Australian Government

Murray–Darling Water & Environment Research

Griffith UNIVERSITY Queensland, Australia

Long-term persistence and connectivity of in-channel refuge waterbodies in the Darling (Baaka) River

Responses to flow variability and implications for climate change

June 2024

Murray-Darling Water and Environment Research Program

Project 11.2, June 2024

Long-term persistence and connectivity of in-channel refuge waterbodies in the Darling (Baaka) River

Responses to flow variability and implications for climate change

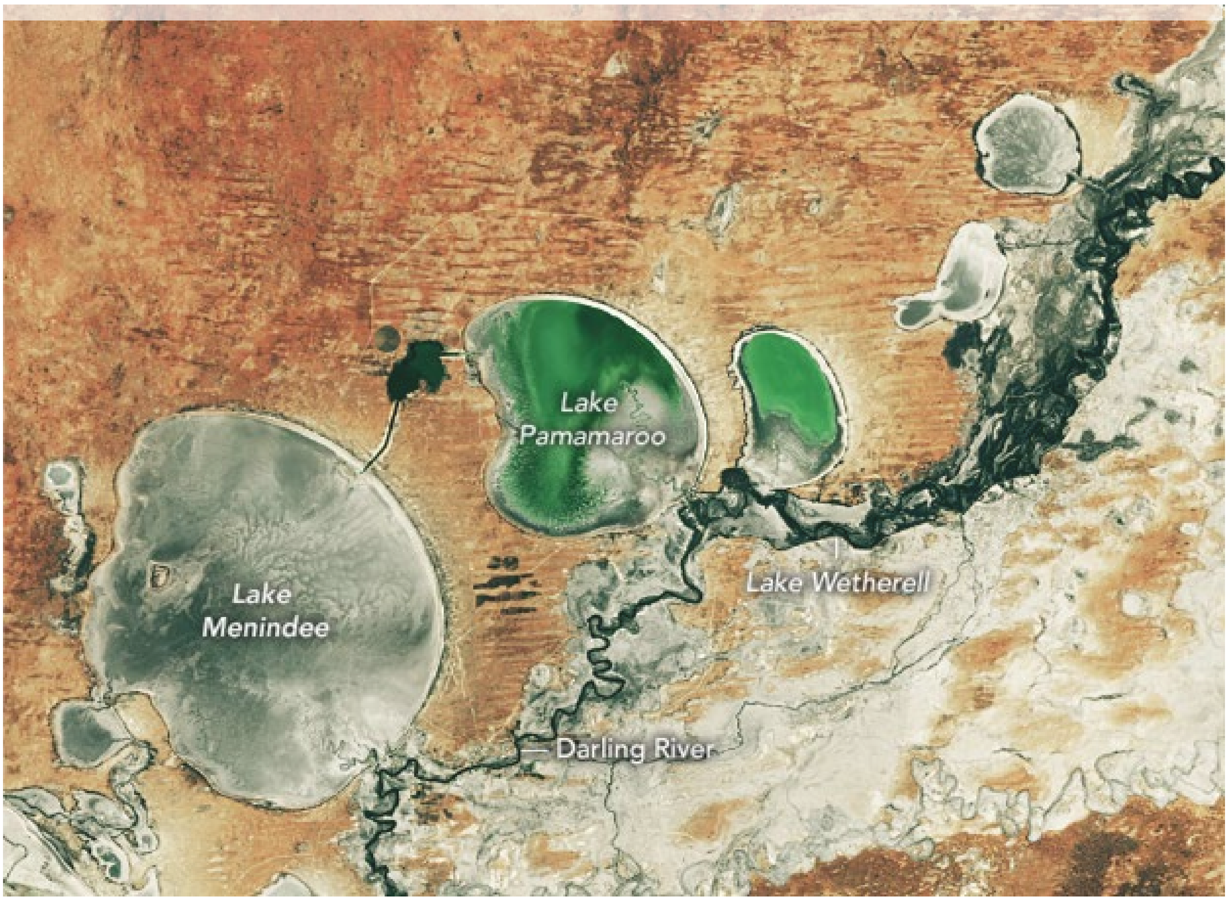

Image: Landsat imagery courtesy of NASA Goddard Space Flight Center and U.S. Geological Survey

Report prepared by:

Kaitlyn O'Mara, Ben Stewart-Koster, Gabrielle Hunt, Mark Kennard

Report citation

O'Mara, K., Stewart-Koster, B., Hunt, G., Kennard, M. (2024). "Long-term persistence and connectivity of in-channel refuge waterbodies in the Darling (*Baaka*) River: responses to flow variability and implications for climate change". Final Report for MD-WERP project 11.2. Australian Rivers Institute, Griffith University, Brisbane.

Author contact details

kaitlyn.omara@griffith.edu.au

https://www.griffith.edu.au/australian-rivers-institute

.

Table of Contents

Executive summary

In-channel persistent surface water provides critical refuge habitat for aquatic organisms in the Murray-Darling Basin. Refuge habitats ensure the survival of aquatic organisms during low and cease to flow conditions, which have increased in frequency and duration since pre-development in the Basin. Replenishing river flows are vital for maintaining water volume and quality in refuge habitats and minimising thermal and oxygen stress. Refuges that do not receive sufficient inflowing water are susceptible to temperature and oxygen conditions that lead to fish deaths, which have occurred, for example, in the Darling (*Baaka*) River near Menindee. Flow is also important for establishing connectivity among persistent refuge habitats, facilitating fish movement and the transport of nutrients and energy throughout the Basin.

Many parts of the Murray-Darling Basin, including the Darling River, were identified as being in poor condition in the Sustainable Rivers Audit. Riverine connectivity supports healthy aquatic habitat and allows organisms to move away from unfavourable conditions. Full connection of the river channel is uncommon in the Darling River due to the arid and semi-arid climate of western New South Wales and the modification of flow for agriculture and other uses. Ensuring refuge habitats receive enough inflowing water is therefore a challenge in this region and managers need tools to improve understanding of the relationships between river flow and connectivity of persistent refuge habitats. Developing models that allow managers to predict connectivity at various spatial scales is useful for informing decision-making regarding flow management to support the ecological integrity of the basin.

To identify persistent refuge habitats in the Darling River (Louth to Menindee) and quantify their connectivity, this study used 35 years of Landsat satellite imagery and a series of geoprocessing and spatial analyses to convert these images into a linear graph network. Graph theory has been demonstrated as an effective tool for quantifying the connectivity of river networks in the Murray-Darling Basin and elsewhere and was used in this study to identify important hub and stepping stone habitats, which represent ecologically important locations for local and large-scale dispersal, respectively. The persistent in-channel waterbodies represented the nodes on the graph and models were developed to quantify their connectivity in relation to environmental predictors at the whole of reach scale and at specific waterbodies. The connectivity of the whole reach over the 35-year period (1987 – 2023) was modelled using extreme gradient boosting with river flow, rainfall, and interannual trends as predictors. Using the same technique, a subset of this connectivity data (1987 - 2009) was analysed with modelled flow data representing baseline flow to facilitate prediction under wetter and drier climate change scenarios over the same period. Nine waterbodies were selected for individual analysis due to their potential importance as either disconnected/isolated, highly connected, or large (highly persistent) waterbodies. Their probability of full connection to immediately neighbouring waterbodies at any given flow rate was modelled using logistic regression to identify flow thresholds that would ensure full connection both upstream and downstream.

Persistent waterbodies were highly spatially variable in terms of trends in inundation and connectivity over the 35-year period. Waterbodies in the upper part of the study reach experienced seasonal variations in inundation, including less wetted area during summer, while waterbodies in the lower part of the reach were less variable in their inundation within years. The middle part of the reach contained both highly persistent (highly inundated most

of the time) and highly dynamic (fluctuating between mostly inundated and dry or almost dry) waterbodies.

The highly persistent stretch of waterbodies in the middle part of the reach was also identified as a highly connected part of the reach due to frequent connections to neighbouring waterbodies. Some of these waterbodies were identified as both hub and stepping stone habitats in the connectivity analysis, indicating that they may serve important ecological functions for both local and large-scale dispersal along the reach. Distance between waterbodies played a role in their connectedness, and some of the most disconnected waterbodies were also the most isolated from their nearest neighbours. The groups of hub and stepping stone waterbodies in the middle of the reach were separated by stretches of channel containing highly disconnected and isolated waterbodies, indicating that dispersal between hubs would often not be possible.

Weirs played a significant role in surface water persistence and connectivity, with some of the largest and most persistent habitat located immediately upstream from each of the weirs. However, the interception of flow had a clear impact on connectivity, with long stretches of river downstream from each weir containing few small, isolated waterbodies.

At the reach scale, flow measured at the gauges along the study reach was found to be the most important predictor of connectivity. Interannual climate trends and monthly rainfall also appeared to influence reach scale connectivity and a lagged connectivity variable was a useful predictor of connectivity in the management scenario models when using the Bourke gauge. The climate prediction analysis using the modelled wet and dry climate scenarios showed that overall, connectivity would slightly increase in a wetter climate and decrease in a drier climate. Under the dry scenario high connectivity spells would likely occur less often and under the wet scenario low connectivity spells would likely occur less often compared to baseline connectivity.

At the individual waterbody scale, logistic regressions between flow and connectivity showed that probabilities of full connection varied greatly among the selected waterbodies. Flows above the 75th percentile were likely required to fully connect the most disconnected/isolated waterbody and the most connected waterbodies would likely remain connected to their nearest neighbouring waterbodies until flows receded below ~400 ML/day. The model performance of the logistic regressions appeared to be related to isolation with much higher predictive accuracy for the more isolated/disconnected waterbodies. The findings suggest these models are an effective way to predict the probability and duration of connectivity of these waterbodies using flow management scenarios. The approach could also be applied to other waterbodies of interest that were not modelled in this study.

The overall approach using graph theory to integrate 35 years of remote sensing information provided an effective way to quantify the connectivity of in-channel persistent aquatic habitat in the Darling River. These waterbodies likely play critical roles in supporting fish biodiversity through their function as low flow refuges and potential stepping stone habitats for fish migration and dispersal. Overall, the analysis found that connectivity of persistent aquatic habitat in the Darling River is temporally and spatially variable and related to river flow, climate trends, and rainfall. Changes in climate will likely lead to changes in overall connectivity, as well as changes in high and low connectivity spells. The models provided can be used by managers to predict connectivity across the whole reach and at individual waterbodies under different river management scenarios, including climate change and environmental flow delivery. The models can also be further updated as more hydrological data are developed in coming years.

Abbreviations

Abbreviation	Definition
AUC	Area Under the ROC Curve. AUC provides an aggregate measure (between 0 and 1) of performance across all possible classification thresholds in a logistic regression. Higher values indicate good model performance.
BC	Betweenness centrality
CSIRO	Commonwealth Scientific and Industrial Research Organisation
GIS	Geographic information system
GL	Gigalitre
MAE	Mean absolute error
ML	Megalitre
NDC	Node degree centrality. Represents the number of direct connections to neighbouring adjacent waterbodies.
RMSE	Root Mean Squared Error. A performance indicator for a regression model, measuring the average difference between values predicted by a model and the actual values. The units are the same as the response variable.
ROC	Receiver Operating Characteristic. A ROC curve is a graphical plot used to show the diagnostic ability of binary classifiers in a logistic regression.
SLC	Scan line corrector

1. Introduction

The ongoing persistence of aquatic habitat in river channels is essential for sustaining fish populations and maintaining healthy aquatic ecosystems (Bunn and Arthington 2002). Temporal variation in the connectivity among aquatic habitats plays an important role in metapopulation dynamics of instream fish populations with persistent waterholes providing refuge habitat during extended dry spells and reconnecting events providing important dispersal opportunities (Datry et al. 2017; Coats et al. 2021). Mapping the presence of persistent surface water and analysing its connectivity through time is critical to understanding dispersal opportunities for fish and identifying when aquatic habitats may be at risk of declines in water quality due to prolonged low and cease to flow events (Davis et al. 2013; McJannet et al. 2014). Predicting the response of waterbody persistence and connectivity to altered flow conditions due to climate change and river management is important for informing management strategies that aim to maintain the health of the aquatic ecosystem into the future (MDBA 2024).

Maintaining healthy aquatic ecosystems as flow alteration occurs due to climate change can be a challenge for water managers, particularly in river systems that are already degraded due to regulation, water infrastructure, and land use change, such as the Murray-Darling (Davies et al. 2010). The Murray-Darling River system is situated in an arid and semi-arid climate, with low catchment streamflow yields and high transmission loss causing natural river intermittency during dry periods (Stewardson et al. 2021). However, hydrological changes due to river regulation and climate change are evident primarily through an increase in the frequency and duration of low and cease-to-flow periods (NSW Government 2021). These changes have altered the hydraulics of the system by increasing the occurrence of lentic conditions in a previously mostly lotic system (Mallen-Cooper and Zampatti 2018, 2020). Additionally, societal, economic, cultural, and environmental values of the Murray-Darling are threatened by loss or decline of crops and degradation of the aquatic ecosystem as the river has a reduced capacity to meet these demands during extended low and cease to flow periods (Davies et al. 2010; Bates et al. 2023). The trade-off among ensuring flows are adequate to maintain crops and drinking water, cultural values, and ecosystem health has presented a challenge to management authorities to deliver water plans that minimise harm and loss in a highly variable and changing climate (Swirepik et al. 2016; Jackson and Head 2020). Sustainable management of water for the environment has flow on benefits for farming and cultural values because they both rely on good water quality that is maintained by healthy ecosystems (MDBA 2023a). Because low and cease to flow events are increasingly common in the Murray-Darling due to river regulation and climate change (Mallen-Cooper and Zampatti 2020; NSW Government 2021), understanding the persistence of in-channel waterbodies and the flows required to connect them is critical to maintaining the health of the Basin's aquatic ecosystems.

In-channel pools that retain water through dry conditions are known as persistent waterbodies (Mueller et al. 2016). Persistent waterbodies provide important refuges for ecological communities during dry periods and the survival and ecology of aquatic organisms is dependent on the habitat and water quality within the refuge waterbody (Carini et al. 2006; Lobegeiger 2010; Waltham et al. 2014). Flows that reconnect these persistent waterbodies sustain the ecosystem through resilience and resistance of ecological communities (Lobegeiger 2010). Waterbodies that are frequently connected by flow are likely to have smaller variations in habitat area compared to disconnected waterbodies due to more frequent replenishing and flushing from upstream flows, which also improves water quality through removal of excess nutrients, replenished oxygen, and reduced likelihood of thermal stratification occurring (Sheldon et al. 2003; Hamilton et al. 2005; Waltham et al. 2014). Conversely, persistent waterbodies with less frequent reconnecting flow are likely to experience greater reductions in habitat area and deeper (>3m) pools are likely to experience thermal stratification due to increasing temperatures and infrequent flushing (Hamilton et al. 2005; Silcock 2009; Schmarr et al. 2013).

Thermal stratification is a critical process that can result in cool bottom water layers to be less oxygenated, restricting fish to warm surface layers that become progressively oxygen depleted as fish respire and water volumes diminish (Waltham et al. 2014). These oxygen changes, combined with water temperatures above thermal tolerances, cause physiological and metabolic stress to organisms and sudden mixing of stratified water can lead to mass mortality events such as fish deaths (Waltham et al. 2014; Sheldon et al. 2021). Ten major fish death events have been documented in the Murray Darling Basin between 2000 and 2024, several of which occurred in the Menindee section of the Darling River (in 2004, 2018-2019, 2023, and 2024) that resulted in the devastating loss of millions of native fish (Koehn 2021; NSW DPI Fisheries 2023; ABC News 2024). Many of these events were not limited to one persistent waterbody but included fish deaths in numerous waterbodies along stretches of river spanning 100's of kilometres (Koehn 2021; Sheldon et al. 2021).

While fish deaths have received significant research and media attention due to their devastating ecological and social outcomes (Jackson and Head 2020), non-lethal impacts on aquatic organisms also occur in response to extended low and cease to flow conditions, including altered food web dynamics (Furst et al. 2019). High quality basal food resources that are abundant during high flow periods (usually diatom dominated phytoplankton communities) are replaced by high densities of cyanobacteria common to lentic environments during dry periods, which are a lower quality food for aquatic consumers (Furst et al. 2019). Connectivity is important for maintaining habitat, water, and food quality in persistent waterbodies, and it additionally serves an important function by providing dispersal pathways and opportunities for fish movement between waterbodies and throughout the river network (Poff et al. 1997; Bunn and Arthington 2002). River regulation can increase the likelihood of problematic ecological impacts through the reduction of reconnecting flows that maintain water quality and facilitate fish movement (Montoya and Ravlich 2019; Sheldon et al. 2021).

In addition to reducing the risks of poor water and habitat quality, longitudinal connectivity throughout the Murray-Darling River system is critical for the survival of aquatic organisms, where dispersal, spawning, and recruitment are intrinsically linked to hydrology (Gehrke et al. 1995; McGregor et al. 2018; Price et al. 2020). The spatial scale on which fish population dynamics operate in the Basin varies among species, with large bodied species moving 10's-100's (e.g. Murray Cod) or 1000's of kilometres (e.g. Golden Perch) and populations of small bodied species (e.g. Australian Smelt) existing on smaller site or reach scale spatial scales (Koehn and Nicol 2016; Price et al. 2020; Thiem et al. 2021). A riverine landscape that permits large-scale movement of migratory species, such as Golden Perch, fosters life history and genetic diversity and promotes population resistance and resilience (McNeil et al. 2011; Barrow et al. 2021). River flow intermittency in the Basin causes fish and other organisms to be restricted to in-channel persistent waterbodies for extended periods, only being able to move to other parts of the Basin during reconnecting flows (Marshall et al. 2016). In-channel barriers within the Basin severely impede fish movement, confounding the impacts of reduced dispersal opportunity during dry conditions (Baumgartner et al. 2014a; Marshall et al. 2021). To ensure future resistance and resilience of aquatic communities, it is important to understand how both in-channel barriers and variations in river flow impact the connectivity of persistent in-channel aquatic habitat (Branco et al. 2014).

Remote sensing has proven to be an effective tool for mapping persistent surface water (McJannet et al. 2014; Mueller et al. 2016). Additionally, the connectivity of river networks has previously been determined using graph theory (Dale and Fortin 2010; Erős et al. 2011; Gao et al. 2018) and established graph metrics can be used to describe the connectivity among waterbodies within the river network, including their function as 'hub' and 'stepping stone' habitats (Galpern et al. 2011; Bishop-Taylor et al. 2017). Hubs are habitats that are highly connected to their immediate neighbouring habitats, allowing opportunities for local dispersal and refuge seeking (Davis et al. 2013; Yu et al. 2023). Stepping stones are habitats that allow longer distance dispersal and are important for highly mobile organisms and obligate movement spawners (Bishop-Taylor et al. 2017). Stepping stones are critical habitats for maintaining population diversity through dispersal and allowing emigration from unfavourable habitat in response to environmental disturbance or range expansion in response to climate change (Saura et al. 2014; Karstens et al. 2022).

This study combined remote sensing and spatial graph techniques to identify persistent waterbodies within a reach of the Darling River main channel and determine how the connectivity among the persistent waterbodies has changed over time. This study also used statistical modelling to quantify the relationships between connectivity and climate and predict connectivity changes that are likely to arise in response to altered flow conditions associated with a changing climate. The results of the study will provide managers with:

1. Information on the locations of specific waterbodies that are of potential ecological significance in terms of their persistence and connectivity in the Darling River from Louth to Menindee

2. Models of the connectedness of the whole reach and predictors of connectivity. These models can be used by managers to predict changes to connectivity under specific flow management and climate scenarios when they become available.

3. A modelling technique that quantifies the probability a waterbody will be connected to both upstream and downstream neighbouring waterbodies at any given flow rate.

2. Methods

The Murray-Darling is Australia's largest continuous river system (~5,500 km) with a basin area of >1 million km^2 (Mallen-Cooper and Zampatti 2018). The river system intersects four states (Queensland, New South Wales, Victoria, and South Australia) and is made up of 18 main river valleys, with either the Darling or the Murray River receiving water from the rivers that flow through these valleys (MDBA 2023a). The Murray-Darling Basin plays a key role in supporting the Australian people, containing 40% of Australian farms and supplying water to 2.4 million people (MDBA 2023a). The reliance on water from the river to support farms and people has driven the cumulative construction of weirs, reservoirs, diversion channels, and farm dams along the river and surrounding floodplain, resulting in highly regulated and intersected flow throughout the Basin (Leblanc et al. 2012). Water extraction and climate change have substantially reduced river flows around the Basin, including discharge to the sea, causing changes to the natural hydrology of the river (Thoms and Sheldon 2000; CSIRO 2008; Kirby et al. 2013).

2.1 Study reach

The study reach included a section of the Darling (*Baaka*) River channel, between the towns of Louth and Menindee in western New South Wales (Fig. 1). The Darling River catchment is 650 000 km^2 in area and is situated in the central part of the Murray-Darling Basin (Thoms et al. 2022). The Barwon, Border, Gwydir, Namoi, and Macquarie rivers contribute major runoff to the Darling River, while the tributaries that flow from the west, including the Culgoa, Paroo, and Warrego contribute minor runoff to the Darling (Thoms et al. 2022). The section of the Darling River chosen as the study reach includes approximately 664 km of deeply incised meandering river channel that flows in a southwest direction and is surrounded by mostly low relief arid floodplain and oxbow lakes (MDBA 2023b). While flow in this section of the river is mostly generated from upstream catchments, the reach plays an important role in delivering water to the southern Basin (MDBA 2023b). The major land use adjacent to the study reach is dryland grazing of cattle for beef and sheep for wool, with some cropping also present in the form of cotton and fruit (MDBA 2023b). Water infrastructure includes large on-farm dams of water pumped from the river, large storages in the Menindee Lakes region (including Menindee Lake storage (capacity 1731 GL)), and several weirs along the channel (MDBA 2023c, b). There is one weir immediately upstream of where the study reach begins in the north (Louth Weir Upstream) and five weirs along the study reach, including Louth Downstream, Tilpa, Wilcannia, Menindee Main, and Weir 32 weirs, listed in order of upstream to downstream (NSW Government and WaterNSW 2019). The section of river channel between the Menindee Main Weir and Weir 32 has records of large fish deaths, as do several other refuge waterbodies downstream of the study reach (Sheldon et al. 2021). A new weir is currently under construction to replace the existing failed weir at Wilcannia (NSW Government 2024). The study reach is classified as moderately to substantially modified in terms of catchment and hydrological disturbance, which has had significant impact on the health of the local aquatic ecosystem (Thoms et al. 2022). The condition of the aquatic ecosystem of the Darling River was found to be poor in the sustainable rivers audit, and approximately one third of the fish biomass was comprised of invasive species such as carp during the millennium drought (Davies et al. 2010).

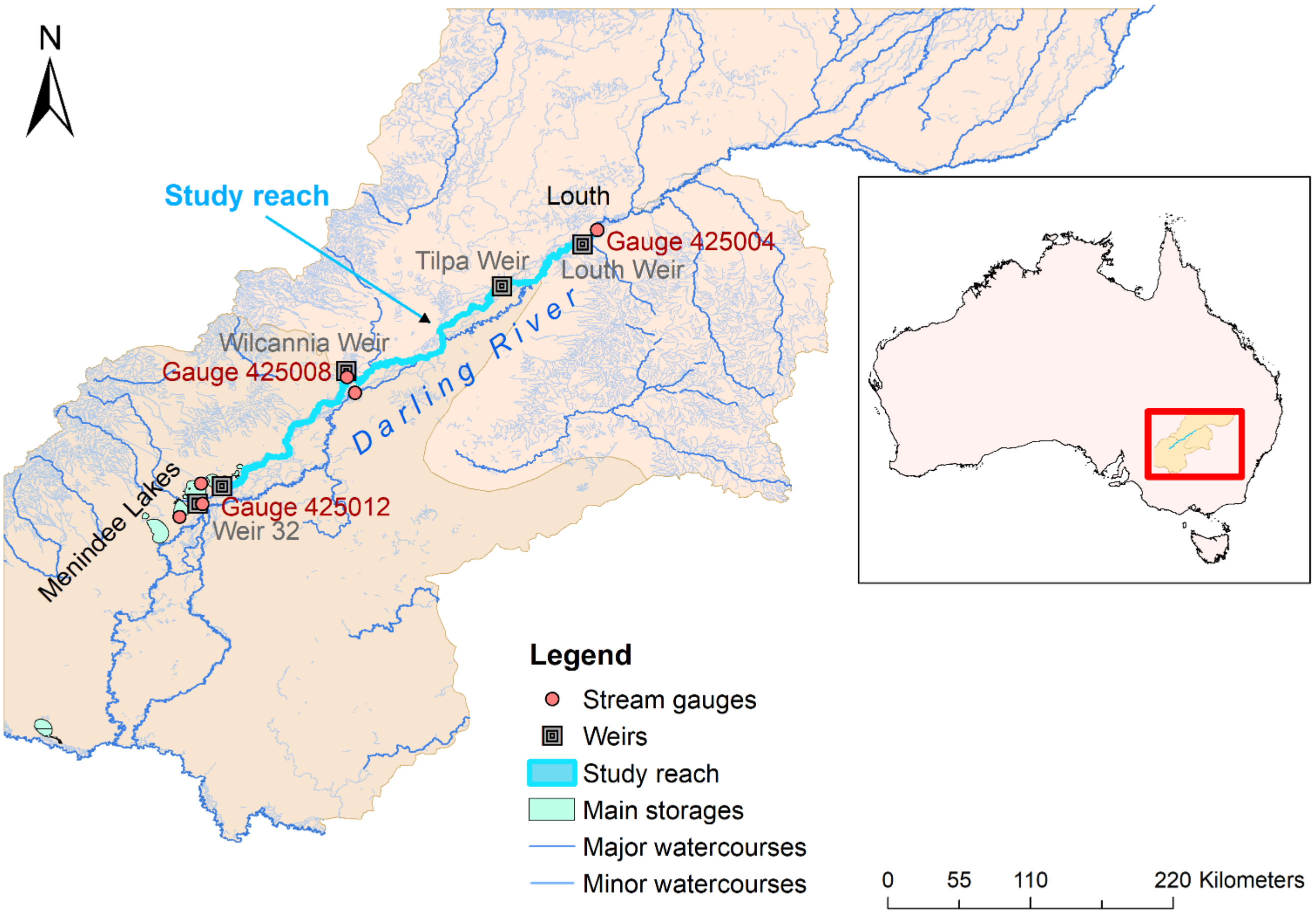

Figure 1. Map showing the Barwon-Darling and Lower Darling catchments in western New South Wales. The section of the Darling River chosen for this study is highlighted in blue and is bound by the town of Louth in the North and Menindee Lake in the south. The gauges from which flow data was used are labelled on the map.

