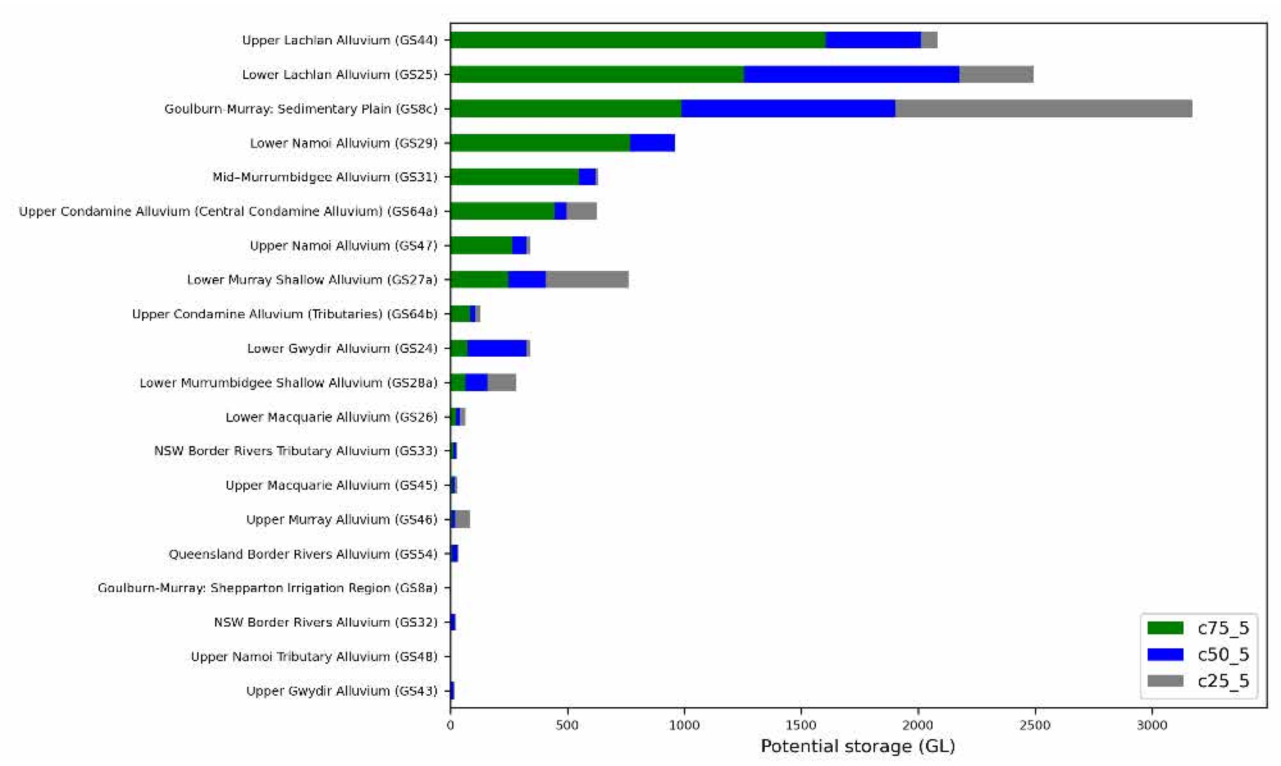

Figure 21 Potential storage volume estimates for unconfined areas of resource units within 5 km of major rivers at 25%, 50% and 75% screening confidence intervals.

The sensitivity analysis revealed that the depth to groundwater trend was the most sensitive spatial screening criterion across almost all resource units, with many values at 1.0 (Table 5).

Salinity also showed high sensitivity in several regions, particularly in the Lower Lachlan, Lower Namoi, Goulburn-Murray and Lower Murray Shallow Alluvium. Both the DTW and salinity criteria were assessed using a static upper threshold limit (>0 m/y and < 3000 mg/L respectively) as the spatial uncertainty was captured in the standard error surfaces calculated as part of the spatial interpolation. The soil vertical hydraulic conductivity (Ks) parameter exhibits high sensitivity in the Upper Lachlan Alluvium and Mid-Murrumbidgee Alluvium, while regolith is most sensitive in the Mid-Murrumbidgee Alluvium (Table 5). Slope was insensitive across all areas due to the low topographic relief across the resource unit areas. No suitable areas were identified in the Upper Namoi Tributary and Upper Gwydir resource units at the 75% confidence interval. These insights highlight the critical factors affecting the suitable areas in different resource units informing the reasons for differences in screening confidence and assessment robustness. The results indicate where investigations could be targeted to reduce uncertainty in site specific studies during entry-level MAR feasibility assessments (NRMMC-EPHC-NHMRC, 2009).

Table 5 Unconfined spatial screening criteria sensitivities to areas identified at 75% confidence interval.

Resource unit	Soil K	Slope	Regolith	Depth to water	Salinity
Upper Lachlan Alluvium (GS44)	1.0	0.0	0.3	0.2	0.2
Lower Lachlan Alluvium (GS25)	0.0	0.0	0.0	1.0	0.3
Lower Namoi Alluvium (GS29)	0.0	0.0	0.0	1.0	0.0
Goulburn-Murray: Sedimentary Plain (GS8c)	0.0	0.0	0.0	0.0	1.0
Upper Namoi Alluvium (GS47)	0.3	0.0	0.1	1.0	0.2
Upper Condamine Alluvium (GS64a)	0.0	0.0	0.0	0.1	1.0
Mid–Murrumbidgee Alluvium (GS31)	0.9	0.1	1.0	0.1	0.0
Lower Murray Shallow Alluvium (GS27a)	0.1	0.0	0.0	0.7	1.0
Upper Condamine Alluvium (Tributaries) (GS64b)	0.1	0.0	0.3	0.2	1.0
Lower Gwydir Alluvium (GS24)	0.0	0.0	0.0	1.0	0.0
Lower Murrumbidgee Shallow Alluvium (GS28a)	0.0	0.0	0.0	1.0	0.1
NSW Border Rivers Tributary Alluvium (GS33)	0.0	0.0	0.1	0.9	1.0
Lower Macquarie Alluvium (GS26)	0.2	0.0	0.0	0.5	1.0
Queensland Border Rivers Alluvium (GS54)	0.0	0.0	0.0	1.0	0.0
NSW Border Rivers Alluvium (GS32)	0.0	0.0	0.1	1.0	0.3
Upper Macquarie Alluvium (GS45)	0.0	0.0	0.0	1.0	0.2
Goulburn-Murray: Shepparton Irrigation Region (GS8a)	0.0	0.0	0.1	0.0	1.0
Upper Murray Alluvium (GS46)	0.0	0.0	0.0	0.2	1.0
Upper Namoi Tributary Alluvium (GS48)					
Upper Gwydir Alluvium (GS43)					

5.3.2 Confined MAR potential

Table 6 presents potential storage volumes and characteristics for the alluvial resource units with confined aquifers. Across all units, around 9700 GL of potential storage was identified, about half of which (4700 GL) was located within 5 km of major rivers which could be used to source water for recharge. However, as with the unconfined aquifer potential, storage capacity is spread over a very large area (>20,000 km^2) so it is unrealistic to assume it could be fully utilised. The spatial distributions of confined storage potential at different screening confidence intervals are shown in Figure 22. The assessment showed that most of the storage potential is located within distinct regions of 5-6 resource units (Figure 22). The Lower Namoi Alluvium (GS29) shows significant potential storage volumes (>3300 GL) across confidence intervals (CIs) and a robust screening criteria score of 0.76. The Lower Murrumbidgee Deep Alluvium (GS28b) had the second highest potential storage volume at 75% CI (3280 GL) but a lower robustness score (0.13).

The Lower Gwydir Alluvium (GS24) and Lower Lachlan Alluvium (GS25) also exhibit notable potential storage volumes and recharge rates. The Mid-Murrumbidgee Alluvium (GS31) stands out with consistent potential storage volume and high proximity to major rivers (95.15%). Other units like the Goulburn-Murray Sedimentary Plain (GS8c) and Lower Murray Deep Alluvium (GS27b) have lower potential storage volumes. Several units, including the Queensland Border Rivers Alluvium (GS54) and Upper Lachlan Alluvium (GS44), show no potential storage. Long-term average water level declines vary, with the highest observed in the Lower Murray Deep Alluvium (GS27b) at 9.6 m. However, due to high salinity and low hydraulic conductivity, this resource unit did not show significant injection potential.

There are significant differences in estimates of potential injection volumes compared with a recent study across NSW groundwater source areas (Gonzalez and Page, 2024). Estimated volumes for resource units in the current study are larger those made for equivalent groundwater sources, in some cases (e.g. Lower Namoi) by an order of magnitude. This is mainly due to the different assumptions made for constraining injection pressure. In this study, the constraint was based on not exceeding 1.5 times overburden pressure for a given recharge rate following Australian guideline recommendations (NRMMC-EPHC-NHMRC, 2009). Median heads at the edge of cells (250 m from any of the 4 injection wells in each 1 km^2 cell) were around 3 m. In contrast, the former study assumed an injection pressure limit of <1 m head increase at the edge of each cell to avoid potential impacts to neighbouring bores. This comparison highlights that if aquifer properties (e.g. transmissivity, storativity) are generally favourable in an area, the main determinant of injection potential is the allowable pressure increase for managing risks to neighbouring assets and the aquifer/aquitard integrity. Ultimately, site specific investigations are needed to determine the actual hydraulic capacity of a confined aquifer location to determine the acceptable radius of influence and select injection pressures to manage these risks.