2.2 Summarising water presence and persistence using Landsat imagery

Landsat satellite images (30m x 30m pixels) were used to estimate monthly water presence and long-term water persistence along the study reach using Google Earth Engine (Gorelick et al. 2017). The purpose of this analysis was:

1. To produce monthly summary images of where water was in the river.
2. To produce a summary image of long-term water persistence (for the period May 1987 to December 2022).

These raster images were required for the connectivity analysis. The water persistence raster image (2) was used to define persistent waterbodies in the main channel of the study reach, and their connectivity over the time period was analysed by sequentially overlaying each of the monthly raster images (1) and creating a graph network.

Detailed methods for calculating the water presence and persistence rasters from Landsat images are given in Appendix 1 and briefly described here:

Four datasets from the full Landsat record, Landsat 5, 7, 8 and 9, were accessed through Google Earth Engine, to derive estimates of monthly water presence from May 1987 to December 2022 along the study reach of the Darling River, NSW.

The three Landsat datasets used were:

- USGS Landsat 9 Level 2, Collection 2, Tier 1
- USGS Landsat 8 Level 2, Collection 2, Tier 1
- USGS Landsat 7 Level 2, Collection 2, Tier 1
- USGS Landsat 5 Level 2, Collection 2, Tier 1

Images from each of these datasets were processed by renaming bands and applying pixel-based masking (Fig. 2). Images were then removed if they were affected by Scan Line Corrector failures. Following this, images from each of the datasets were merged into one dataset and only the pixels within the buffered study reach polygon were retained. Images with >20% cloud cover were excluded, and the remaining images were used to calculate water presence using the Modified Normalised Difference Water Index (MNDWI; Xu 2006). Due to the potential for low quality data on the edges of Landsat images, a border of 6km was trimmed from each image.

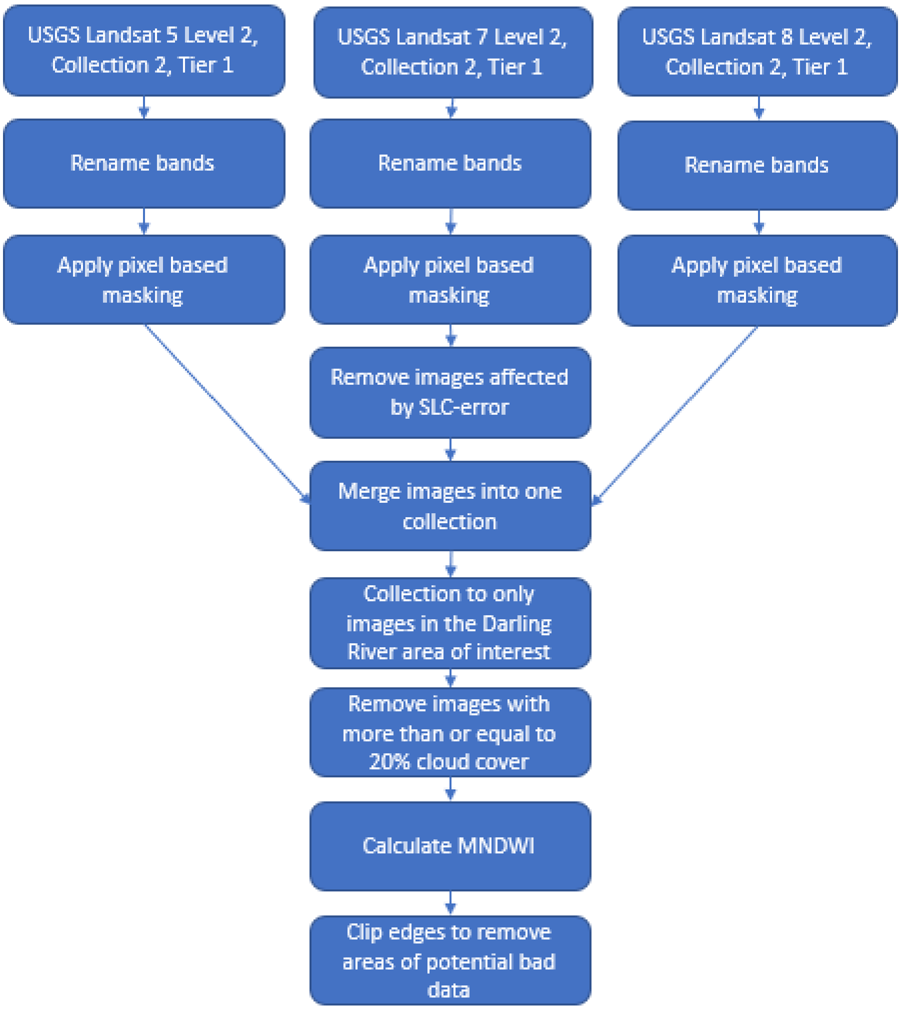

Figure 2. Schematic process to produce a collection of cloud-masked water presence images from global Landsat collections.

Water presence was summarised for each month by combining water bands from separate images within each month to find the maximum value. This process was repeated for 'clear' bands, and the water and clear bands were then added together so that they contained values of 2 (water and clear), 1 (no water and clear), or 0 (not clear (i.e. bad data)).

To calculate the single water persistence raster for the time period May 1987 to December 2022, the water observations and the clear observations were separately summed across all months in this period (Fig. 3). Following this, water persistence for the whole period was calculated as the total number of water observations over the total number of clear observations:

$$Water\ persistence\ (\%) = \frac{(Sum\ of\ water\ observations)}{(Sum\ of\ clear\ observations)} \times 100$$

The Google Earth Engine code for the Landsat geoprocessing is accessible on GitHub at: https://github.com/MDBAuth/MDWERP_11.2

2.3 Defining waterbody persistence and connectivity

To model the persistence and connectivity of waterbodies within the lower Darling River (Louth to Menindee) a series of GIS and graph network analyses were performed using the software ArcGIS Pro (ESRI 2019), and R (R Core Team 2021) in the R Studio IDE (RStudio Team 2020).

Surface water persistence was defined from the summary persistence raster, using similar methods to those used by Mueller at al. (2016) to map surface water persistence in Australia from a 25 year series of Landsat satellite images. Firstly, the summary raster of water persistence over the period of May 1987 to January 2023 was used to define the persistent waterbodies within the reach, with waterbodies defined as: clumps of five or more adjoining pixels (Krause et al. 2021) that were inundated at least 80% of the time, using the R package 'raster' (Hijmans 2018). These waterbodies were converted into a polygon shapefile layer and data on waterbody size was stored in an attribute table (Fig. 3). The waterbody polygons were examined to ensure they were correctly ordered following the river channel in a downstream direction. Connections between the waterbodies within a cost raster of the river (where all cells within the channel had cost = 1) were then generated using the Optimal Regions Connections tool in ArcGIS Pro and the shape length of the line between the edge of each adjacent waterbody polygon was assigned as the distance between waterbodies.

Graph theory has been used in ecological applications to describe the connectivity among habitat patches and can be applied to intermittent rivers to assess the connectivity of persistent waterbodies that serve ecological functions of drought refugia and dispersal stepping stones (Dale and Fortin 2010; Erős et al. 2011). Using graph theory, a graph network is created for each time observation, where waterbodies are termed 'nodes' and connecting flows between adjacent waterbodies are referred to as 'links' (Dale and Fortin 2010). Monthly water observation rasters derived from Landsat satellite imagery were used in this study to create 381 graphs that summarised the monthly connectivity of each node and the whole network over the study period. Because the study reach was a single channel of the Darling River, the graph produced in this study was linear, where each node was assigned a link only to its closest upstream and/or downstream nodes if they were connected by water in each monthly raster.

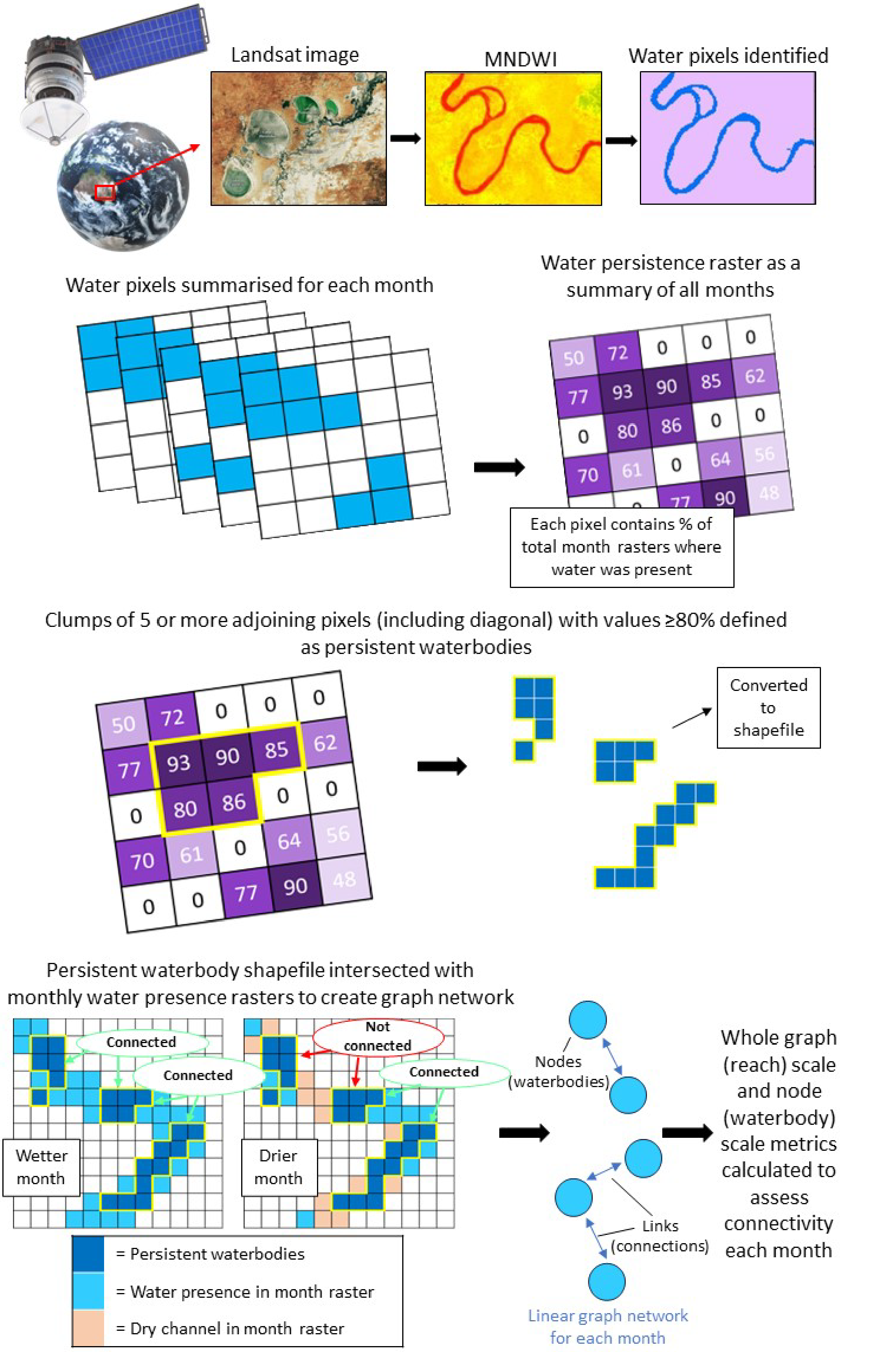

Figure 3. Conceptual diagram of methods used to convert Landsat satellite imagery into a graph network to analyse the persistence and connectivity of waterbodies in the main channel of the Darling River from May 1987 to December 2022.

Monthly water presence rasters (for the same period (May 1987 to January 2023) were used to quantify waterbody persistence and connectivity. To calculate the connectivity of the waterbodies over time, an adjacency matrix was created that stored information about whether each pair of adjacent waterbodies were joined by water for each month raster in the time series using the R package 'sf' (Pebesma 2018). The adjacency matrix was then converted into a graph using the R package 'igraph' (Csardi and Nepusz 2006) and several reach level and waterbody (node) level statistics were calculated from the graph. At the reach level, the proportion of waterbodies that were connected each month was used to define reach-scale connectivity. At the waterbody level, both inundation extent and connectivity were estimated.

Inundation extent of each waterbody was calculated as the area of inundation observed via Landsat (% of total defined waterbody area inundated each month) to study how dynamic waterbodies were in terms of wetting and drying trends over time. The inundation data was converted to frequency of occurrence percentages by separating the inundation values into bins of 10% to understand how dynamic inundation was for each waterbody. This revealed that inundation in the 0-10% and 90-100% bins most frequently occurred across all waterbodies. The frequency of 0-10% inundation extent ranged from 5-34% across waterbodies, while the frequency of 90-100% inundation extent ranged from 46-86% across waterbodies. The presence of frequencies of 0-10% more than 20% of the time (given that the waterbodies were defined as having water at least 80% of the time) likely exists due to variations in which pixels associated with each waterbody were inundated month to month. The waterbody persistence definition uses individual pixels, but the inundation extent metric examines the inundation of the whole waterbody, which may vary in which pixels were wet month to month. Larger waterbodies contained more pixels and were therefore more likely to vary in which pixels were inundated each month.

Waterbody connectivity was assessed using two separate graph theoretic metrics:

1. Node degree centrality
2. Betweenness centrality

Node degree centrality quantifies the number of connections between a waterbody and its immediately neighbouring upstream and downstream waterbodies (0 = no connections, 1 = connected to one adjacent waterbody, 2 = connected to two adjacent waterbodies). The frequency of connections to adjacent waterbodies over time was used to study local scale connectivity trends and identify hubs for local dispersal and refuge seeking (Bishop-Taylor et al. 2017). Betweenness centrality is defined as the proportion of all shortest paths between all waterbodies on the graph that pass through a waterbody and was used to identify stepping stone habitats important for large scale dispersal (Erős et al. 2011; Bishop-Taylor et al. 2017). Median betweenness centrality was compared during different flow conditions using four time periods to represent flow conditions experienced during the study period. The four time periods used were all years (1987 to 2023), the Millenium drought (2001-2009; MDBA 2023d) to represent a dry period, 1988-1990 to represent a wet period, and 1991-1993 to represent a period of average flow. The wet period was calculated as a minimum of three months in three consecutive years that had flow above the 90th percentile. The average flow period was calculated as a minimum of six months in three consecutive years that had flow between the 25th and 75th percentile.

2.4 River flow and rainfall data for predictor variables

Historical monthly river flow rate data was downloaded from WaterNSW (2023) for the gauges 425008 (Wilcannia main channel) and 425012 (Weir 32 upstream). Historical flow data from the Louth gauge (425004) was not used in the analyses because data was not available prior to 1993 for this gauge. Rainfall data was downloaded from the Australian Water Outlook (Australian Government, Bureau of Meteorology) and clipped to a shapefile of the river reach before extracting rainfall totals for each month in R Studio. The rainfall data therefore represented only rain falling directly on the river, assuming the contributions of runoff would be captured in the flow gauge data. Historical river flow and rainfall data for the study period are shown in Figure 4.

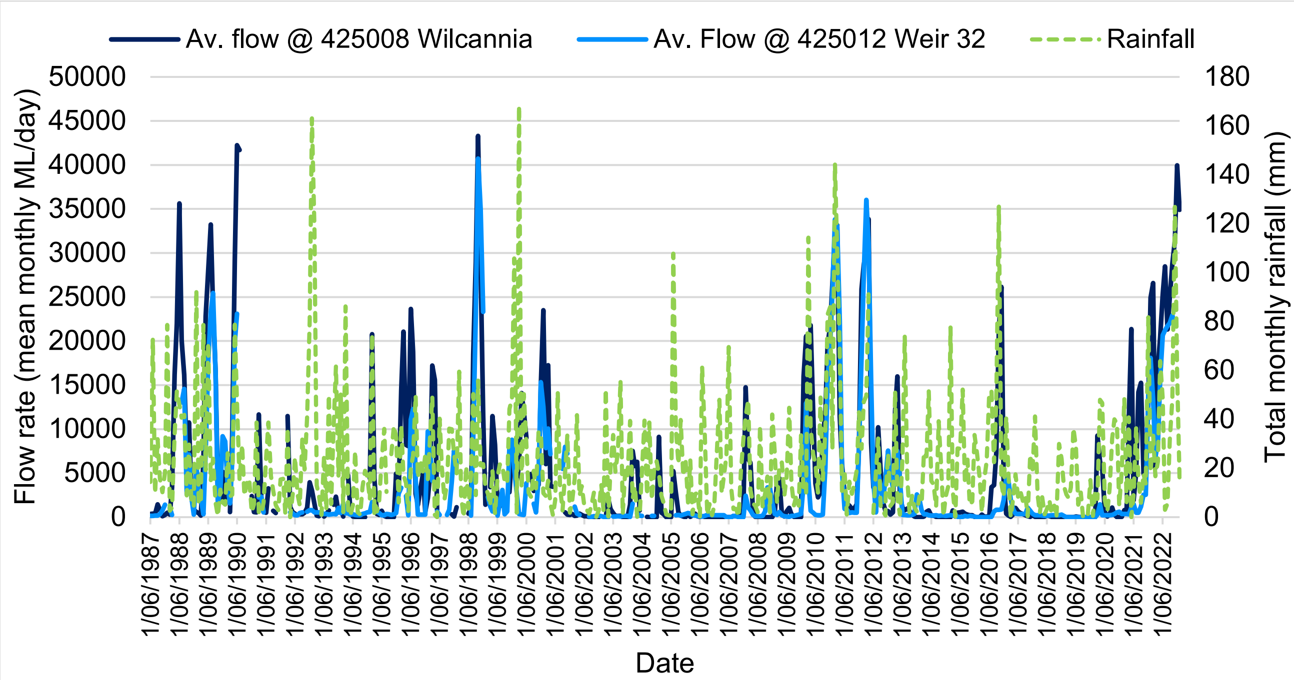

Figure 4. Average monthly historical river flow and rainfall data downloaded for the period May 1987 to January 2023.

2.5 Modelling reach level connectivity and predicting connectivity under different climate scenarios

To understand the relationship between river hydrology and reach level connectivity of the persistent waterbodies, a regression analysis was performed with several hydrological predictor variables of river flow and rainfall. An average of the flow rate values for gauges 425008 (Wilcannia main channel) and 425012 (Weir 32 upstream) were used to represent flow along the study reach. A set of predictor variables were chosen to understand the relative importance of environmental and climate predictor variables on reach level connectivity over time (Table 1), including river flow, rainfall, and lag variables of each. Exploratory data analysis revealed that an arcsine square root transformation was the most appropriate transformation for the response variable (proportion of waterbodies connected each month) in terms of data normality and model predictions. Flow variables were log transformed and rainfall variables did not require any transformations. The study period included droughts and large floods which resulted in multiple years of dry or wet conditions. To account for these longitudinal dry and wet trends, the continuous variable ‘Year’ was also included in the analysis. Due to gaps in historical gauge data, a 12-month flow variable was not included in the historical model. The relationship between the predictor variables and reach level connectivity was examined with regression using extreme gradient boosting in the R package 'xgboost' (Chen et al. 2015).

Table 1. Variables used in connectivity XGBoost regression models with historical data (1987-2023) and modelled data (1987-2009).

Variable type	Variable	Data used in historical model	Data used in climate scenario model	Data transformation applied
Response	Connectivity of persistent waterbodies	Proportion of waterbodies connected to 1 or more other waterbodies	Proportion of waterbodies connected to 1 or more other waterbodies	Arcsine square root
Predictors	Flow	Monthly flow (average)	Monthly flow (total)	Log (χ + 1)
		Monthly flow lagged by one month (average)	Monthly flow lagged by one month (total)	Log (χ + 1)
			Flow in 12 months prior (total)	Log (χ + 1)
	Rainfall	Total monthly rainfall	Total monthly rainfall	None
		Total rainfall 3 months prior	Total rainfall 3 months prior	None
		Total rainfall 12 months prior	Total rainfall 12 months prior	None
	Climate trends	Year (numeric)	Year (numeric)	None

Gradient boosting is a data driven modelling approach that builds a predictive model by adding new models to a base learner model sequentially, so that at each iteration a new base-learner model is trained with reference to the error of the whole ensemble learnt so far (Natekin and Knoll 2013). This is done using gradient boosting machine learning that consecutively fits new models to provide a more accurate estimate of the response variable (Natekin and Knoll 2013). This is different from random forest or neural network techniques, which build strong models by combining a large number of simple models (Hansen and Salamon 1990; Breiman 2001). The extreme gradient boosting technique was used in this study because of its fast computation and advanced model fitting capabilities (Chen et al. 2015).

To fit the model of the response variable reach connectivity (proportion of waterbodies connected each month) with historical river flow and rainfall data (1987 – 2023), an XGBoost regression model (root mean square error evaluation) was performed using 70% of the dataset for training and 30% for testing, using 100 boosting iterations. The root mean square error (RMSE) of the testing dataset was generated to evaluate the overall model fit and gain scores were generated to evaluate the relative importance of each predictor in the model. A 5-fold (3 repeat) cross validation XGBoost model was also run on the whole dataset to assess the model performance, evaluating using RMSE and mean absolute error (MAE) statistics.

To predict changes to reach level connectivity under modelled flow scenarios (baseline, wet, and dry climate scenarios), modelled flow data was used (Podger et al. 2010; Dutta et al. 2012). The wet and dry flow scenarios are based on 2030 climate scenarios for the wettest and driest predictions based on scaling of the 1895-2009 historical baseline (Podger et al., 2010). An average of the modelled data from the three gauges along the reach (Louth

(425004), Wilcannia (425008), and Weir 32 (425012)) was used to represent flow in this analysis. Baseline data was used to train an XGBoost regression model (root mean square error evaluation), and either the wet or dry scenario dataset was used as input test data to make predictions. The R squared statistic and root mean square error (RMSE) was generated to evaluate the overall model fit.

Low and high spell statistics were used to evaluate differences in connectivity among the baseline, wet, and dry scenarios using the hydrostats R package (Bond 2022). Low spells dates and duration were obtained for periods where connectivity was <25%, and high flow spells dates and duration were obtained for periods where connectivity was >75%. Periods between spells of less than two months were considered to be 'in spell' for the purpose of spell calculations.

2.6 Predicting connection of selected waterbodies at various flow rates

Nine waterbodies were chosen out of the 437 defined persistent waterbodies to examine in further detail in terms of the river flow required to fully connect them to adjacent upstream and downstream waterbodies. The waterbodies chosen were the three largest in area, the three most connected (highest frequency of node degree centrality = 2), and the three most disconnected (highest frequency of node degree centrality = 0). The two most disconnected waterbodies were also the most isolated in terms of river distance to nearest upstream and downstream neighbouring waterbodies. The largest were chosen due to their importance as persistent refuge habitat, the most connected were chosen for their role in enabling fish passage, and the most disconnected/isolated were chosen for their role as stepping stone habitats.