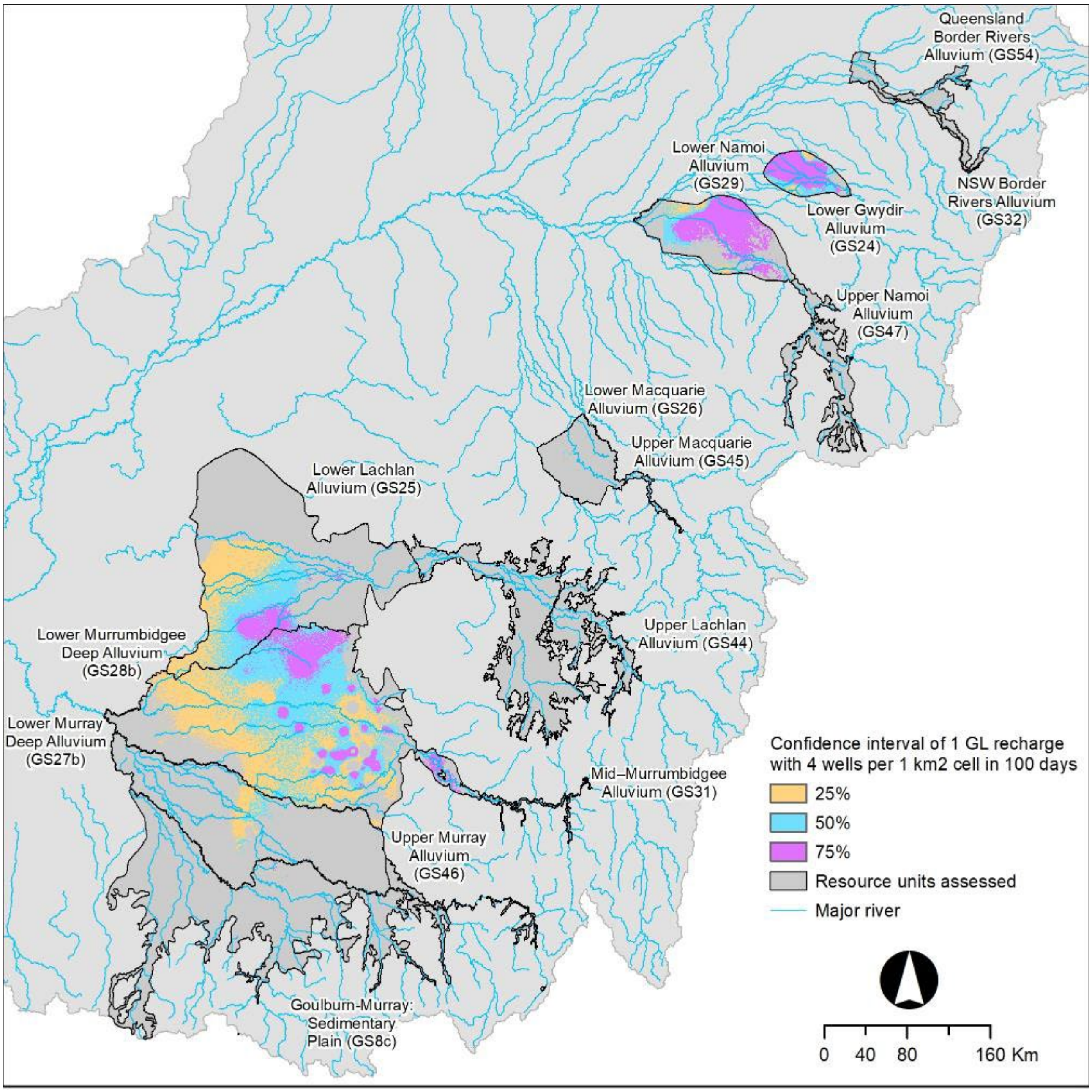

Figure 22 Potential to achieve injection target in confined aquifer areas at 25%, 50% and 75% screening confidence levels across the main alluvial resource units in the Murray-Darling Basin.

The screening robustness, indicating the proportional difference between estimates at 25% and 75% confidence intervals, varied across resource units. These variances are depicted in stacked bar charts of volumes in Figure 23 and Figure 24. The Lower Namoi Alluvium (GS29) and Lower Gwydir Alluvium (GS24) showed high robustness (0.76 and 0.68, respectively), while the Lower Murrumbidgee Deep Alluvium (GS28b) and Lower Lachlan Alluvium (GS25) had lower robustness (0.13). The Mid-Murrumbidgee Alluvium (GS31) demonstrated perfect robustness (1.0) meaning that the assessment was insensitive to the groundwater salinity and head criteria due to the low salinities observed and low interpolation errors of salinity and hydraulic heads. The percentage of volumes within 5 km of major rivers is highest for the Mid-Murrumbidgee Alluvium (95.15%) and Lower Gwydir Alluvium (90.53%).

Table 6 Summary of storage potential at different screening confidence intervals (CI) in the confined aquifers of the main alluvial resource units in the Murray-Darling Basin.

Resource unit	Potential storage volume at 25% CI (GL)	Potential storage volume at 50% CI (GL)	Potential storage volume at 75% CI (GL)	Screening criteria robustness	Percent volume at 75% CI within 5 km of major rivers
Lower Namoi Alluvium (GS29)	4398	4010	3330	0.76	42.14
Lower Murrumbidgee Deep Alluvium (GS28b)	24548	12770	3280	0.13	25.63
Lower Gwydir Alluvium (GS24)	2236	2070	1530	0.68	90.53
Lower Lachlan Alluvium (GS25)	9543	4980	1260	0.13	58.33
Mid–Murrumbidgee Alluvium (GS31)	330	330	330	1	95.15
Goulburn-Murray: Sedimentary Plain (GS8c)	23	13	10	0.43	90
Queensland Border Rivers Alluvium (GS54)	0	-	-	-	-
Upper Lachlan Alluvium (GS44)	0	-	-		-
Lower Murray Deep Alluvium (GS27b)	1300	354	0	-	-
Upper Macquarie Alluvium (GS45)	0	-	-	-	-
Lower Macquarie Alluvium (GS26)	18	14	0	-	-
Upper Namoi Alluvium (GS47)	0	-	-	-	-
Upper Murray Alluvium (GS46)	0	-	-	-	-
NSW Border Rivers Alluvium (GS32)	0	-	-	-	-

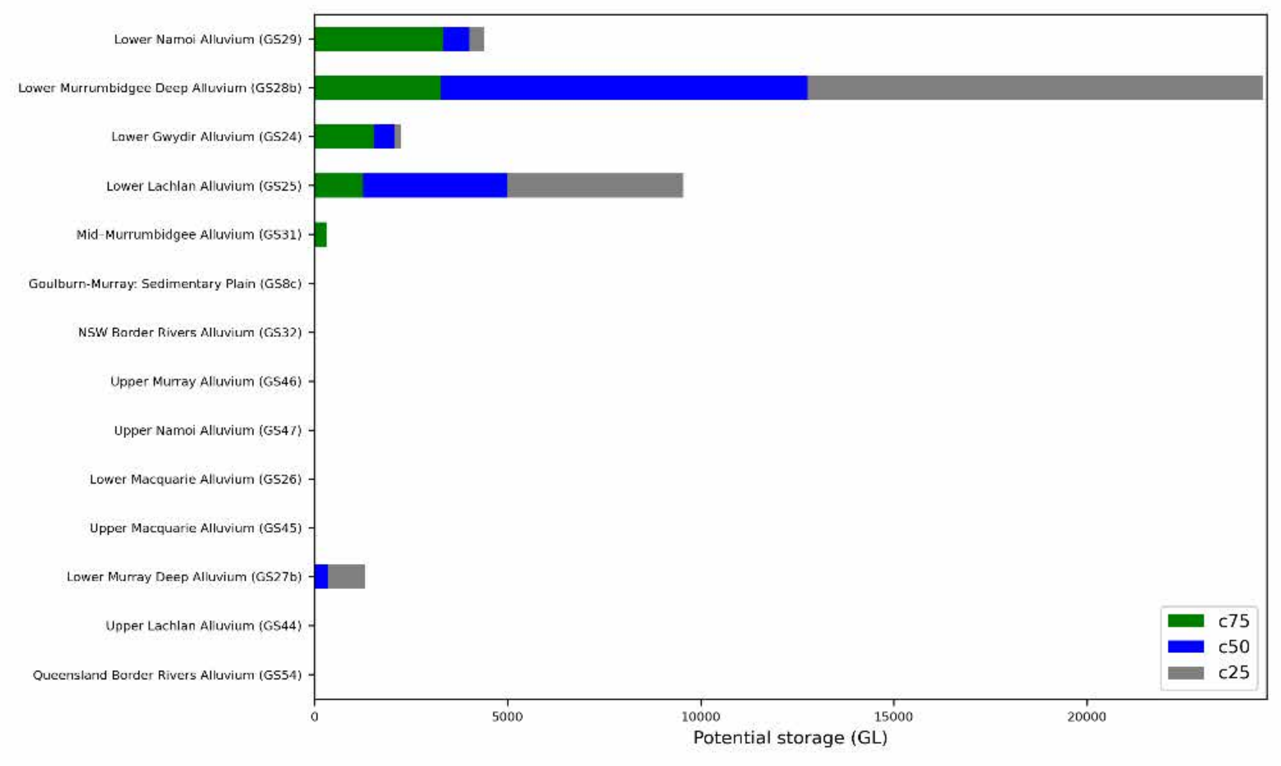

Figure 23 Potential storage volume estimates for resource units with confined aquifers at 25%, 50% and 75% screening confidence intervals.

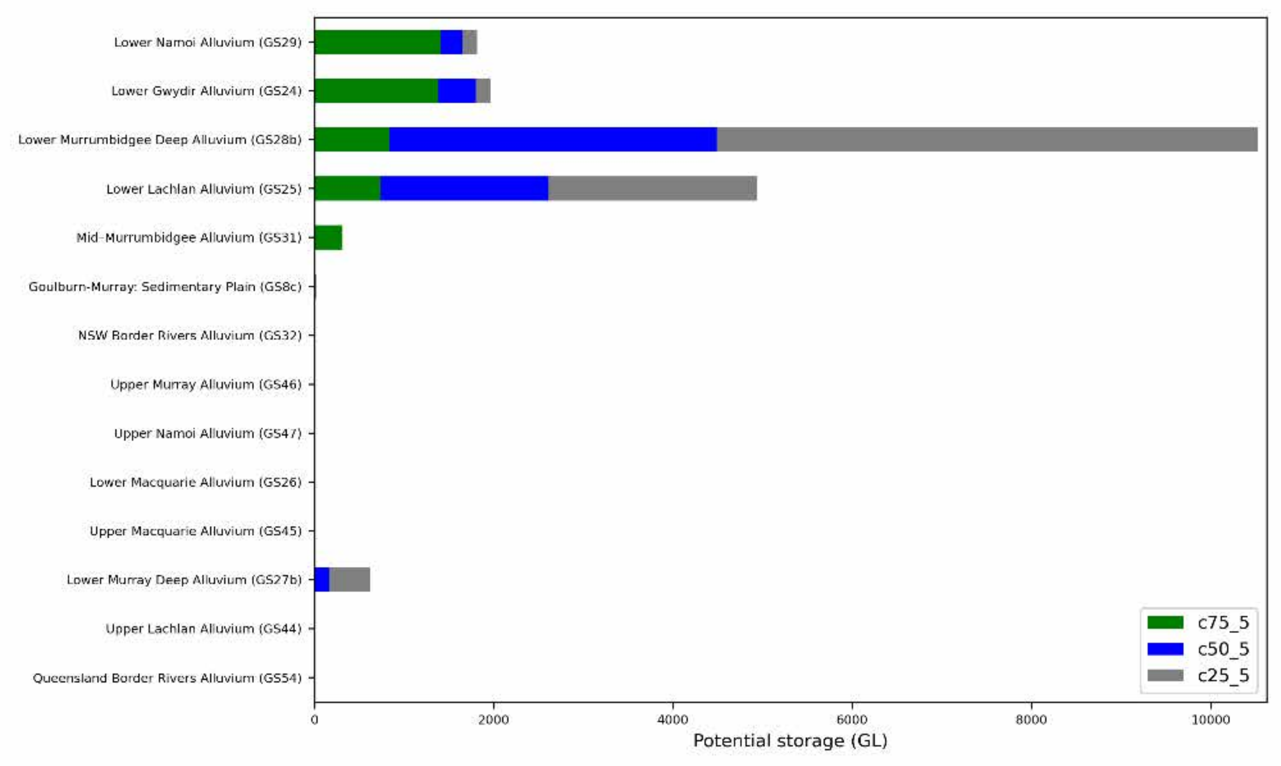

Figure 24 Potential storage volume estimates for resource units with confined aquifers within 5 km of major rivers at 25%, 50% and 75% screening confidence intervals.

The five hydrogeological factors (effective saturated thickness, hydraulic conductivity, transmissivity, salinity, and head decline) significantly influenced the estimated storage volumes for different resource units (Table 7). Aquifer thickness (and effective thickness) directly impacts aquifer storativity and transmissivity, with thicker zones offering more potential.

Table 7 Summary of confined aquifer potential storage and spatially averaged hydrogeological criteria.

Resource unit	Potential storage volume at 75% CI (GL)	Feasible area at 75% CI (km^2)	Effective saturated thickness (m)	Hydraulic conductivity (m/d)	Transmissivity (m^2/d)	Salinity (µS/cm)	Head decline (m)
Lower Namoi Alluvium (GS29)	3334	4872	28	20	289	2910	3.3
Lower Murrumbidgee Deep Alluvium (GS28b)	3281	3588	89	31	1651	7110	7.1
Lower Gwydir Alluvium (GS24)	1531	1646	34	46	797	3243	3.7
Lower Lachlan Alluvium (GS25)	1260	5702	21	29	386	3598	2.7
Mid–Murrumbidgee Alluvium (GS31)	330	1445	6	36	102	2350	4.0
Goulburn-Murray: Sedimentary Plain (GS8c)	10	5746	32	5	87	12042	5.6
Queensland Border Rivers Alluvium (GS54)	0	0	13	6	35		5.0
Upper Lachlan Alluvium (GS44)	0	9139	1	14	6	4260	6.2
Lower Murray Deep Alluvium (GS27b)	0	3660	28	3	46	11780	9.6
Upper Macquarie Alluvium (GS45)	0	50	3	11	21	3209	2.0
Lower Macquarie Alluvium (GS26)	0	0	7	10	35	4652	7.0
Upper Namoi Alluvium (GS47)	0	2895	1	9	4	2408	5.3
Upper Murray Alluvium (GS46)	0	254	7	5	16	3564	2.0
NSW Border Rivers Alluvium (GS32)	0	0	7	5	12		1.9

Hydraulic conductivity and transmissivity are key to recharge efficiency with higher values enabling greater injection at lower pressure head. For example, the Lower Murrumbidgee Deep Alluvium, with high average transmissivity and hydraulic conductivity, shows a substantial storage volume of 3281 GL, reflecting its capacity for recharge across large areas (>3000 km^2) (Table 7). However, in other resource units with large feasible areas, such as the Upper Lachlan Alluvium (>9000 km^2), storage potential was limited due to much lower average hydraulic conductivity, transmissivity and thickness, restricting injection potential despite the vast area. Salinity levels also played a role in limiting volume potential, as higher salinity may reduce recovered water quality making MAR less viable, e.g. Goulburn-Murray Sedimentary Plain where average salinity was >12,000 µS/cm (Table 8). All resource units showed areas of long-term groundwater head decline that are reflected in the spatially averaged values. Although this did not influence injection potential (this was limited by pressure head responses for a given recharge rate), declining heads suggest the current extraction rates in some regions are above historical recharge rates. These factors combine to influence how effectively each area can receive additional recharge and efficiently store water for long-term use.

5.3.3 Lower Namoi MAR site conceptualisation and cost estimate

An infiltration basin site was conceptualised for the Lower Namoi area as shown in Figure 25. This would target the upper, unconfined aquifer of the Narrabri Formation (NSW Government, 2018). The area of interest is within an area of high screening confidence (>75%) and recharge potential (16-18 ML/ha). The potential recharge area is assumed to be within the 2 km^2 extent shown in Figure 25. The total aquifer capacity within this zone is 32,000-36,000 ML requiring 6400-7200 ML/y of recharge over five years to reach capacity (disregarding any aquifer losses). Infiltration rates, based on vertical soil K estimates are 0.15-0.17 m/d. With 90-120 days per year to recharge, 8-10 basins of 6.25 ha each would be required to reach the recharge rate of 6400-7200 ML/y. The site is 4-5 km from the Namoi River with a pump lift of 9-11 m required.

Median allocation trade prices in the Namoi River system (SS21) over the period of record from 2008 to 2024 were significantly higher ($195/ML) during low flows (measured near Wee Waa, station 419059) at a flow exceedance probability >60% (Mann-Whitney $p < 0.0001$) compared to high flows ($112/ML). MAR would target the higher part of the hydrograph where the opportunity cost of water was assumed to range between the 25th and 75th percentile of trade prices ($75-150/ML). Flow rates stochastically varying between 129,000-194,000 ML/y, corresponding to the 60% exceedance probability rate ±20% across the 50-year annual time series (1976-2024), were used to trigger recharge and recovery. Annual storage efficiency was assumed in the range of 0.8-0.9, to account for potential hydraulic losses through seepage into the underlying, semi-confined Gunnedah Formation should these volumes not be recognised in the lower aquifer. Groundwater quality in the region is fresh and unlikely to be limiting fresh water recovery through mixing with groundwater (NSW Government, 2018).

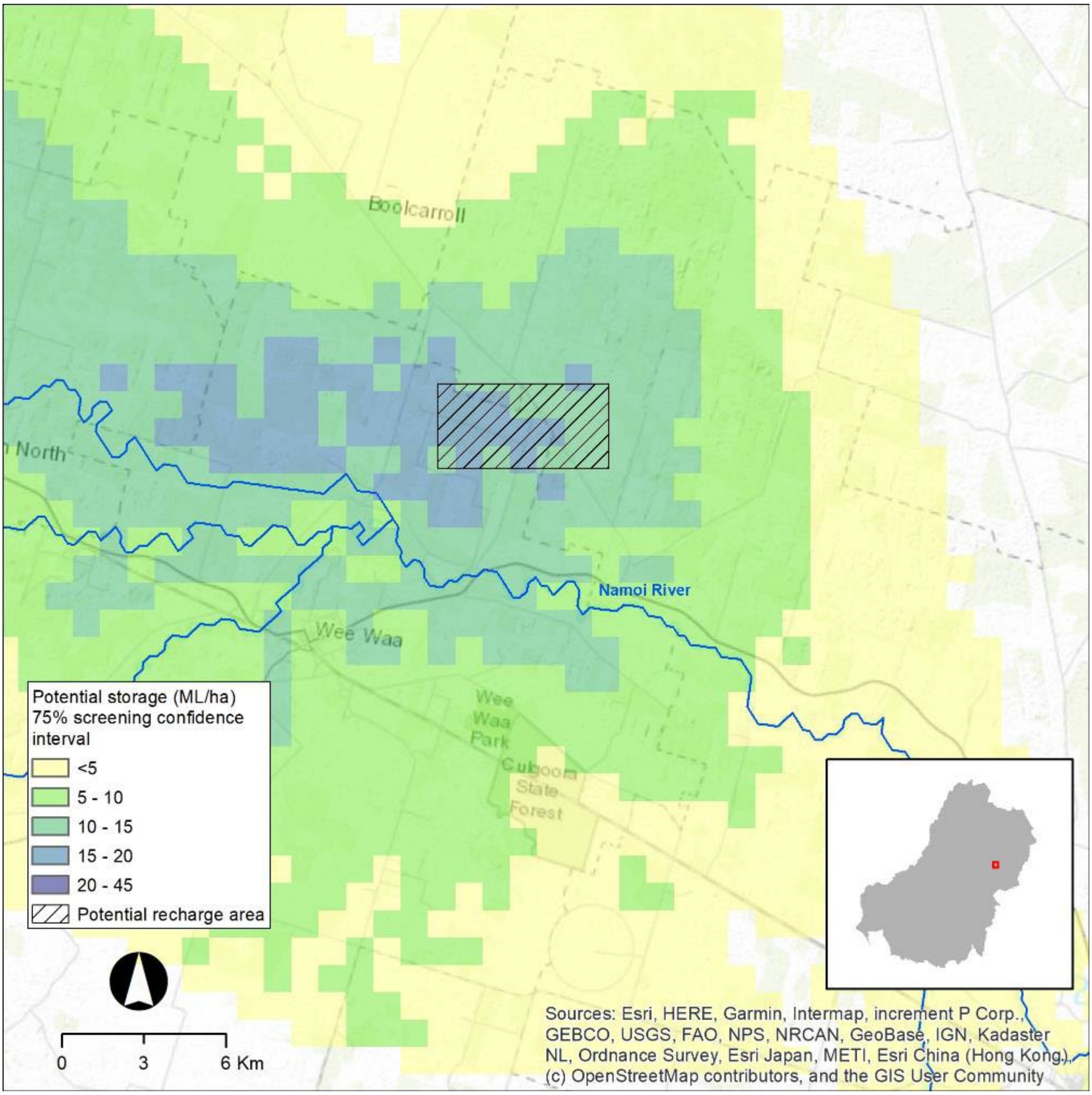

Figure 25 Lower Namoi conceptual infiltration basin site.