Logistic regressions were used to quantify the flow required to maintain full connections between these selected waterbodies and both of their adjacent upstream and downstream waterbodies following a reconnecting flow event. Flow at the Wilcannia gauge (425008) was used as the predictor variable and the node degree centrality statistic (0 = full disconnection or 2 = full connection) was used as the binary response variable in the binomial generalized linear model. Model performance was assessed using the model summary statistics (coefficients, z, and *p* values), and statistics calculated from the receiver operating characteristic (ROC) curve. The statistics calculated from the ROC curve (using the pROC R package (Robin et al. 2011)) included the area under the curve (AUC), sensitivities, and specificities. Sensitivity and specificity refer to the proportion of actual full connections correctly identified and actual no connections correctly identified, respectively. The cut-off probability for flow associated with full connection was then determined as the intersection of the model sensitivity and specificity. The intersection method produced a similar accuracy to the 'topleft' method for each selected waterbody and was used so that false positive full connections were not assigned over false negatives (i.e. to ensure the flow threshold for full connection was not underestimated)(Bewick et al. 2004). This cut-off probability was then used to locate the associated flow rate at Wilcannia (425008 gauge) that would indicate connection to neighbouring adjacent waterbodies. This threshold corresponds to the flow rate at which the specific waterbody is likely to remain connected to both of its immediate neighbouring waterbodies following a reconnecting flow. Flows first must pass upstream waterbodies for these thresholds to be relevant and the thresholds therefore do not represent volumes required for reconnection following disconnection.

2.7 Assessing connectivity in relation to the Bourke gauge to guide decision making

The reach and waterbody scale models described above used flow at the gauges along the study reach because their proximity to the waterbodies translated to better model performance than models using gauges further upstream. However, due to water managers using the Bourke gauge (425003) for allocating downstream flows concerning the study reach and to ensure the models could be used to guide water allocation decision making, models using flow at the Bourke gauge were also produced. Flow at the Wilcannia (425008) and Bourke gauges (425003) over the study period was correlated (Pearson's $R^2 = 0.77$, $t = 21.1$, $df = 305$, $p < 0.001$; Fig. 5a), but flow at Bourke lagged by one month was more highly correlated with flow at Wilcannia (Pearson's $R^2 = 0.82$, $t = 25.4$, $df = 307$, $p < 0.001$; Fig. 5b). Therefore, flow at Bourke lagged by one month (i.e. flow for the month prior to each connectivity observation) was used as the flow predictor variable in logistic regressions that estimated the flow needed to connect groups of waterbodies along the reach and in reach scale regressions predicting the overall connectivity of the reach under various flow and connectivity scenarios.

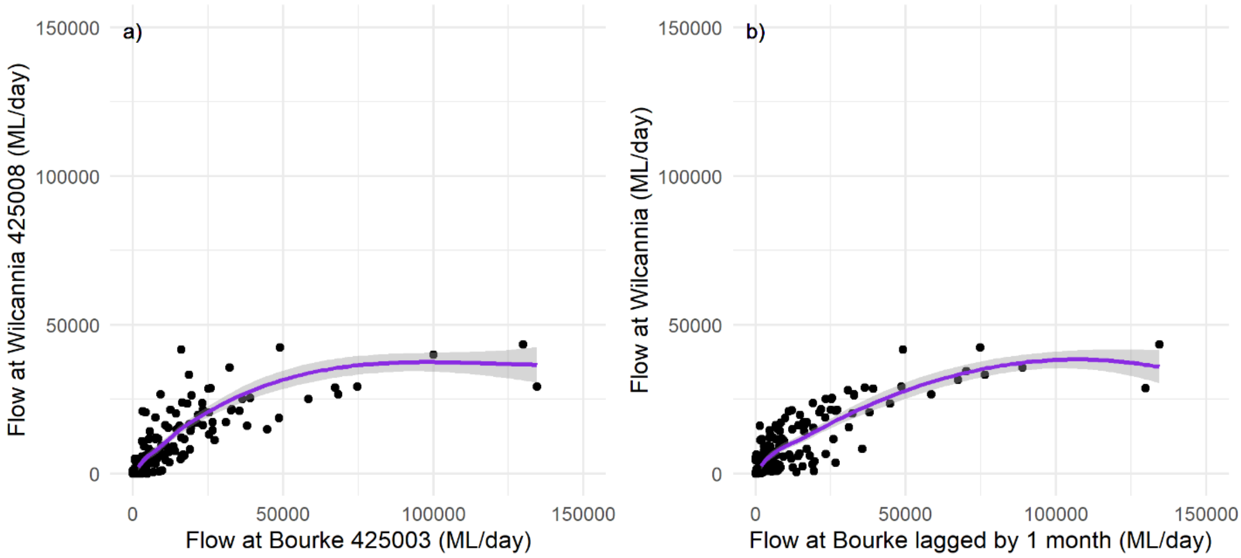

Figure 5. Flow at 425003 Bourke (a) and flow at 425003 Bourke lagged by one month (b) plotted against flow at 425008 Wilcannia.

To determine how flows of varying volumes released at Bourke would affect connectivity along the reach, a set of waterbody scale models similar to the those described in Section 2.6 were used, substituting the predictor variable (flow at Wilcannia) with lagged flow at the Bourke gauge (425003). Everything else in the logistic regression models was kept the same. The set of waterbodies chosen for this analysis was determined by locating groups of waterbodies along the reach that had similar overall node degree centrality metrics but were not located immediately upstream of weirs (due to the artificial flow conditions upstream of weirs which affected model accuracy). The three most downstream waterbodies in each group were modelled and the model suitability for use in decision making was assessed with AUC statistics. These models overall did not perform as well as the logistic regressions using the flow at Wilcannia but many of the waterbodies still had relatively high AUC values, indicating that they are suitable for guiding decision making. Further, flows released at Bourke and travelling down the study reach need to be large enough to pass the most disconnected waterbodies before they can reach any downstream waterbodies. Therefore, while some of the groups of waterbodies in the lower reach have lower flow thresholds, these thresholds do not indicate that these flows are sufficient enough to connect these waterbodies if upstream waterbodies have not received flows sufficient for connection, but rather indicate that they will remain connected for longer than waterbodies with higher thresholds as reconnecting flow recede.

The logistic regressions modelled using flow data from Bourke provide an approximate guideline of the flows needed to maintain connectivity among different groups of waterbodies along the reach. However, prior connectivity is likely to play a significant role in the overall connectivity of the reach when flows are released at Bourke because the reach is located in an area of highly variable climate conditions. Therefore, a further reach scale analysis was performed that also included prior connectivity as measured by the graph theoretic analyses described in Section 2.3. Specifically, a generalized linear model was used with flow (lagged by one month and log transformed) and lagged connectivity (connectivity in the month before) as predictor variables. The lagged connectivity variable was included to understand how current connectivity would impact the predicted connectivity across a range of flow release volumes. The connectivity response variable (proportion of waterbodies connected each month) and its lagged predictor variable were both arcsine square root transformed. After training the model, reach scale connectivity (% of waterbodies connected) was predicted for a range of prior connectivity and flow values. Due to large month to month variations in connectivity following high flow events, the model was not suitable for predicting the connectivity resulting from flow releases when connectivity in the month prior was already high. This was because the relationship between lagged connectivity and connectivity changed when lagged connectivity exceeded ~60% (Fig. A2.2). Therefore, predictions were made across a range of flow values for lagged connectivity between 0 and 60%.

2.8 Sensitivity analysis

The value of 80% water presence over time used for defining the persistent waterbodies was chosen using a combination of expert opinion and methods used in previous studies of surface water persistence mapping in Australia (Mueller et al. 2016). However, the chosen cutoff value remains somewhat arbitrary in relation to there being little published data available to support the validity of this value in defining waterbody persistence. Therefore, a sensitivity analysis was performed by running the spatial and graph analysis using various cutoff values for water presence. As stated above, the data presented in the results is based on waterbodies defined as being inundated 80% or more of the time, with a minimum of five adjoining pixels. Values of 85% and 90% water presence were included in the sensitivity analysis and the results of this analysis are presented in Appendix 4.

3. Results

3.1 Waterbody persistence, size, and inundation

A total of 437 persistent waterbodies were identified in the 664 km Louth to Menindee reach of the Darling River channel (Fig. 6) using the defining criteria (five or more adjoining pixels being inundated ≥ 80% of the time between May 1987 and January 2023). These waterbodies ranged in size from 0.0045 – 3.3 km^2 (4,491 – 3,304,284 m^2), with most of the waterbodies < 0.05 km^2 in area (Fig. 7) and only two waterbodies > 1 km^2, which were located at the southern end of the reach towards Menindee Lakes. There were also three persistent bodies of water located close to the main channel near Bijijie and Balaka lakes that were not connected to any other waterbodies during the study period.

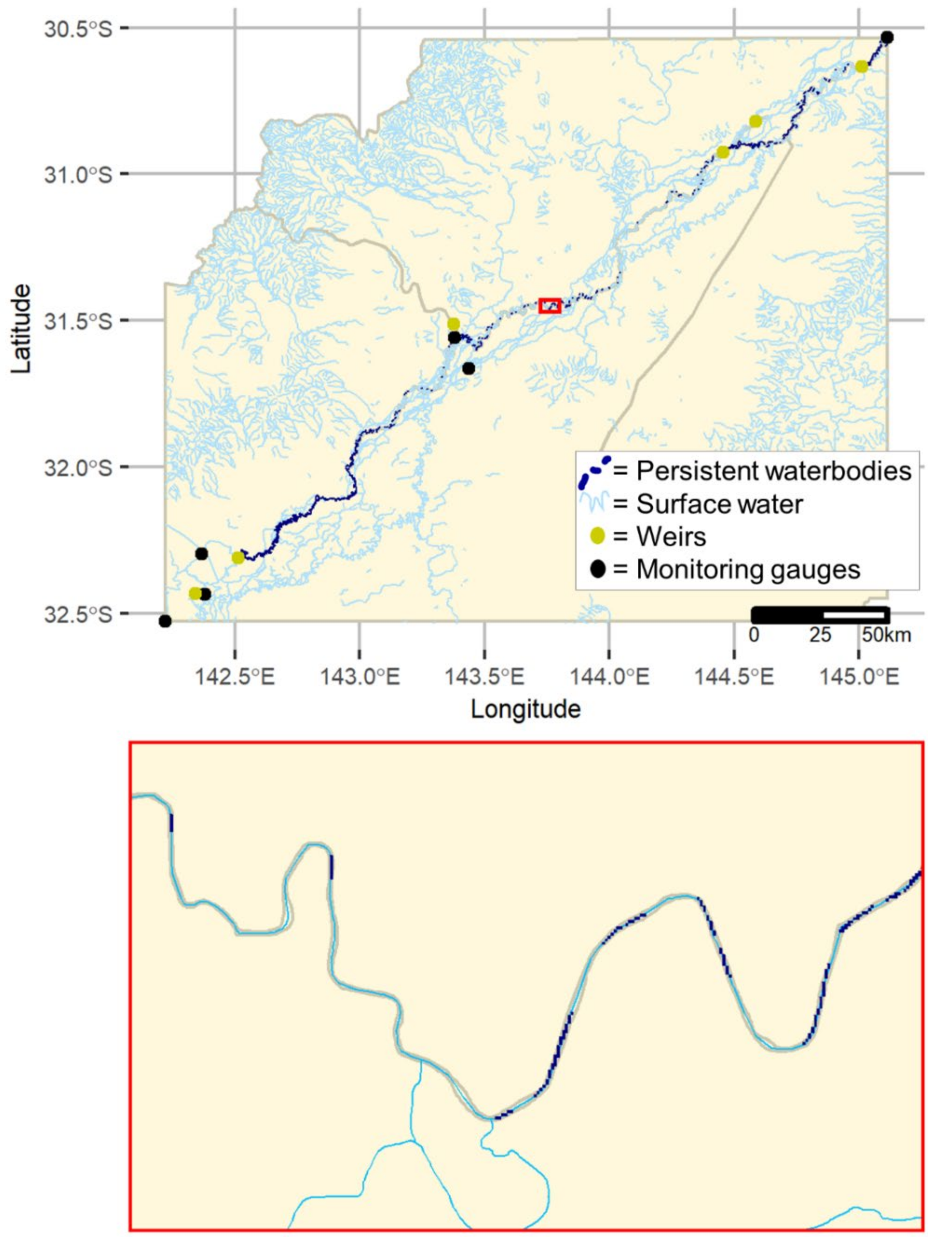

Figure 6. Persistent waterbodies in the study reach of the Darling River, NSW, with a zoomed in example section. A buffer of 300m was applied to waterbodies in the full map (top panel) to make them visible and the size to scale is shown in the zoom section (bottom panel).

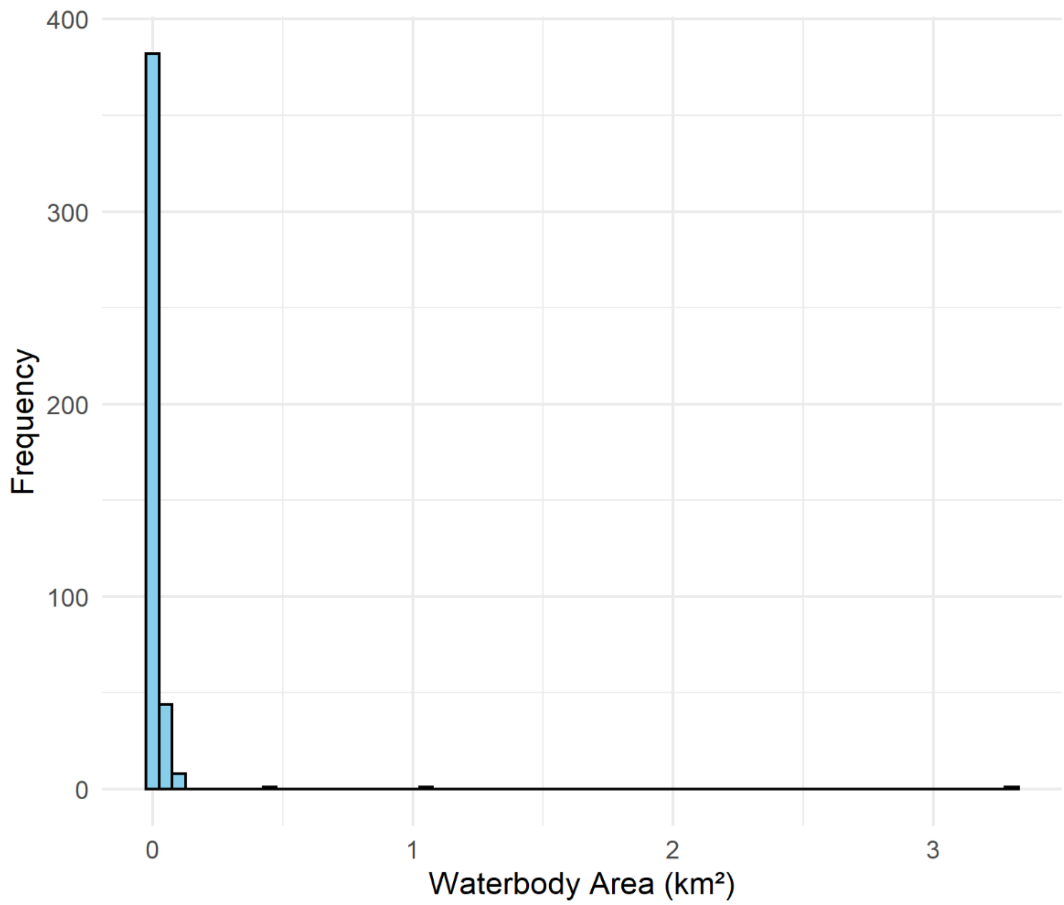

Figure 7. Frequency histogram of persistent waterbody area (n = 437).

Waterbody inundation (% of defined waterbody area covered by water each month) was also quantified to further study waterbody persistence by identifying waterbodies that occasionally experienced drying or near drying and those that were almost always fully inundated. Inundation of waterbodies in the upper part of the study reach was variable across time and space (Fig. 8a), with many waterbodies in this part of the reach less inundated in summer than autumn or spring (Fig. 8b). These waterbodies were also more likely to experience complete or near complete drying (0-10% inundation) than a cluster of highly inundated waterbodies in the middle of the study reach (Fig. 9). Waterbodies in this cluster were on average more inundated than waterbodies in the upper and lower parts of the reach, and less likely to experience drying (Fig. 8 & 9). Waterbodies in the lower part of the study reach were on average 60-75% inundated (Fig. 8a) and appeared to experience near complete inundation less often than those in the middle reach (Fig. 9). In contrast to the waterbodies in the upper part of the reach, the inundation of the lower waterbodies did not vary seasonally (Fig. 8b).

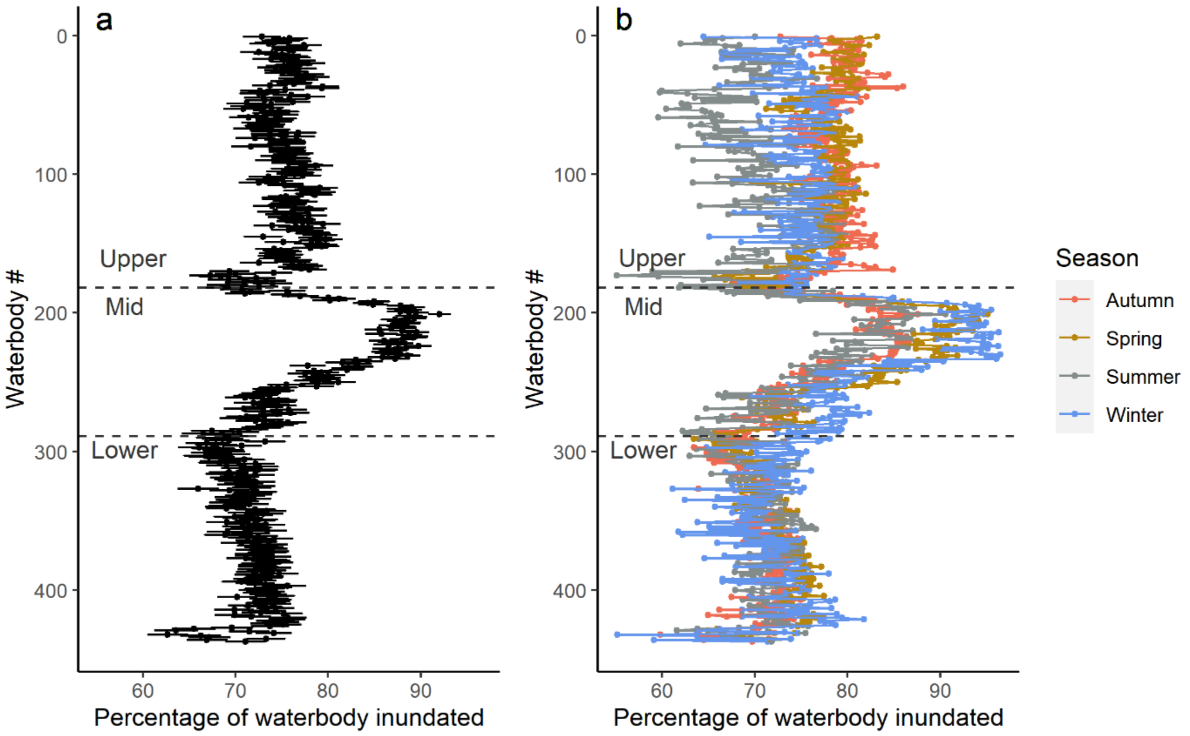

Figure 8. Mean inundation area (as a percentage of the defined persistent waterbody) across all months, including standard error bars (a) and by season (b).

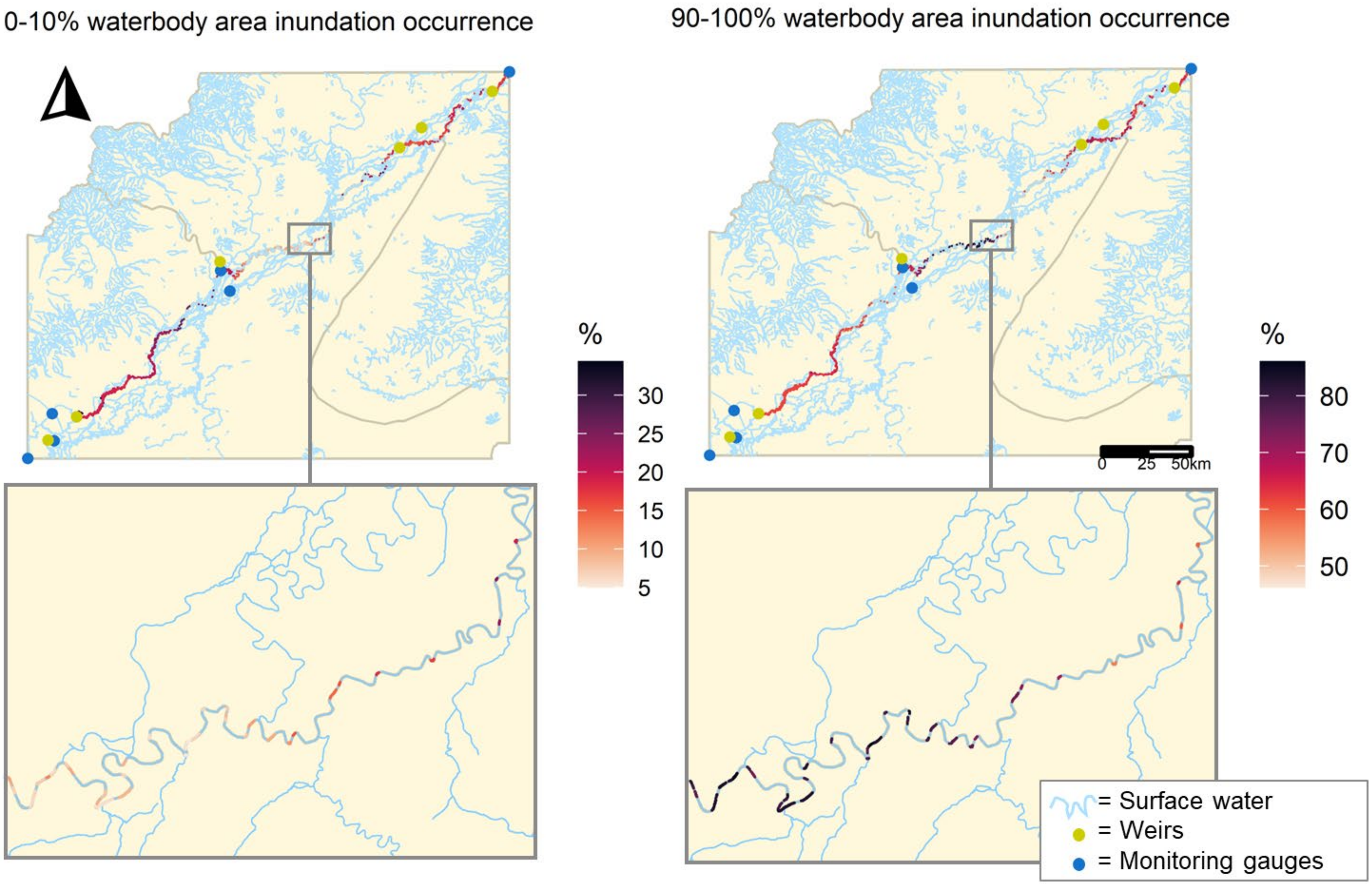

Figure 9. Maps of the study reach (Louth to Menindee section of the Darling River) showing the percentage of time during the study period (1987 to 2023) that 0-10% inundation of the waterbody occurred (Left) and 90-100% inundation of the waterbody occurred (Right). To make the waterbodies visible on the map for display purposes, a buffer of 500m was applied to the waterbodies on the top panels, and a buffer of 50m on the bottom panels containing the zoomed in section maps.

3.2 Waterbody connectivity

Connectivity of the defined persistent waterbodies varied along the reach and through time (Fig. 10-12). There appeared to be several stretches of river channel with waterbodies that had less frequent connections to adjacent waterbodies than the rest of the reach, indicating that these areas may present dispersal challenges to fish during dry periods. These stretches were present in the upper and middle parts of the reach and contained clusters of waterbodies that were more often disconnected than connected to their nearest upstream and downstream neighbouring waterbodies. Three of these clusters were located immediately downstream of the weirs, indicating a significant impact of the weirs on connectivity (Fig. 10). Between the Tilpa and Wilcannia weirs, there were further clusters of highly disconnected waterbodies (indicated on Fig. 10a by red bars) that were juxtaposed in the upstream and downstream direction by highly connected stretches of the river (indicated by dark blue bars on Fig. 10a) which were identified as hubs (waterbodies with frequent NDC = 2 values). This spatially variable connectivity was present in an island chain like pattern along the river channel, with several refuge hubs and frequent limited opportunity for fish dispersal among them. Most waterbodies in the lower part of the reach were more frequently connected than disconnected to their nearest adjacent waterbody, except for a few off-channel persistent waterbodies in the area surrounding Menindee Lakes that were captured in the buffer applied to the study area but always disconnected during the study period (Fig. 10).