Across all simulations, the total cumulative volume recharged over the life of the scheme was between 200-250 GL (but never exceeding 36 GL in aquifer storage at one time), and the total cumulative volume recovered was between 87-104 GL. This was due to annual storage losses of 10-20% of the stored volume (annual recovery efficiency of 80-90%). Median present values and levelised costs of recharged and recovered water for the conceptual Lower Namoi MAR site are given in Figure 26 and the full range of disaggregated cost estimates are given in Table 8.

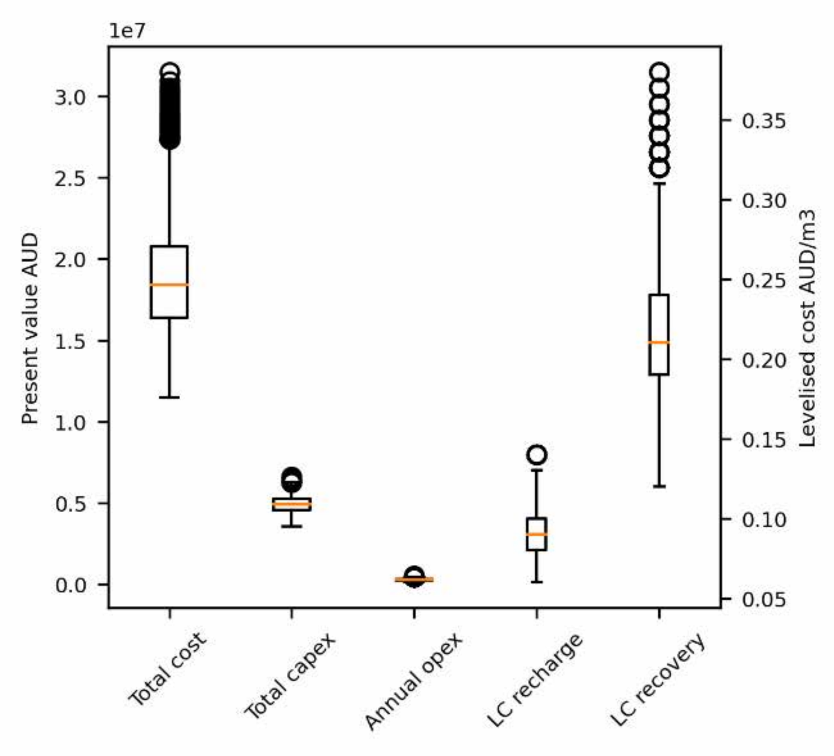

Figure 26 Present values and levelised costs for the Lower Namoi conceptual MAR site.

Table 8 Summary of disaggregated cost estimates for the Lower Namoi conceptual MAR site.

		Median		Min		Max
Capacity ML/y		6800		6400		7199
Recovery Efficiency		0.85		0.8		0.9
Infiltration rate m/d		0.16		0.15		0.17
Total capex AUD	$	4,920,135	$	3,623,034	$	6,585,171
Total opex AUD	$	13,214,132	$	6,808,416	$	25,214,922
Basin construction AUD	$	3,074,791	$	2,148,843	$	4,375,162
Pumps & pipes AUD	$	1,518,173	$	911,889	$	2,224,246
Observation bores AUD	$	171,150	$	120,000	$	209,650
Feasibility studies AUD	$	366,500	$	239,017	$	493,977
Maintenance AUD	$	2,360,442	$	1,314,572	$	4,334,774
Pumping cost AUD	$	600,008	$	293,859	$	1,207,902
Opportunity cost water AUD	$	9,399,886	$	4,376,597	$	19,001,636
Monitoring AUD	$	840,280	$	464,236	$	1,573,374
Annual opex AUD	$	269,676	$	138,947	$	514,590
LC recharge AUD/m3	$	0.09	$	0.06	$	0.14
LC recovery AUD/m3	$	0.21	$	0.12	$	0.38
Total volume recharged ML	200520		167438		251965	
Total volume recovered ML	86783		70016		103904	

The total median estimated cost of the project over the 50-year horizon is around $18 million. Total median capital costs including basin construction, pumps and pipes, observation bore drilling and feasibility studies are about $5 million. Total median operating costs are about $13 million and around $250k annually. Median levelised cost (LC) of recharge is $0.09/m^3 and LC of recovery is $0.21/m^3 ranging around $0.12-0.30/m^3 (Figure 26). These estimates are within the range expected based on costings of similar infiltration sites (Gonzalez et al., 2024; Ross, 2022; Ross and Hasnain, 2018). Based on indicative hydro-economic modelling, LC of recovery for a well injection scheme of similar capacity (e.g. >4 GL/y) could be expected to range between $0.30-$0.80/m3 depending on storage efficiency and recharge rate (Gonzalez et al., 2024). These costs are generally lower than alternative water supply options, e.g. recycled water for supplementing reservoirs and groundwater costs around $2.00/m^3, while stormwater harvesting ranges from $0.60–2.50/m^3 (WSAA, 2020). Desalination has higher costs, with capital costs between $665–3900/m^3 and operating costs of $0.52–0.88/m^3 (Pearson et al., 2021). Dam storage costs across 98 sites ranged from $0.43–2.21/m^3, with a median of $1.07/m^3, while costs accounting for evaporation ranged from $0.72–2.78/m^3 (Petheram and McMahon, 2019).

Analysis of disaggregated capital and operating costs revealed that LC of recovery were driven by opportunity costs of water (50%, total around $9 million over 50 years) followed by basin construction ($3 million) and maintenance (around $2 million) (Figure 27). For MAR in the Lower Namoi, the opportunity cost of water is not necessarily the actual cost of obtaining volumes for recharge through purchase of temporary allocations. Instead, it is assumed that water sourced for MAR has an associated opportunity cost due to the scarcity of the resource (Gonzalez et al., 2024). Annual recharge volumes of up to 7200 ML as modelled here would rely on the availability of source water which for context, is about 3% of the 241,000 ML of available water in the Lower Namoi regulated river water source in 2024-25 (NSW Government, 2024c). Recharge volumes of 6800-7200 ML/y comprised up to 5% of flows at the lower end of the flow rates triggered for recharge.

Cost estimates for this conceptual scheme are based on coarse data and assumptions and should be considered as indicative. Local investigations would be required to refine the hydrogeological characterisation, hydrologically model recharge, storage and recovery, and conceptualise the scheme in more detail to more accurately and precisely estimate technical feasibility and economic viability as part of a staged, risk-based assessment process (NRMMC-EPHC-NHMRC, 2009).

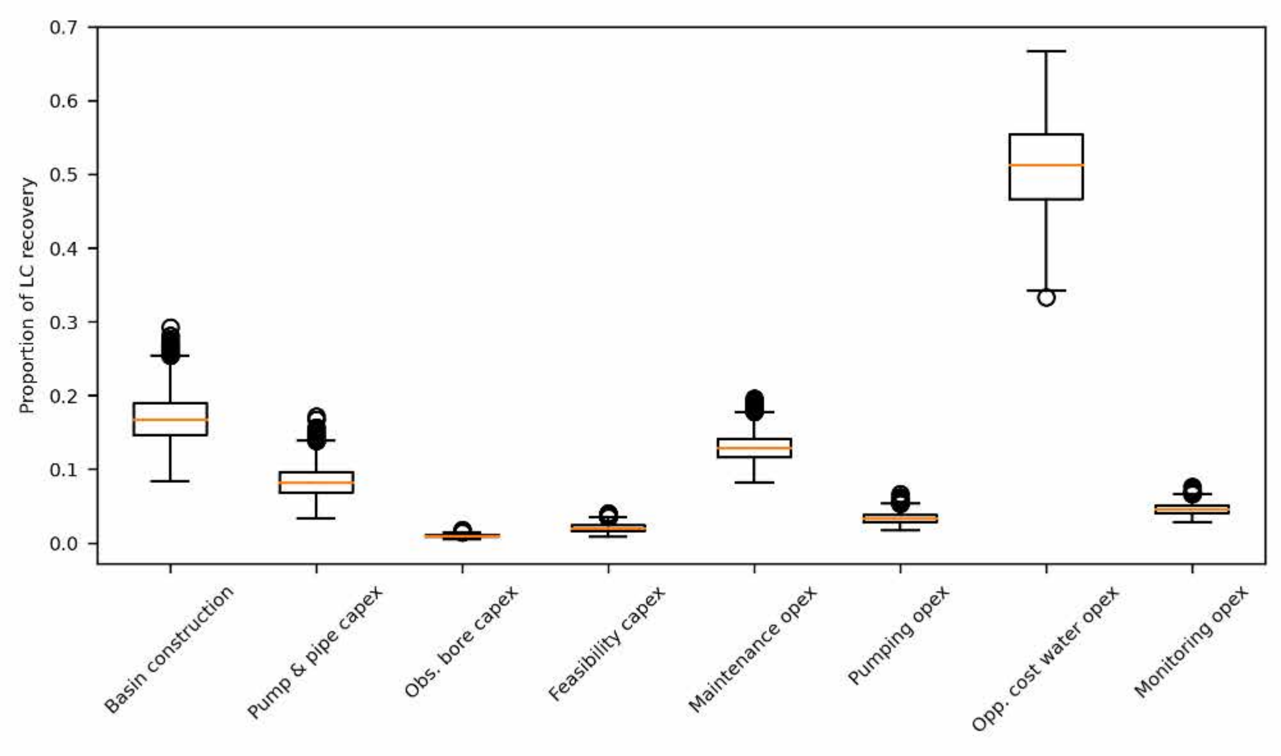

Figure 27 Disaggregated capital and operating costs for the Lower Namoi conceptual MAR site as a proportion of levelised cost of recovery.

In water market environments, understanding market dynamics is crucial for developing operating rules and reducing uncertainty in the economic viability of MAR. Factors such as water availability, climate patterns, weather forecasts, commodity price fluctuations, and demand patterns influence market behaviour (Grafton et al., 2011; Seidl et al., 2020). This knowledge helps inform operational rules and plans for optimal recharge and recovery timing, ensuring cost efficiency and benefits. In systems like Australia's Murray-Darling Basin, operators must decide on strategies for sourcing, storing, and distributing water through MAR. Options include using held entitlements and allocations, buying additional permanent water rights and trading temporary rights, relying on temporary trades at market spot prices, or using futures market strategies (Gonzalez et al., 2024).

A global sensitivity analysis revealed the most sensitive parameter affecting the variability in LC of recovery was the social discount rate followed by the opportunity cost of water, the flow rate used to trigger recharge and recovery, and the recovery (or storage) efficiency (Figure 28). This assessment used a social discount rate range of 3-7%. Using a lower range of social discount rates in projects with long horizons benefits is justified by the need to account for intergenerational equity and the long-term impacts (Harrison, 2010). Lower discount rates give more weight to future costs and benefits. This approach is particularly relevant for projects related to environmental sustainability, infrastructure, and climate change mitigation, where benefits accrue over extended periods. Lower discount rates can better reflect the ethical considerations of intergenerational equity and the long-term nature of certain public investments. The commonly adopted 7% discount rate may no longer be appropriate given current economic conditions and the growing disparity between generations (Turan and Gurluk, 2023).

The opportunity cost of water was highly sensitive as it formed a large proportion of LC of recovery (about 50%) and this variable interacted with the discount rate range tested as future costs were subject to adjustment according to the net-preset-value function (Figure 28). The flow rate trigger for recharge and recovery that was determined from the relationship between flows and allocation prices was also sensitive. Advice and agreement on the most appropriate discount rate to assume in the context of the project which may be set out in specific funding application requirements, would reduce uncertainty in the assessment. Narrowing the range of opportunity costs of water, and related to this, the operational rules for which part of the hydrograph to target for optimal performance, would also be effective in reducing uncertainty. Finally, improving the understanding of the recovery or storage efficiency of the system, both from a technical and regulatory perspective, would further reduce cost estimation variance.

An infiltration-based MAR scheme of the scale conceptualised here could be structured to deliver multiple benefits to users and the environment due to the diversity of agricultural land uses, presence of regional population centres, and groundwater dependent ecosystems in the southern part of the region. The Lower Namoi resource unit area includes 6,100 km² of dryland agriculture, 1,100 km² of irrigation, and 0.8 km² of horticulture (ABARES, 2024b). In the 2020-21 Australian Agricultural Census for the Narrabri LGA, the key commodities were wheat ($169M), cotton ($147M), and chickpeas ($39M). Cotton, chickpeas, and canola had the highest gross values per hectare ($7,743, $1,370, and $1,306, respectively) (ABARES, 2024a).

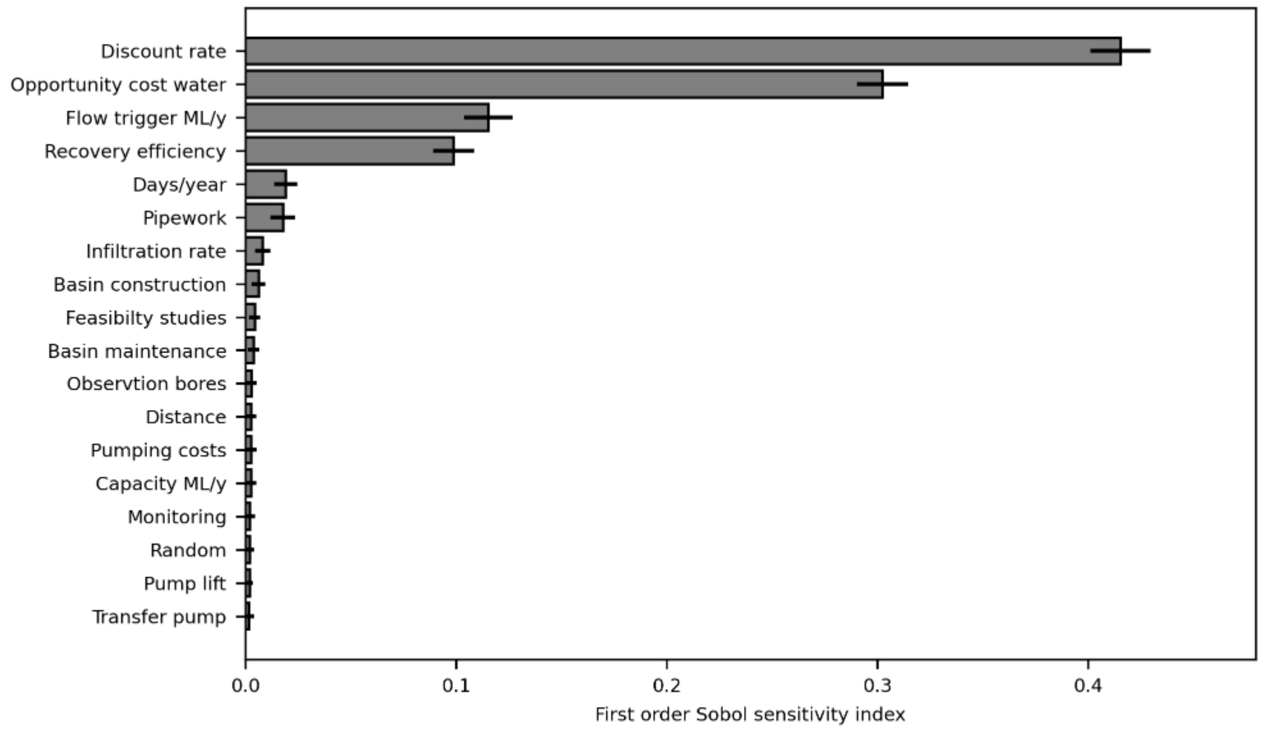

Figure 28 First order global sensitivities of variables used for estimating levelised cost of recovery for the Lower Namoi conceptual MAR site.

The case for increasing water security in the Lower Namoi region is well supported. Between 2017-2020, the region experienced severe drought conditions, with general security licence allocations reduced to zero for two consecutive years and high security allocations cut to 75% during a Stage 4 Critical drought (NSW DPIE, 2021). Groundwater extraction exceeded the long-term average annual extraction limit (LTAAEL) of 92.6 GL for three consecutive years (2017-2020), with the maximum annual extraction during 2016-2023 reaching 124% of the LTAAEL, highlighting a strong reliance on groundwater during dry periods (NSW Government, 2024b). Groundwater levels in the Lower Namoi have declined at an average rate of 0.19 meters per year from 1971-2021 (Fu et al., 2022). Despite some recovery post-Millennium Drought (Fu et al., 2023), groundwater resilience and sustainability issues in the region were ranked among the highest in the alluvial aquifer of the Murray-Darling Basin (Rojas et al., 2023a).

Possible frameworks for implementation of MAR in the Basin context have been proposed that encompass four main objectives (Page et al., 2022):

1. Supplement existing entitlement holders' supply
2. Improve productive capacity, water quality or environmental outcomes
3. Support individual or collective use or trade
4. Actively enable conjunctive use of surface and groundwater

The choice of frameworks depends on the desired outcomes, objectives, and context. These frameworks are not mutually exclusive and can be combined to improve outcomes for both users and the environment. They serve as tools for guiding discussions among resource managers and stakeholders on suitable arrangements. A key next step is to test these frameworks within various state policies and regulations to assess any necessary adjustments for their implementation. For example, using MAR to mitigate the risks of general security surface water allocation reductions and carry-over restrictions during dry periods or the use of supplementary water entitlements for recharge during high flow events (Merritt et al., 2021).

Given the level of consumptive use in the Lower Namoi region and the gross value of agricultural production with associated socio-economic implications, MAR that supports individual or collective use or trade of water banked in the aquifer is logical. Outcomes could also include a level of improvement to the resource condition and environmental outcomes e.g. reducing demand for surface water during low-flow periods and improving outcomes for associated GDEs. In the context of the frameworks above this would be a combination of 2 and 3.

In the Lower Namoi case, the scheme could use surface water during periods of water availability or low cost to recharge groundwater that is stored in a designated consumptive pool. On a small scale, individual irrigators or service providers could recharge groundwater on behalf of local beneficiaries, such as farmers, at a cost for future extraction or trade. The system could be scaled up to allow the banked water to be sold to other users, with the aquifer serving as a delivery mechanism for extraction at different locations. Because recharge volumes are tied to a specific consumptive pool, users would receive a secure, tradeable entitlement for the stored water. This model could attract private investment but could also be part of a public scheme. Economic benefits may include the development of markets for recharge entitlements and infrastructure investment. Cost recovery could involve tradeable water allocations to cover recharge, storage, and delivery costs. A percentage of banked water could also be reserved for environmental purposes by attributing to a non-consumptive water at local or resource scale. Regulatory conditions, ideally based on aquifer hydraulic properties, would determine the number of licenced extraction points that could access banked volumes and participate in a multi-user scheme. If restricted to the immediate zone of recharge, the number of potential users would be limited to the dozen or so groundwater licences in the area totalling around 15 GL/y (Merritt et al., 2021).

6 Summary and conclusions

6.1 Groundwater use

Groundwater in the Murray-Darling Basin is distributed across different types of aquifers including unconsolidated sedimentary plain and alluvial aquifers, tertiary limestone aquifers and aquifers in shallow and deep formations of the Great Artesian Basin. Out of these, the alluvial aquifers are the most developed for groundwater use for irrigation and other purposes. Recent groundwater reporting (2012-2019) shows that close to 75% of groundwater use in the MDB is concentrated in eight alluvial aquifer systems that are managed as 22 different resource units. This study implemented a consistent methodology to develop improved understanding of the status and trends of groundwater resources at the basin scale focusing on these 22 resource units to help better inform groundwater management.

Analysis of recent groundwater extraction data for the period 2012-2019, when there is high confidence in metered data, reveals that surface water and groundwater use have a complementary relationship across the Basin. Groundwater use varied between 8% and 18% of total water use from 2012 to 2019 and was found to be inversely proportional to surface water availability. That is, groundwater use increased when surface water availability and use decreased. This pattern of groundwater could be caused by several reasons. Often a short-term increase in groundwater use is caused by increased groundwater irrigation to offset lower seasonal rainfall (Doble et al., 2023; Walker, 2023). Such increases in groundwater use have been observed during the 2012-2019 period. When surface water and groundwater allocations are available, surface water sources are generally preferred for economic reasons. This complementary pattern of existing water use between surface water and groundwater sources in the Basin is favourable for management solutions like managed aquifer recharge.