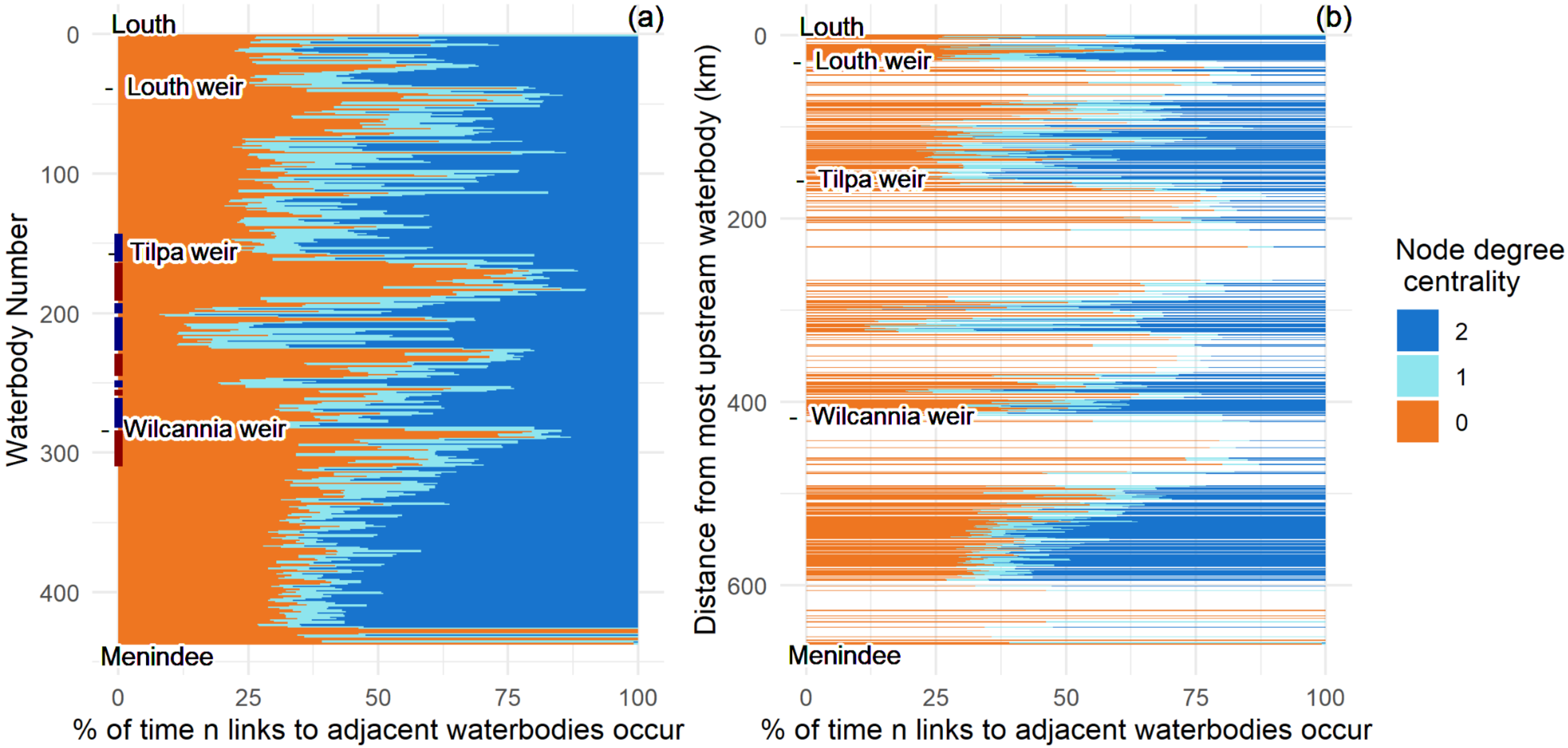

Figure 10. Node degree centrality (number of connections to adjacent waterbodies) summarised for monthly connectivity from 1987-2023 for each waterbody number (a) and each waterbody in terms of its river distance from the most upstream waterbody in the study reach (b). Node degree centrality (0 = no connections to either adjacent waterbody, 1 = connection to only one upstream or downstream adjacent waterbody, 2 = connection to both upstream and downstream adjacent waterbody). Chains of connected (dark blue) and disconnected (dark red) waterbodies are indicated by coloured bars on the vertical axis of panel (a). The position of weirs in relation to the waterbodies is shown on each plot.

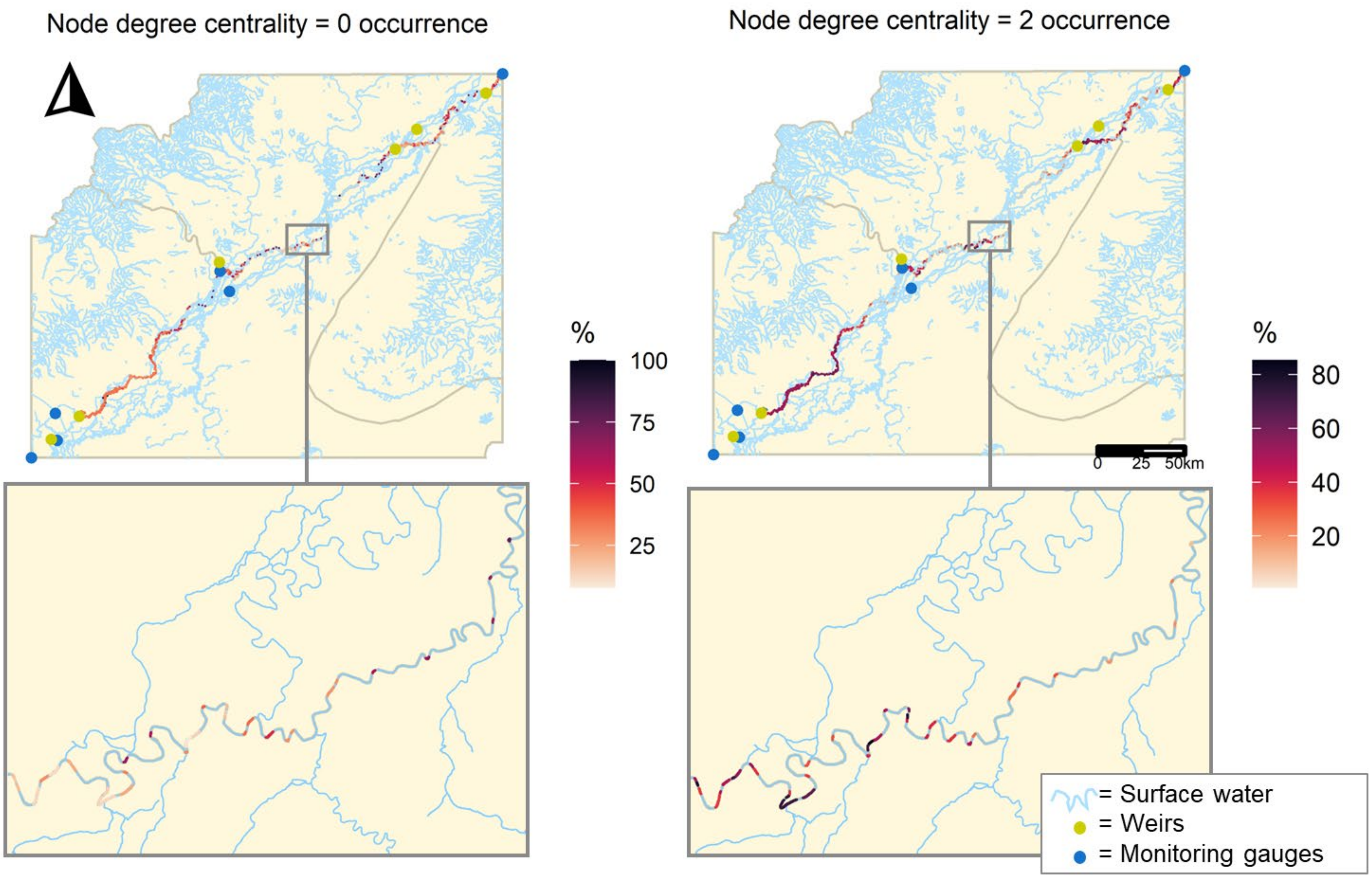

Figure 11. Maps of the study reach (Louth to Menindee section of the Darling River) showing the percentage of time during the study period (1987 to 2023) that 0 connections to adjacent waterbodies occurred (Left) and connections to both adjacent waterbodies occurred (Right). An example section of the river is zoomed below each map to show greater detail. To make the waterbodies visible on the map for display purposes, a buffer of 500m was applied to the waterbodies on the top panels, and a buffer of 50m on the bottom panels containing the zoomed in section maps.

Important stepping stone habitats (waterbodies with high betweenness centrality) were identified in the lower part of the study reach, indicated by the bubble shape of the blue line at the bottom of Figure 12. Betweenness centrality statistics showed that the part of the Darling River that bends to surround Four Mile Lake (waterbodies #316 - 425) was highly connected to the rest of the study reach at most times during the study period, aside from extremely dry periods such as the Millenium drought (Fig. 12-13). During the Millenium drought, the betweenness centrality of waterbodies in this stretch was low or zero as shown by the yellow line at the bottom of Figure 12. Betweenness centrality also showed that there were some other parts of the river that were highly connected in wet years but were much less connected in average flow or drought periods (Fig. 12). Further, there were three stretches of river (waterbodies #43-52, 169-191, 284-299) that had low betweenness centrality in all flow conditions, including during wet conditions.

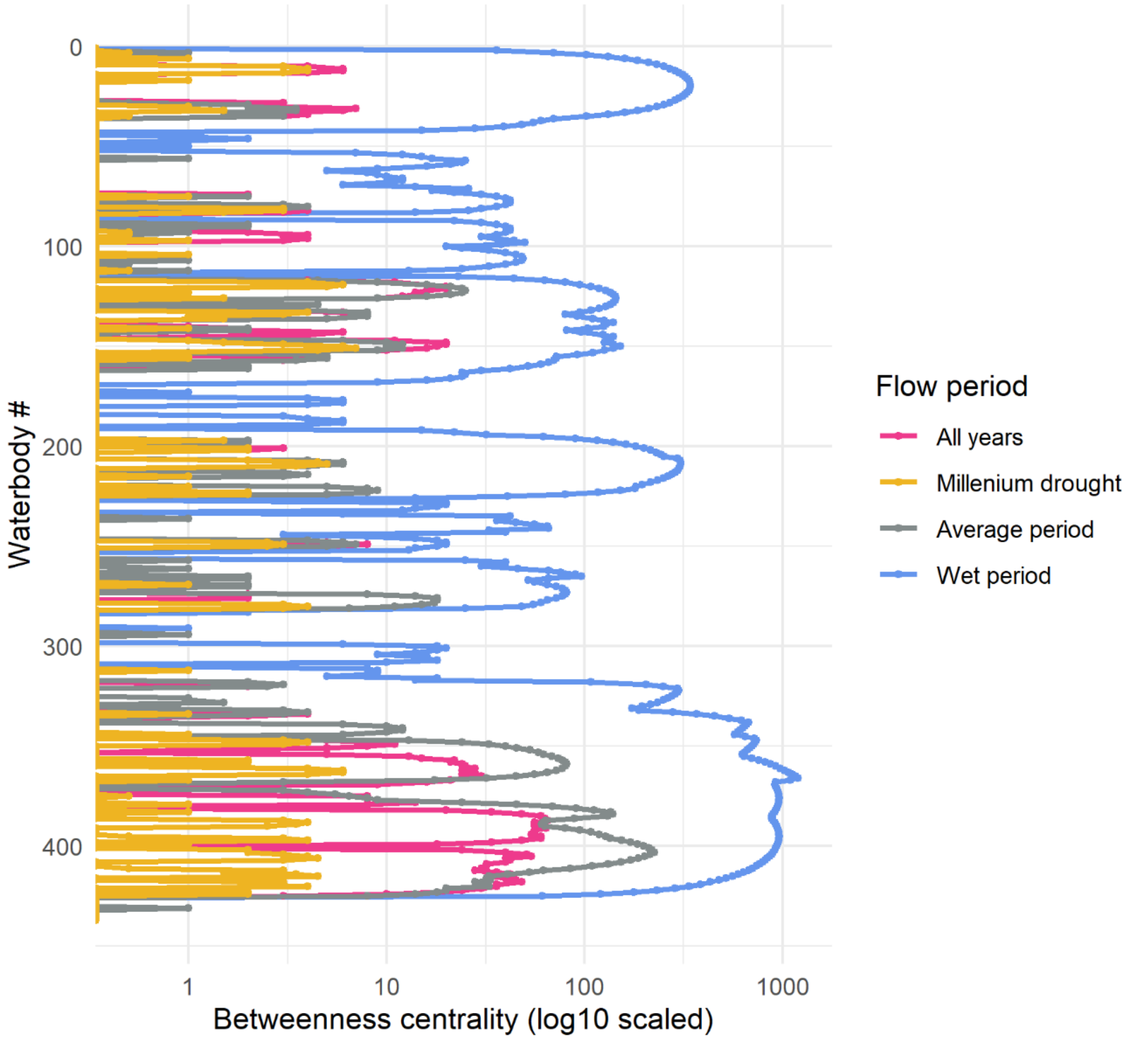

Figure 12. Persistent waterbody median betweenness centrality (log10 scaled) for all years, an average flow period (1991-1993), the Millenium drought (2001-2009), and a wet period (1988-1990).

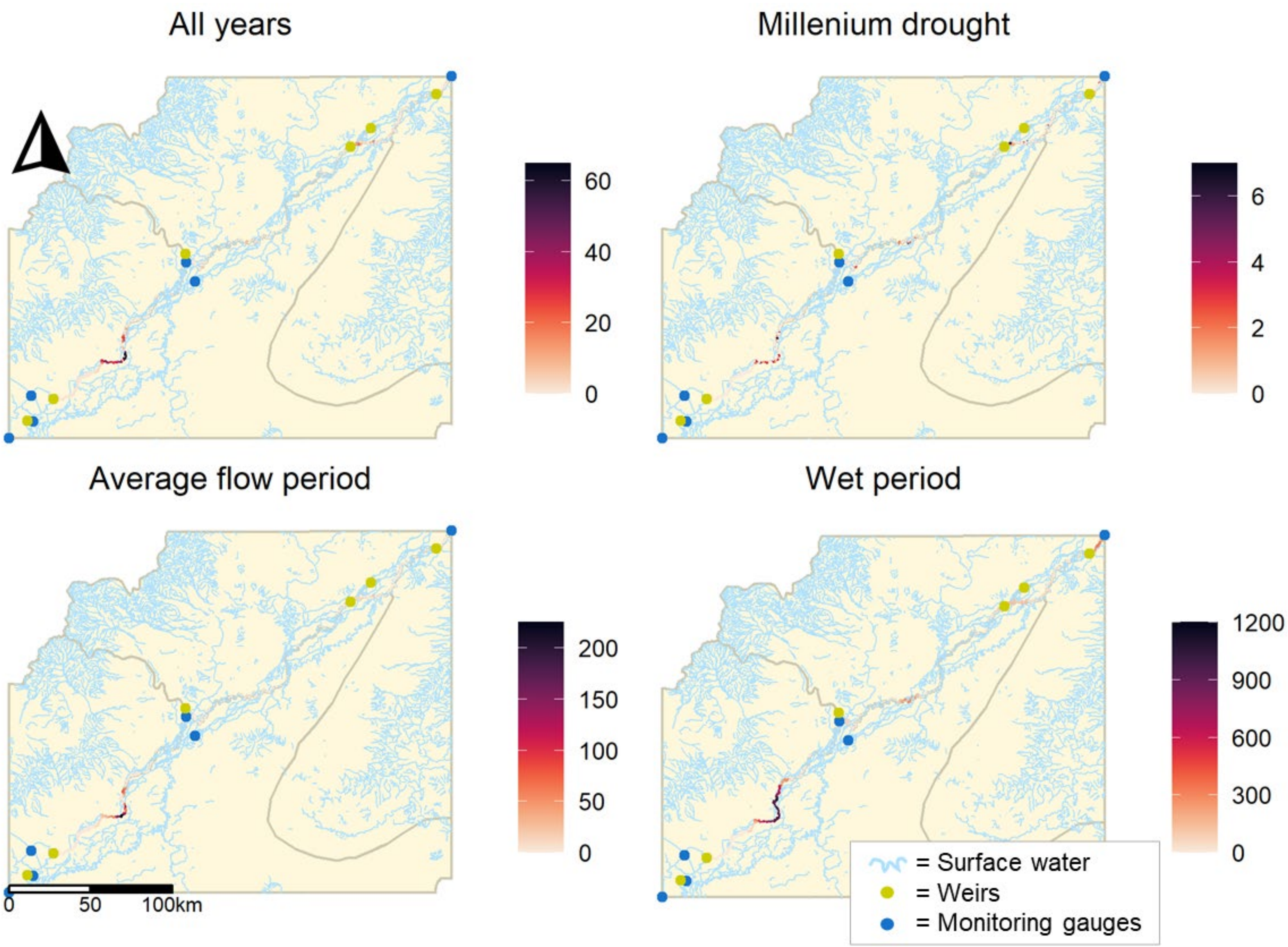

Figure 13. Maps of the study reach (Louth to Menindee section of the Darling River) showing median betweenness centrality for each persistent waterbody for all years, an average flow period (1991-1993), the Millenium drought (2001-2009), and a wet period (1988-1990). To make the waterbodies visible on the map for display purposes, a buffer of 500m was applied to the waterbodies.

There were 13 waterbodies identified as having high importance for connectivity due to their function as both hubs and stepping stones (waterbodies that were in the top 10% of mean values for both node degree centrality and betweenness centrality metrics). These 13 waterbodies were present as four strings of adjacent hub and stepping stone waterbodies and one lone waterbody. All these waterbodies were located in the middle section of the reach upstream of Wilcannia and downstream of a large stretch of river containing very few persistent waterbodies (Fig. 14). Distances between the waterbodies in each of the strings of adjacent hub and stepping stone waterbodies were generally small, facilitating their function as both local and large-scale dispersal habitats. The hub and stepping stone waterbodies shown in the zoomed in section on Figure 14 were also part of the cluster of waterbodies that were highly inundated (90-100% inundated more than 80% of the time; Fig. 9).

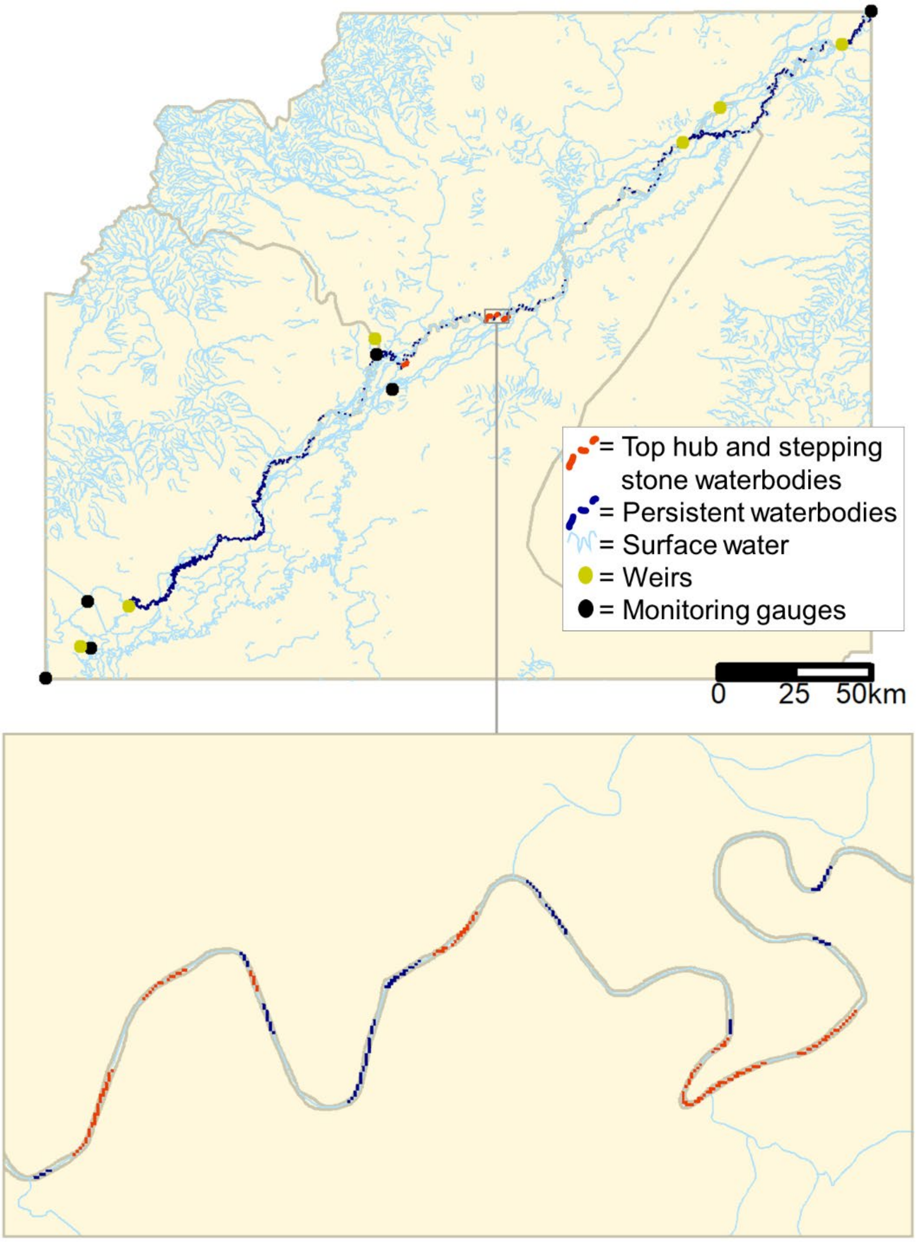

Figure 14. Waterbodies serving functions as both hubs and stepping stones in the network, with a zoomed in section as an example showing most of these hub/stepping stones. Waterbodies were identified if they were in the top 10% of mean values for both node degree centrality (hubs) and node betweenness centrality (stepping stones). On the top map, a buffer of 300 m was applied to the persistent waterbody layer and a buffer of 800 m was applied to the hub and stepping stone waterbodies layer to make them visible for display purposes.

3.3 Reach scale connectivity

Connectivity of persistent in-channel waterbodies along the Louth to Menindee reach of the Darling River, as represented by the percentage of waterbodies connected in each month, experienced both seasonal and interannual variation during the study period (Fig. 15). Monthly variations in connectivity alluded to a seasonal effect within each year, except for some years of extreme drought, during which connectivity remained low throughout the year (e.g. 2001-2003, Fig. 15a). Interannual variability in connectivity of the reach loosely matched the climate trends experienced in the region over the study period. Mean yearly reach connectivity was >50% from 1988 to 2001, followed by a sharp decline in connectivity as the effects of the Millenium drought were experienced in the river channel (Fig. 15b). The longest unconnected period was then experienced in the reach, with <15% of waterbodies connected throughout 2002. Low connectivity was intermittently reprieved with connection events in 2004 and 2005 before another two years of highly disconnected conditions in 2006 and 2007. Connectivity patterns similar to pre-drought occurred in 2008 and 2009, preceding a decade of variable but downward trending connectivity along the reach. This downward trend in connectivity was reversed when the wet conditions of 2020 began, ending the study period with the most connected years of the whole period and a mean connectivity >80% was experienced along the reach from 2020 to 2023.