6.2 Groundwater level trends and causal analysis

We conducted a robust analysis of groundwater level trends in the alluvial aquifers using observed groundwater level data from 910 observation bores during the last 50-year period, between 1971 and 2021. Trends were analysed for minimum, mean and maximum DTW. Trend analysis showed statistically significant increasing DTW at an average rate of 0.11 m/y across the alluvial aquifer systems during this period and a range of 0.03 m/y to 0.19 m/y. Spatial and temporal patterns in groundwater level trends were investigated using two clustering analysis techniques. The analysis identified six distinct clusters for trends in groundwater level data across the 910 bores. These clusters differed in the way groundwater levels behaved before during and after the Millennium Drought (between 1997 and 2009). About 50% of bores belonged to one cluster that showed consistent and continuous increasing DTW. The second biggest cluster, with 26% of bores, showed stable groundwater levels before 1996 and then a decreasing trend in groundwater levels during and after the Millennium Drought period.

We used a machine learning model to investigate causal influence of climatic and other covariates like rainfall, evapotranspiration, flood events and groundwater extraction on observed groundwater level trends. A single ML model based on feed-forward neural networks was trained and validated using this data set to predict average monthly groundwater levels within each resource unit. The model was able to satisfactorily predict both seasonal and long-term trends in groundwater levels.

Explainable AI techniques were used together with the trained and validated ML model to investigate the sensitivity of groundwater level predictions to different covariates. The analyses provide interesting insights into causal relationships between groundwater levels and relevant covariates and how these relationships evolved over time. This approach was used for causal attribution analysis of 14 resource units over a period of 32 years between 1988 and 2020. Limitation in data availability for some important covariates was overcome by using 'proxy' data. For example, number of groundwater extraction bores drilled over the years was used as proxy data for representing change in groundwater extractions over the years.

The sensitivity analysis using explainable AI techniques informed that groundwater development (the number of bores) was the most important overall factor influencing groundwater level predictions. The analyses could be significantly improved using groundwater extraction data, which unfortunately is not readily available across the MDB and for long periods. Although the number of groundwater bores here is monotonically increasing, actual extractions would rise and fall year to year depending on climate and surface water availability. Spatial and temporal characteristics of groundwater level changes across multiple resource units were represented in the ML model using the name of the resource unit and year. These features also consistently came across as sensitive factors influencing model predictions. Practically the former factor (resource unit names) represents the variability in hydrogeological characteristics across different aquifer units in the Basin. Future modelling efforts could unpack these further by including relevant biophysical variables in the ML modelling.

Flood extent was also identified as an important factor that influences groundwater level predictions. In fact, bore hydrograph response was more sensitive to flood extent than rainfall. This is indicative of groundwater levels responding much more to flood events in the basin than to rainfall events. Direct recharge from rainfall is a relatively smaller component of recharge for alluvial aquifers. This result highlights the importance of localised groundwater recharge during flood events and its role in 'bouncing back' groundwater storage after major flood events. This effect of groundwater storage responding to 2011-12 flood events can be observed for most clusters (Figure 6).

The sensitivity of groundwater levels to flood events also highlights the opportunity of using high flow events for managed aquifer recharge using schemes like riverbank infiltration, especially where groundwater storage potential exists near flood plains.

6.3 Managed Aquifer Recharge

Potential aquifer storage volumes for unconfined systems in the Murray-Darling Basin varied significantly across groundwater resource units and confidence intervals. At a 75% confidence interval, about 6500 GL of storage potential was identified within 5 km of major rivers. However, this capacity was spread over large areas, making it unrealistic to fully realize this potential through managed aquifer recharge (MAR). Targeting areas with greater long-term decline and locally available storage space could efficiently enhance water security. The Lower Namoi, Goulburn-Murray, and Mid-Murrumbidgee had the highest average potential recharge heights, suggesting greater potential for MAR at site scales. The sensitivity analysis showed that depth to groundwater was the most sensitive criterion, followed by salinity.

Approximately 9700 GL of potential storage was identified across confined resource units, with 4700 GL near major rivers for recharge. However, the storage was spread over a large area, limiting full utilization. The Lower Namoi Alluvium showed the highest potential storage (3300 GL) with high robustness, followed by the Lower Murrumbidgee Deep Alluvium (3280 GL) but with lower robustness. The Mid-Murrumbidgee Alluvium had a highly robust estimate (330 GL) mostly within 5 km of rivers. Hydrogeological factors, such as aquifer thickness, conductivity, transmissivity, and salinity, influenced injection and storage potential. Assessment of MAR feasibility was conducted at Basin scale and results should be considered indicative of regional potential. Local scale investigations are required to validate potential and assess site viability according to Australian risk-based guidelines for MAR project evaluation including technical and socio-economic factors.

An infiltration basin site was conceptualized for the Lower Namoi area, targeting the upper, unconfined aquifer of the Narrabri Formation. The area had high screening confidence and recharge potential, with a total aquifer capacity locally of 32,000-36,000 ML. To achieve this, 8-10 basins of 6.25 ha each would be required. The project's median cost over 50 years was estimated at \$18 million, with capital costs of \$5 million and operating costs of \$13 million. The median levelised cost of recovered water was 0.09/m^3 (ranging \$0.12-30/m^3). Costs compare favourably against alternative options e.g. recycled water, stormwater harvesting, desalination and unit costs of dam storage. The most sensitive parameter affecting the variability in the levelised cost (LC) of recovery was the social discount rate, followed by the opportunity cost of water, operational rules based on river flow rates and trade prices, and aquifer storage efficiency. Reducing uncertainty in the assessment could be achieved by conducting investigations to narrow the range of these variables.

6.4 Limitations and knowledge gaps

We highlight the basin-scale nature of the study and its intent to provide an understanding of trends and other characteristics across the basin. The study focussed on groundwater level trends, resilience and sustainability characteristics of alluvial aquifers across the MDB considering resource unit as the basic spatial unit for the analyses. Thus, while the trend, resilience, stress and sustainability characteristics reported in this study reflect average characteristics across the resource unit, it can obscure significant local variations. Interpretation of the results for individual resource units and smaller areas need to consider and account for this. Aquifer water management by states and regulatory agencies often consider management responses that are localized, considering unique aquifer characteristics and the specific risk factors present in different subregions. Effective water management at such local scale requires the identification of local risk receptors and specific trigger thresholds. Interpretation of the results presented in this study in the context of local management of groundwater resource units is not warranted. Aquifers within the Murray-Darling Basin exhibit substantial variability in terms of hydrological properties, recharge rates, and connectivity with surface water resource. The regional scale of analysis in this study may overlook these localized features, leading to potential gaps in understanding critical local stressors and sustainability triggers. Assessments at resource unit level may not provide sufficient granularity to inform local management decisions, which can result in generalized strategies that fail to address specific needs. Nevertheless, analysis at the aggregated level provides a useful indication of the broad trends and characteristics in groundwater.

We focused on analysing groundwater levels, usage, and related data from the past 50 years. The estimates of system characteristics such as resilience, stress, and sustainability are most applicable to this historical period. Due to the potential impacts of climate change on water demand and availability, the findings may not fully apply to future conditions but can be extrapolated to provide some indication. The trend analysis relied on annually aggregated observation data to include sufficient data to summarise long-term patterns at the resource unit level. Exploration of intra-annual trends, including correlation with seasonal climate and extraction patterns, requires different data quality criteria.

Predictive analyses for plausible climate change and water resource development scenarios would require comprehensive modelling studies. Similarly, detailed evaluation of conjunctive surface water-groundwater management and adaptation measures would necessitate developing scenarios informed by biophysical and socioeconomic factors and supported by detailed modelling. The simple ML model developed for sensitivity and causal attribution analysis in this study was a point-scale, spatially averaged model for resource units and considered causal factors for which data was readily available. Groundwater use data was available for a relatively shorter period (2006 onwards) for most SDL resource units in our analysis. Regulatory changes implemented through water sharing plans can affect groundwater use and lead to changes in groundwater levels. Such causal relationships would be better articulated in data-driven models when longer term groundwater use data becomes available.

A broad range of factors could have causal relationships with groundwater level changes. For example, changes in surface water – groundwater interactions caused by changes in the flow regime could have a direct influence on river recharge and groundwater levels in many areas. More detailed investigations considering spatial and temporal variabilities are required to infer causal relationships in these areas. The inferences reported in this study are drawn based on statistical correlations and covariances among variables representing climatic and other processes. The model's sensitivity analysis regarding factors such as rainfall and flood recharge is limited by the spatial and temporal scale of the training and validation data and the limited availability of groundwater extraction data. Detailed analyses of processes like recharge and its spatial-temporal variations would require physics-based numerical models.

The assessment of MAR potential in this study was a desktop exercise, providing a basin-scale overview of storage potential and MAR probabilities across groundwater resource units. The development of MAR schemes in specific areas requires detailed, local investigations using a risk-based approach. This begins with entry-level viability assessments and progresses to field investigations, water quality and residual risk assessments before moving to pilot projects and full-scale implementation and need to consider a range of technical and socioeconomic factors. Soil and hydrogeological parameters affecting actual recharge rates, storativity and storage efficiency and recoverability are the most critical factors for assessing MAR scheme performance from a technical perspective. This is evidenced in the sensitivity of results to input data and assumptions when comparing this study with other assessments of MAR potential. This study did not assess policy or regulatory conditions required for accommodating MAR in resource planning. Potential frameworks for implementation proposed in the literature are discussed and illustrated with a case study of a conceptual site in this study but it is recognised that there are gaps in current policy frameworks that need to be addressed for MAR to become part of the standard water management tools for practitioners to implement.

Future studies should incorporate sub-resource unit or aquifer-specific analyses to better capture local variations and facilitate the development of targeted management response using risk-based approaches. Evaluation of stress, resilience and sustainability for future scenarios of climate change warrants studies to develop improved understanding of groundwater demand corresponding to such scenarios and risk-based modelling approaches to undertake predictive assessments. Studies should also focus on identifying the data needs and monitoring network investments targeting hotspots of resilience and sustainability issues. Research should focus on adaptive management frameworks that can progressively and iteratively improve groundwater management.

6.5 Conclusions

Groundwater has historically been a relatively small component of overall water use in the Murray-Darling Basin. Increased groundwater use is observed in the basin in periods of reduced surface water availability. This pattern of use, combined with significant potential for enhanced groundwater storage through managed aquifer recharge, enables potential development of conjunctive surface water and groundwater management strategies for combating impacts of climate change on water security in the basin.

The study conducted in-depth analyses of groundwater level trends and the resilience, stress and sustainability of the alluvial aquifers. Findings from the study showed that prioritisation of aquifer management must be underpinned by a comprehensive understanding of observed trends, aquifer storage, rate of depletion and replenishment, stress levels and ecosystem functions of the aquifer.

The study also revealed the potential of novel data-driven and machine learning based approaches to develop simple models and gain insights about aquifer responses to climatic and other drivers. The ML-based models in general provide new approaches for modelling groundwater systems using different types of conventional and unconventional data types. Improved models and better insights could be achieved in future with investments in better data collection. Explainable AI methods have significant potential to help make inferences about complex process interactions (e.g. flood recharge) based on statistical relationships between relevant measured variables.

Potential aquifer storage volumes in the Murray-Darling Basin vary significantly across different groundwater resource units. In unconfined aquifers, approximately 6500 GL of storage potential was identified within 5 km of major rivers, though the large area covered makes full utilization through managed aquifer recharge (MAR) unrealistic. Focused targeting of areas with greater long-term decline and locally available storage could enhance water security, with the Lower Namoi, Goulburn-Murray, and Mid-Murrumbidgee showing the highest recharge potential. In confined aquifers, about 4700 GL of storage potential was identified within 5 km of rivers, but again, the extensive area (>20,000 km^2) limits full MAR utilization. The Lower Namoi Alluvium had the highest storage potential (3300 GL) with high robustness, while the Lower Murrumbidgee Alluvium had a similar volume (3280 GL) but lower robustness. Groundwater levels, salinity aquifer thickness and hydraulic conductivity were sensitive variables that affected recharge and storage potential.

An infiltration basin site was conceptualized for the Lower Namoi area, targeting the upper, unconfined aquifer of the Narrabri Formation, with a local capacity of 32,000-36,000 ML. To achieve this, 8-10 basins of 6.25 ha each would be required. The project's median cost over 50 years is $18 million, with capital costs of $5 million and operating costs of $13 million. The median levelised cost of recovered water is $0.09/m^3. Costs compare favourably against alternative water supply options. The social discount rate is the most sensitive parameter affecting cost variability, followed by the opportunity cost of water and operational rules. In this scenario, surface water could be used during periods of availability or low cost to recharge groundwater with volumes stored in a separate consumptive pool. Individual irrigators or service providers could recharge groundwater for local beneficiaries at a cost for future extraction or trade. The system could scale up, allowing banked water to be sold to other users, with the aquifer serving as a delivery mechanism. Users would receive a secure, tradeable entitlement for stored water. This model could attract private investment or be part of a public scheme, with economic benefits including markets for recharge entitlements and infrastructure investment.

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Appendix

Table A.1 Metered groundwater annual actual take reported in (MDBA, 2020b). BDL: Baseline Diversion Limit and SDL: Sustainable Diversion Limit as defined in Schedule 4 of the Basin Plan.

Code	Resource unit	Baseline Diversion Limit (GL/y)	Sustainable Diversion Limit (GL/y)	Actual annual take (GL/y)									
				2012-13	2013-14	2014-15	2015-16	2016-17	2017-18	2018-19	Max	Min	Avg
GS64a	Upper Condamine Alluvium (Central Condamine Alluvium)	81.4	46.0	32.3	55.1	41.1	42.0	48.0	50.5	57.7	57.7	32.3	46.7
GS64b	Upper Condamine Alluvium (Tributaries)	45.5	40.5	33.9	32.9	30.6	32.6	32.8	33.7	35.6	35.6	30.6	33.2
GS54	Queensland Border Rivers Alluvium	14.0	14.0	8.85	11.3	11.8	12.8	10.8	14.0	14.4	14.4	8.85	12.0
GS32	NSW Border Rivers Alluvium	8.40	8.40	2.84	5.59	5.41	3.98	3.38	6.37	8.98	8.98	2.84	5.22
GS33	NSW Border Rivers Tributary Alluvium	0.41	0.41	0.16	0.17	0.17	0.17	0.17	0.17	0.16	0.17	0.16	0.17
GS27a	Lower Murray Shallow Alluvium	81.9	81.9	2.26	4.10	5.90	5.40	5.97	8.39	11.9	11.9	2.26	6.27
GS27b	Lower Murray Deep Alluvium	88.9	88.9	56.2	45.2	67.5	85.5	36.7	78.9	110.7	110.7	36.7	68.7
GS46	Upper Murray Alluvium	14.1	14.1	12.3	10.7	9.87	11.2	8.66	14.0	17.8	17.8	8.66	12.1
GS28a	Lower Murrumbidgee Shallow Alluvium	26.9	26.9	5.25	6.47	7.15	6.21	6.47	8.17	8.32	8.32	5.25	6.86
GS28b	Lower Murrumbidgee Deep Alluvium	273.6	273.6	179.6	230.3	300.3	268.5	151.5	323.1	377.9	377.9	151.5	261.6
GS31	Mid-Murrumbidgee Alluvium	53.5	53.5	35.5	36.1	40.1	32.4	30.3	42.7	55.6	55.6	30.3	39.0
GS25	Lower Lachlan Alluvium	123.4	117.0	87.2	104.9	120.5	97.5	91.4	127.2	131.8	131.8	87.2	108.6
GS44	Upper Lachlan Alluvium	94.2	94.2	44.2	42.3	57.2	55.7	37.9	75.4	89.4	89.4	37.9	57.4
GS26	Lower Macquarie Alluvium	70.7	70.7	26.9	29.7	32.0	35.2	18.6	40.8	47.4	47.4	18.6	32.9
GS45	Upper Macquarie Alluvium	17.9	17.9	13.7	14.1	15.3	15.9	13.5	21.0	23.0	23.0	13.5	16.6
GS29	Lower Namoi Alluvium	88.3	88.3	61.1	104.3	105.1	93.0	51.2	95.3	116.2	116.2	51.2	89.5
GS47	Upper Namoi Alluvium	123.4	123.4	90.1	113.6	102.4	93.7	70.1	105.7	112.2	113.6	70.1	98.3
GS48	Upper Namoi Tributary Alluvium	1.77	1.77	0.55	0.38	0.21	0.23	0.18	0.28	0.19	0.55	0.18	0.29
GS24	Lower Gwydir Alluvium	33.0	33.0	29.3	46.4	43.3	35.5	23.8	35.5	37.5	46.4	23.8	35.9
GS43	Upper Gwydir Alluvium	0.72	0.72	0.07	0.07	0.07	0.07	0.12	0.07	0.07	0.12	0.07	0.08
GS8a	Goulburn-Murray: Shepparton Irrigation Region	244.1	244.1	41.3	35.5	43.7	79.5	54.2	43.4	96.3	96.3	35.5	56.3
GS8c	Goulburn-Murray: Sedimentary Plain	203.5	223.0	101.2	98.4	136.5	141.5	138.9	120.9	149.1	149.1	98.4	126.6

Table A.2 Groundwater resource units and corresponding unconfined and confined aquifer systems (MDBA, 2020a; NSW Government, 2024a).

State	Code	Resource unit	Unconfined aquifer system	Confined aquifer system
VIC	GS8a	Goulburn-Murray: Shepparton Irrigation Region (GS8a)	Shepparton Formation 0-25 m	
VIC	GS8c	Goulburn-Murray: Sedimentary Plain (GS8c)	Shepparton Formation 0-25 m	Calivil Formation 25-80 m, Renmark Group 70-250 m
NSW	GS24	Lower Gwydir Alluvium (GS24)	Narrabri Formation 0-30 m	Gunnedah Formation 30-90 m
NSW	GS25	Lower Lachlan Alluvium (GS25)	Shepparton, Calivil Formation 0-70 m	Renmark Formation 50-400 m
NSW	GS26	Lower Macquarie Alluvium (GS26)	Shallow alluvium 0-60 m	Deep alluvium 60-120 m
NSW	GS27a	Lower Murray Shallow Alluvium (GS27a)	Shepparton Formation 0-70 m	
NSW	GS27b	Lower Murray Deep Alluvium (GS27b)		Calivil Formation & Renmark Group 70-350 m
NSW	GS28a	Lower Murrumbidgee Shallow Alluvium (GS28a)	Shepparton Formation 0-40 m	
NSW	GS28b	Lower Murrumbidgee Deep Alluvium (GS28b)		Calivil Formation & Renmark Group 40-400 m
NSW	GS29	Lower Namoi Alluvium (GS29)	Narrabri Formation 0-40 m	Gunnedah Formation 40-120 m
NSW	GS31	Mid–Murrumbidgee Alluvium (GS31)	Cowra Formation 0-40 m	Lachlan Formation 40-90 m
NSW	GS32	NSW Border Rivers Alluvium (GS32)	Shallow alluvium 0-30 m	Deep alluvium 30-170 m
NSW	GS33	NSW Border Rivers Tributary Alluvium (GS33)	Shallow alluvium 0-40 m	
NSW	GS43	Upper Gwydir Alluvium (GS43)	Shallow alluvium 0-30 m	
NSW	GS44	Upper Lachlan Alluvium (GS44)	Cowra Formation 0-60 m	Lachlan Formation 60-150 m
NSW	GS45	Upper Macquarie Alluvium (GS45)	Shallow alluvium 0-25 m	Deep alluvium 25-60 m
NSW	GS46	Upper Murray Alluvium (GS46)	Shepparton Formation 0-40 m	Lachlan Formation 40-100 m
NSW	GS47	Upper Namoi Alluvium (GS47)	Narrabri Formation 0-40 m	Gunnedah Formation 40-170 m
NSW	GS48	Upper Namoi Tributary Alluvium (GS48)	Shallow alluvium 0-20 m	
QLD	GS54	Queensland Border Rivers Alluvium (GS54)	Shallow alluvium 0-30 m	Deep alluvium 30-100 m
QLD	GS64a	Upper Condamine Alluvium (Central Condamine Alluvium) (GS64a)	Shallow alluvium 0-140 m	
QLD	GS64b	Upper Condamine Alluvium (Tributaries) (GS64b)	Shallow alluvium 0-140 m	

Table A.3 Spatial screening criteria and rationale for assessment of MAR potential in unconfined aquifer conditions.