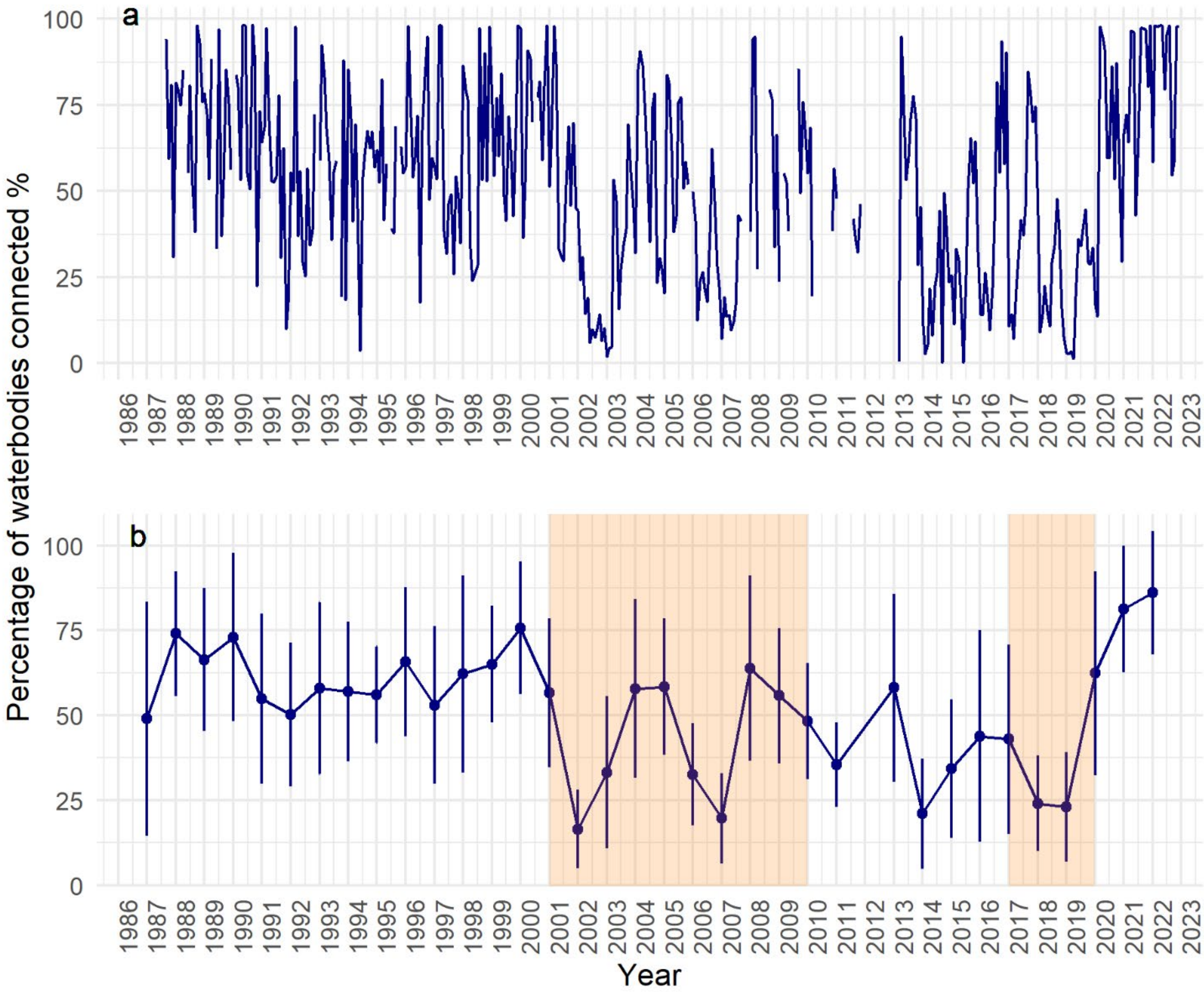

Figure 15. Monthly connectivity (a) and mean (± SD) yearly connectivity (b) of persistent waterbodies along the Louth to Menindee reach of the Darling River from May 1987 to December 2022. Drought periods are shown on (b) by orange shading.

3.4 Predictors of reach scale connectivity and climate scenario evaluations

River flow and climate trends over the study period were correlated with reach-scale connectivity, according to the analysis using extreme gradient boosting. Average monthly flow was the best predictor of reach scale connectivity over the full study period (Fig. 16), followed by year (representing wetting or drying climate trends across years). Rainfall variables accounted for some variation in connectivity but were less important than flow, indicated by lower individual gain scores (Fig. 16).

The RMSE of the testing dataset (0.26) was within one standard deviation of the response variable on the arcsine square root scale (where data ranged between 0.05 - 1.5). Five-fold cross validation errors of the full data were 0.29 for RMSE and 0.23 for MAE. The importance of the variables was similar between the historical and modelled flow regressions (Fig. 16). Therefore, the XGBoost model was then used to predict connectivity using modelled wet and dry scenarios, using the baseline modelled data as the training dataset.

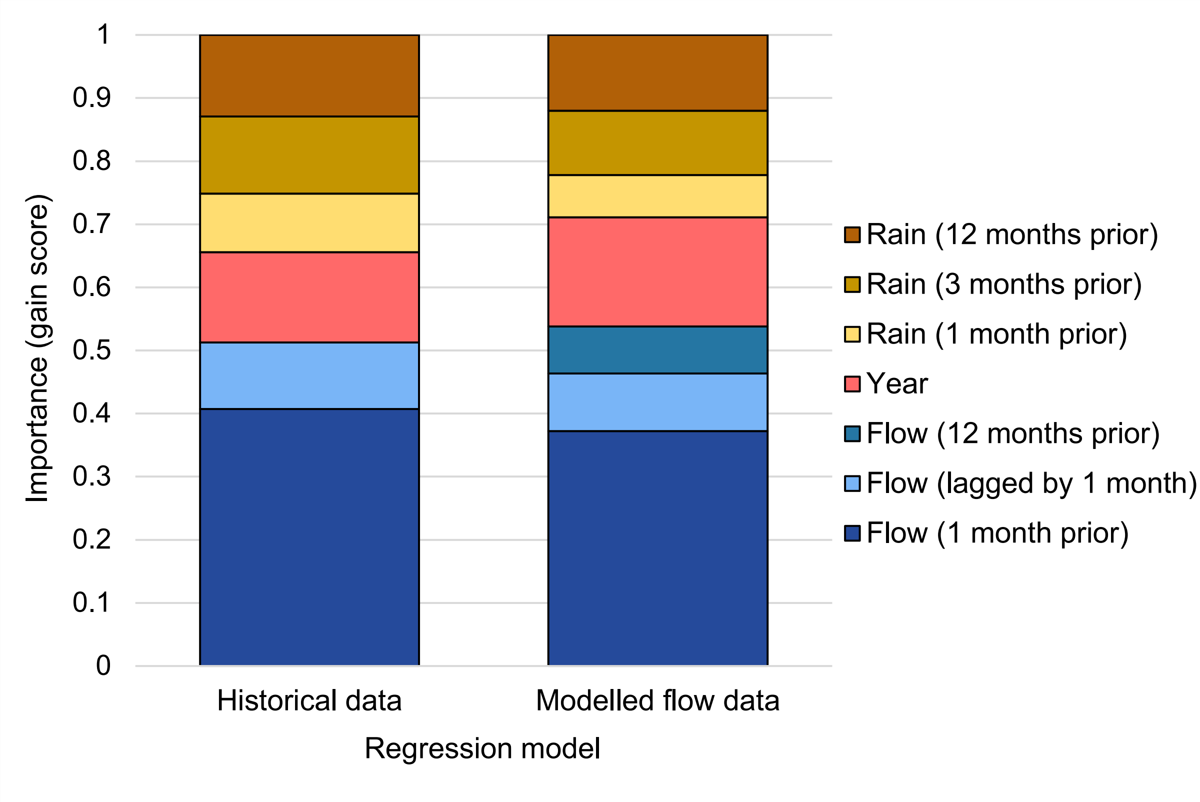

Figure 16. Gain scores showing the importance of each predictor variable in the XGBoost regressions with historical flow data (1987-2023) and modelled flow data (1987-2009).

A simple linear regression shows the direct relationship between flow and the connectivity of persistent waterbodies along the reach (Fig. A2.1).

Modelling connectivity under wet and dry scenarios

Connectivity of the persistent waterbodies varied between baseline, wet, and dry scenarios, with differences between scenarios more pronounced in some years than others (Fig. 17). Overall, small changes between the baseline and wet or dry scenarios were evident across the entire 23 years (1987-2009), where most of the months in the wet scenario had higher connectivity than the baseline, and most of the months in the dry scenario had lower connectivity than the baseline (Fig. 17). The mean difference between the baseline and wet scenarios was 2.55 (±13.0) while the mean difference between the baseline and dry scenarios was -2.85 (±15.5), indicating that overall, a wetter climate would likely increase connectivity of waterbodies along the reach while a drier climate would likely reduce connectivity.

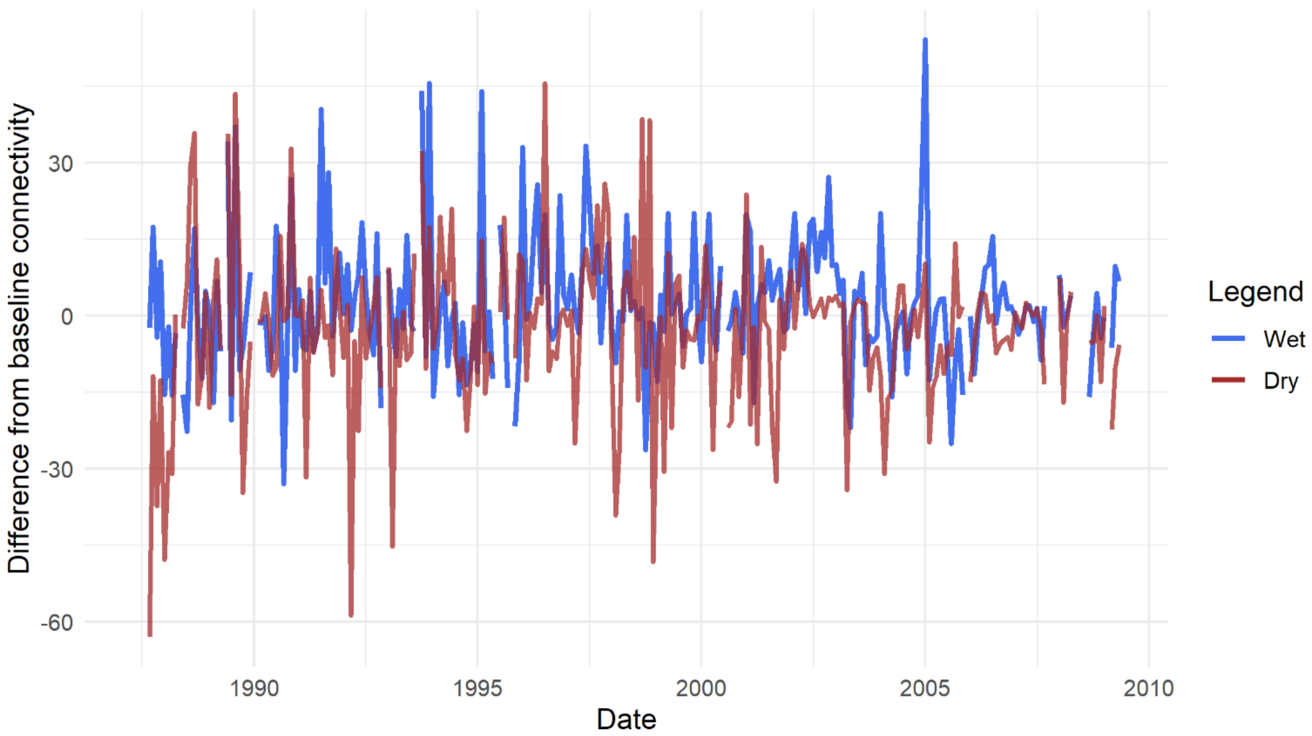

Figure 17. Difference from baseline connectivity (percentage scale) for both wet and dry scenarios.

While there was only a small observable difference between the monthly variations in connectivity among the three scenarios, spell analysis showed that compared to baseline conditions, the wet and dry scenarios would likely cause significant changes to both low and high connectivity spells. The spell analysis found that compared to baseline conditions, low connectivity spells would likely occur less often under the dry scenario but on average last longer (Table 2, Fig. 18a). Dry scenario high connectivity spells were predicted to occur less often and on average last fewer months than the baseline scenario (Table 2, Fig 18b). The spell analysis showed that a wetter climate would positively influence connectivity spells by both reducing the frequency and average duration of low connectivity spells and increasing the frequency of high connectivity spells, compared to baseline conditions.

Table 2. Spell frequency (no. of spells per year) and duration (months) for low connectivity spells (where connectivity falls below 25%) and high connectivity spells (where connectivity is above 75%, with a maximum of two consecutive months below the 75% threshold included in the spell).

Scenario	Spell type	Spell frequency	Min. spell duration	Mean spell duration	Max. spell duration
Baseline	Low (<25% connectivity)	0.74	1	2.29	12
Wet		0.39	1	2.22	8
Dry		0.57	1	2.62	11
Baseline	High (>75% connectivity)	1.04	1	3.41	10
Wet		1.17	1	2.74	12
Dry		0.78	1	2.89	15

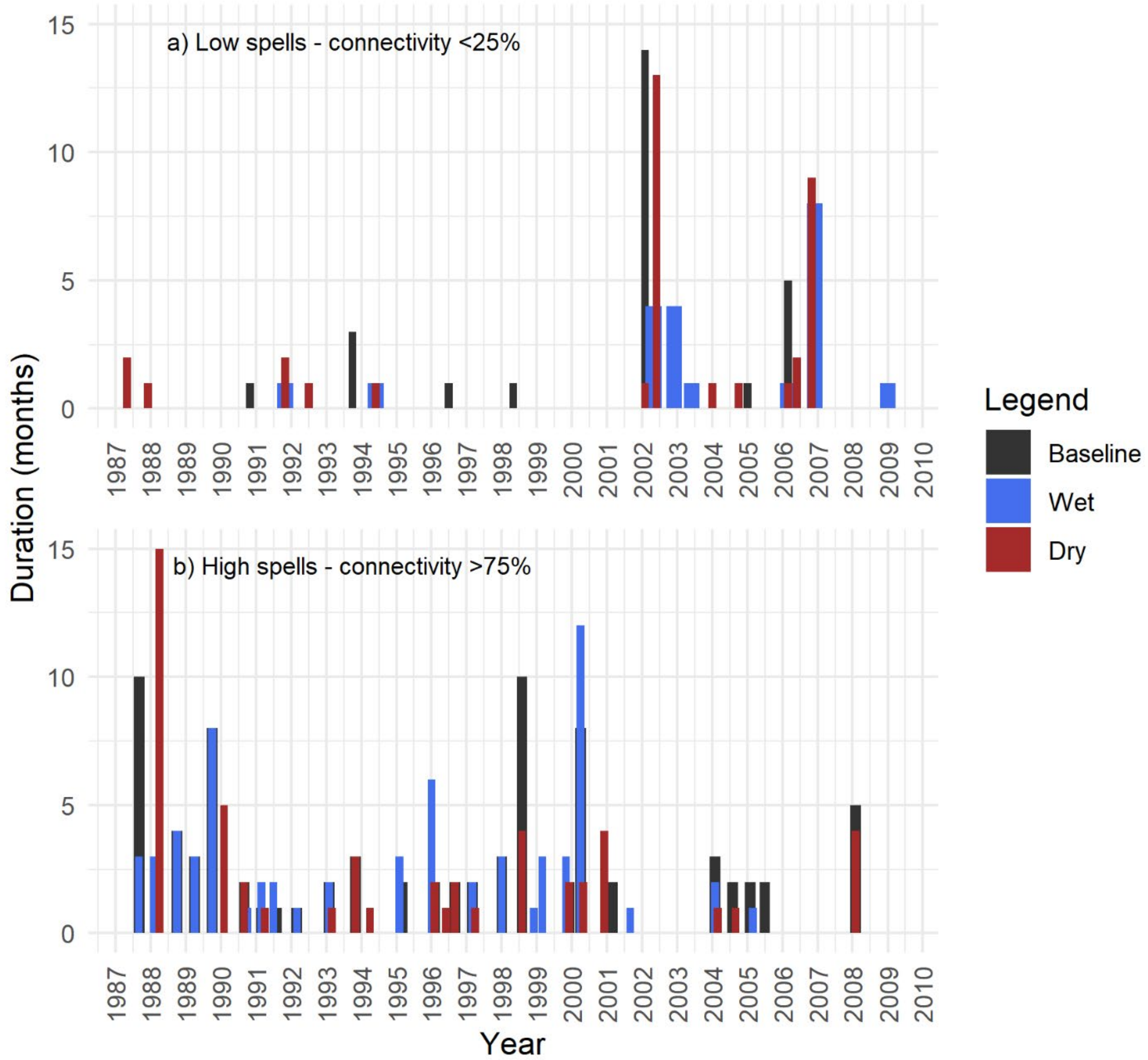

Figure 18. Low (a) and high (b) connectivity spell start date and durations for the baseline connectivity data as well as the predicted connectivity under wet and dry climate scenarios.

3.5 Flow and connectivity of selected waterbodies

Waterbodies that were either the most or least connected in the reach, as well as the largest, were selected to be studied in further detail due to their importance for in-channel habitat connectivity and persistence (geographic locations given in Appendix 3; Table A3.1). The top three disconnected and top three most connected waterbodies were all located in the middle section of the study reach (Fig. 19). Two of the three most disconnected waterbodies were located 3 km (waterbody #285) and 7 km (waterbody #289) downstream of Wilcannia, while the most disconnected waterbody (#183) was located between Wilcannia and Tilpa weirs, approximately 75 km downstream of Tilpa Weir. Two of these three disconnected waterbodies were also the most isolated in terms of river distance from both their upstream and downstream neighbouring adjacent waterbodies. Waterbody #183 was 18.4 km from its nearest upstream and 35.7 km from its nearest downstream neighbouring waterbody, while waterbody #285 was 20.4 km from its nearest upstream and 7.5 km from its nearest downstream waterbody. The significant isolation of waterbody #183, along with its disconnection frequency (disconnected 85% of the time over the study period), makes it likely to be a significant persistent refuge habitat for both local organisms and migrating fish.

The three most connected waterbodies in the study reach were located ~ 94 – 118 km (river distance) upstream of Wilcannia. Distances to their nearest neighbouring waterbody were substantially less than that of the most disconnected waterbodies, ranging from 0.03 to 0.16 km. Waterbodies in this part of the river were close together and often connected, forming a significant interconnected network of waterbodies in between the most isolated waterbodies in the reach. One of these waterbodies (#220) was also identified as both an important hub and stepping stone habitat. The three largest waterbodies in the study reach were weir pools, with waterbody 152 located on the upstream side of the Tilpa Weir and waterbodies 425 and 431 located on the upstream side of the main Menindee storage.

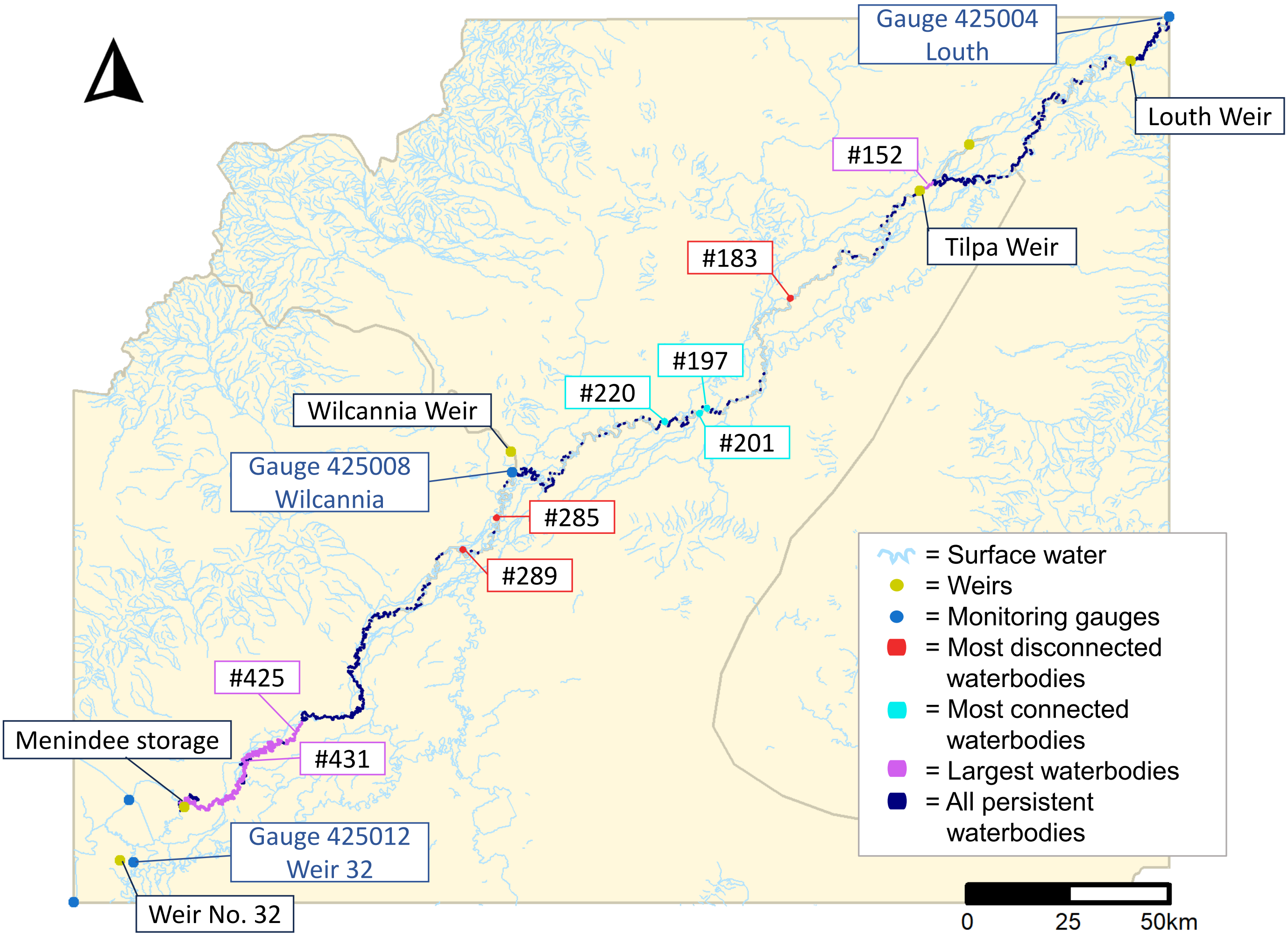

Figure 19. Locations of selected waterbodies within the study reach from Louth to Menindee. To make the waterbodies visible on the map a buffer was applied around each waterbody and the sizes of the waterbodies on this map are therefore not geographically correct. A buffer of 300 m was applied to the persistent waterbody layer and the largest waterbodies layer. A buffer of 800 m was applied to the most disconnected and most connected waterbodies layers.

Most of the selected waterbodies had a relationship with river flow (Fig. 20), with higher median flow values (and larger ranges of flow values) for full connections (NDC = 2) than no connections (NDC = 0). The three most disconnected/isolated waterbodies had a strong relationship with flow, with clear separations between the fully connected (NDC = 2) and not connected (NDC = 0) boxplots for each of the three waterbodies (Fig. 20a-c), and this relationship tended to decline as connectivity increased (Fig. 20d-i). The strength of these relationships (Fig. 20a-c) translated to excellent model performance with high AUC values (>0.85; Table 3), indicating that the connectivity of the most disconnected waterbodies can be effectively predicted using flow at the Wilcannia gauge. Generally, AUC values below 0.7 indicate relatively low predictive accuracy and as such the relatively low AUC values at the highly connected and largest waterbodies indicates their connectivity cannot be predicted effectively using flow at the Wilcannia gauge (Table. 3). The model performance for the largest waterbodies was particularly poor, which may reflect their artificial hydrology as weir pools. Regression coefficients can be found in Table A3.1.

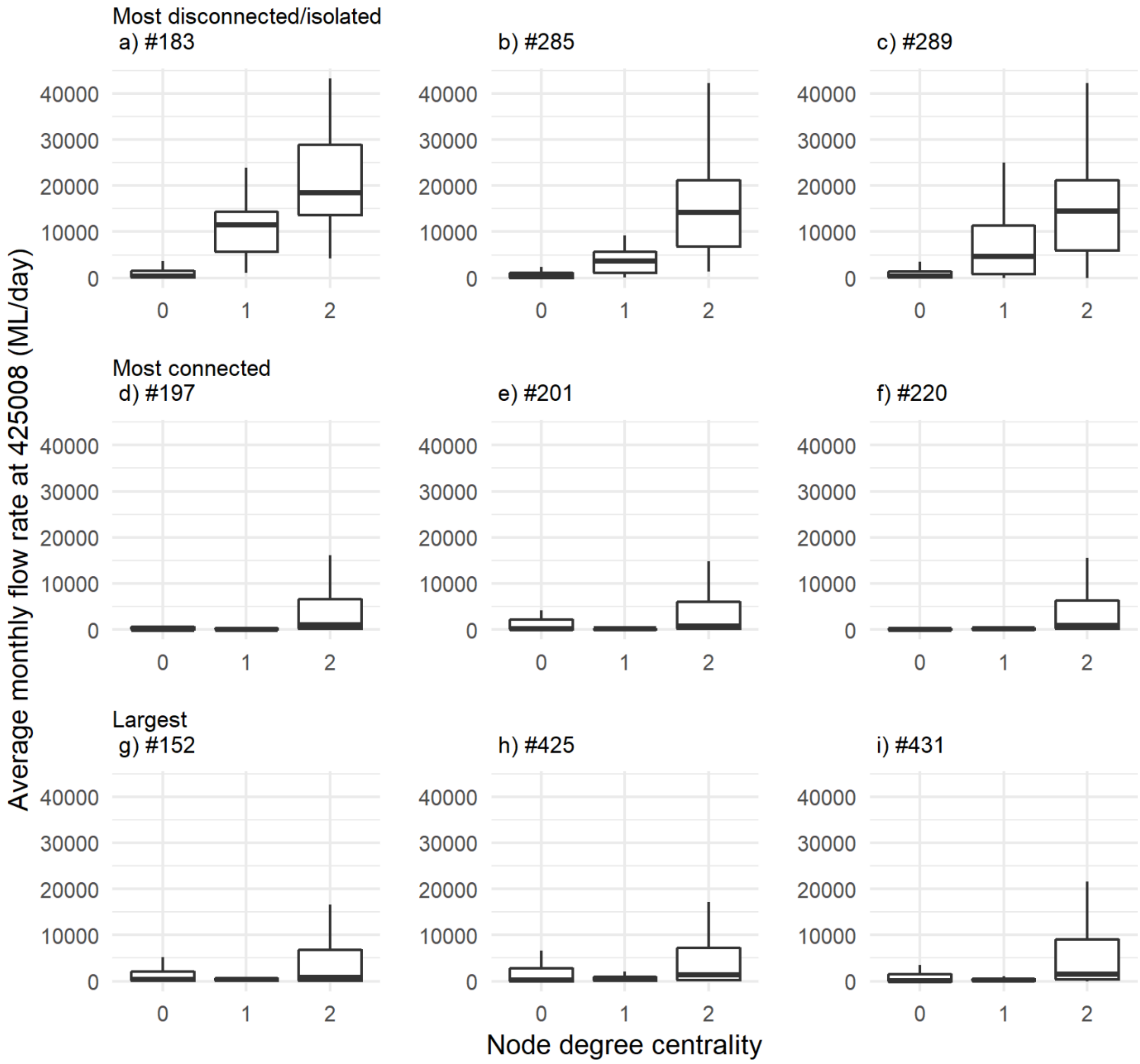

Figure 20. Boxplots showing distribution of flow data for each level of node degree centrality (NDC; number of connections to adjacent waterbodies) for the nine selected waterbodies, including the most disconnected (top row), most connected (middle row), and largest (bottom row) persistent in-channel waterbodies along the Louth to Menindee study reach. Historical flow data from the Wilcannia gauge (425008) was used for the y axis. Outliers were removed during plotting.

Table 3. Connectivity metrics for selected waterbodies (NDC = node degree centrality percentage of months each value occurred, BC = betweenness centrality). Also given is a flow rate threshold (ML/day) at Wilcannia (gauge 425008) for which connection to both adjacent waterbodies is more likely than no connections to adjacent waterbodies, as determined by logistic regression ROC curve. Percentage of months in the modelled data for the Wilcannia gauge (425008) in which each of the thresholds is exceeded is provided. Fit of logistic regression model is shown by model AUC, coefficients are provided in Table A3.1.

								% of time threshold exceeded in modelled flow data		
Significance of waterbody	**Waterbody #**	**Area (m^2)**	**NDC = 0 %**	**NDC = 2 %**	**Median BC**	**AUC**	**Flow threshold (ML/day) for connection to both adjacent waterbodies**	**Baseline**	**Wet**	**Dry**
Most isolated/ disconnected	183	4476	85	10	0	0.95	7229	16	22	12
	285	5387	80	15	0	0.92	4427	23	30	17
	289	6288	80	13	0	0.86	3684	25	33	18
Most connected	197	4479	15	77	2	0.74	331	60	67	49
	201	6271	8	85	3	0.66	417	56	63	46
	220	6272	15	79	5	0.78	196	78	83	70
Largest	152	121341	23	65	10	0.58	537	52	60	43
	425	443301	33	53	3	0.65	521	53	61	44
	431	3307551	34	52	1	0.70	548	52	60	43

The modelled threshold flow value required to fully connect or maintain connection of the three most isolated/disconnected waterbodies (~3600 – 7500 ML) to their adjacent upstream and downstream waterbodies differed substantially from the flow (~190 - 420 ML) required to maintain connectivity of the most connected waterbodies (Table 3; Fig. 21). The short distance between waterbodies in the highly connected group is likely to contribute to these waterbodies staying connected as flows recede, as well as other factors not studied here. The high thresholds required to connect the most disconnected waterbodies suggests these waterbodies are likely to disconnect as flows recede much sooner than the highly connected waterbodies. The flows needed to connect or maintain connection of the most disconnected waterbodies to both of their nearest upstream and downstream neighbours are well above the 50th percentile, including flow above the 75th percentile (of the duration of the study period) to fully connect waterbody #183. Under a drier climate, connectivity of these three waterbodies is likely to be further reduced, with flow in the dry climate scenario only exceeding the threshold values required for full connection of these waterbodies 12-18% of the time compared to 16-25% for baseline data, indicating a reduction in threshold exceedance of ~30% for disconnected/isolated waterbodies (Table 3).

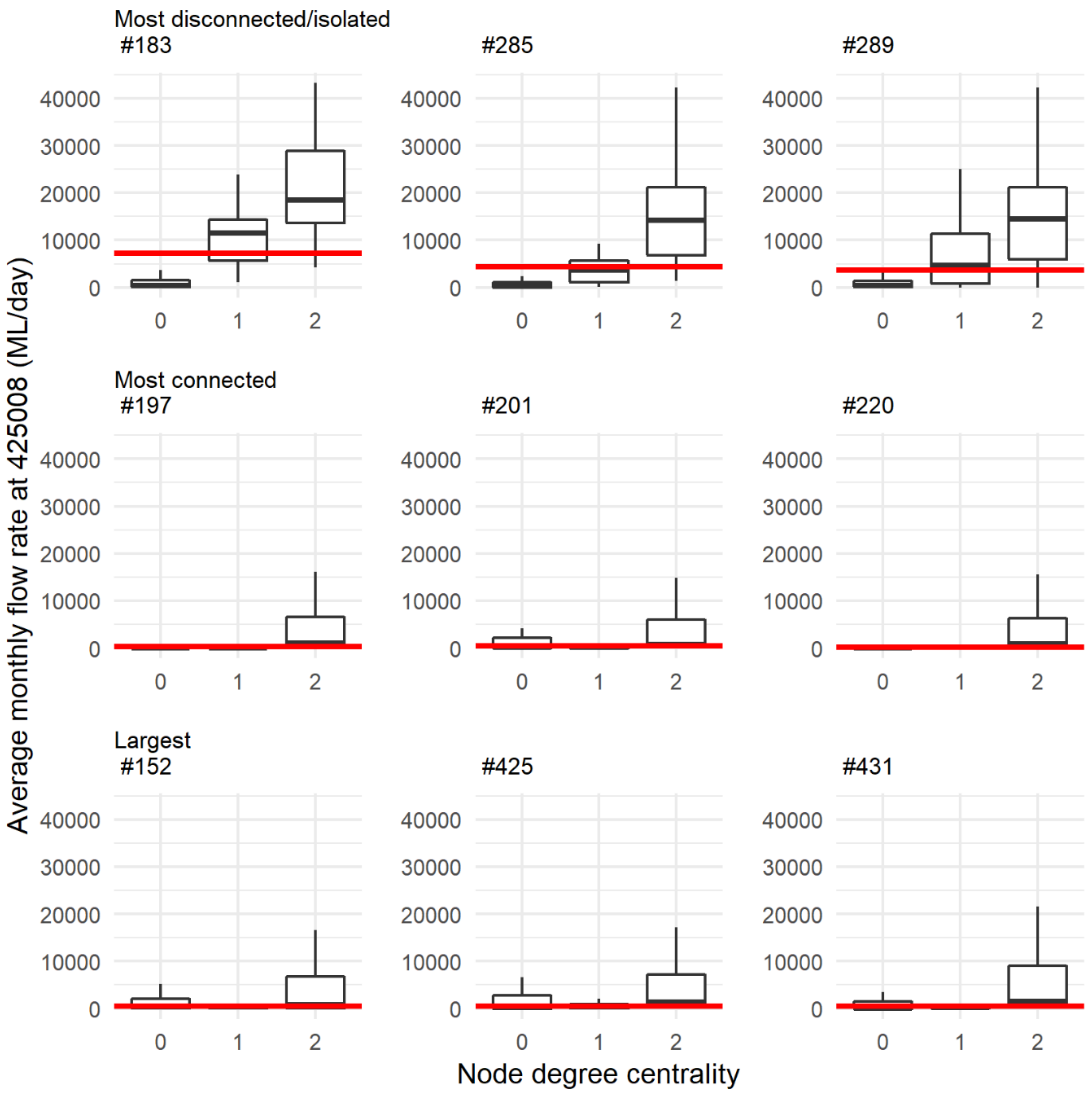

Figure 21. Boxplots showing distribution of flow data (gauge 425008) for each level of node degree centrality (number of connections to adjacent waterbodies) for the nine selected waterbodies. Red lines indicate threshold values for full connection, determined from receiver operating curves of logistic regressions. Outliers were removed during plotting.

3.6 Modelling connectivity with flow at Bourke to guide decision making

The waterbody scale connectivity analysis (Section 3.2) showed that there were several groups of waterbodies along the reach with similar overall mean connectivity to their immediate neighbours (indicated by the NDC metric). These groups were mostly present immediately upstream and downstream of each weir (e.g. Group 1 downstream of Louth Weir and Group 2 downstream of Tilpa Weir; Fig. 22). Additional groups of adjacent waterbodies with similar NDC values included a small defined group between the Tilpa and Wilcannia weirs (Group 3; Fig 22) and a large group at the bottom of the study reach (Group 4; Fig. 22). The three most downstream waterbodies in each of these four groups were modelled using logistic regression to study connectivity of each group in relation to flow at the Bourke gauge. Groups immediately upstream of weirs were not chosen to be modelled due to the artificial flow and connectivity conditions created by the weirs. The models were used to obtain threshold values of flow at Bourke for which the waterbodies in the groups would connect (given that all waterbodies upstream of the group were connected) and remain connected until flows dropped below the threshold values.

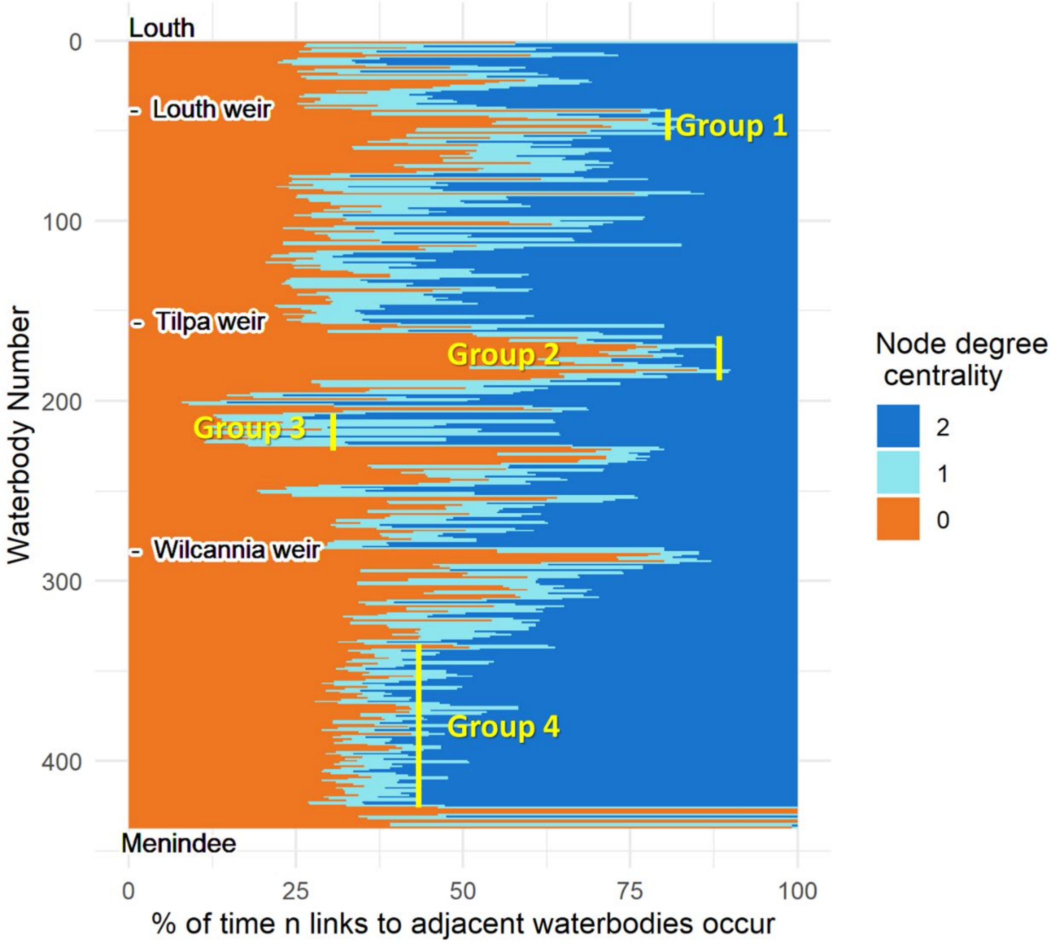

Figure 22. Groups of waterbodies that had similar average connectivity to their immediate upstream and downstream neighbouring waterbodies over the study period. The three most downstream waterbodies in each group were modelled using logistic regressions with flow at the Bourke gauge as the predictor. Groups immediately upstream of weirs were not chosen to be modelled due to the artificial flow and connectivity conditions created by the weirs.

The logistic regressions found that connectivity of waterbodies in Groups 1, 2 and 3 could be predicted with good accuracy using flow at the Bourke gauge (see relatively high AUC for these groups in Table 4). Connectivity of waterbodies in Group 4 could not be predicted accurately with the Bourke gauge (indicated by low AUC). A flow rate of ~2150 was identified for connecting waterbodies in Group 1, but the models suggest that flows much greater than this would be needed for a flow release to pass Group 2 waterbodies. Waterbody #183 in Group 2 was found to require a flow of 4366 ML/day to connect to its neighbouring waterbodies, and given this waterbody was the most disconnected in the reach, waterbodies downstream would likely also reconnect if this flow rate were to be maintained for long enough. Once connected, waterbodies within Group 3 would likely remain connected to each other until flows receded to ~550 ML/day (Table 4).

Table 4. Results of the binary logistic regressions of three waterbodies within each group of waterbodies. The overall percentage of time each value of node degree centrality occurred in the connectivity dataset is given for each waterbody, followed by logistic regression model results, including model AUC, and the threshold value at which for full connection to both immediately neighbouring waterbodies (NDC = 2) is expected to occur. Models with the best AUC (where >0.7) were identified to represent flows at which each group would have within-group connectivity and are highlighted in bold.

Group	Waterbody #	NDC = 0 %	NDC = 1 %	NDC = 2 %	AUC	Flow @ Bourke (ML/day) for full connection
1	46	54	24	22	0.89	1675
	47	71	8	21	0.90	2111
	48	72	10	18	**0.91**	**2146**
2	183	85	5	10	0.91	4366
	184	76	14	10	**0.92**	**4063**
	185	64	13	23	0.87	1742
3	222	12	36	52	**0.84**	**561**
	223	11	21	68	0.81	435
	224	17	16	67	0.82	380
4	423	27	8	65	0.62	630
	424	27	8	65	0.60	553
	425	33	14	53	0.64	638

Given the highly variable connectivity along the reach from month to month, it is important to consider the connectivity in the month prior when predicting connectivity at various flow rates. Therefore, reach scale connectivity was predicted at a range of flow rates and prior connectivity levels and the predictions (percent of waterbodies connected) are given in a lookup table (Table 5). The appropriate row headings should be located by matching the connectivity of the reach at the time of the flow release and the values along that row indicate the predicted reach scale connectivity at each of the four example flow rates. For example, if the connectivity along the reach at the beginning of March is 50% and 10,000 ML/day (equating to 300,000 ML in a 30-day month) is released from Bourke, a connectivity of 67% is predicted for the following month of April.

Table 5. Lookup table of predicted reach scale connectivity (% of waterbodies connected to a neighbouring waterbody) across a range of different flows (column headings indicate flow values used in model) and at different prior connectivity conditions (row headings). Flow is average monthly flow rate in ML/day. To obtain the total monthly flow volume associated with each prediction, multiply the flow rate by the number of days in the month.

	Average lagged monthly flow rate at Bourke (ML/day)			
Prior connectivity (%)	**1,000**	**5,000**	**10,000**	**15,000**
0	32	39	42	44
5	38	46	49	51
10	41	49	52	54
15	44	51	55	56
20	46	53	57	58
30	50	57	60	62
40	53	60	64	65
50	56	64	67	68
60	59	67	70	71

4. Discussion

This study identified long term persistent waterbodies in the Louth-Menindee reach of the Darling River that form a network of aquatic habitats to support fish metapopulations and other aquatic biodiversity. The approach used remote sensing imagery from the complete Landsat record to quantify monthly inundation of these waterbodies and their connectivity along the reach. With the full time series of the Landsat record, metrics of connectivity were related to river flow and local rainfall, with flow proving to be the most important predictor of connectivity along the whole reach. Within the reach, critical flow thresholds were identified that would connect key waterbodies to their neighbours, enhancing opportunities for fish movement within the reach and beyond.

Persistent aquatic habitat in intermittent rivers is important for the survival of aquatic organisms during low flow and cease to flow conditions (Sheldon et al. 2010). Connectivity among these persistent habitats supports good water quality and facilitates the transfer of nutrients and energy, movement of organisms for foraging or finding higher quality habitat, and dispersal to complete life cycles and maintain biodiversity at broad spatial scales (McNeil et al. 2011; Preite and Pearson 2017). As such, maximising connectivity and maintaining persistent high quality aquatic habitat is important for the conservation of native fish and other organisms that rely on connected persistent habitat throughout the riverscape (Bunn and Arthington 2002; Fausch et al. 2002; Soulé et al. 2004). The findings of this study provide managers with a specific tool to predict the likely impact of flow management scenarios on the connectivity of this section of the Darling River. The approach could also be used to study the connectivity between floodplain wetlands and the main channel. Additionally, the approach could be applied in other areas of the Murray-Darling Basin, or at a whole of catchment/basin scale. The choice of study scale should be informed by the scale on which the models can be used to allocate flows for reconnecting persistent waterbodies.

Reconnecting flows are important in highly regulated rivers where flows that would naturally reconnect habitats are intercepted by in-channel structures such as weirs and dams or extracted for off-channel storage in farm dams (Mallen-Cooper and Zampatti 2020). The reduction of reconnecting flows can increase the likelihood of problematic ecological impacts such as reduced water quality in persistent waterbodies and can severely impact fish metapopulation dynamics where hydrological requirements for spawning, recruitment, and migration are not met (Gehrke et al. 1995; Perry and Bond 2009; Bond et al. 2015; Koehn et al. 2019; Stocks et al. 2021). The Murray-Darling Basin contains several species of freshwater fish with broad spatial distributions that utilise hydrological connectivity to disperse throughout the Basin (Baumgartner et al. 2014a, b). The rate and timing of reconnecting flows is important for the spawning and recruitment of native fish species (Stocks et al. 2021) and aptly timed flow releases can boost recruitment success (Sharpe and Stuart 2018). Species that do not migrate large distances, such as Murray Cod, still rely on sufficient reconnecting flows to support flow and temperature preferences for seasonal spawning and recruitment (Sharpe and Stuart 2018). Migrating species, such as Golden Perch, need vast lengths of connected channel to support their spatially broad metapopulation dynamics, where adult Golden Perch migrate upstream, juveniles make large scale active movements (1000's of kilometres) and larvae drift >1600km downstream in the Murray-Darling Basin (Zampatti et al. 2018, 2021; Stuart and Sharpe 2020). The section of Darling River studied here has previously been found to contain a high proportion of migrant Golden Perch (Zampatti et al. 2019), demonstrating the importance of maximising connectivity along the entire reach and beyond.

Waterbody size and impacts of weirs on persistence and connectivity

The persistent waterbodies defined in this study were highly spatially variable in terms of their size and location. Most of the waterbodies were small, close to the minimum threshold of adjoining pixels (i.e. five 30m x 30m pixels) used in the method of defining persistence. Further, some of these waterbodies were separated by only one or two dry pixels, indicating that it may be more appropriate to consider these closely neighbouring waterbodies as single waterbodies. The larger waterbodies were mostly present upstream of each of the weirs, and two of the three largest waterbodies were weir pools. Despite being man made, weir pools are considered important persistent refuge habitat, offering moderate ecological value for native fish in the Murray-Darling Basin (McNeil et al. 2013). However, they can also provide habitat favoured by invasive species such as carp (Scott et al. 2016; Koehn et al. 2018) and the additional impacts they have on downstream connectivity must be considered against their value as refuge habitat. Research in the northern Basin upstream of the Darling River study reach has shown that fish movement opportunity is majorly impeded by instream structures, even minor weirs, when there is flow (Marshall et al. 2021). This study found few persistent waterbodies immediately downstream of the Louth (downstream), Tilpa, and Wilcannia weirs, and these were amongst the most disconnected waterbodies of the reach, indicating that the weirs have a significant impact on downstream water persistence and connectivity. Most of the weirs have functional fishways to mitigate their barrier effect to fish, however this analysis shows that it would take significant flow to obtain enough connectivity along the stretches of river downstream of each weir for fish to be able to reach the fishways.

Waterbody persistence and connectivity

The persistent waterbodies identified in this study varied greatly in their trends of inundation over time. Some waterbodies were less than 10% inundated around 20% of the time, while others were more than 90% inundated around 80% of the time, and most had a mean inundation of 70-80%. Temporal variation in the spatial position and depth of persistent waterbodies were not quantified in this study but may contribute to explaining why some waterbodies were highly dynamic in terms of their inundation and risk of drying, where highly dynamic waterbodies may be shallower or experience slight shifts in their location within the channel over time with sediment erosion and deposition (Pearson et al. 2022; Tibby et al. 2023). Conversely, those that were consistently inundated may represent deeper waterbodies (Wallace et al. 2015). Matching inundation data from these waterbodies with field collected data on depth from previous studies (e.g. Pearson et al. 2022) may offer insight into how the shape and volume of waterbodies influences their persistence dynamics. Of course, connectivity can also contribute to the inundation changes experienced by persistent waterbodies over time (Wallace et al. 2015). In this study, the chain of consistently highly inundated waterbodies in the middle of the study reach were also the most connected, receiving top-ups from water inflowing from their upstream neighbouring waterbodies, which may partially explain their persistent nature. In dryland rivers, frequency of inflowing water from upstream is an important determinant of aquatic refuge size and likelihood of drying (Hamilton et al. 2005).

Waterbody connectivity was highly spatially variable and likely influenced by the river distance between neighbouring waterbodies. This analysis identified hubs (waterbodies frequently connected to their nearest neighbours) that were spread out along the river channel. Although these hubs were separated by groups of waterbodies with low connectivity, they present important areas of connected refuges for fish to move locally within during periods of less than average flow. Two of these groups of hubs, located upstream of Wilcannia, were also important stepping stone habitats (waterbodies with high betweenness centrality), linking the lower and upper parts of the reach. Some waterbodies in the lower part of the reach around Four Mile Lake were also found to be important stepping stones, allowing fish to move between the Menindee and Wilcannia regions under most flow conditions except during periods of drought.

Model performance, limitations, and use for management

The 35-year study period encompassed highly variable flows and climate trends in the Darling River region, which ensured the connectivity models and subsequent predictive models can predict connectivity under a wide range of flow conditions. During the study period, flow conditions were historically extreme and alternated between drought and flood cycles from 2001 onwards.

At the whole of reach scale, flow was the most important predictor of connectivity, however, a range of other variables also played a role in accurate predictions. Climate trends were evident in patterns of reach scale connectivity and the variable 'Year' (representing broad climate trends over time) was an important predictor in the model. This result indicated that the connectivity of the Darling River is likely to be sensitive to climate variations and future development of the model with modelled flow data that integrates more recent climate (beyond 2009 when the currently available model data ends) would improve model performance. The reach scale models using flow at the Bourke gauge showed that connectivity at the time of releasing water has a significant influence on how much of the river a given volume of water will reconnect. Therefore, determining the connectivity of the river before allocating a specific volume of water to be released will help managers to anticipate the probable effectiveness of the volumes to be released. Quantifying this connectivity is relatively straightforward following the methodology laid out in the Methods section and using the code provided in https://github.com/Kaitlyn-OMara/MD-WERP_11.2. The accuracy of the predictions provided in Section 3.6 could then be determined by quantifying connectivity before and after a flow release.