Criterion	Method	Threshold range	Rationale
Aquifer presence	Lateral extent of resource units with unconfined aquifers (MDBA, 2020b)	Presence/absence	Resource units are management boundaries that follow regional hydrogeology but can comprise multiple aquifers (Table)
Slope	Percent rise calculated from 9 second DEM (Hutchinson et al., 2008)	<5% - <10%	Slope is a predictor of permeability; high slope produces higher runoff
Regolith thickness	Median estimates of regolith thickness (Wilford, 2015)	>8 m - > 12 m	Represents the thickness of unconsolidated material above bedrock, used as proxy for alluvial aquifer thickness, thin aquifers have limited additional storage potential, minimum of 10 m is assumed ± 20%
Soil vertical hydraulic conductivity (Ks)	Depth weighted harmonic mean of estimated Ks from pedological transfer function on gridded soil properties (Crosbie et al., 2025; Grundy et al., 2015)	>0.08 - >0.11 m/d	Assumes a minimum recharge volume of 1 GL across 10 ha over 90-120 days of recharge
Groundwater salinity	Interpolated 75th percentile bore salinities for each resource unit (BOM, 2023)	<3000 mg/L	High groundwater salinity limits recovery efficiency (Clark et al., 2015); upper limit of <3000 mg/L for irrigation of a range of moderately to highly salt tolerant crops (ANZECC-ARMCANZ, 2000), interpolation standard error represents uncertainty
Groundwater level decline	Long term level trend magnitudes interpolated for each unconfined resource unit (BOM, 2023)	>0 m/y	Infiltration up to the height of long-term level decline, interpolation standard error represents uncertainty

Table A.4 Spatial screening criteria and rationale for assessment of MAR potential in confined aquifer conditions.

Criterion	Method	Threshold range	Rationale
Aquifer presence	Lateral extent of resource units with confined aquifers (MDBA, 2020b)	Presence/absence	Resource units are management boundaries that follow regional hydrogeology but can comprise multiple aquifers
Groundwater salinity	Interpolated 75th percentile bore salinities for each resource unit (BOM, 2023)	<3000 mg/L	High groundwater salinity limits recovery efficiency (Clark et al., 2015); upper limit of <3000 mg/L for irrigation of a range of moderately to highly salt tolerant crops (ANZECC-ARMCANZ, 2000), interpolation standard error represents uncertainty
Groundwater level decline	Long term groundwater level trend magnitudes interpolated for each resource unit (BOM, 2023)	>5 m/y	MAR targeting areas of significant long-term head declines, interpolation standard error represents uncertainty

Table A.5 Summary of groundwater level trend magnitudes (m/y) for aquifers across the main alluvial systems of the MDB (1971-2021).

Aquifer system	n bores	Min (m/y)	Mean (m/y)	Max (m/y)
Border Rivers Alluvium (unconfined)	53	-0.116	0.011	0.190
Condamine Alluvium (unconfined)	431	-0.271	0.055	0.273
Cowra Formation (unconfined)	43	-0.005	0.066	0.212
Macquarie Alluvium (unconfined)	22	-0.233	0.028	0.218
Narrabri Formation (unconfined)	86	-0.133	0.059	0.270
Shepparton Formation (unconfined)	2868	-0.276	0.045	0.273
Border Rivers Alluvium (confined)	32	-0.056	0.087	0.420
Calivil, Renmark formations (confined)	899	-0.076	0.122	0.458
Gunnedah Formation (confined)	714	-0.074	0.128	0.473
Lachlan Formation (confined)	270	-0.067	0.107	0.432
Macquarie Alluvium (confined)	84	-0.075	0.089	0.412

Table A.6 Summary of 75th percentile bore salinities for aquifers across the main alluvial systems of the MDB (BOM, 2023).

Aquifer system	n bores	Min µS/cm	Mean µS/cm	Max µS/cm
Border Rivers Alluvium (unconfined)	12	312	3479	17640
Condamine Alluvium (unconfined)	188	413	3333	24750
Cowra Formation (unconfined)	77	164	7710	47753
Macquarie Alluvium (unconfined)	16	166	6462	42975
Narrabri Formation (unconfined)	117	148	7474	49727
Shepparton Formation (unconfined)	23043	140	7218	51200
Border Rivers Alluvium (confined)	13	503	1479	5091
Calivil, Renmark formations (confined)	1616	140	7894	50600
Gunnedah Formation (confined)	97	230	9311	50900
Lachlan Formation (confined)	61	282	8392	50650
Macquarie Alluvium (confined)	30	170	7501	42350

Causal analysis including measured extraction data (shorter-term analysis)

This section is a continuation of Section 3.3 (Results of Causal Attribution Analysis) presenting a shorter- term model (2007-2021) at six resource units only (where extraction data is available). Here, observed extraction volumes are used in place of the ‘number of bores’ variable. The results are shown in Figure A.1. Although the model is able to simulate regular seasonal dynamics, many peaks and troughs are missed. Long-term trends are not evident due to the short timeline.

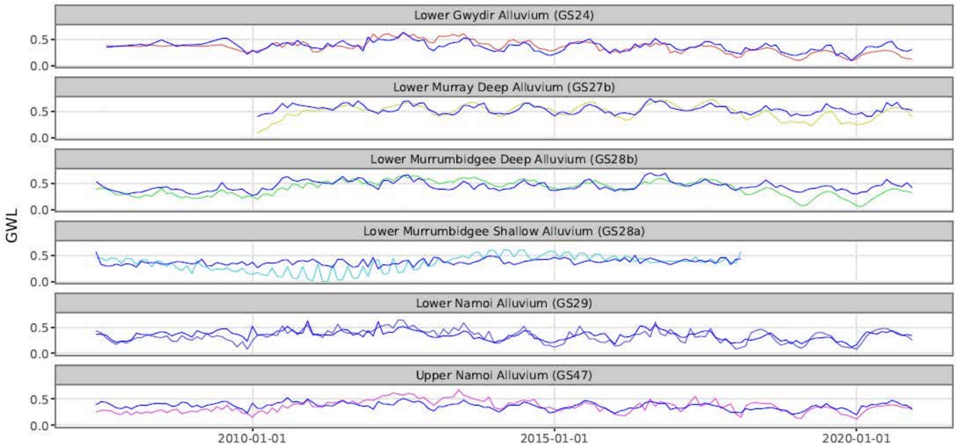

Figure A.1 Groundwater level predictions (blue) from model using measured extractions as a predictor. This model covers six resource units from 2007-2021.

The ranking of feature importance in this model is shown in Table A.7. In the longer-term model, the temporal variable of Year was much more important than in the shorter-term model, indicating that long-term trends are better identified. Strong geographical differences were again evident through the strength of the resource unit variable. The current month's precipitation and extraction data were not found to be important to the model – indicating a possible mismatch between data aggregations, or lags in the response of groundwater levels.

Table A.7 Input variables ranked by importance for the two models (top five listed).

Shorter-term model	Longer-term model
Resource unit	Number of bores
Flood extent %	Resource unit
Extractions – 12-month sum	Year
Season	Flood extent %
Rain – 12-month sum	Rain – 12-month sum

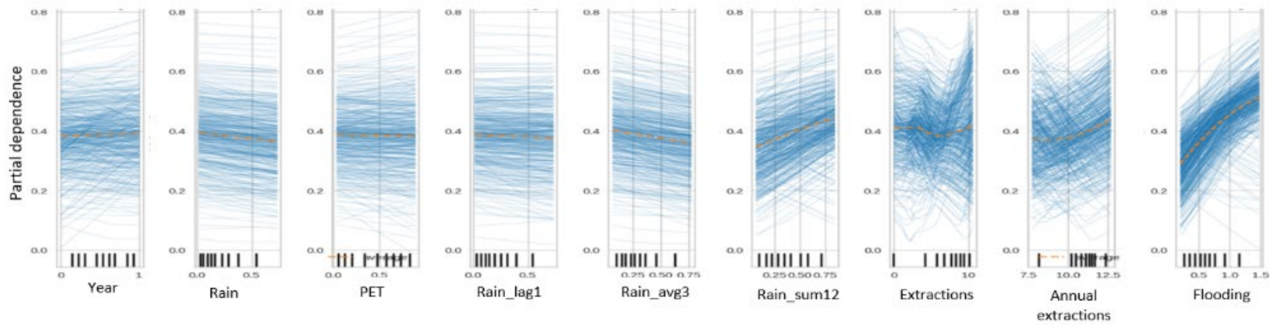

Figure A.2 Partial dependence plots for model including measured groundwater extractions.

On the partial dependence plots for the shorter-term model, an interesting relationship was found between the annual measured extractions and the groundwater predictions, as shown on Figure A.2. The impact of annual extractions on groundwater levels differed greatly amongst observations, with the crossing blue lines indicating the presence of interactions. These erratic blue lines for the extraction variable indicate that extractions affect groundwater levels differently at every bore and time. Plotting the SHAP values over time for this variable on Figure A.3, it is evident that the influence of groundwater extractions on groundwater levels varies substantially in this model by resource unit, season and year. Yet on the right panel of Figure A.3, the impact of extractions appears independent of the volume of extractions.

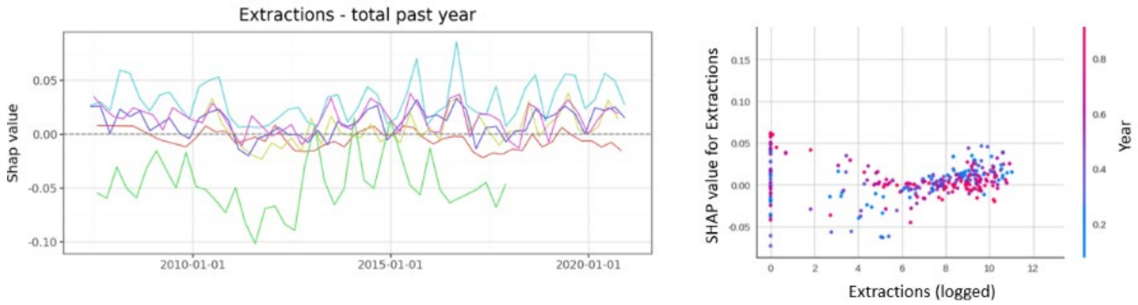

Figure A.3 SHAP values - impact of annual extractions on groundwater level predictions in model (2007-2021). The impact differs by resource unit, season and year. Impact is not dependent on the volume extracted (right panel).