Focusing on specific waterbodies, the logistic regressions provided a probability of full connection to nearest upstream and downstream waterbodies following a reconnecting flow and can be used in two ways. First, managers can obtain information on the flow needed to sustain critical refuge habitat by maintaining connectivity to neighbouring waterbodies as flows recede, either to maintain water quality and prevent desiccation, or to facilitate movement of organisms to other waterbodies. Second, predictions can be made to determine the likely connection of key waterbodies under given river management scenarios, including environmental flows. The accuracy of the logistic regression models was strongly related to the relative isolation of the waterbodies with models performing better for more disconnected/isolated waterbodies. This is likely because highly connected waterbodies are connected under most flow conditions, making it difficult for the model to identify a critical threshold where disconnection would occur.

To apply these models directly to water allocations, managers first need to consider the main desired ecological outcomes of the flows to be allocated. If the aim is to connect the whole reach so that fish passage can occur, or to understand what proportion of the reach will be connected in a dry, average, or wet year with a given amount of flow released, the reach scale connectivity model is the suitable tool for setting flow allocations. Alternatively, if the goal is to maintain water quality or prevent drying of specific waterbodies that may provide aquatic refuge habitat, then using the waterbody scale logistic regression models will provide managers with an understanding of the flows likely required to maintain connectivity of those specific waterbodies to their nearest upstream and downstream neighbouring waterbodies.

Understanding the ecological outcomes of these reconnecting flows is important for assessing and improving how well the use of the models achieves desired outcomes. At the reach level, studies of fish movement could be linked to the connectivity analysis to determine what varying levels of connectivity means for movement opportunity. For example, O'Mara et al., (2021) studied recent fish movements in the Mitchell River using sulfur isotopes and found that movement was related to hydrological connectivity, with more fish that had recently immigrated present at highly connected sites than sites of low connectivity. Similarly studying recent immigration of Golden Perch to various waterbodies along the study reach at multiple time points would help to understand their short-term response to variations in hydrological connectivity. At the waterbody level, studies on depth, water and habitat quality, and the ecology of the biological communities in specific refuge waterbodies would help to understand the ecological outcomes of reconnecting flows on specific habitats. For example, Leigh and Sheldon (2009) sampled two rivers in northern Australia and found that macroinvertebrate composition was driven by hydrological connectivity of in-channel waterbodies. Additionally, Waltham et al., (2013) undertook a detailed assessment of in-channel waterbodies in the Flinders and Gilbert river catchments, linking waterbody ecology to water quality changes throughout the dry season. If there are sites within the study reach that have ecological monitoring data available (e.g. macroinvertebrate composition, fish abundance, or fish condition), they would be suitable candidate locations for further research linking the connectivity analysis with ecological data to understand local scale outcomes of reconnecting flows and whether these are consistent among waterbodies or vary spatially or with waterbody size and depth.

Conclusions

Australia is facing an uncertain climate future and extreme climate events are becoming increasingly common, warranting the need to expand knowledge on long-term persistence and connectivity of critical aquatic habitat and make predictions for the future (Maggini et al. 2013). In highly flow-modified systems such as the Darling River, aquatic organisms are at risk of decline if climate change were to exacerbate existing stressors of land and river modification (Pratchett et al. 2011). By using graph network theory, this study showed that water persistence and connectivity in the Darling River varies spatially and is influenced by the water interception and barrier effect of in-channel weirs. Hub and stepping stone waterbodies were identified as important habitats that, using the models developed here, can be sustained by allocated flows that maintain their ecological function. Linking the persistence and connectivity analysis produced in this study with ecological endpoints such as fish population dynamics is important for ensuring allocated flows have the desired ecological outcomes.

References

ABC News (2024) Why are fish still dying in the Darling River at Menindee — and what can we do to prevent it? https://www.abc.net.au/news/science/2024-04-30/murray-darling-basin-menindee-fish-kills-causes-solutions/103745622

Barrow JS, Yen JDL, Koehn JD, et al (2021) Lifetime movement history is associated with variable growth of a potamodromous freshwater fish. J Anim Ecol 90:2560–2572

Bates WB, Chu L, Claire H, et al (2023) A tale of two rivers–Baaka and Martuwarra, Australia: Shared voices and art towards water justice. Anthr Rev 20530196231186960

Baumgartner L, Zampatti B, Jones M, et al (2014a) Fish passage in the Murray-Darling Basin, Australia: Not just an upstream battle. Ecol Manag Restor 15:28–39

Baumgartner LJ, Conallin J, Wooden I, et al (2014b) Using flow guilds of freshwater fish in an adaptive management framework to simplify environmental flow delivery for semi-arid riverine systems. Fish Fish 15:410–427

Bewick V, Cheek L, Ball J (2004) Statistics review 13: receiver operating characteristic curves. Crit care 8:1–5

Bishop-Taylor R, Tulbure MG, Broich M (2017) Surface-water dynamics and land use influence landscape connectivity across a major dryland region. Ecol Appl 27:1124–1137

Bond N (2022) hydrostats: Hydrologic Indices for Daily Time Series Data. R package.

Bond NR, Balcombe SR, Crook DA, et al (2015) Fish population persistence in hydrologically variable landscapes. Ecol Appl 25:901–913

Branco P, Segurado P, Santos JM, Ferreira MT (2014) Prioritizing barrier removal to improve functional connectivity of rivers. J Appl Ecol 51:1197–1206

Breiman L (2001) Random forests. Mach Learn 45:5–32

Bunn SE, Arthington AH (2002) Basic principles and ecological consequences of altered flow regimes for aquatic biodiversity. Environ Manage 30:492–507

Carini G, Hughes JM, Bunn SE (2006) The role of waterholes as ‘refugia’ in sustaining genetic diversity and variation of two freshwater species in dryland river systems (Western Queensland, Australia). Freshw Biol 51:1434–1446

Chen T, He T, Benesty M, et al (2015) xgboost: extreme gradient boosting. R Packag. version 0.4-2 1:1–4

Coats SC, Wilson M, McIntosh AR (2021) Contextualizing the relative importance of habitat connectivity for metapopulation persistence: A case study of a critically endangered fish. Aquat Conserv Mar Freshw Ecosyst 31:1956–1969

Csardi G, Nepusz T (2006) The igraph software package for complex network research. InterJournal, complex Syst. 1695:1–9

CSIRO (2008) Water availability in the Murray-Darling Basin. A report to the Australian Government from the CSIRO Murray-Darling Basin Sustainable Yields Project. CSIRO Australia

Dale MRT, Fortin M-J (2010) From graphs to spatial graphs. Annu Rev Ecol Evol Syst 41:21–38

Datry T, Corti R, Heino J, et al (2017) Habitat fragmentation and metapopulation, metacommunity, and metaecosystem dynamics in intermittent rivers and ephemeral streams. In: Intermittent rivers and ephemeral streams. Elsevier, pp 377–403

Davies PE, Harris JH, Hillman TJ, Walker KF (2010) The sustainable rivers audit: assessing river ecosystem health in the Murray–Darling Basin, Australia. Mar Freshw Res 61:764–777

Davis J, Pavlova A, Thompson R, Sunnucks P (2013) Evolutionary refugia and ecological refuges: key concepts for conserving Australian arid zone freshwater biodiversity under climate change. Glob Chang Biol 19:1970–1984

Dutta D, Hughes J, Vaze J, et al (2012) A daily river system model for the Murray-Darling Basin: development, testing and implementation. In: 34th Hydrology and Water Resources Symposium. pp 1057–1066

Erős T, Schmera D, Schick RS (2011) Network thinking in riverscape conservation–a graph-based approach. Biol Conserv 144:184–192

ESRI (2019) ArcGIS Pro. ArcGIS Desktop. Redlands, CA Environ. Syst. Res. Inst.

Fausch KD, Torgersen CE, Baxter C V, Li HW (2002) Landscapes to riverscapes: bridging the gap between research and conservation of stream fishes: a continuous view of the river is needed to understand how processes interacting among scales set the context for stream fishes and their habitat. Bioscience 52:483–498

Furst D, Aldridge K, Bice C, et al (2019) The influence of longitudinal hydrological connectivity on resource availability and lower order food web structure in the Murray River

Galpern P, Manseau M, Fall A (2011) Patch-based graphs of landscape connectivity: A guide to construction, analysis and application for conservation. Biol Conserv 144:44–55

Gao Y, Xiao X, Ding M, et al (2018) Evaluation of plain river network hydrologic connectivity based on improved graph theory. In: IOP Conference Series: Earth and Environmental Science. IOP Publishing, p 12002

Gehrke PC, Brown P, Schiller CB, et al (1995) River regulation and fish communities in the Murray-Darling river system, Australia. Regul Rivers Res Manag 11:363–375

Gorelick N, Hancher M, Dixon M, et al (2017) Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sens Environ 202:18–27

Hamilton SK, Bunn SE, Thoms MC, Marshall JC (2005) Persistence of aquatic refugia between flow pulses in a dryland river system (Cooper Creek, Australia). Limnol Oceanogr 50:743–754

Hansen LK, Salamon P (1990) Neural network ensembles. IEEE Trans Pattern Anal Mach Intell 12:993–1001

Hijmans RJ (2018) raster: Geographic data analysis and modeling. R Packag. version 3.5-15 2:8

Jackson S, Head L (2020) Australia's mass fish kills as a crisis of modern water: Understanding hydrosocial change in the Murray-Darling Basin. Geoforum 109:44–56

Karstens S, Dorow M, Bochert R, et al (2022) Stepping stones along urban coastlines—improving habitat connectivity for aquatic fauna with constructed floating wetlands. Wetlands 42:76

Kirby M, Chiew F, Mainuddin M, et al (2013) Drought and climate change in the Murray-Darling Basin: a hydrological perspective. Drought Arid Semi-Arid Reg A Multi-Disciplinary Cross-Country Perspect 281–299

Koehn JD (2021) Key steps to improve the assessment, evaluation and management of fish kills: lessons from the Murray–Darling River system, Australia. Mar Freshw Res 73:269–281

Koehn JD, Balcombe SR, Zampatti BP (2019) Fish and flow management in the Murray–Darling Basin: Directions for research. Ecol Manag Restor 20:142–150

Koehn JD, Nicol SJ (2016) Comparative movements of four large fish species in a lowland river. J Fish Biol 88:1350–1368

Koehn JD, Todd CR, Zampatti BP, et al (2018) Using a population model to inform the management of river flows and invasive carp (*Cyprinus carpio*). Environ Manage 61:432–442

Krause CE, Newey V, Alger MJ, Lymburner L (2021) Mapping and monitoring the multi-decadal dynamics of Australia's open waterbodies using Landsat. Remote Sens 13:1437

Leblanc M, Tweed S, Van Dijk A, Timbal B (2012) A review of historic and future hydrological changes in the Murray-Darling Basin. Glob Planet Change 80:226–246

Leigh C, Sheldon F (2009) Hydrological connectivity drives patterns of macroinvertebrate biodiversity in floodplain rivers of the Australian wet/dry tropics. Freshw Biol 54:549–571

Lobegeiger J (2010) Refugial waterholes project: research highlights. Dep Environ Resour Manag

Maggini R, Kujala H, Taylor M, et al (2013) Protecting and restoring habitat to help Australia's threatened species adapt to climate change. NCCARF (National Climate Change Adaptation Research Facility) and CSIRO

Mallen-Cooper M, Zampatti BP (2020) Restoring the ecological integrity of a dryland river: why low flows in the Barwon–Darling River must flow. Ecol Manag Restor 21:218–228

Mallen-Cooper M, Zampatti BP (2018) History, hydrology and hydraulics: Rethinking the ecological management of large rivers. Ecohydrology 11:e1965

Marshall JC, Lobegeiger JS, Starkey A (2021) Risks to fish populations in dryland rivers from the combined threats of drought and instream barriers. Front Environ Sci 9:671556

Marshall JC, Menke N, Crook DA, et al (2016) Go with the flow: the movement behaviour of fish from isolated waterhole refugia during connecting flow events in an intermittent dryland river. Freshw Biol 61:1242–1258

McGregor G, Lobegeiger J, Marshall J, et al (2018) Review of Water Plan (Moonie River) 2003 : ecological risk assessment report. Department of Environment and Science Brisbane, Brisbane SE - 1 online resource (iii, 62 pages)

McJannet D, Marvanek S, Kinsey-Henderson A, et al (2014) Persistence of in-stream waterholes in ephemeral rivers of tropical northern Australia and potential impacts of climate change. Mar Freshw Res 65:1131–1144

McNeil DG, Gehrig SL, Cheshire KJM (2013) The protection of drought refuges for native fish in the Murray-Darling Basin. A report to the Murray Darling Basin Authority. South Australian Research and Development Institute, Aquatic Sciences, Adelaide

McNeil DG, Gehrig SL, Sharpe C (2011) Resistance and resilience of Murray-Darling Basin fishes to drought disturbance. South Australian Research and Development Institute, Aquatic Sciences, Adelaide

MDBA (2024) Key elements of the Basin Plan. Murray Darling Basin Authority. https://www.mdba.gov.au/water-management/basin-plan/key-elements-basin-plan. Accessed 15 May 2024

MDBA (2023a) Our reliance on the Basin for water. Murray-Darling Basin Authority. https://www.mdba.gov.au/basin/why-murray-darling-basin-matters/our-reliance-basin-water. Accessed 14 Mar 2024

MDBA (2023b) Barwon-Darling catchment. https://www.mdba.gov.au/basin/catchments/northern-basin-catchments/barwon-darling-catchment. Accessed 22 Mar 2024

MDBA (2023c) Current Basin water in storage report. Murray-Darling Basin Authority. https://www.mdba.gov.au/publications-and-data/data-and-dashboards/current-basin-water-storage-report. Accessed 22 Mar 2024

MDBA (2023d) Managing drought. Murray Darling Basin Authority. https://www.mdba.gov.au/climate-and-river-health/climate/drought/managing-drought. Accessed 11 Mar 2024

Montoya D, Ravlich E (2019) Murray Darling Basin: fish kills and current conditions.

Mueller N, Lewis A, Roberts D, et al (2016) Water observations from space: Mapping surface water from 25 years of Landsat imagery across Australia. Remote Sens Environ. https://doi.org/10.1016/j.rse.2015.11.003

Natekin A, Knoll A (2013) Gradient boosting machines, a tutorial. Front Neurorobot 7:21

NSW DPI Fisheries (2023) Preliminary report into the 2023 fish deaths in the Lower Darling-Baaka River: summary of available Fisheries data

NSW Government (2021) Cease-to-flow and low-flow events in the Barwon–Darling River. NSW Department of Planning, Industry and Environment. PUB21/479.

NSW Government (2024) Wilcannia Weir replacement project. NSW Department of Planning and Environment. https://water.dpie.nsw.gov.au/our-work/water-infrastructure-nsw/regional-projects/wilcannia-weir. Accessed 22 Mar 2024

NSW Government, WaterNSW (2019) Western Weirs Program. Department of Planning and Environment.

O'Mara K, Venarsky M, Stewart-Koster B, et al (2021) Connectivity of fish communities in a tropical floodplain river system and predicted impacts of potential new dams. Sci Total Environ 788:147785

Pearson MR, Reid M, Ryder D, Miller CE (2022) The drivers and consequences of change to the physical character of waterholes on an Australian dryland river. University of New England

Pebesma EJ (2018) Simple features for R: standardized support for spatial vector data. R J. 10:439

Perry GLW, Bond NR (2009) Spatially explicit modeling of habitat dynamics and fish population persistence in an intermittent lowland stream. Ecol Appl 19:731–746

Podger G, Yang A, Brown A, et al (2010) Proposed river modelling methods and integrated river system modelling framework design for use in basin plan modelling. *Murray-Darling Basin Authority, CSIRO Water for a Healthy Country National Research Flagship*.

Poff NL, Allan JD, Bain MB, et al (1997) The natural flow regime. Bioscience 47:769–784

Pratchett MS, Bay LK, Gehrke PC, et al (2011) Contribution of climate change to degradation and loss of critical fish habitats in Australian marine and freshwater environments. Mar Freshw Res 62:1062–1081

Preite CK, Pearson RG (2017) Water-quality variability in dryland riverine waterholes: a challenge for ecosystem assessment. In: Annales de Limnologie-International Journal of Limnology. EDP Sciences, pp 221–232

Price A, Balcombe S, Humphries P, et al (2020) Murray-Darling Basin Environmental Water Knowledge and Research Project: Fish Theme Research Report

R Core Team (2021) R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

Robin X, Turck N, Hainard A, et al (2011) pROC: an open-source package for R and S+ to analyze and compare ROC curves. BMC Bioinformatics 12:1–8

RStudio Team (2020) RStudio: Integrated Development for R. RStudio, PBC, Boston, MA URL http://www.rstudio.com/

Saura S, Bodin Ö, Fortin M (2014) Stepping stones are crucial for species' long-distance dispersal and range expansion through habitat networks. J Appl Ecol 51:171–182

Schmarr D, Mathwin R, Cheshire D, McNeil D (2013) Aquatic ecology assessment and analysis of the Cooper Creek, South Australia

Scott DC, Arbeider M, Gordon J, Moore JW (2016) Flood control structures in tidal creeks associated with reduction in nursery potential for native fishes and creation of hotspots for invasive species. Can J Fish Aquat Sci 73:1138–1148

Sharpe C, Stuart I (2018) Environmental flows in the Darling River to support native fish populations. Commonw Environ Water Off

Sheldon F, Barma D, Baumgartner LJ, et al (2021) Assessment of the causes and solutions to the significant 2018–19 fish deaths in the Lower Darling River, New South Wales, Australia. Mar Freshw Res 73:147–158

Sheldon F, Boulton AJ, Puckridge JT (2003) Variable connection structures invertebrate composition in dryland rivers. Rec South Aust Museum Monogr Ser 7:119–130

Sheldon F, Bunn SE, Hughes JM, et al (2010) Ecological roles and threats to aquatic refugia in arid landscapes: dryland river waterholes. Mar Freshw Res 61:885–895

Silcock J (2009) Identification of Permanent Refuge Waterbodies in the Cooper Creek & Georgina-Diamantina River Catchments for Queensland and South Australia: Final Report to South Australian Arid Lands Natural Resource Management Board. South Australian Arid Lands Natural Resource Management Board

Soulé ME, Mackey BG, Recher HF, et al (2004) The role of connectivity in Australian conservation. Pacific Conserv Biol 10:266–279

Stewardson MJ, Walker G, Coleman M (2021) Hydrology of the murray–darling basin. In: Murray-Darling Basin, Australia. Elsevier, pp 47–73

Stocks JR, Davis S, Anderson MJ, et al (2021) Fish and flows: Abiotic drivers influence the recruitment response of a freshwater fish community throughout a regulated lotic system of the Murray-Darling Basin, Australia. Aquat Conserv Mar Freshw Ecosyst 31:3228–3247

Stuart IG, Sharpe CP (2020) Riverine spawning, long distance larval drift, and floodplain recruitment of a pelagophilic fish: a case study of golden perch (*Macquaria ambigua*) in the arid Darling River, Australia. Aquat Conserv Mar Freshw Ecosyst 30:675–690

Swirepik JL, Burns IC, Dyer FJ, et al (2016) Establishing environmental water requirements for the Murray–Darling Basin, Australia's largest developed river system. River Res Appl 32:1153–1165

Thiem JD, Baumgartner LJ, Fanson B, et al (2021) Contrasting natal origin and movement history informs recovery pathways for three lowland river species following a mass fish kill. Mar Freshw Res 73:237–246

Thoms M, Rayburg S, Neave M, et al (2022) The physical diversity and assessment of a large river system: the Murray–Darling Basin, Australia. Large Rivers Geomorphol Manag Second Ed 861–890

Thoms MC, Sheldon F (2000) Water resource development and hydrological change in a large dryland river: the Barwon–Darling River, Australia. J Hydrol 228:10–21

Tibby J, Marshall JC, Lobegeiger JS, et al (2023) Sedimentation from landscape clearance-induced soil erosion threatens waterhole persistence in a semi-arid river system, southern Queensland, Australia. Mar Freshw

Res 74:1050–1070

Wallace J, Waltham N, Burrows D, McJannet D (2015) The temperature regimes of dry-season waterholes in tropical northern Australia: potential effects on fish refugia. Freshw Sci 34:663–678

Waltham N, Burrows D, Butler B, et al (2013) Waterhole ecology in the Flinders and Gilbert catchments. A Tech Rep to Aust Gov from CSIRO Flinders Gilbert Agric Resour Assessment, part North Queensl Irrig Agric Strateg 460

Waltham NJ, Burrows D, Butler B, Wallace J (2014) Water quality and fish refugia in riverine waterholes in northern Queensland potentially subject to irrigation development. In: Proceedings of the 7th Australian Stream Management Conference. Townsville, Queensland. pp 150–155

WaterNSW (2023) WaterInsights. https://waterinsights.waternsw.com.au/. Accessed 27 Sep 2023

Xu H (2006) Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery. Int J Remote Sens 27:3025–3033

Yu Z, Lu M, Xu Y, et al (2023) Network structure and stability of the river connectivity in a rapidly urbanizing region. Sci Total Environ 894:165021

Zampatti BP, Fanson BG, Baumgartner LJ, et al (2021) Population demographics of golden perch (*Macquaria ambigua*) in the Darling River prior to a major fish kill: a guide for rehabilitation. Mar Freshw Res 73:223–236

Zampatti BP, Fanson BG, Strawbridge A, et al (2019) Basin-scale population dynamics of Golden Perch and Murray Cod: relating flow to provenance, movement and recruitment in the Murray–Darling Basin

Zampatti BP, Leigh SJ, Bice CM, Rogers PJ (2018) Multiscale movements of golden perch (*Percichthyidae: Macquaria ambigua*) in the River Murray, Australia. Austral Ecol 43:763–774

Appendix 1: Landsat methodology

The purpose of this analysis was:

1. To produce monthly summary images of where water was in the river.
2. To produce a summary image of long-term water persistence (for the period May 1987 to December 2022).
3. To use the water persistence raster image (2) to define persistent waterbodies in the main channel of the study reach and analyse their connectivity over the time period by sequentially overlaying each of the monthly raster images (1) and creating a graph network.

The study area for this project is the Darling River between Louth and Menindee. To clip images to this area, a custom shapefile was built by applying a buffer of 1000m around the Darling River. The buffer was used to account for any deviations in the linework and ensure that the full width of the river was captured.

Three datasets from the full Landsat record, Landsat 5, 7, 8 and 9, were accessed through Google Earth Engine (Gorelick *et al.* 2017), to derive estimates of monthly water presence from May 1987 to December 2022 along the study reach.

The three Landsat datasets used were:

- USGS Landsat 8 Level 2, Collection 2, Tier 1
- USGS Landsat 7 Level 2, Collection 2, Tier 1
- USGS Landsat 5 Level 2, Collection 2, Tier 1

These datasets have already been atmospherically corrected to surface reflectance, reducing the need for pre-processing. The images contain metadata and QA bands (as a bitmask) which can be used to filter datasets and mask out low-quality pixels (e.g. pixels affected by clouds) respectively.

An image cloud threshold of 20% was applied (define by metadata values of CLOUDY_PIXEL_PERCENTAGE), i.e. images with greater than or equal to 20% cloud detected in them were removed. Since the remaining images could still contain some cloudy pixels, these images were processed to mask out pixels based on the provided bitmask. On the edges of Landsat 5 and 7 scenes there can be low quality data, so a border of 6km was trimmed from each image footprint. Landsat 7 data was only used up to the 30th of May 2003, after which point the Scan Line Corrector (SLC) failed (USGS 2023) resulting in no data stripes throughout each image.

Pixels containing water were detected using the Modified Normalised Difference Water Index (MNDWI; Xu 2006). See Fig A1.1 for schematic of how the processing the collection is done. For each image a threshold of zero was applied to the MNDWI band to produce binary water/not-water values for pixels. Monthly summary images were produced, such that, if water had been detected in any pixel throughout the month it was flagged as ‘water’. Pixels were also flagged as ‘clear and dry’ where the red band reflected greater than zero. It is very unlikely that the red band will ever reflect absolute zero, other than when no data is present. Pixels with ‘bad’ data (e.g. cloudy, shadow or no data) were also converted to a binary band (1 = bad pixel; 0 = good pixel).

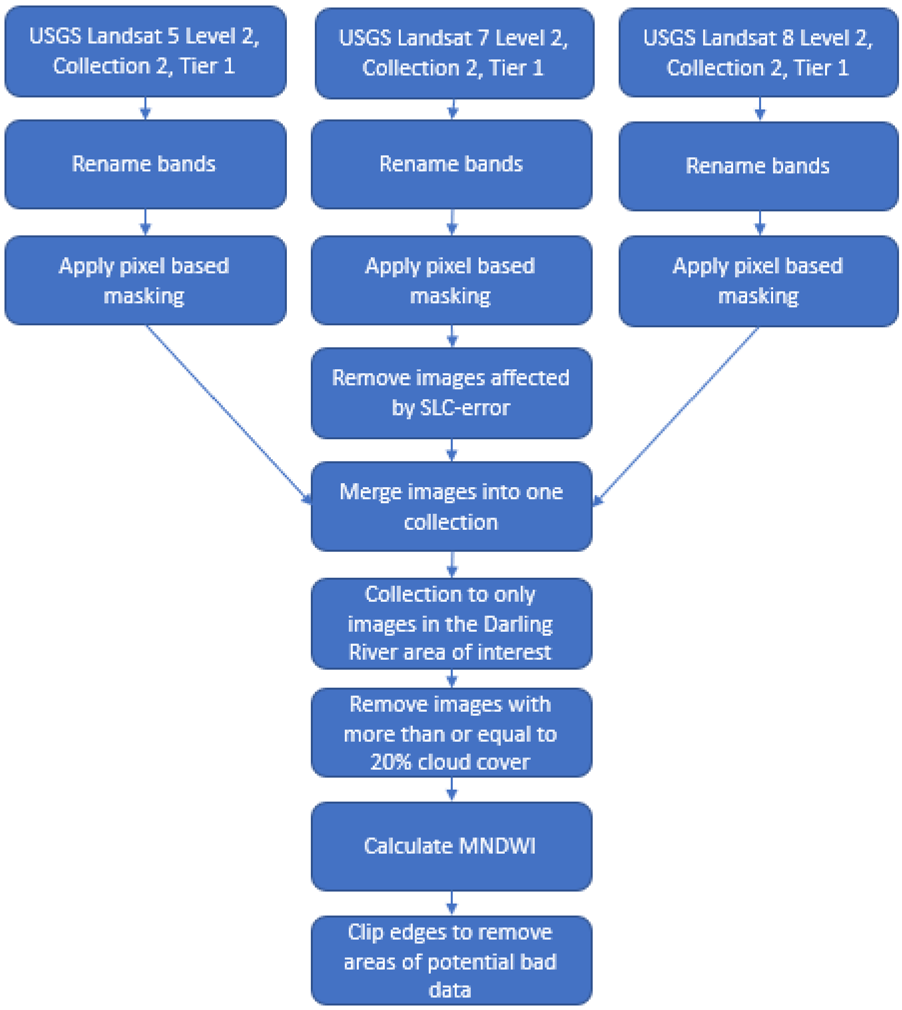

Figure A1.1. Schematic process to produce a collection of cloud-masked water presence images from global Landsat collections.

To calculate monthly summary images, for each month, all images occurring in a month had the water and clear pixels calculated in separate bands. The maximum of the images (if there is more than one in a month) is calculated. Then the bands for water (1 = water, 0 = not water) and clear (1 = clear, 0 = not clear), are added together (Fig. A1.2). There are three options available then, clear, and wet (2), clear and dry (1) and not clear (0) (Fig. A1.3). This final monthly image is then exported to Google Cloud. All images were exported in ESPG:32654.

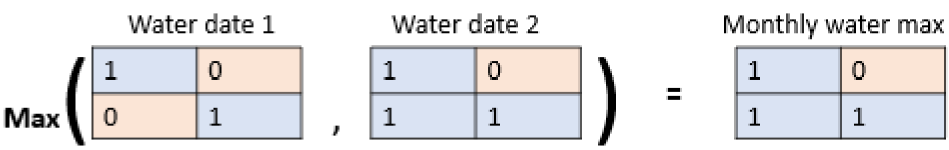

Figure A1.2. The 'water' bands from two separate images are combined to find the maximum value. This process is repeated for 'clear' bands.

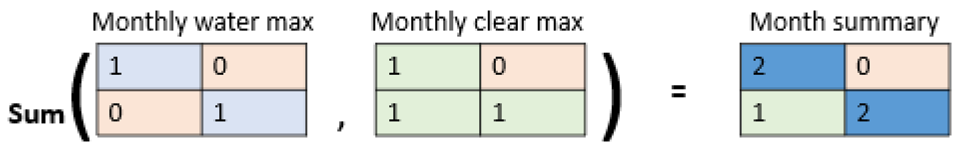

Figure A1.3. Two separate bands, 'water' and 'clear', are summed together to form one band.

A single raster summarising the water persistence over time was needed to produce a shapefile of persistent waterbodies along the study reach. To calculate water persistence for the time period May 1987 to December 2022, the water observations and the clear observations were separately summed across all months in this period (Fig. A1.4). Following this, water persistence for the whole period was calculated as the total number of water observations over the total number of clear observations:

$$Water\ persistence\ (\%) = \frac{(Sum\ of\ water\ observations)}{(Sum\ of\ clear\ observations)} \times 100$$

It's important to note here the data limitations that an observation was not available for every day. Nonetheless, given the usual duration of inundation this metric can provide a good understanding of inundation dynamics.

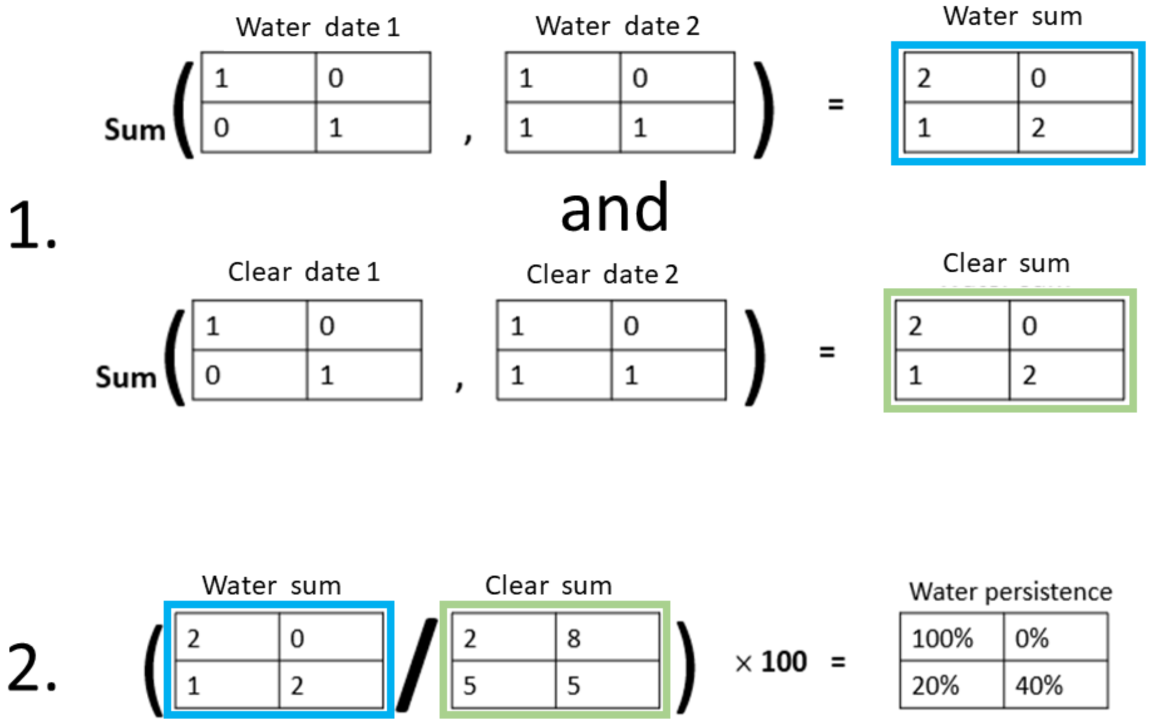

Figure A1.4. Schematic of the methods used to calculate the summary water persistence raster that was used to define the persistent waterbodies.

Appendix 2: Flow and reach scale connectivity

The direct relationship between flow and reach scale connectivity is shown in Figure A2.1

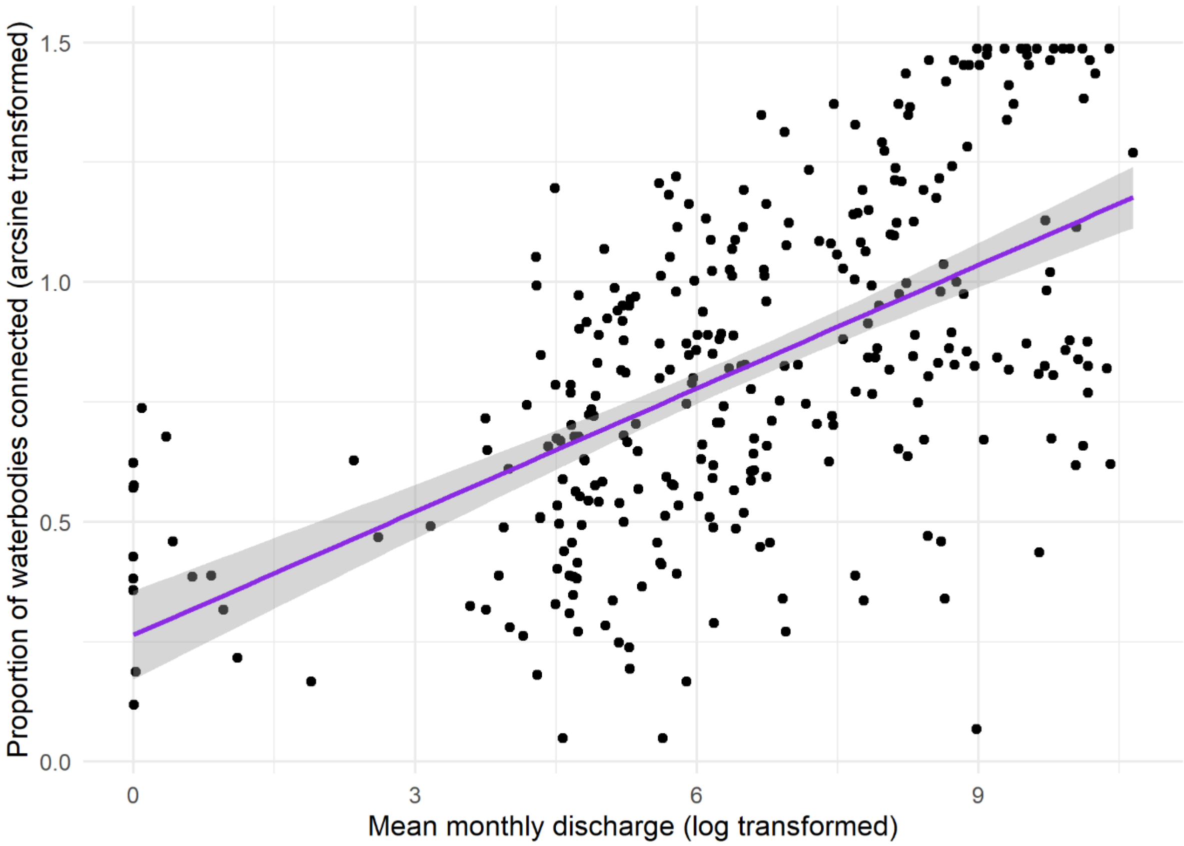

Figure A2.1. Scatterplot including linear regression (with 95% confidence interval) showing the correlation between river flow (log transformed average of the Wilcannia (425008) and Weir 32 (425012) gauges) and reach-scale connectivity (proportion of waterbodies connected each month (arcsine square root transformed).

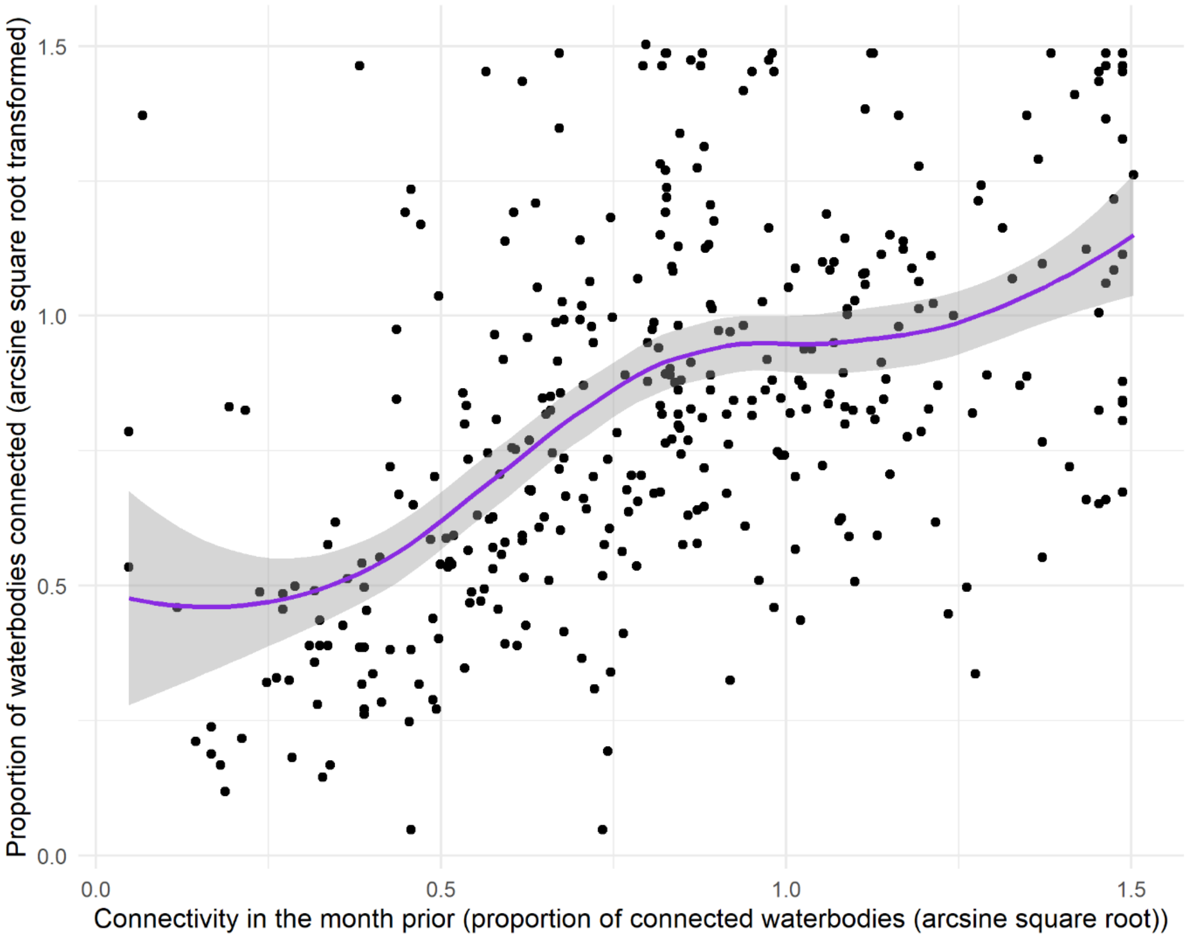

Figure A2.2. Scatterplot of lagged connectivity (connectivity in the month prior) and connectivity. Both variables were proportional data that was arcsine square root transformed. Fit line is shown with 95% confidence interval.

Appendix 3: Selected waterbodies locations and model coefficients

*Table A3.1. Geographic co-ordinates of the waterbodies of interest described in Section 3.5 and the model coefficients for each of the logistic regressions. * = p < 0.05, ** = p < 0.01, *** = p < 0.001.*

				Intercept coefficients		Flow coefficients	
Significance of waterbody	**Waterbody #**	**Centroid Latitude**	**Centroid Longitude**	**estimate**	**z**	**estimate**	**z**
Most isolated/ disconnected	183	-31.167225	144.113218	-3.7	-10.2***	0.00017	7.7***
	285	-31.661510	143.336820	-2.5	-11.1***	0.00012	7.1***
	289	-31.732915	143.247911	-2.6	-11.1***	0.00012	6.7***
Most connected	197	-31.414355	143.892835	1.3	7.6***	0.00010	2.7**
	201	-31.426021	143.873319	2.2	9.8***	0.00004	1.3
	220	-31.444552	143.781430	1.3	7.9***	0.00009	2.7**
Largest	152	-30.913923	144.477991	0.8	5.6***	0.00004	2.2*
	425	-32.162945	142.802116	0.4	3.1**	0.00002	1.3
	431	-32.292784	142.636319	0.3	2.3*	0.00003	2.1*

Appendix 4: Sensitivity analysis

A sensitivity analysis using three different values (80, 85, 90) for the minimum water presence to determine the persistent waterbodies from the water persistence raster summary layer was performed. As expected, the number of defined persistent waterbodies differed when the minimum water presence value changed, with 437 waterbodies at the 80% level, 320 waterbodies at the 85% level, and 203 waterbodies at the 90% level. Only one of the most disconnected waterbodies was present at the 85% level, and only one of the most connected waterbodies was present at the 85% and 90% level. All three largest waterbodies were still present at the 85% and 90% minimum water presence levels.

Table A4.1. Indication of whether the selected waterbodies identified at the 80% minimum water presence level were considered waterbodies at the 85% and 90% minimum water presence levels.

Significance of waterbody	Waterbody #	Present at 85%	Present at 90%
Most isolated/ disconnected	183	Y	N
	285	N	N
	289	N	N
Most connected	197	N	N
	201	Y	Y
	220	N	N
Largest	152	Y	Y
	425	Y	Y
	431	Y	Y

Waterbody sizes were similar among the three minimum water presence levels, aside from a reduction in the size of the few largest waterbodies as the minimum water presence percentage increased (Fig. A4.1). This was expected and not considered to affect the results of the analysis given the high similarity in size distributions among the three levels.

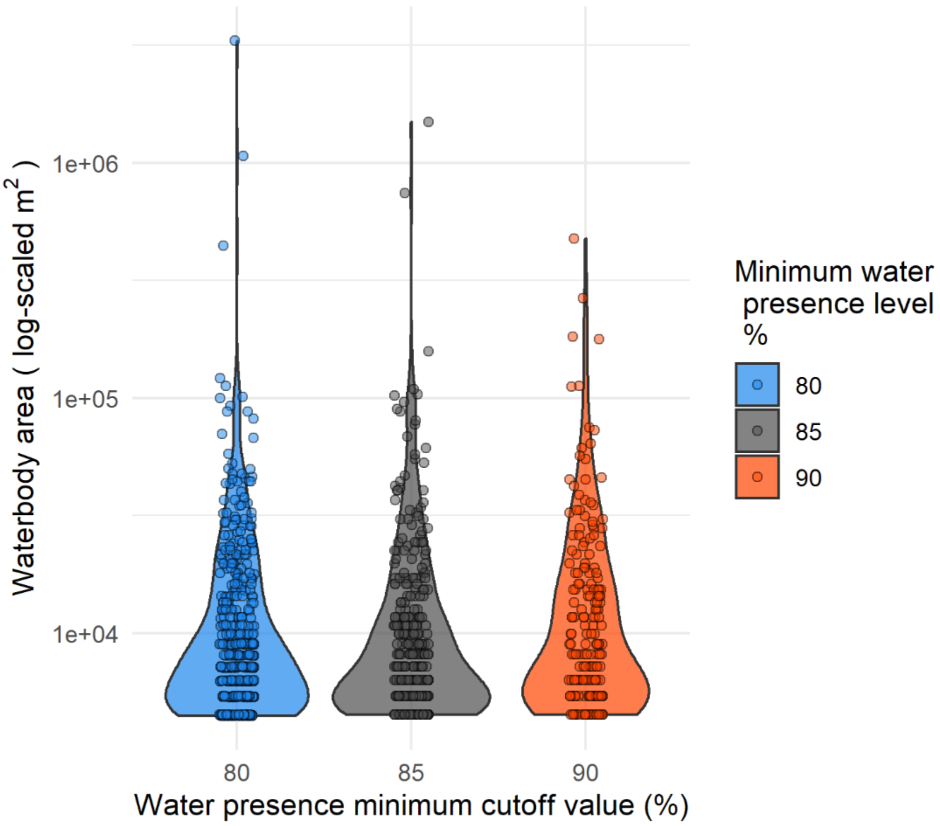

Figure A4.1. Violin plots showing waterbody sizes for each of the three cut-off percentage values used in the sensitivity analysis. The y-axis was log-scaled due to the data being highly skewed towards smaller sizes.

Although there was a different number of defined persistent waterbodies among the various chosen minimum water presence levels, this did not significantly impact the results of the connectivity analysis. At the reach level, the minimum water presence value chosen had a negligible effect on connectivity (Fig. A4.2), with both monthly and yearly mean values for 80% or 85% criteria almost identical. Reach scale connectivity values were similar for the 90% compared to the 80% and 85% criteria, with small variations from the 80% and 85% criteria during years when connectivity is lowest, indicating that the connectivity among the waterbodies that remain persistent at the 90% threshold for minimum water presence is likely to be slightly less impacted by extreme dry years.

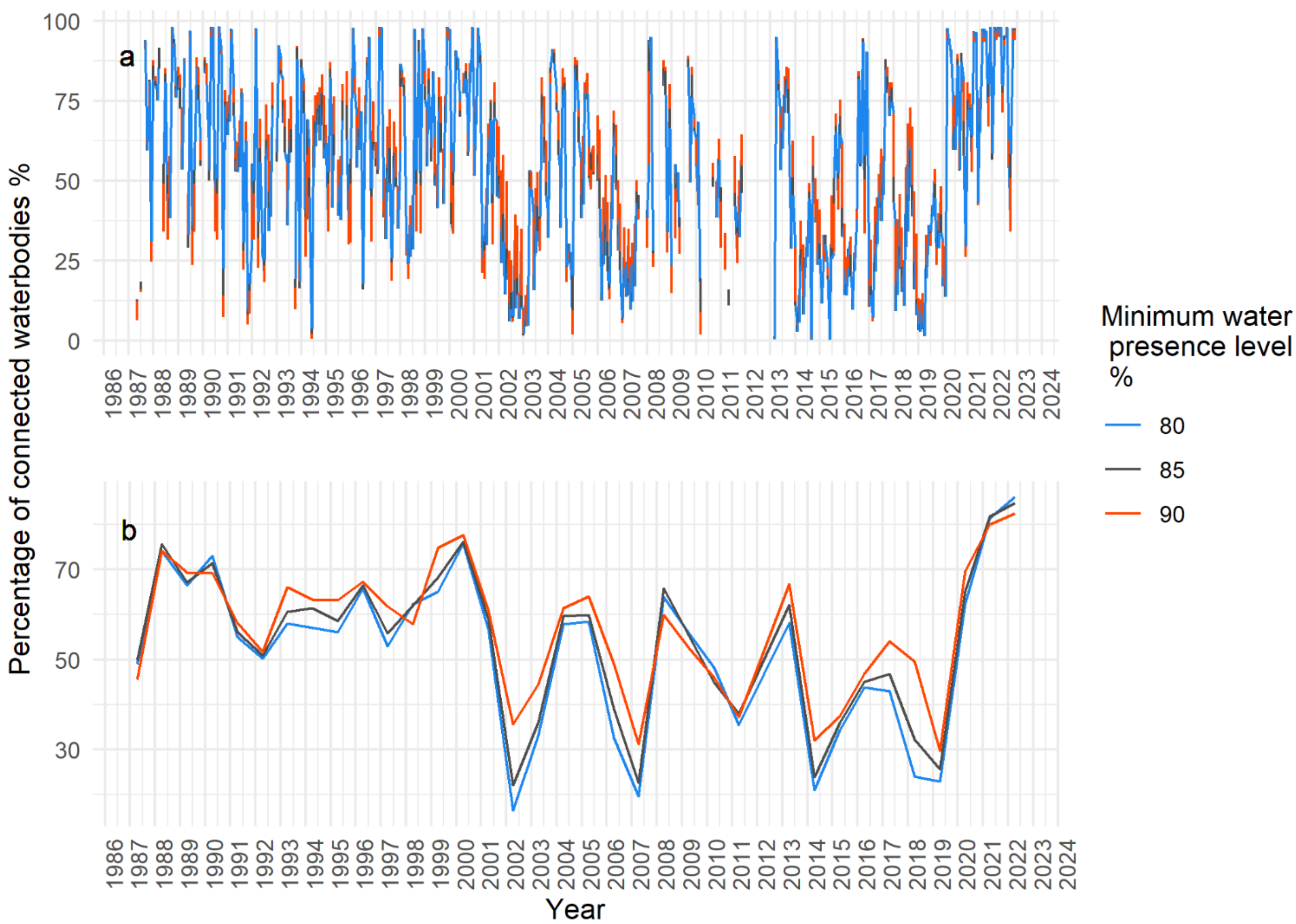

Figure A4.2. Monthly (a) and yearly mean (b) reach scale connectivity using three different minimum water presence values from the water persistence raster to define the persistent waterbodies.